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Yoshiteru Nakamori *Editor*

Knowledge Technology and Systems

Toward Establishing Knowledge Systems Science

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Preface

What is information technology? We imagine tangible devices such as computers and cell phones. We also associate it with the technology of processing intangible information using these devices. The latter belongs to soft technology that has no physical entity to operate. Soft technology develops tools that support human intellectual activities such as perception, thinking, and judgment, and manipulates the information generated from those activities. To better understand information technology, let us think about what information is. We have heard that information is data organized to support decision-making. Here, data includes the raw data that no one has yet interpreted and the interpreted data by someone, that is, knowledge of someone. Nowadays, we often hear the big data, which is large-scale, complex, and rapidly changing "data" that mixes raw data and knowledge. Information technology converts such data into information.

Imagine, then, the technology for interpreting the information thus obtained, building new theories, and predicting the future. Can we continue to call it information technology? We hesitate to say yes. Look for suitable terminology. As is widely recognized, if new theories and future predictions reach a level that helps us make decisions, we call them knowledge. Consider defining knowledge technology as soft technology that converts information into knowledge, imitating the definition of information technology above. However, although the term only changes from information to knowledge, the level of knowledge varies from person to person. There is a big difference between simply knowing something and mastering it. It is said that true knowledge is constructed by knowing and experiencing. We can define knowledge technology as a technology that converts information into knowledge. With this definition, however, the scope of knowledge technology is unclear as the scope of knowledge depends on people. Let us consider this issue below.

What power can we have by mastering knowledge? We can judge things with it. We can convert data and information into new knowledge, thereby creating ideas. Focusing on this ability, *define knowledge technology as soft technology that underpins the human creative activities of converting data and information into knowledge, creating new ideas based on that knowledge, and validating those ideas.* Such a definition will be subject to objections from other disciplines. They may complain that it is an act beyond rights to give a new name to technology developed in other fields. To create value from data through knowledge creation, we need to selectively use technologies in data science, statistical analysis, systems analysis, idea creation frameworks, and business management. If we regard all these technologies as knowledge technologies, we can resolve the ambiguity in the scope of knowledge technology. The above definition argues that the "knowledge" of knowledge technology is the ability of judgment or meta-knowledge.

Consider a corporate management method called knowledge management. It aims at supporting creative work by sharing the information and knowledge held by companies and intellectual assets such as know-how and experience possessed by individuals. For successful knowledge management, it is necessary to integrate the tacit knowledge of individuals with company-wide data and information. In other words, knowledge management is not just about managing knowledge. Thus, “knowledge” in knowledge management is regarded as knowledge in a broad sense, including data, information, and even ideas or wisdom. If we follow this usage, we get another reason for defining knowledge technology as described above. In short, knowledge technology manipulates data, information, and ideas or wisdom, not just knowledge. In summary, knowledge technology in this book is a general term for soft technologies contributing to somewhere in the process from data collection to value creation. It covers soft technological aspects of information technology, systems technology, and management technology.

This book focuses on people's idea creation and decision-making. The scope of application covers a wide range of human creative activities. Examples include creating ideas for new products and services, responding appropriately to hospital patients, deciding on summer menus for a restaurant, and developing technologies that balance economic development with environmental protection. In this way, knowledge technology also includes technology for processing people’s preferences and values. Call technology that handles large amounts of data mathematically or intelligently “mathematical or intelligent knowledge technology” and technology such as a business framework that promotes people’s free-thinking “participatory knowledge technology.” Chapter 1 defines knowledge technology using an idea creation spiral model and organizes the challenges of knowledge technologies responsible for the respective processes of the model. Chapters 2–9 introduce mathematical or intelligent knowledge technologies by researchers at the forefront of knowledge technology development.

Although this book does not introduce recent developments in participatory knowledge technology, we must use it with mathematical or intelligent knowledge technology to create ideas for solving complex problems in the real world. Chapter 1 defines the knowledge system and calls to develop a methodology for building a knowledge system. Roughly speaking, it is a system that creates ideas from data and knowledge. Based on the proposition that knowledge emerges by the interaction between explicit knowledge and tacit knowledge, *define the knowledge system as a system that promotes interaction between codified knowledge and personalized knowledge and creates ideas for solving a specific problem.* Here, codified knowledge includes data and information. Personalized knowledge is empirical knowledge or wisdom that is difficult to document. Therefore, a knowledge system involves codified knowledge retainers (i.e., knowledge bases) and personalized knowledge retainers (i.e., the human knowledge resource). These elements change over time while maintaining the overall functionality. If a new issue appears, people reconfigure their knowledge system immediately to address it. A company is a knowledge system to pursue profits, but to develop new products, the company combines necessary elements to form a small knowledge system that crosses the company.

Mathematical or intellectual knowledge technology is powerful, but it is necessary to understand its limitations when building a knowledge system. For one thing, a mathematical model is just a simplification of complex phenomena and does not cover all the concerns of the relevant people. For another thing, a mathematical model explains only past phenomena. Therefore, to create a future different from the past, we must incorporate the ideas of those involved in the problem. Therefore, when building a knowledge system, we need to use mathematical or intelligent knowledge technology and participatory knowledge technology in a complementary manner. Chapter 1 illustrates the complementary use of these technologies in building a knowledge system, although its specific construction is beyond the scope of this book.

Contributors to Chaps. 2–9 are active researchers at the International Society for Knowledge and Systems Sciences, founded in 2003. Individual researchers are developing specific technologies, while this Society covers technologies for the entire process of creating valuable ideas from data. This Society aims at co-evolving knowledge science and systems science. Knowledge science, which deals with the subjectivity of people represented by knowledge management, must learn the idea of systems science that suggests optimal behavior based on systematic and objective information. Systems science, contrarily, needs to incorporate the methods of knowledge science that utilize the vivid ideas of people. Review the subtitle of this book. It is “Toward Establishing Knowledge Systems Science.” It tells that we aim to integrate knowledge science and systems science to establish a new field for problem-solving in the age of big data.

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Chapter 1
Defining Knowledge Technology and Systems

Yoshiteru Nakamori

1.1 Knowledge Technology and Challenges

"Technology" here refers to "soft technology" that does not have a physical entity to operate. Human creative activities and decision-making belong to soft technology. People acquire such technologies from experience and validate them through tests and experiments in social life. This section defines knowledge technology that belongs to soft technology and discusses challenges in its development.

1.1.1 Defining Knowledge Technology

Very generally, knowledge technology can be defined as follows. Knowledge technology builds and operates tools and systems that manage knowledge-intensive activities and deal with the knowledge generated by those activities (Wang, 2011). But if we focus on the power of knowledge, we can paraphrase this definition. Knowledge is recognition memorized personally or socially, but there is an important reason to use the term knowledge rather than information. Knowledge is the ability to judge. Knowledge can convert data and information into new knowledge, thereby creating ideas. Define knowledge technology, focusing on this ability.

> *Knowledge technology is soft technology that underpins the human creative activities of converting data and information into knowledge, creating new ideas based on that knowledge, and validating those ideas.*

Knowledge technology is a general term for soft technologies that contribute to at least one process from data collection to value creation. It covers soft technological

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aspects of information technology, systems technology, and management technology.

1.1.1.1 A Value Creation Spiral Model

This section introduces a value creation spiral model and regards knowledge technology as the technology used in at least one of the processes of the model. Figure 1.1 shows the OUEI spiral model (Nakamori, 2021) to create value from data that consists of the following four processes.

1. Observation: converting data or knowledge into information
2. Understanding: converting information into knowledge
3. Emergence: creating ideas from the knowledge
4. Implementation: validating the value of ideas

First, mobilize available media to collect the information necessary without compromise. Instead of relying on "How-to," pursue "Why-What." Instead of hurrying to produce ideas directly, grasp the essence of the collected information to create knowledge. Produce problem-solving ideas based on the knowledge

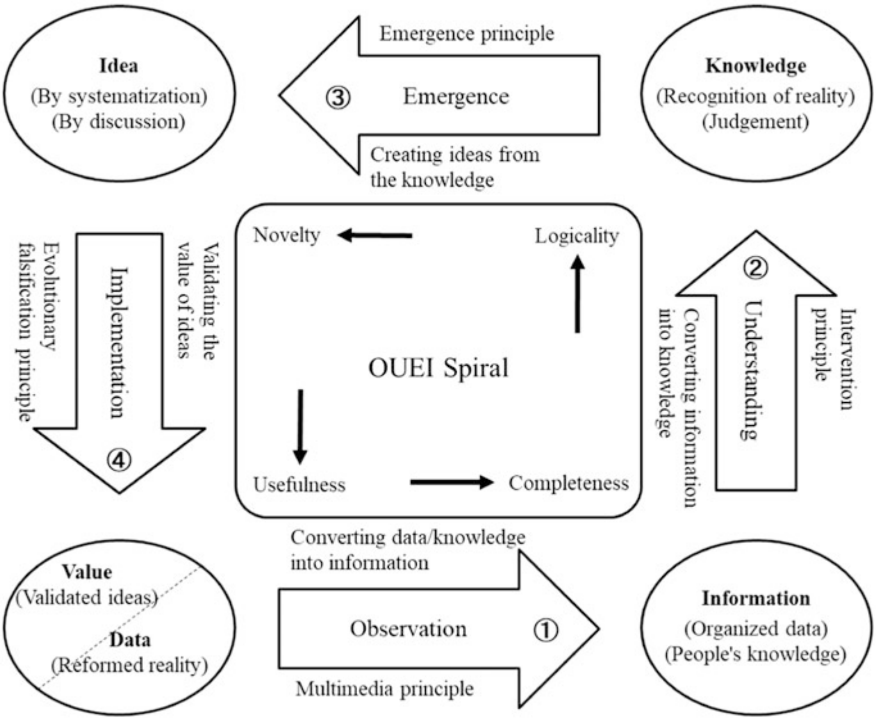

Fig. 1.1 The OUEI spiral of describing the processes of creating value from data

constructed. Keep in mind falsifiability when validating ideas through practice. Figure 1.1 presents principles to follow in respective processes, which are the multimedia principle, intervention principle, emergence principle, and evolutionary falsification principle. Figure 1.1 also shows four keywords: completeness, logicality, novelty, and usefulness, which indicate the goals to be achieved using knowledge technology in the respective processes. Sections 1.1.1.2 and 1.1.1.3 will explain these principles and goals in detail.

1.1.1.2 Principles of Providing Action Guidelines

The knowledge construction systems methodology (Nakamori, 2019), to be introduced in Chap. 8, takes the position of constructive evolutionary objectivism, which consists of four principles. Nakamori (2021) offers to use the four principles as guidelines for running the four processes of the OUEI spiral.

1.1.1.2.1 Multimedia Principle

The original multimedia principle in Wierzbicki and Nakamori (2007) states that since words are just approximate codes to explain complex reality, we should use multimedia to collect visual and auditory information to stimulate creativity. But with the rapid development of information and communication technology, this requirement has become outdated. It has become easier for us to obtain data in various formats nowadays. Therefore, the modern meaning of this principle must be as follows. "Collect large amounts of complex data in various formats on various media, depending on the purpose. Then, use appropriate technology according to the media to organize them as information. The development of knowledge technology that makes this possible is progressing rapidly."

1.1.1.2.2 Intervention Principle

In this age of big data, advanced technologies for collecting information are developing one after another. But "when converting information into knowledge," we must be actively involved in the process. Otherwise, we will lose the opportunity to understand the knowledge deeply. In other words, rather than automating the process of analyzing information, we must deepen our understanding by proactively intervening in it. Do not rely entirely on existing statistical methods or artificial intelligence in developing prediction models. It is crucial to actively intervene in the data analysis, such as determining model structure or variables. Doing so will give us confidence in the knowledge we have created and, as a result, improve our ability to justify and promote the ideas generated by that knowledge.

1.1.1.2.3 Emergence Principle

One of the properties of the system is emergence. It is a phenomenon that new features not found in the lower level appear in the upper level. If a set of codified knowledge or a group of people with various knowledge becomes a system, it will have the ability to create new ideas. Two types of knowledge technology that induce emergence are:

- Systematization: Stimulating people's creativity by structuring (associating and visualizing) various knowledge
- Creative Technologies: Creating ideas by planning and directing the interaction of people with various knowledge

Note that, in the former case, ideas would not emerge automatically. People involved and analysts need a comprehensive understanding of systematized knowledge to generate ideas.

1.1.1.2.4 Evolutionary Falsification Principle

Hypotheses, theories, models, and tools develop evolutionarily. A measure of their evolutionary goodness of fit is the number of successful disproof tests or the number of critical discussion tests that have led to a subjective consensus on their effectiveness. This idea is an integration of falsificationism and demonstrative subjectivism.

- Falsificationism: New ideas can be the result of inappropriate inductive reasoning. Therefore, we must examine their robustness against observations and experiments that deny them. Strict scientific falsification testing is difficult for business problems, but we need to think of a validation method that reflects its spirit as much as possible.
- Demonstrative subjectivism: Ideas are subjective because people create them. Therefore, justification must rely on intersubjective arguments. Here, intersubjectivity is the establishment of consent among multiple people.

1.1.1.3 Goals of Respective Processes

Figure 1.1 shows the goals of four processes we must accomplish according to the above four principles. These are also criteria for the ex-post evaluation of the value creation activities.

1.1.1.3.1 Completeness

If there is not enough data, it is necessary to narrow the scope of the analysis. On the contrary, if too much data is collected, the speed becomes slower due to selection.

However, it is generally hard to collect just enough data for the purpose, both in quality and quantity. That is because we do not know in advance what is just enough. Nevertheless, do not give up on pursuing data completeness. Envision the necessary data for the purpose as follows: (a) Imagine what ideas are necessary to reach the purpose, (b) Think about what knowledge and information are necessary to generate those ideas, and (c) Identify the big picture of the data needed.

1.1.1.3.2 Logicality

Descriptions of models and theories must be concrete and logical so that people can understand them well. To explain the analysis results logically, it is necessary to fully understand the strengths and weaknesses of the knowledge technology used. When the problem is difficult to analyze mathematically, we can use a knowledge technology called a framework that synthesizes expert opinions. But even if using professional intuition, a logical explanation is needed. People never act unless they are convinced. Logicality is very important to justify an idea and put it into practice.

1.1.1.3.3 Novelty

The problems to solve are future problems, not past problems. Past solutions do not always work in the future. To address new issues, we need to produce innovative ideas. Here, there are two types of novelty. One is a revolutionary novelty that no one in the world has ever considered. The other is a novelty for us, but someone in the world has already considered it. Most new ideas may be the latter type. In this case, we need to analyze the execution result of others to know their effectiveness. If our idea is the former type, we cannot implement it smoothly. People are not convinced just by being new. To persuade people, remember the logicality above.

1.1.1.3.4 Usefulness

Ideas for social projects and new products need to be particularly useful. In the case of commercial activities, we can use knowledge technologies to measure the value that new ideas bring to the customers. For example, Aaker (2011) proposes to measure value by three benefits: the functional benefit, the emotional benefit, and the self-expression benefit. We can also examine the utility quantitatively by the profit fluctuations. On the other hand, the usefulness of ideas from non-profit activities, such as theoretical research and academic investigations, is measured by their contribution to the development of society and scholarship.

1.1.2 *Challenges in Developing Knowledge Technology*

This section summarizes Nakamori (2021) to present the challenges of developing knowledge technologies used in the four processes of the OUEI spiral model.

1.1.2.1 Challenges in Converting Data/Knowledge into Information

When we try to collect information to solve a given problem, we can find two types of information with different origins. One is the data organized for decision-making, and the other is the knowledge of others transmitted by letters, symbols, or voices. As shown below, the knowledge technologies for dealing with these two are naturally different.

1.1.2.1.1 Converting Data into Information

Knowledge technology to convert not only numerical data but also text, voice, and image data into information has made remarkable progress today. Technological development began with the tabulation and graphing of structured data. It evolved into the discovery of meaning from numerical data and text data. Recently, developing technologies to manage big data has been attracting attention. The more complex the data and knowledge are, the more complex the technology that processes them becomes. Users want to know what information to collect when faced with a problem. Therefore, challenge the following technological development:

Challenge 1. Develop a measurement optimization framework for collecting just enough quantitative information to explain and solve the problem.

Traditionally, data analysts analyze given or obtained data to gain insights. This inductive reasoning is empirical statistical inference, and the conclusion may change with the emergence of new data. Consider a hypothetical reasoning method called abduction. Abduction begins with a purposeful observation of facts. Having a sense of purpose makes abduction different from other knowledge creation methods. Instead of inferring based on given data, as in induction, consider identifying the data needed for inference. Develop a measurement optimization framework that systematically searches for data that substantiates the hypothesis about what caused the situation at hand.

1.1.2.1.2 Converting Knowledge into Information

The larger the quantified dataset, the harder it is to understand it without qualitative interpretation. Therefore, using big data effectively requires thick data (Jemielniak, 2020). Thick data is data related to insights such as human experience and the quality of behavior. Some idea creation methodologies incorporate knowledge technologies for the collection of such knowledge. Soft systems methodology (Checkland, 1981) and organizational knowledge creation theory (Nonaka & Takeuchi, 1995) have a process in which participants verbalize the problem situation. Big data can answer who, what, and when, but not why. What is needed now is a qualitative survey that answers why. Therefore, challenge the following technological development:

Challenge 2. Develop a hypothesis collection framework that asks "Why" what we are seeing is happening.

There are many methodologies for collecting the opinions of experts or stakeholders to explain what is happening. Equally or even more important than developing a measurement optimization framework is developing a hypothesis collection framework for organizing various views on the data. We are entering an age of increasingly flooded data. But analyzing the data that happens to be acquired does not always lead to the correct decision-making. Collect data following the hypotheses and construct the knowledge to create ideas.

1.1.2.2 Challenges in Converting Information into Knowledge

Knowledge is recognition memorized personally or socially. Notably, knowledge has the power to generate new knowledge from information if it becomes judgments or a judgment system valid objectively. "Knowledge" in knowledge technology has this power. We can divide the knowledge technology that converts information into knowledge into two categories. They are mathematical or intelligent knowledge technology and participatory knowledge technology.

1.1.2.2.1 Utilizing Well-Established Rational Analysis Methods

The human activity system dealt with in this book is not a system with a theoretically clear internal structure. As inferring relationships between variables from data is the central issue of the analysis, multivariate analysis methods are the primary tools. In the age of big data, machine learning to perform modeling automation is getting more and more attention. But it is logically impossible to judge whether the constructed model accurately describes the original phenomenon. Therefore, challenge the following technological development:

Challenge 3. Advance knowledge technology along the dimension of complexity. Balance the accuracy and understandability of the model.

Prediction models cannot accurately predict the future. Prediction models reproduce past trends based on historical data. A prediction model is useful when the situation continues in the same way as in the past. Nevertheless, we must continue to build prediction models to understand the complex world. Here, keep in mind to balance the accuracy and understandability of the model. Understanding the model increases the chances of coping with changing circumstances. Since it is necessary to understand the model for generating ideas, Sect. 1.1.1.2.2 introduced the intervention principle as a guideline for converting information into knowledge. Promote the development of knowledge technology that allows people to participate in model building actively. It is an important issue even in an age when big data and artificial intelligence dominate.

1.1.2.2.2 Utilizing the Cultivated Intuition of People

Another approach to understanding and modeling complex phenomena is to utilize expert/participant empirical knowledge and sophisticated intuition. This approach includes qualitative data analysis methods to extract knowledge from recorded sentences and participatory methods to collect knowledge from participants. The knowledge management system is a system for sharing various knowledge accumulated by individuals throughout the organization and effectively managing and sharing it for corporate management. However, it is difficult to express "experience-based knowledge" or "tacit knowledge" in words. Even if codification is successful, it is essential to interact with experienced people to understand it. Therefore, challenge the following technological development:

Challenge 4. Advance knowledge technology along the dimension of human relations. Balance systemic desirability and cultural feasibility.

There are two types of knowledge handled with knowledge technology. We need to communicate and share in a way that suits each. One is rational knowledge. As the volume of information increases, the complexity increases, so it is necessary to develop knowledge technology that produces knowledge from complex information. It is the evolution of knowledge technology along the dimension of complexity mentioned above. The other is intuitive knowledge. There is a kind of knowledge that we cannot obtain without the same experience. It is intuitive knowledge gained from long-term experience and human relations. Therefore, it is also necessary to develop knowledge technologies along the dimension of human relations. These knowledge technologies must co-evolve because there is a need to balance systemic desirability and cultural feasibility in solving business or social problems. Note that the terms "systemic desirability" and "cultural feasibility" originate in soft systems methodology (Checkland, 1981).

1.1.2.3 Challenges in Creating Ideas from the Knowledge

Here, we consider two approaches to creating ideas. One is idea generation based on systematized knowledge, and the other is idea generation through people's discussion using creative technologies. The former is the systems thinking approach, and the latter is the knowledge management approach.

1.1.2.3.1 Creating New Ideas Through the Systematization of Knowledge

Imagine creating ideas by knowledge systematization. But systematizing knowledge does not automatically generate ideas. The existence of people who understand systematic knowledge and generate ideas is indispensable. Mathematical models are a kind of systematized knowledge. Optimization, risk analysis, and simulation technologies using mathematical models inspire us to create new ideas. Agent-based simulation (Axelrod, 1997; Holland & Miller, 1991) and system dynamics (Forrester, 1961; Sterman, 2000) support abduction (hypothetical reasoning). But we cannot get rid of anxiety about the validity of the hypothesis. It is attractive to build a simulation system linked to a comprehensive knowledge base, which is also systematized knowledge. Therefore, challenge the following technological development:

Challenge 5. Develop simulation technology for hypothetical reasoning linked with a comprehensive knowledge base and big data.

Mathematical models built with the data from the past to the present have limitations in predicting the future. That is, while we can enjoy the progress of pattern recognition and natural language processing, we must be careful about future predictions. Data mining and machine learning are not theoretical, so the interpretation of the results is left to the analyst. Hilbert (2016) states, "in the future, the combination of theory-driven models and big data will become the gold standard for computational social sciences." However, it is a problem to set the conditions too freely and keep them away from reality. Too much deviation from the knowledge of the comprehensive knowledge-based system would be difficult to achieve. We should also pay attention to trends in big data to confirm what is happening now. Develop a simulator that supports hypothetical reasoning about the impact of new ideas within a realistic range.

1.1.2.3.2 Creating New Ideas with Creative Technologies

Consider ways to create ideas through the interaction of people with different knowledge and information. An organization consists of diverse people with diverse experiences and abilities. There exist many creative technologies that help them work together to create ideas. Knowledge management, which uses these technologies, has been established as one of the corporate management methods. It aims to lead to creative work by sharing the information and knowledge held by a company and intellectual assets such as know-how and experience possessed by individuals. Building a knowledge management system is essential for any organization. But equally important is to create an environment that facilitates knowledge creation. Therefore, challenge the following technological development:

Challenge 6. Develop knowledge technology that systematically integrates personnel, technology, organization, culture, and management to strengthen the ability to create ideas through knowledge management.

The purpose of knowledge management is to generate ideas through the interaction of people. Generating ideas with confidence requires systematized knowledge. From the opposite angle, the purpose of knowledge systematization is to combine the collected knowledge to generate ideas. However, we cannot expect new ideas to emerge automatically. Therefore, those involved in the problem must lead the emergence. To that end, they can leverage knowledge management ideas such as organizational knowledge creation theory. Thus, the fusion of systems thinking and knowledge management is extremely promising.

1.1.2.4 Challenges in Validating the Value of Ideas

Implementing new products and services is costly and requires internal approval. Once approved, the persons in charge move on to implement the idea. At that time, they will consider ways to promote and validate it.

1.1.2.4.1 Justifying and Promoting the Ideas

Justification does not guarantee that a new idea is objectively correct or valid. Verification of an idea requires its practice, and justification is the act of obtaining permission to practice it. In this sense, it may be correct to say that it is permission or authorization rather than justification. There is a lot of uncertainty in the data and statistics, so we need to justify the idea through a detailed discussion. Design thinking (Brown, 2008) has the processes of justification and promotion. It recommends failing quickly and cheaply because failure after spending money and time is a pain. The main methods of justifying ideas in design thinking are prototyping and storytelling. They appeal to the sensibility rather than the reason of the audience. Therefore, challenge the following technological development:

Challenge 7. Consider ways to appeal to people's sensibilities, not only to their reason, for justifying and promoting ideas.

Let us consider ways to make an idea persuasive. First, we must be able to confidently claim that we have seriously pursued the goals of the value creation process: completeness of observation, logicality of understanding, and novelty of the idea. Once we get approval for an idea internally, we will run a campaign to promote it. Think about the knowledge technology that supports promotion. Recently, marketing that appeals to consumers' emotions has been attracting attention. It aims to create economic value by talking about the tastes and spirits derived from the creator's sensibility, appealing to the consumer's sensibility, and evoking excitement and empathy.

1.1.2.4.2 Implementing the Ideas and Verifying the Value

Verification means putting the idea into practice and seeing if it has value. There are agreed methods to confirm the results of scientific experiments or the effects of new drugs. However, it is not scientifically possible to test the effectiveness of ideas for dealing with economic and business problems. Nevertheless, it is necessary to pursue a method of verification that is as objective as possible. At the same time, we must reflect on our actions in idea creation. Recall the internalization process of the organizational knowledge creation theory. Therefore, challenge the following technological development:

Challenge 8. Consider ways to verify ideas through rating the actions that created ideas in addition to quantitative evaluations of ideas.

The evolutionary falsification principle incorporates the traditional falsificationism claimed by Popper (1934). People may derive new theories through inappropriate inductive reasoning or intuitive inspiration. So, they must show their robustness through observations or experiments that deny it. It is difficult to use this principle in social or business issues strictly. Consider ways to verify ideas by rating the actions that created them. It is relatively easy to make a quantitative evaluation because we can get numerical data such as an increase in sales. However, the quantitative assessment is not perfect due to the lack of data on other approaches we did not implement. One way to make up for that is to assess the adequacy of the actions that led to idea creation.

1.2 Knowledge Systems and Challenges

This section defines the knowledge system and discusses challenges in its construction. The Longman Dictionary of Contemporary English describes the term "system" as follows:

1. A system is a group of related parts that work together as a whole for a particular purpose.
2. A system is an organized set of ideas, methods, or ways of working.
3. A system is a group of computers that are connected.

In the above, it does not matter what the elements of the group are. English dictionaries do not clarify them, but the system has features to achieve its purpose: emergence characteristics, a hierarchical structure, and the ability to survive against changing environments. Here, emergence is a phenomenon in which new properties appear in the upper layer due to the interaction between the elements in the lower layer. In the case of the knowledge system, it refers to the phenomenon where new knowledge emerges by combining existing knowledge.

1.2.1 Defining Knowledge Systems

The knowledge system first meets Definition 1 above. It also fits Definition 2 above when built to solve a particular problem. When dealing with large-scale organizational or social issues, it has the aspect of Definition 3 above. After defining the knowledge system, Sect. 1.2.1.2 introduces knowledge systems engineering (Wang, 2004) that builds and operates knowledge systems.

1.2.1.1 Systems Managing and Creating Knowledge

Roughly speaking, a knowledge system is a system that creates ideas from data and knowledge. Focusing on the importance of the interaction between explicit and tacit knowledge in knowledge creation, define:

> *A knowledge system is a system that promotes interaction between codified and personalized knowledge and creates ideas for solving a specific problem.*

Here, codified knowledge includes data and information, not only knowledge. Personalized knowledge is empirical knowledge or wisdom that is difficult to document. A knowledge system includes codified knowledge retainers (i.e., knowledge bases) and personalized knowledge retainers (i.e., the human knowledge resource). Wang and Wu (2015) stated as follows. Due to the abstraction and intangibility of knowledge, people tend to accumulate knowledge from carriers such as books, newspapers, and electronic media. But in essence, people or organizations themselves are carriers of knowledge. They compose the fundamental elements of a knowledge system.

The knowledge system does not mean artificial intelligence because it includes carriers of personalized knowledge. However, the elements that behave intelligently with codified knowledge are welcome. Therefore, we use mathematical or intelligent knowledge technologies to systematize knowledge. At the same time, we use participatory knowledge technology to promote interaction between codified knowledge and personalized knowledge. A knowledge system will achieve its goal through the complementary use of these knowledge technologies. This claim shares the idea with the organizational knowledge creation theory (Nonaka & Takeuchi, 1995) that knowledge emerges through the interaction between explicit and tacit knowledge.

A company is a knowledge system aimed at survival and growth. A large company hierarchically manages many subsystems. Each subsystem needs a talent structure to drive the emergence of ideas to achieve better results. Thus, each subsystem is a knowledge system with its purpose. A company temporarily forms cross-organizational teams according to its purpose. For example, a new product development team consists of people from R & D, sales, public relations sections, etc. The team will be a knowledge system that promotes idea creation by systematizing the necessary data, information, and knowledge.

Knowledge technology is the meta-knowledge that contributes to creating a part of or all the knowledge system. There is a need for meta-meta-knowledge, or a knowledge system construction methodology, that provides strategies (including usage of individual technologies and their combinations) to develop an entire knowledge system. We will discuss this in Sect. 1.2.2.3. Before that, to see what a knowledge system looks like, let us look back at the proposal of Professor Zhongtuo Wang of the Dalian University of Technology, who advocated knowledge systems engineering.

1.2.1.2 Knowledge Systems Engineering

Wang (2004, 2011) proposed to develop a new field of systems engineering called knowledge systems engineering. It aims for the organization and management of knowledge systems. Imagine broadly managing the information and knowledge of an entire company. The purposes of knowledge systems engineering are:

- To provide the appropriate information to the right people at the right time,
- To create, acquire, share, and utilize the knowledge needed for an organization to succeed, and
- To create new knowledge to meet the growing demand beyond knowledge management.

With enterprise knowledge systems in mind, Wang and Wu (2015) show the architecture of a knowledge system that consists of five components: personnel, organization, technology, business, and culture. All these components in the architecture are necessary and interdependent. Personnel works together using technologies to produce products or services. Organizational culture supports the strategic positioning of knowledge management within the organization. People shape the culture, manage the content, deliver the process, work with the technology, and create value in the knowledge system.

Below are the goals of developing knowledge systems engineering with corporate knowledge systems in mind. Note that these goals roughly correspond to the processes of the OUEI spiral model.

1.2.1.2.1 Knowledge Gathering and Capture (Corresponding to Observation)

Knowledge systems engineering uses knowledge technologies to collect and organize numerical and textual data. Available technologies and systems include data mining, text mining, web technologies, cloud computing, databases, text-bases, data warehouses, data lakes, data marts, and more.

Knowledge systems engineering scans various internal and external sources to gain knowledge. Internal knowledge comes from staff, technical information, business processes, day-to-day processes, and organizational culture. On the other hand, external knowledge comes from customers, suppliers, competitors, or personal and professional networks. Knowledge capture technologies and systems include knowledge elicitation, search engines, intelligent agents, knowledge maps, knowledge repositories, and knowledge portals.

1.2.1.2.2 Knowledge Discovery and Creation (Corresponding to Understanding)

Since its origin is systems engineering, knowledge systems engineering seeks knowledge through mathematical analysis and modeling. At the same time, it recommends converting information into knowledge by expert intuition. It maintains an organization's knowledge repository and seeks to use that knowledge effectively to create value. In parallel, it facilitates the transfer and sharing of knowledge among employees, ensuring that the entire organization can make the most of it.

Knowledge systems engineering recommends developing knowledge-sharing systems to generate ideas in the next step. They are, for example, lesson learned systems, practice systems for sharing tacit knowledge in a community, and new types of knowledge-based systems for structuring/validating knowledge assets. To transfer and share tacit knowledge, it recommends "soft approaches" such as face-to-face education in addition to "hard approaches" using information and communication technology.

1.2.1.2.3 Knowledge Sharing and Exchange (Corresponding to Emergence)

As knowledge is transferred and shared from one to another, people combine different knowledge to create new ideas. This process of transmitting and combining knowledge focuses on synthesizing the understanding of a given subject from different perspectives. Systems that support the generation of ideas through systemization include help desk systems, fault diagnosis systems, advisor systems, and decision support systems. Examples of inference systems include rule-based reasoning systems, constraint-based reasoning systems, case-based reasoning systems, and diagrammatic reasoning systems.

Think about ways to create ideas by systematizing knowledge. Building a system that integrates reasonably acquired knowledge, intuitively acquired knowledge, and ever-increasing information does not automatically generate new ideas. The system users create new ideas, exploring the overall meaning of the integrated knowledge. Knowledge systems engineering creates ideas by utilizing mathematical and participatory technologies in a complementary manner.

1.2.1.2.4 Knowledge Integration and Application (Corresponding to Implementation)

Wang and Wu (2015), quoting Conway and Sligar (2002), summarize what to keep in mind when practicing new ideas.

- Cost of practice: New solutions put risks and financial burdens on the organization. Costs include upfront investment such as hardware, software, labor costs for development, and technical and non-technical operating costs.
- Organizational competence: The organization needs to balance its three functions: customer satisfaction, product leadership, and organizational management. Outstanding performance in one direction can lead to prosperity. Conversely, incapacity in another can threaten the survival of the organization.
- Proof of success: The organization needs to align the objectives of its knowledge management programs with the success criteria of its business and develop a set of evaluation methods that reflect this coordination.

Since there is a wide range of other risks, a disciplined approach to risk management is essential. However, overspending on risk management may reduce the value created by the initiative. Therefore, a sense of balance is needed.

1.2.2 Challenges in Developing Knowledge Systems

The knowledge system uses both codified knowledge and personalized knowledge to generate ideas. To get ideas for building knowledge systems, let us learn two systems methodologies: Meta-synthesis Systems Approach and Critical Systems Thinking. The former promotes a large-scale project by using both quantitative and qualitative methods. The latter suggests appropriate technologies to solve a complex problem. Based on these, this section calls for developing a systems methodology to build knowledge systems using mathematical or intellectual knowledge technologies and participatory knowledge technologies in a complementary manner.

1.2.2.1 Meta-Synthesis Systems Approach

In the mid-1980s, when China was transitioning from a planned economy to a market economy, Qian et al. (1990) proposed a new systems methodology called the meta-synthesis systems approach. It addresses the problems of open, complex, and giant systems that are difficult for reductionist approaches to tackle. Its working philosophy is “from reliable qualitative hypotheses to rigorous quantitative verification.” Yu and Tu (2002) clarified three types of meta-synthesis. They are (a) qualitative meta-synthesis, (b) qualitative-quantitative meta-synthesis, and (c) meta-synthesis from qualitative understanding to quantitative verification. Gu and Tang (2005) described a way to achieve three types of meta-synthesis by the Synchronous-Asynchronous-Synchronous process (or Expert Meeting-Analysis/Synthesis-Evaluation Meeting). Below is a brief description of this approach.

1.2.2.1.1 Expert Meeting

Qualitative meta-synthesis is performed from data collection to the expert meeting as follows. Before the expert meeting, the persons in charge collect the data and knowledge necessary to solve the problem. Then, at the expert meeting, the participants define the problem, select the methods, and set the hypotheses based on their knowledge while referring to the quantitative data. In this way, they perform a qualitative meta-synthesis. Many tools and methods are available to support, facilitate, and analyze discussions at the expert meeting, such as brainstorming (Osborn, 1963), affinity diagram (Kawakita, 1967), and scenario planning (for instance, see Wade, 2012).

1.2.2.1.2 Analysis

This approach begins with qualitative analysis and proceeds to detail quantitative calculations. Qualitative analysis methods are analytical frameworks such as logic tree (see Chevallier, 2016) and SWOT analysis (Humphrey, 2005). Quantitative analysis methods are mathematical systems engineering methods. At this stage, each analyst (or each group) independently builds models, such as predictive, evolutionary, economic, and expert models.

Gu (2010, 2015) recommends the following "Mining Six" as methods to be used from the stage of data collection to this analysis: data mining, text mining, web mining, model mining (obtaining calculation results from prediction models), psychological mining (digging into the ideas behind human psychology), and expert mining (requesting judgment regarding conflicting opinions and mining results).

1.2.2.1.3 Synthesis

Qualitative-quantitative meta-synthesis lasts from data collection to this stage. This stage uses different models and their integration to analyze the different scenarios quantitatively created at the expert meeting stage. We can use traditional systems engineering and operations research here. If necessary, we can check the behavior of complex systems by system dynamics or agent-based simulation. For new problems, new ideas are sought based on human imagination, intuition, and insight. Here, the idea creation frameworks such as mind map (Buzan & Buzan, 1996) and cross SWOT analysis (Weihrich, 1982) are available.

Analysts try to create an integrated idea by referring to the above analysis results. But this task is difficult even for a good analyst. The meta-synthesis systems approach plans qualitative-quantitative meta-synthesis at this stage, but it is not easy to mathematically synthesize knowledge of different expressions. We need to take advantage of the subjectivity of the participants in question. We can use the approach developed in Nakamori (2021), which synthesizes qualitative and quantitative knowledge using a knowledge construction diagram.

1.2.2.1.4 Evaluation Meeting

The meta-synthesis systems approach finally justifies the ideas at the evaluation meeting. Participants of the evaluation meeting are different from those of the first expert meeting. Participants of the expert meeting are experts in their respective fields. On the other hand, participants of the evaluation meeting include decision-makers and managers. Meta-synthesis from Qualitative Understanding to Quantitative Verification continues from the first data collection to this stage. At the evaluation meeting, participants evaluate the models, computational programs, analysis results, etc., and finally decide whether to implement the ideas or not. In some cases, they must return to the previous stage.

To make a final decision, participants can use consensus-building methods to converge their opinions. In most cases, they repeat this process until they reach a satisfactory implementable conclusion. If participants still have different views, synthesize them in the following way.

- (Utilization of documents) Participants in the evaluation meeting should carefully read the opinions of others and try to reach a consensus.
- (Through interviews) The facilitator interviews participants individually to hear their opinions that are difficult to express at the meeting and synthesize them.
- (At the meeting) A quality meeting should have an atmosphere that makes it easy for participants to express their opinions. Focus on the Japanese word “Ba,” which means place or environment, including both virtual and physical space. Nonaka et al. (2000) emphasize the importance of designing effective “Ba” to promote knowledge creation.

1.2.2.2 Critical Systems Thinking and Practice

Critical Systems Thinking suggests ways to combine the various available methodologies for successful intervention in complex social problem situations. Here, let us first look at the historical background of the emergence of this thinking. Until the 1970s, system researchers sought to analyze systems in the same way that natural scientists had achieved success. However, in the 1970s and 1980s, some systems researchers criticized that such traditional systems thinking could not address strategic issues that were not structured. Those critics developed organizational cybernetics (Beer, 1972), soft systems thinking (Ackoff, 1974; Checkland, 1981; Churchman, 1971), and critical systems heuristics (Ulrich, 1983) as alternatives to the traditional approaches. These approaches have different philosophical and sociological assumptions and compete with each other.

The motivation for developing critical systems thinking was to successfully intervene in complex social problem situations by combining various available methodologies, including traditional systems methodologies (see, for example, Flood & Jackson, 1991b, Mingers & Gill, 1997). The first achievement was the "system of systems methodologies" (Jackson & Keys, 1984). It recommends using a combination of appropriate systems methodologies to address different problem situations and different objectives. The second achievement was "pluralism" as a central belief in critical systems thinking. Pluralism encourages the best use of different methodologies based on the assumptions of different paradigms (Jackson, 1987). Then, total systems intervention (Flood & Jackson, 1991a, 1991b) succeeded in providing guidelines for the practical use of critical systems thinking. In summary, critical systems thinking is essentially about putting all the different management science methodologies, methods, and models to work, in a coherent way, according to their strengths and weaknesses and the social conditions prevailing, in the service of a general project of improving complex societal systems (Jackson, 2001).

Critical Systems Practice seeks to translate the philosophy and principles of critical systems thinking into practical application. It sets out four stages that are necessary to ensure this happens: Explore (the problem situation), Produce (an intervention strategy), Intervene (flexibly), and Check (on progress) (Jackson, 2020).

Stage 1. Explore the Problem Situation

- View it from five systemic perspectives (explained later).
- Identify primary and secondary issues.

Stage 2. Produce an Intervention Strategy

- Appreciate the variety of systems approaches.
- Choose appropriate systems methodologies (explained later).
- Choose appropriate system models and methods.
- Structure the problem, schedule, and set objectives for the intervention.

Stage 3. Intervene Flexibly

- Stay alert to the evolving situation (revisit Stage 1).
- Stay flexible about appropriate methodologies, models, and methods (revisit Stage 2).

Stage 4. Check on Progress

- Evaluate the improvements achieved.
- Reflect on the systems approaches used.
- Discuss and agree on the next steps.

The following describes five systemic perspectives in Stage 1: machine, organism, cultural/political, societal/environmental, and interrelationships (Jackson, 2020).

- The machine perspective regards the situation in question as a machine made up of connected parts to pursue a goal. Parts must be present and properly installed.
- The organism perspective provides an ideal-type model of an organism to diagnose pathologies in a problem situation or suggest system design to survive and thrive.
- The cultural/political perspective focuses on how humans think, act, and interact.
- The social/environmental perspective identifies ignored stakeholders, discrimination, inequality, etc., and suggests considering impacts on disadvantaged people and the environment.
- Finally, the interrelationships perspective reminds us of the interrelationships between the issues identified.

In Stage 2, we must choose the most suitable systems methodologies, methods, models, and tools, to address the issues highlighted by using the above perspectives. Jackson (2019) recommends using SOSM (System of Systems Methodologies), which provides a guideline for choosing methodologies. SOSM places available methodologies onto a two-dimensional plane of problem complexity and relationship complexity (Jackson & Keys, 1984). Williams and Hummelbrunner (2010) provide a toolkit of methods, models, tools, and techniques, which the critical systems practitioner can choose from in constructing appropriate systemic responses to complex problem situations.

"Critical systems thinking" primarily addresses business and social management issues. When companies or local governments are in crisis, critical systems practice considers rethinking strategies, risk considerations, social and environmental responsibility initiatives, and more. On the other hand, this book addresses problems that require mathematical or intelligent knowledge technologies. In the following, we discuss building a knowledge system utilizing mathematical or intellectual knowledge technology and participatory knowledge technology in a complementary manner.

1.2.2.3 Developing a Methodology for Building Knowledge Systems

As mentioned above, the knowledge system contributes to problem-solving by complementary use of codified knowledge and personalized knowledge. Building such a knowledge system requires using mathematical or intelligent knowledge technologies and participatory knowledge technologies in a mutually complementary manner, as shown in Fig. 1.2.

Figure 1.2 assumes that mathematical or intelligent knowledge technologies are responsible for the four processes of the OUEI spiral model: Observation, Understanding, Emergence, and Implementation. The analysts and decision-makers oversee the selection and evaluation of these technologies. They use participatory

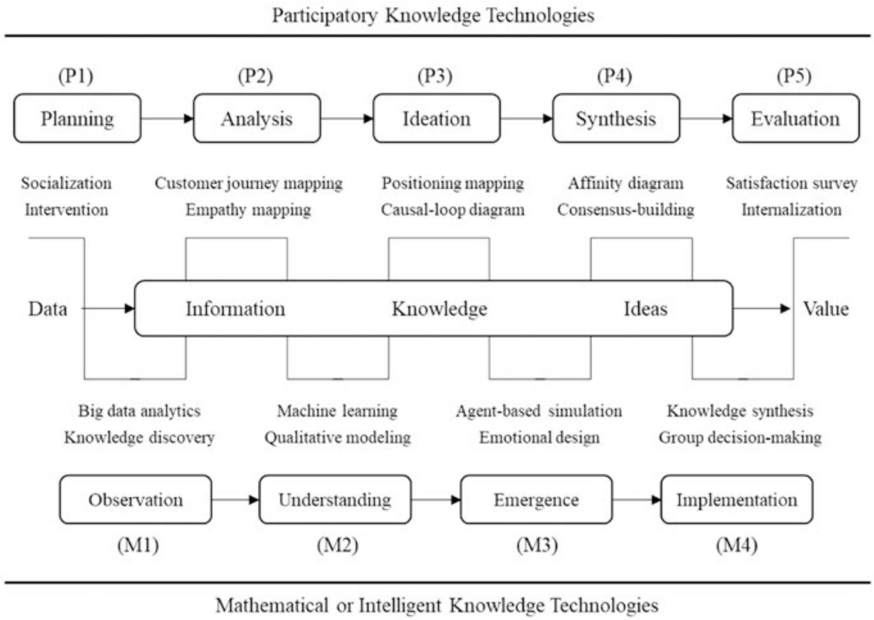

Fig. 1.2 Knowledge technologies to develop a knowledge system

knowledge technologies to manage the construction of a knowledge system. Knowledge technologies shown in the figure are just examples. In practice, we choose appropriate knowledge technologies according to the problem. Establishing a methodology for building a knowledge system is a future task.

Consider creating a knowledge system using the knowledge technologies shown in Fig. 1.2. For instance, imagine a company developing a new product or service. The project team will utilize knowledge technologies as follows.

1.2.2.3.1 (P1) Planning

For the smooth progress of the project, the project leader must carefully listen to the thoughts of management, engineers, sales staff, and, most importantly, consumers. The project team follows the ideas of "socialization" and "intervention" to create a project plan, as follows:

- Socialization is the first process of the organizational knowledge creation model in Nonaka and Takeuchi (1995), which aims at understanding each other's feelings that are difficult to put into words. The project team invites some staff from relevant departments and listens to their ideas about a new product or service. They establish a rough consensus on the direction of the project.
- Intervention corresponds to "Stage 2: Produce an intervention strategy" in the above-mentioned critical systems practice. The project team determines the scope

of data/knowledge to collect, the analytical and modeling methods to use, the simulation methods, and so on. Recall that the expert meeting in the meta-synthesis systems approach has an intervention role.

1.2.2.3.2 (M1) Observation

The information organized from the data usually suggests some meaning. Therefore, some knowledge technologies for converting data into information claim that they extract meaning or even knowledge. The following “big data analytics” and “knowledge discovery” are such knowledge technologies. Here, the project team’s focus is on the function of converting data into information.

- *Big data analytics* examines large amounts of data to uncover hidden patterns, correlations, and other insights. It provides information to know the trends of competitors and consumer preferences. The project team organizes production and sales data for related products and services as information for use in (M2) “machine learning” and (M3) “agent-based simulation.”
- Knowledge discovery originally refers to discovering rules in a dataset. Here, the project team collects the opinions and wishes of consumers through an online review and organizes them as information. They use this information for (M2) “qualitative modeling” and (M3) “emotional design.”

1.2.2.3.3 (P2) Analysis

“Customer journey mapping” and “empathy mapping” are technologies for collecting evaluation information on products and services. The project team can use the information collected by these technologies in (M2) “qualitative modeling” and (M3) “emotional design.” They can also refer to this information in (P4) “consensus-building” and (M4) “group decision-making.”

- Customer journey mapping is a technology that organizes customer behavior in chronological order to clarify problems (Blokdyk, 2020). The project team records customer behavior, sorts out satisfaction and dissatisfaction with products and services, and discovers improvements.
- Empathy mapping is a technology that lists customer behaviors, thoughts, and emotions to clarify their feelings (Curedale, 2016; Kelley & Kelley, 2013). Guess what they are thinking from the customers’ words. Guess what they are feeling from the customers’ behavior.

1.2.2.3.4 (M2) Understanding

The project team can use various statistical models here for demand forecasting. Here, suppose they focus on “machine learning,” which automatically processes large amounts of data, and "qualitative modeling," which extracts rules from text data.

- Machine learning is a technology in which a computer iteratively learns from data and finds patterns hidden in the data. For example, they can use neural networks to build a demand forecast model consisting of a set of if-then rules from a large amount of numerical data.
- Qualitative modeling (or qualitative data analysis) is a technology for extracting meaning from text data (see, for instance, Miles et al., 2019). Grounded Theory (Holton & Walsh, 2017; Strauss, 1987) is one of the qualitative modeling technologies. The project team finds the products and services consumers want through text data. They use the qualitative data obtained by (M1) "Observation" or (P2) "Analysis."

1.2.2.3.5 (P3) Ideation

It is desirable to conduct thought experiments before performing simulations with the model. Thought experiments can provide ideas for setting rules when performing (M3) "agent-based simulation." The project team uses "positioning mapping" to locate existing products and services and seek directions for improvement. They can use the "causal loop diagram" to consider the impact of new products and services.

- Positioning mapping is a technology that shows the position of a business in the market. Referring to the information and knowledge in (M1) "Observation" and (M2) "Understanding," the project team compares the products and services of their company and other companies by plotting them on the plane spanned by appropriate axes.
- The causal-loop diagram is a communication tool to explain the interdependencies between complex system elements intuitively and easily. Originally it was a qualitative model of system dynamics (Forrester, 1961). It has become widely used as a tool for systems thinking (Kim & Anderson, 1998; Senge, 1990). Sterman (2000) details various causal-loop diagrams before implementing business dynamics.

1.2.2.3.6 (M3) Emergence

A mathematical model built by past data does not adequately predict demand for products that the company has never offered in the past. Also, it is difficult to predict demand that reflects the emotional changes of consumers. The project team can use "agent-based simulation" and "emotional design."

- The agent-based simulation reproduces system-wide behavior by assuming local interactions of multiple agents. The project team uses agent-based simulation to predict the overall sales impact of the release of various new products and

services, considering the discussions in (P2) "Analysis" and (P3) "Ideation." They evaluate the simulation results and choose ideas to pass to (P4) "Synthesis" and (M4) "Implementation."
- Emotional design (Norman, 2003) discusses how emotions have a crucial role in the human ability to understand the world. The project team can collect emotional content in the text data they have. But it is more efficient to collect it systematically by an independent survey. To create ideas for new products and services, they use technologies for emotional design/emotional product development.

1.2.2.3.7 (P4) Synthesis

The project team needs to classify and evaluate different ideas. They can use the "affinity diagram" for this purpose. If the opinions diverge, they need to use "consensus building" methods to put together them.

- The affinity diagram is a technology that collects large amounts of language data (including ideas, opinions, issues, etc.) and organizes them into groupings based on their natural relationships (Kawakita, 1967). The project team can use this technology in (P1) "Planning" as well. Here, they rank the ideas regarding a new product or service by various criteria.
- Consensus-building is a technology used at the evaluation meeting of the meta-synthesis systems approach. The project team can use a consensus-building method to converge their opinions. It reveals the diverse values underlying participants through discussions and seeks mutual consensus in decision-making. The project team invites people from other departments to coordinate their views.

1.2.2.3.8 (M4) Implementation

The project team can use "knowledge synthesis" and "group decision-making" technologies when discussions are not converging or when they want to make more rational decisions. They also must discuss promotions to put the idea into practice.

- Knowledge synthesis is a technology to synthesize knowledge in various fields and forms. The project team can use this technology to synthesize ideas. Referring to consumer opinion, the team combines ideas derived from rational knowledge and ideas based on empirical knowledge.
- Group decision-making refers to the decision-making when acting as a group. Group decision-making methods support people's wise decisions, using, for instance, social choice functions. The project team can logically decide the final ideas with this knowledge technology.

1.2.2.3.9 (P5) Evaluation

The project team must assess the results by verifying the accuracy of the model and forecasts and by conducting a "satisfaction survey" or reputation analysis after executing the idea. In addition, they need to accumulate the experience and knowledge gained by the project and the results. The term "internalization" means learning from practice.

- The satisfaction survey uses a defined metric to assess consumer satisfaction with a product or service. The project team can use indicators such as the "net promoter score" (Reichheld & Markey, 2011) or the "key performance indicator" (Parmenter, 2019).
- Internalization is famous as the final process of the organizational knowledge creation model of Nonaka and Takeuchi (1995). Project members must look back on the project and internalize empirical knowledge.

The following chapters will introduce the state-of-the-art mathematical or intelligent knowledge technologies shown in Fig. 1.2. Each chapter is a review or research paper dealing with an independent problem, utilizing the knowledge technology in charge and knowledge technologies to support it.

Finally, conclude this chapter by calling for the following challenge:

Challenge 9. Develop a methodology for building knowledge systems according to the type and scale of the problem.

In the above, we have talked about the selection of knowledge technology. But in reality, we need to develop a methodology that can suggest other knowledge system elements such as personnel, organization, and business.

Systems science started with the development of mathematical knowledge technology and began the development of participatory knowledge technology later. However, to date, the fusion of these (the so-called hard and soft) approaches has not been successful. Figure 1.2 shows that even though hard and soft systems approaches are difficult to fuse, we must use them in complementary ways to develop knowledge systems. Thereby, we can facilitate interactions between codified and personalized knowledge. Developing a methodology for building knowledge systems contributes to establishing knowledge systems science, which focuses on knowledge creation and utilization.

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Chapter 2
Big Data Analytics in Healthcare

Chonghui Guo and Jingfeng Chen

2.1 Big Data-Driven Paradigm

The cross-integration of information technology and economic society has led to the rapid growth of data, which has become a basic national strategic resource. Big data is increasingly exerting an important influence on global production, circulation, distribution, consumption activities, economic operation mechanism, social lifestyle, and national governance capacity (Chen et al., 2012; Ji et al., 2017; Lynch, 2008; Naeem et al., 2022; van Elten et al., 2022). In the context of big data, the advantages of the data-driven paradigm are constantly highlighted. Generally speaking, the big data-driven paradigm is described from three aspects: external embedding, technology augmentation, and enabled innovation, reflecting a "correlation + causality" viewpoint in a "data-driven + model-driven" manner (Bakker & Tsui, 2017; Chen, Wu, et al., 2018). Recently, governments, academics, and industries around the world have promoted the research and application of big data to an unprecedented height. In 2008 and 2011, Nature and Science published a special issue on big data respectively, discussing the challenges of big data from multiple perspectives. In 2014, *The Bridge*, the journal of the American Academy of Engineering, organized a special issue to discuss the current situation, challenges, and future trends of big data from the perspective of globalization (Shi, 2014).

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As an important strategic resource, big data contains many key management issues and has its own management characteristics. And in the big data environment, the existing management models should also have further development. The paradigm of scientific research is also shifting to the "data-intensive" fourth paradigm, which fosters research into scientific data management, data analysis, data visualization, and new algorithms and tools (Hey et al., 2009).

2.1.1 *The Research Background of Big Data Analytics in Healthcare*

Along with the development and popularization of cloud computing, the Internet, various mobile devices, and the Internet of Things, big data analytics has been one of the current and future research frontiers (Chen et al., 2012; Haque et al., 2020). In the medical field, Mayer-Schönberger and Cukier (2013) elaborated on the reforms from two aspects. One is to provide help for the rapid improvement of the collective medical experience of human beings, which will make everyone become the master of their own diseases, and the other is that inexhaustible medical data innovation is dominant, bringing industrial effects with great commercial value.

However, big data analytics in healthcare, in general, lags behind e-commerce business intelligence and analytics applications because it has rarely taken advantage of scalable analytical methods or computational platforms (Miller, 2012). Fortunately, along with the construction and development of healthcare informatization, medical institution informatization, regional medical informatization, and internet plus medical, healthcare, as an important field of big data & big data analytics, is entering a "big data era." In the clinical sphere, the amount of patient data has grown exponentially because of new computer-based information systems, including clinical data (electronic health records (EHRs), electronic medical records (EMRs), electronic patient records (EPRs), etc.), claims and cost data, pharmaceutical R & D data, and patient behavior data (Groves et al., 2013).

The release of big data analytics in healthcare is transforming the discussion of what is appropriate or right for a patient and right for the healthcare ecosystem, and further changing the paradigm by achieving the new value pathways, as follows. (1) Right living: patients should take more active steps to improve their health; (2) Right care: developing a coordinated approach to care in which all caregivers have access to the same information. (3) Right provider: any professionals who treat patients must have strong performance records and be capable of achieving the best outcomes; (4) Right value: improving value while simultaneously improving care quality; (5) Right innovation: identifying new approaches to healthcare delivery (Groves et al., 2013; Guo & Chen, 2019).

The transformation of the medical paradigm is also accelerating the revolution of the medical model, from one-size-fits-all medicine and stratified medicine to precision medicine, from the bio-psycho-social medical model to the "4P" medical

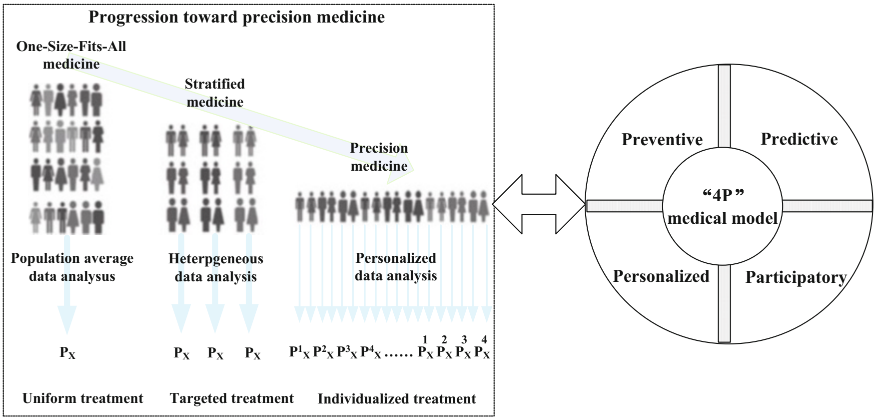

Fig. 2.1 Precision medicine and the "4P" medical model (the left part comes from Hopp et al. (2018))

model, as shown in Fig. 2.1. Specifically, one-size-fits-all medicine requires population average effect analysis, and all patients adopt the uniform treatment; stratified medicine divides patients into groups according to their response to therapy and uses heterogeneous effect analysis to correct for the failure of average effect analysis to account for patient differences; while precision medicine uses personalized effect analysis, which often requires personalized data. In addition, precision medicine, sometimes known as "personalized medicine," is an innovative approach to tailoring disease prevention and treatment by considering differences in people's characteristics, environments, and lifestyles. Thus, the goal of precision medicine is to target the right treatments for the right patients at the right time (Hopp et al., 2018).

During the process of achieving the goal of precision medicine, the "4P" medical model is emerging. The "4P" medical model refers to preventive, predictive, personalized, and participatory, emphasizing prevention first, predictive treatment, individualized diagnosis and treatment, and then public participation. It provides patients with a physician guide to medical science as a tool for living healthier, happier, and more productive lives. In the case of the "4P" medical model, it is the power to predict and prevent disease, feel good, slow or even partially reverse biological aging, and optimize patients' ability to move, think, and perform at patients' best in all aspects of life, environment, mind, and body (Auffray et al., 2009; Bricage, 2017; Sun et al., 2019; Topol, 2015; Wu et al., 2015).

The application and development of big data in healthcare will promote profound revolutions in the medical service model and greatly improve the quality and efficiency of healthcare services. The application of big data and big data analytics in healthcare will improve healthcare quality, long-term care, and patient empowerment, and using this information and knowledge to analyze the efficacy of clinical diagnosis and treatment and healthcare decision support will bring revolutionary reforms to the medical industry (Chen et al., 2012, 2020).

2.1.2 The Research Framework of Big Data Analytics in Healthcare

Healthcare big data not only have the 4 V (volume, variety, value, and velocity) characteristics of big data, but also high dimensionality, heterogeneity, and relational complexity among data objects. Thus, the existing hypothesis-driven research and reductionist approaches to causality have no capability to adjust for confounding and modifying factors in clinical practice. In recent years, some popular research frameworks or the modeling processes of big data analytics in healthcare have been proposed to promote the transformation from data to knowledge. For example, in a data-intensive healthcare environment, Hey et al. (2009) proposed a unified modeling approach that can take full advantage of a data-intensive environment without losing the realistic complexity of health. Based on the cross-industry standard process for data mining (CRISP-DM), Niaksu (2015) and Esfandiari et al. (2014) proposed an extension of the CRISP-DM to address specific challenges of big data analytics in healthcare, and described some specialized tasks and activities for each phase, respectively. Considering healthcare as an adaptive system with a combination of three essential components—decision making, decision informatics, and human interface, Tien and Goldschmidt-Clermont (2009) proposed a decision-making framework from data to information, knowledge, and wisdom, and also a decision informatics paradigm with a feedback loop among multiple data sources, abstracted information, and real-time decision.

From the perspective of systems engineering and service engineering, we put forward the paradigm of big data analytics in healthcare, as shown in Fig. 2.2. Firstly, the fusion and analysis of multi-source heterogeneous data can be used as input for data-driven decision modeling on the one hand, and for building a knowledge map on the other hand. Secondly, descriptive modeling and predictive modeling are carried out by using data mining methods and technologies, where the descriptive modeling mainly includes the feature extraction of objects from high-dimensional sparse data and the complex relation representation between individual objects, while the predictive modeling mainly includes statistical inference and prediction model. Then, normative modeling for obtaining the knowledge is carried out by integrating the knowledge map into the results based on descriptive and predictive modeling. Finally, knowledge can provide decision support for the practical problems in the operation and management of the medical service system.

While based on the literature records related to data mining for EHRs, Chen et al. (2017) adopted the Latent Dirichlet Allocation (LDA) and Topics Over Time (TOT) models to extract topics and analyze topic evolution trends and further summarized the general research framework of data mining for the medical domain by combining the topic co-occurrence relations and domain knowledge, including the data, methods, knowledge, and decision levels, as shown in Fig. 2.3. This research framework can provide a high-level insight for scholars in the medical domain field and guide their choices of medical data mining techniques in healthcare knowledge discovery, medical decision support, and public health management.

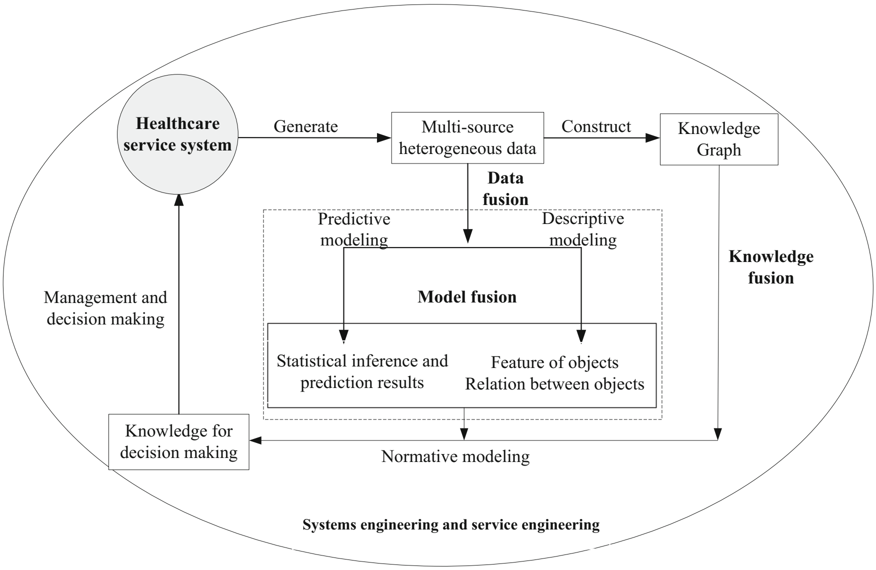

Fig. 2.2 Big data analytics in healthcare from the perspective of systems engineering and service engineering

Further, as the core medical big data, EMRs have become the core foundation of smart hospital construction, and the research on the analysis and utilization of EMRs is of great significance. In order to promote the analysis and utilization of EMRs, an integrated research framework for the generation, analysis, and utilization of electronic medical records was proposed in Fig. 2.4. We found that EMR analysis was helpful to the construction of higher-level hospital intelligent service, and further improve the intelligent service level of the hospital by relying on data mining methods such as classification, recommendation, association rules, text mining, and natural language processing.

In summary, these research frameworks of big data analytics in healthcare are similar, emphasizing data collection and preprocessing methods, big data analytics and modeling techniques, and knowledge for decision support discovery methods to optimize the medical process and further achieve the profound reforms of the medical model.

2.1.3 Analysis of Clinical Diagnosis and Treatment Process

In clinical practice, it is necessary to formulate and implement standardized diagnosis and treatment processes in order to effectively improve the efficiency of medical staff, promote the quality of hospital medical services, and achieve a patient-centered service concept. Shortliffe and Cimino (2006) proposed a clinical diagnosis and

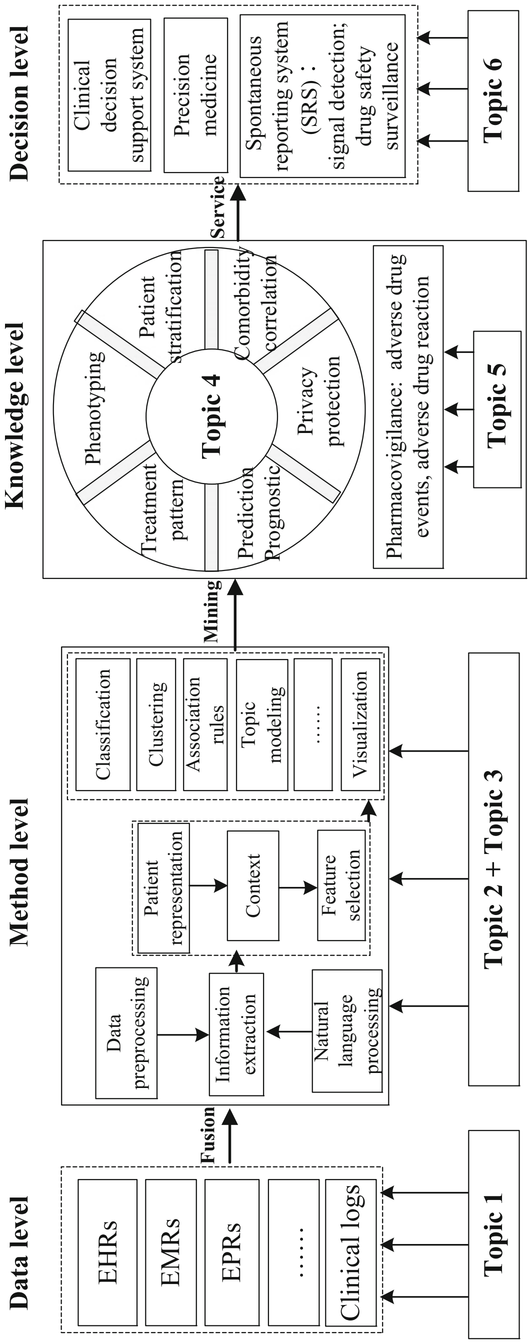

Fig. 2.3 The general research framework of data mining for the medical domain

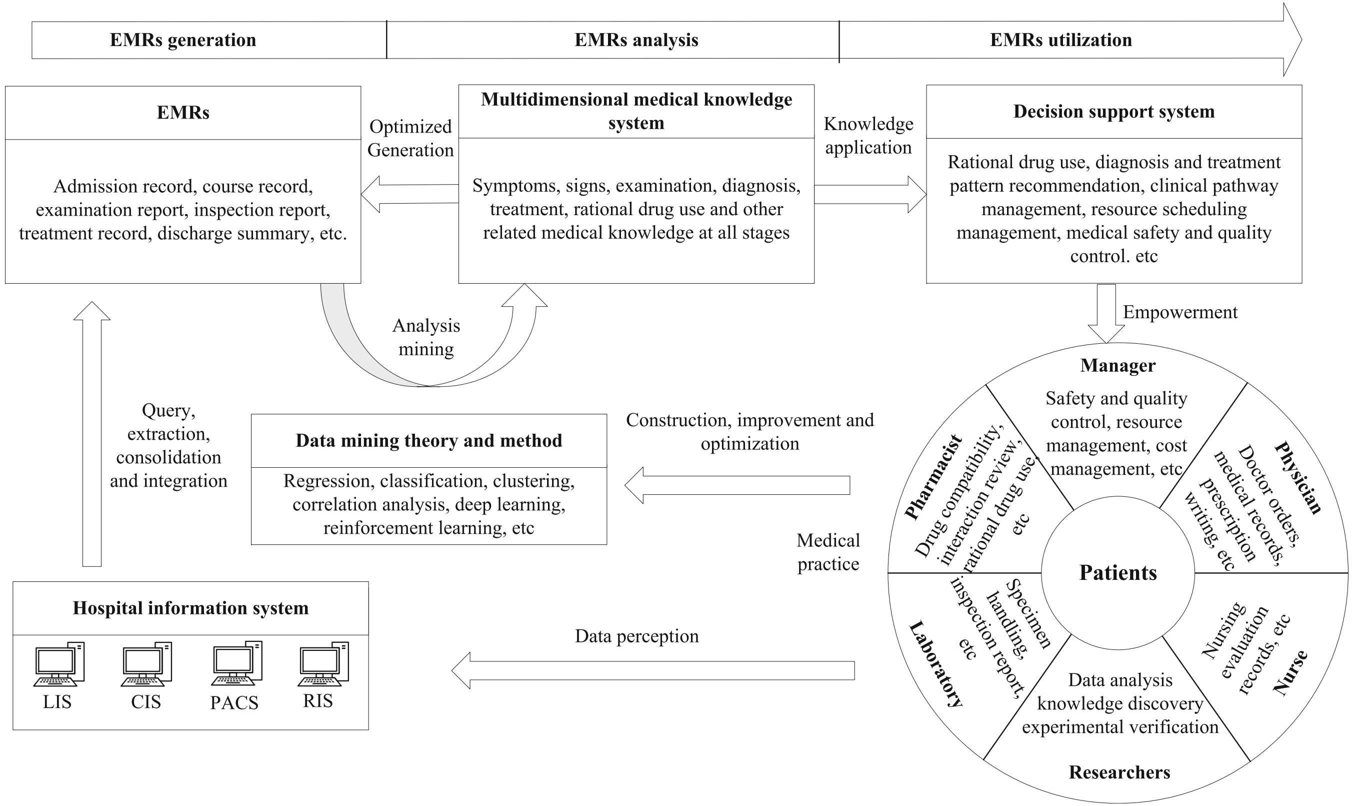

Fig. 2.4 Analysis and utilization framework of EMRs under the background of smart hospital construction

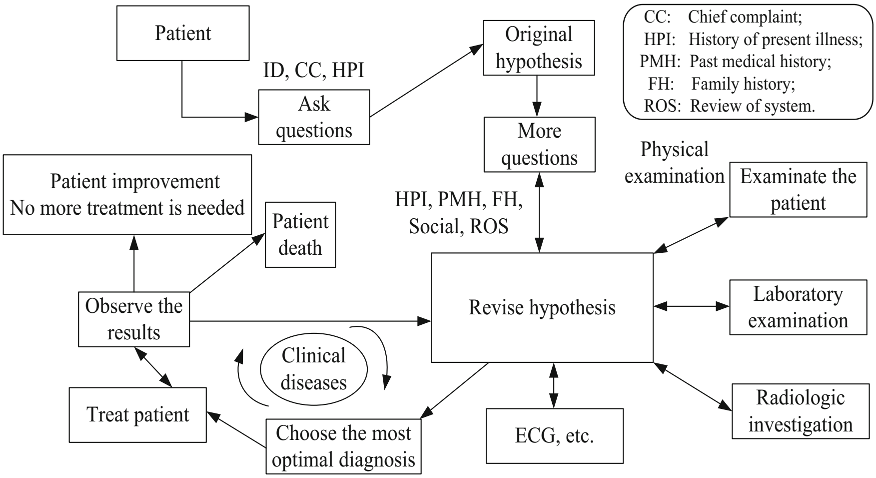

Fig. 2.5 The clinical diagnosis and treatment process based on hypothetic-deductive methods

treatment process based on hypothetic-deductive methods when admitted to a hospital, as shown in Fig. 2.5**.** First, when a new patient is admitted to the hospital with chief complaints (symptoms or diseases), the doctor forms the initial hypothesis (diagnosis) by asking some questions and further revises the hypothesis based on the patient's history of present illness, past medical history, family history, social history, and review of the system. Then, when the patient completes the medical examination, the hypothesis lists revised by the doctor may be effectively reduced to determine the appropriate treatment. Finally, the doctor determines the source of the patient's problems and develops a specific treatment regimen to treat the diseases and observe the outcomes. In addition, when clinical diseases have not been effectively improved, the doctor needs to further revise the hypothesis and treat the patient again.

Whereas clinical data describing patient phenotypes and treatment remains an underutilized source of data, it holds tremendous potential for advancing research and optimizing clinical diagnosis and treatment regimen (Jensen et al., 2012; MIT Critical Data, 2016; Yadav et al., 2018). Thus, we design a clinical diagnosis and treatment process based on data-driven methods to reduce medical costs and improve medical service quality, as shown in Fig. 2.6. Firstly, according to the research framework of big data analytics in healthcare described in Sect. 2.1.2, we can mine diagnosis and treatment patterns from EMRs by data-driven methods, and build two types of rule bases: Admission Information-Diagnosis rule base, and Diagnosis-Treatment rule base. Secondly, when a new patient is admitted to the hospital, the doctor can retrieve the most similar diseases from the Admission Information-Diagnosis rule base on demographic information, symptoms, and laboratory indicators of the patient. Thirdly, the doctor can recommend the most effective treatment pattern for the patient based on the Diagnosis-Treatment rule

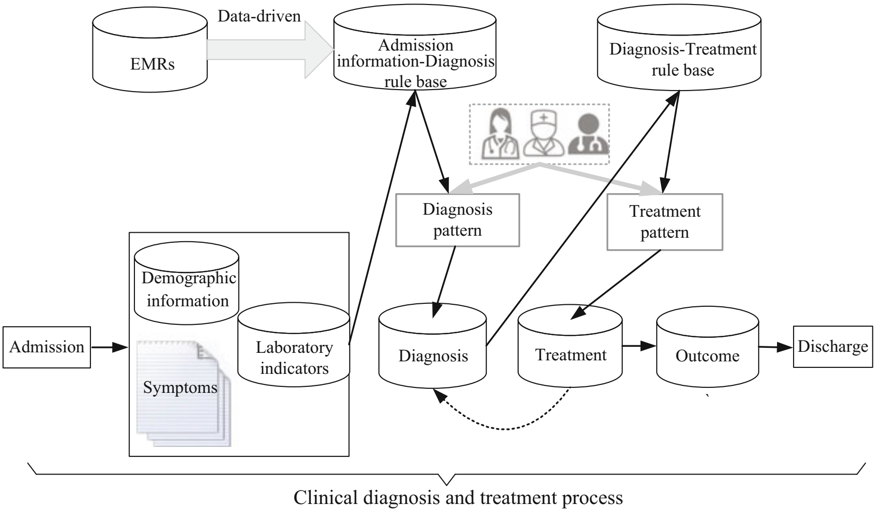

Fig. 2.6 The clinical diagnosis and treatment process based on data-driven methods

base. Finally, if the outcome of the patient is not effectively improved, the doctor needs to further revise the disease type and the corresponding treatment pattern.

Obviously, in the data-driven clinical process, diagnosis-treatment pattern plays an important role to reduce the inflammation that triggers patients' signs and symptoms and improve long-term prognosis by limiting complications. Meanwhile, the diagnosis-treatment pattern should also meet the requirements of rational drug use. Rational drug use requires that "patients receive medications appropriate to their clinical needs, in doses that meet their own individual requirements, for an adequate period of time, and at the lowest cost to them and their community" (World Health Organization, 2012). The goal of rational drug use is also to achieve "5R": right patient, right drug, right dose, right route, and right time. Thus, according to the above analysis, we further describe the role of data-driven diagnosis-treatment pattern mining in the healthcare environment in Fig. 2.7. Concretely, on one hand, after collecting the medical evidence (e.g., pyramid of evidence), medical experts adopt the evidence-based medicine (EBM) approach to design clinical guidance, which can be applied to the diagnosis and treatment process proposed in Fig. 2.5. On the other hand, we can mine the diagnosis and treatment rule database from clinical data by data-driven methods, which is suitable for the clinical diagnosis and treatment process described in Fig. 2.6. Then the clinical guidance can guide the feasibility implementation of diagnosis-treatment patterns by providing domain knowledge, and diagnosis-treatment patterns can enrich, supplement, and perfect the clinical guidance, which both can achieve the goal of "5R" in medical (i.e., rational drug use) and "5R" in healthcare (i.e., new value pathways in the healthcare paradigm discussed in Sect. 2.1.1).

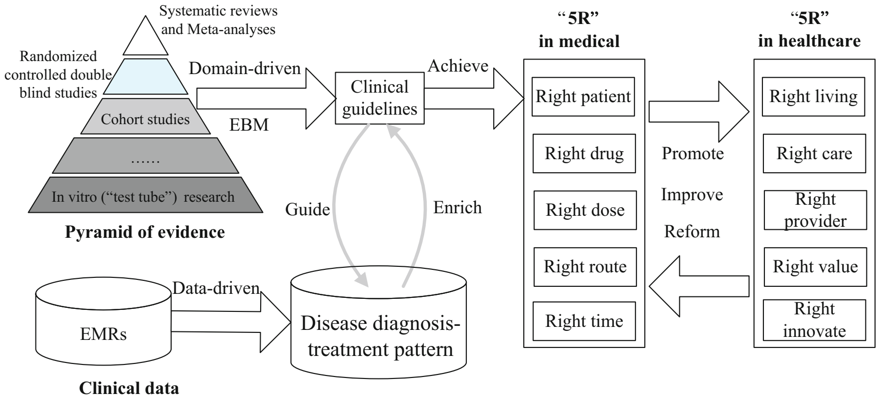

Fig. 2.7 The role of data-driven diagnosis-treatment pattern mining

2.1.4 The Literature Summary of Diagnosis-Treatment Pattern Mining

Data-driven diagnosis-treatment pattern mining is receiving increasing attention in the field of healthcare management. Diagnosis-treatment patterns, as actionable knowledge latent in EMRs representing the best practice for most patients in most time of their clinical processes, can be exploited to help physicians better understand their specialty and learn from previous experiences for clinical guidance improvement (Huang et al., 2015). To the best of our knowledge, unifying diagnosis (UD), clinical pathway (CP), and rational drug use are the main research directions of diagnosis-treatment pattern mining.

2.1.4.1 The Related Work of Unifying Diagnosis (UD)

In medical practice, clinicians are encouraged to seek a UD that could explain all the patient's signs and symptoms in preference to providing several explanations for the distress being presented (Herman, 1994). A UD is a critical pathway to identifying the correct illness and crafting a treatment plan; thus, clinical experience and knowledge play an important role in the science of diagnostic reasoning. Generally, from a brief medical history of a patient, clinicians can use the intuitive system in their brain and rapidly reason the disease types, whereas, for complex and multi-type abnormal results, clinicians must use the more deliberate and time-consuming method of analytic reasoning to deduce the UD, raising the risk of diagnostic errors.

The coexistence of multiple diseases is pervasive in the clinical environment, particularly for patients in the intensive care unit (ICU) (Sareen et al., 2020). According to the statistical results of the MIMIC-III database, which is a freely accessible critical care database, the average number of diagnosis codes for patients in the ICU is 11. Additionally, diagnosis codes are highly fine-grained, closely related, and extremely diverse (Johnson et al., 2016). Thus, it is trivial and difficult for clinicians to make a consistent, accurate, concise, and unambiguous diagnostic decision reasonably.

Furthermore, although the inter-relation of diagnosis codes was considered in previous studies, the researchers commonly used the first three digits of ICD-9 codes to assign diagnosis codes for patients (Diao et al., 2021; Wu et al., 2022); hence, the complexity may increase and prediction performance may reduce when considering all digits of the ICD-9 codes. Additionally, in those studies, reasonable complicated and confusing diagnosis codes could not be classified into a UD using a data-driven method. A UD is the basic principle of clinical diagnostic thinking. Its basic idea is that when a patient has many symptoms and if these symptoms can be explained by one disease, it will never explain different symptoms using multiple diseases. A UD reflects the integrity of the patient and the professionalism of clinicians; however, in previous studies, the main focus was on the UD of a category of diseases from the clinical perspective, such as mood/mental disorders (Malhi et al., 2020), intracranial mesenchymal tumor (Sloan et al., 2021), and arrhythmogenic right ventricular cardiomyopathy (Liang et al., 2016).

2.1.4.2 The Related Work of Clinical Pathway (CP)

CPs are regarded as useful tools that ease the tension of the doctor-patient relationship and enable patients to receive correct and timely diagnosis and treatment with controlled medical costs and improved medical quality (Chen, Sun, et al., 2018). In general, process mining is the most popular method to mine CPs from massive EMRs. When process mining technology is applied to clinical environments, treatment behavior can be measured from EMRs that regularly record patient execution information. What is more, due to strict mathematical logic and reasoning ability, process mining can be used as an objective way to analyze clinical pathways (Rebuge & Ferreira, 2012). For instance, Mans et al. (2008) applied process mining technology to discover the treatment workflow of stroke patients. Bouarfa and Dankelman (2012) proposed a process mining algorithm to extract a consensus model from multiple clinical activity logs, which can automatically detect the abnormal behavior of CPs without the prior knowledge of clinical experts. Lakshmanan et al. (2013) designed a process mining approach for mining CPs correlated with patient outcomes that involve a combination of clustering, process mining, and frequent pattern mining. Huang et al. (2013) presented a process mining method for constructing CP summaries from the collected event logs which regularly record various kinds of medical behaviors by hospital information systems. Yang et al. (2017) presented a process analysis and recommendation framework to extract medical prototypes from activity logs.

In addition, sequential pattern mining and probabilistic topic model have also been applied to discover CPs. For instance, Perer et al. (2015) used a frequent sequence mining algorithm to explore care pathways from EMRs with visual analytics. Huang et al. (2014, 2015) developed a probabilistic topic model to mine treatment patterns hidden in EMRs for clinical pathway analysis and improvement. Hirano and Tsumoto (2014) designed a typicalness index method to mine typical order sequences from EHRs for building clinical pathways. While in clinical practice, considering the complexity of actual treatment activities, variations are widely existent in different stages of CPs. Li et al. (2015) proposed an automatic method to detect CP variation patterns in EMRs and statistically examined their correlation with patient outcomes. Ainsworth and Buchan (2012) developed a collaborative online CP investigation tool that combines the required specialist knowledge and skills from different disciplines, providing a network-based CP variation analysis tool for clinicians and health service managers.

2.1.4.3 The Related Work of Rational Drug Use

Rational drug use is also an important research direction of treatment patterns mining, which requires that the right patient receives the right drug with the right dose and the right route at the right time. EMR data mining technology has been proven that it has good results to analyze drug use efficiency and various drug treatment regimens. For instance, Wright et al. (2015) used sequential pattern mining to automatically infer temporal relationships between medications, visualize these relationships, and generate rules to predict the next medication likely to be prescribed for a patient. Jin et al. (2018) developed a treatment engine to predict next-period prescriptions based on disease conditions, laboratory results, and treatment records of the patient. Chen, Li, et al. (2018) presented a disease diagnosis and treatment recommendation system to recommend medication treatments based on the given inspection reports of patients.

In general, EMRs are heterogeneous and longitudinal in nature, including demographic information, diagnostic information, laboratory indicators, doctor orders, and outcomes. A treatment record is a series of doctor orders, and each doctor's order usually consists of a drug name, delivery route, dosage, start time, and end time. However, in the existing studies, a doctor's order is simplified as an event code and a treatment record is simplified as a code sequence. Thus, the information inherent in doctor orders is not fully used for in-depth analysis (Sun et al., 2016). In this chapter, considering the diversity, temporality, and dynamicity of EMRs, we propose the concept of typical treatment patterns, which can reflect the complexity of EMRs better and enhance the interpretability of mining results.

The rest of the chapter is organized as follows. Section 2.2 highlights the challenges to analyze the large-scale and complex EMRs to mine typical diagnosis-treatment patterns. Section 2.3 describes the UD unifying diagnosis identification and prediction method embedding the disease ontology structure from electronic medical records. Section 2.4 provides four clinical pieces of research on typical treatment patterns in rational drug use and CPs, and discusses the examination of typical treatment pattern mining approaches, limitations, and open issues. Section 2.5 presents the conclusions as well as the challenges.

2.2 Challenges for Typical Diagnosis-Treatment Pattern Mining

EMRs usually contain five kinds of information about patients, such as demographic information, diagnostic information, laboratory indicators, doctor orders, and outcomes. Concretely, demographic information includes the age, gender, address, race and ethnicity, education, and other information of a patient. Diagnostic information includes diagnosis code, disease names, and severity of the diseases. Laboratory indicators record the detailed results of laboratory tests to evaluate the health status of a patient, such as blood routine, urine routine, stool routine, liver function, and kidney function. A doctor order is a medical prescription, including drug name, delivery route, dosage, starting time, and ending time, and a treatment record is a series of doctor orders related to the patient. The outcome is evaluated by doctors when a patient is discharged from the hospital, including treatment efficacy (cured, improved, ineffective, and dead) and treatment efficiency (payment and length of stay) (Chen, Sun, et al., 2018; Dang & Ho, 2017; Sun et al., 2016).

After summarizing our previous works (Chen, Guo, et al., 2018; Chen, Sun, et al., 2018; Sun et al., 2016), we propose a general framework of data-driven typical treatment pattern mining, as illustrated in Fig. 2.8. Our framework has two stages: typical treatment pattern mining and typical treatment pattern evaluation and recommendation. The former includes (1) similarity measure among diagnosis and treatment records; (2) clustering diagnosis and treatment records based on similarity matrix; and (3) typical diagnosis and treatment pattern extraction from each cluster. The latter includes (1) patient cohort division by classification methods; (2) evaluation of diagnosis and treatment records in each patient cohort; and (3) recommendation of the most effective diagnosis and treatment pattern for each patient cohort. In this process, three key technical challenges for the general framework emerge, including how to measure similarity among diagnosis and treatment records, how

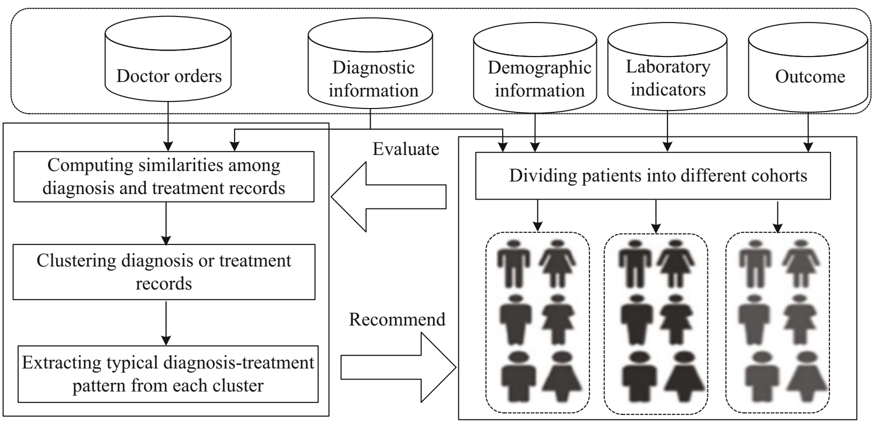

Fig. 2.8 The general framework of data-driven typical treatment pattern mining

to extract typical diagnosis and treatment patterns from EMRs, and how to evaluate and recommend diagnosis and typical treatment patterns.

2.2.1 Measuring Similarity Among Diagnosis and Treatment Records

2.2.1.1 Similarity Measure of Patients' Diagnostic Records

Diagnostic information is one of the most important clinical data. Diagnostic information refers to a record of disease diagnosis made by clinicians based on the health condition of a patient admitted to the hospital. It is stored in the patient's EMR data in the form of a diagnosis code (e.g., ICD-9 and ICD-10). How to calculate the similarity between disease diagnosis codes is a problem to be solved. Diagnosis code is a semantic concept, not a specific numerical value. ICD code of disease diagnosis concept is classified data with a hierarchical structure, which contains medical knowledge. The distance between the two concepts in medical semantics can be judged according to the position of the disease diagnosis concept in the ICD coding tree.

In the real EMR dataset, patient diagnostic information is typically a set of diagnosis codes, as shown in Fig. 2.9. Thus, patient similarity can be transformed into the similarity of the diagnosis code set. Generally, for binary code-level similarity, we can use classical methods, such as Dice, Jaccard, cosine, and overlap, to calculate set-level similarity. However, these methods cannot fully embed semantic similarity. Thus, it is critical to measure the similarity of patients' diagnostic records by fusing the information content measure of diagnosis codes, diagnosis code similarity measure, and diagnosis code set similarity measure.

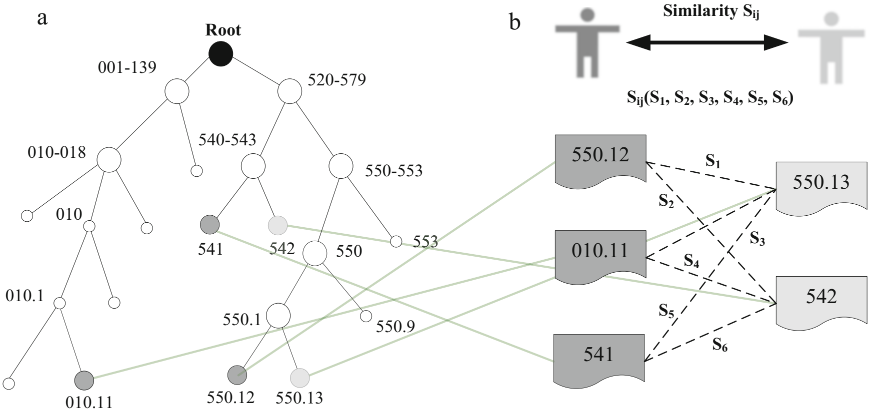

Fig. 2.9 Example of two patients' diagnostic records in the ICD-9 ontology structure

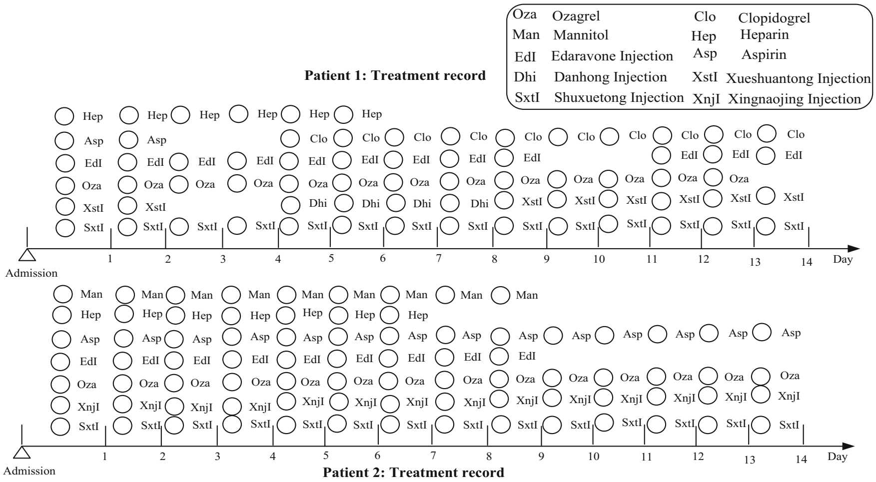

Fig. 2.10 Treatment records of two cerebral infarction patients

2.2.1.2 Similarity Measure of Patients' Treatment Records

The similarity between pairwise treatment records measures how similar a pair of treatment records are according to their doctor order information under a specific clinical context. As discussed in Sect. 2.1.4, a treatment record is a series of doctor orders with timestamps, which can be seen as a temporal event, as shown in Fig. 2.10. In general, the treatment information not only includes nominal terms like drug name, and delivery route, but also figures like dosage, frequency per day, and repeated times, so the recorded information in a treatment record is heterogeneous. The timestamp is also more complex than previously studied as it records both start and end times. In this case, how to measure similarity between pairwise treatment records has become a challenging problem (Sun et al., 2016, 2021).

After analyzing the characteristics of treatment records in Fig. 2.10, there exist three categories of differences illustrated in Fig. 2.11: including (1) doctor order content difference: each doctor order is a set of seven tuples, including drug name, drug efficacy, delivery route, daily dosage, frequency, start and end time; (2) doctor order duration difference: the usage and duration time of the same doctor order are various in different treatment records; and (3) doctor order sequence difference: certain temporal relations exist between doctor orders. Thus, it is necessary to take these differences into full consideration when designing similarity measure methods of pairwise treatment records (Chen, Guo, et al., 2018; Chen, Sun, et al., 2018; Htun & Sornlertlamvanich, 2017; Sun et al., 2016, 2021).

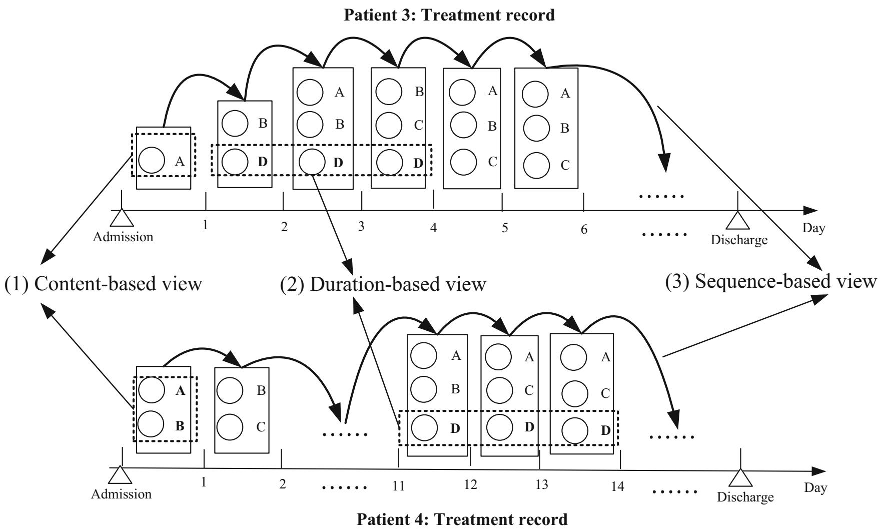

Fig. 2.11 Three-view analysis for treatment records of two patients

2.2.2 Extracting Typical Diagnosis-Treatment Patterns from EMRs

After obtaining the similarity matrix for all diagnosis and treatment records, we first divide all diagnosis and treatment records into several groups by clustering algorithms and then extract a typical diagnosis and treatment pattern from each cluster. Clustering is a technique of partitioning a set of objects into multiple groups (i.e., clusters) so that objects in the same cluster are more similar to each other than to those in other clusters (Cho & Kim, 2017; Han et al., 2011; Wang et al., 2018; Xu & Tang, 2018). For the research on cluster analysis in data-driven management and decisions, Sun, Chen, et al. (2017) discussed the three most popular clustering categories, such as centroid-based clustering, connectivity-based clustering, and density-based clustering, analyzed and addressed five challenges for cluster analysis in new business environments, including clustering dynamic data, clustering a large-scale data set, finding the representatives, handling arbitrary-shaped clusters, and validation measures and consensus clustering, and further provided three practical cases relating to management and decisions, for instance, clustering enhanced information extraction, data-driven operations research, and clustering assisted knowledge discovery.

2.2.2.1 Typical Diagnosis Pattern Extraction from Clustering Results

Some previous studies have proved that defining the core zone of a cluster is an effective approach to extracting stable clustering results (Chen et al., 2020).

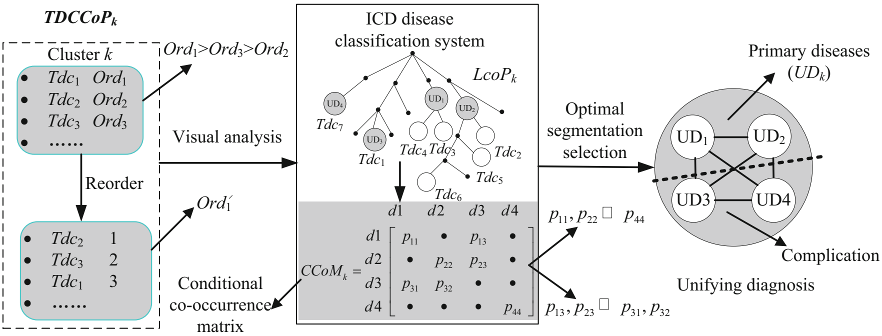

Fig. 2.12 The extraction process of the UD from diagnostic records

Additionally, considering the complex semantic relations among different diagnosis codes, the feature of a cluster cannot be fully described when the diagnostic information (cluster center or exemplar) of only one patient is used. Thus, the core zone of each cluster can be defined to select a group of patients (i.e., core patients) using the *k*-nearest neighbor method, and further, identify typical diagnosis code co-occurrence patterns (TDCCoP) from each cluster by defining a threshold and a sorting function.

To extract typical diagnosis patterns (i.e., UD) from patients' diagnostic records, categorizing the TDCCoP of each cluster reasonably according to the disease taxonomy is a critical step. Chen et al. (2022) proposed a UD identification method, as shown in Fig. 2.12. Specifically, for the TDCCoP_k of cluster *k*, all typical diagnosis codes were visualized in the reconstructed ICD ontology structure and marked in their orders. Then the least common ancestor (LCA) method was used to categorize these codes and define their LCA and the corresponding orders. Furthermore, the conditional co-occurrence matrix was calculated using patient diagnostic information to select the optimal segmentation between primary diseases and complications, where the primary diseases were regarded as UD.

2.2.2.2 Typical Treatment Pattern Extraction from Clustering Results

Clustering large-scale treatment records is also a big challenge to extracting typical treatment patterns. Sun et al. (2016, 2021) proposed a MapReduce enhanced density peaks-based clustering (MRDPC) to address this challenge, as shown in Fig. 2.13. MRDPC is a two-stage procedure. First, the total *N* patients are first randomly divided into m parts, DPC is implemented on each part with an $N_0 \times N_0$ similarity matrix to obtain *k* potential exemplars (i.e., representative objects); then a partial similarity matrix with $m \times k \times N$ is obtained by computing similarities between the selected potential exemplars and all objects, and partial DPC (PDPC) is used to determine *K* final exemplars according to the partial similarity matrix (Sun et al., 2016, 2021).

Then after clustering all treatment records, a typical treatment pattern can be identified from each cluster. In most of the previous applications of exemplar-based

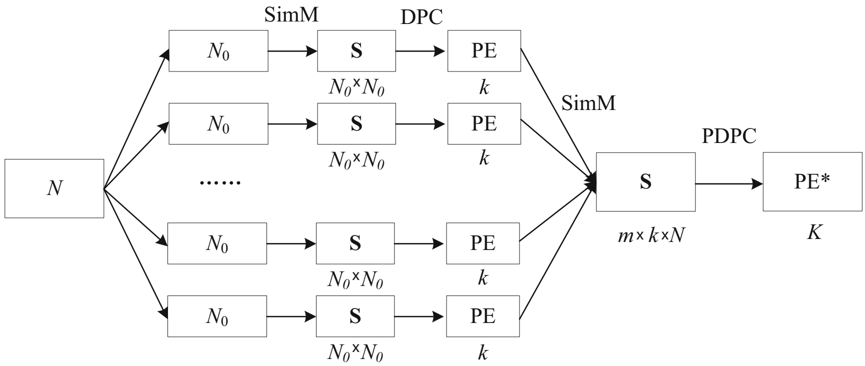

Fig. 2.13 Clustering treatment based on MapReduce Enhanced DPC method

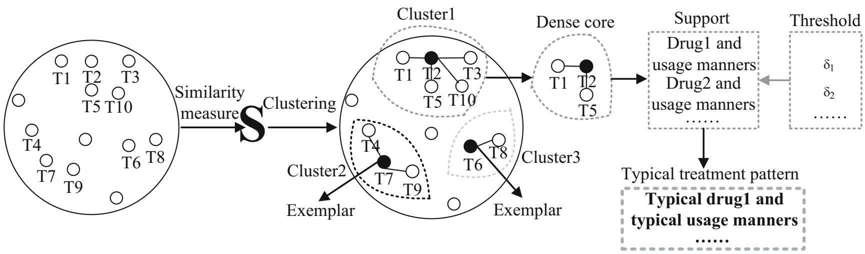

Fig. 2.14 The extraction process of typical treatment patterns from EMRs

clustering (e.g., affinity propagation (AP) and density peaks-based clustering (DPC)), an exemplar can be directly used to describe the corresponding cluster. However, a treatment record can vary in many different directions as a complex temporal and heterogeneous data set, and the exemplar of each cluster cannot well describe the cluster it belongs to. In this case, Sun et al. (2016, 2021) defined the core area of a treatment cluster and extract a semantic description of each treatment cluster by its dense core. Further, the typical treatment pattern can be extracted from the dense core based on the trade-off between the support of drug or usage manners of drug and a threshold defined aforehand, as shown in Fig. 2.14.

2.2.3 Predicting Typical Diagnosis Patterns

After extracting the typical diagnosis pattern (i.e., UD), Chen et al. (2022) further proposed the prediction task based on the health condition of a patient admitted to the hospital, exploring the important features to assign the most possible UDs to new patients. Figure 2.15 shows the proposed UD prediction method. First, three

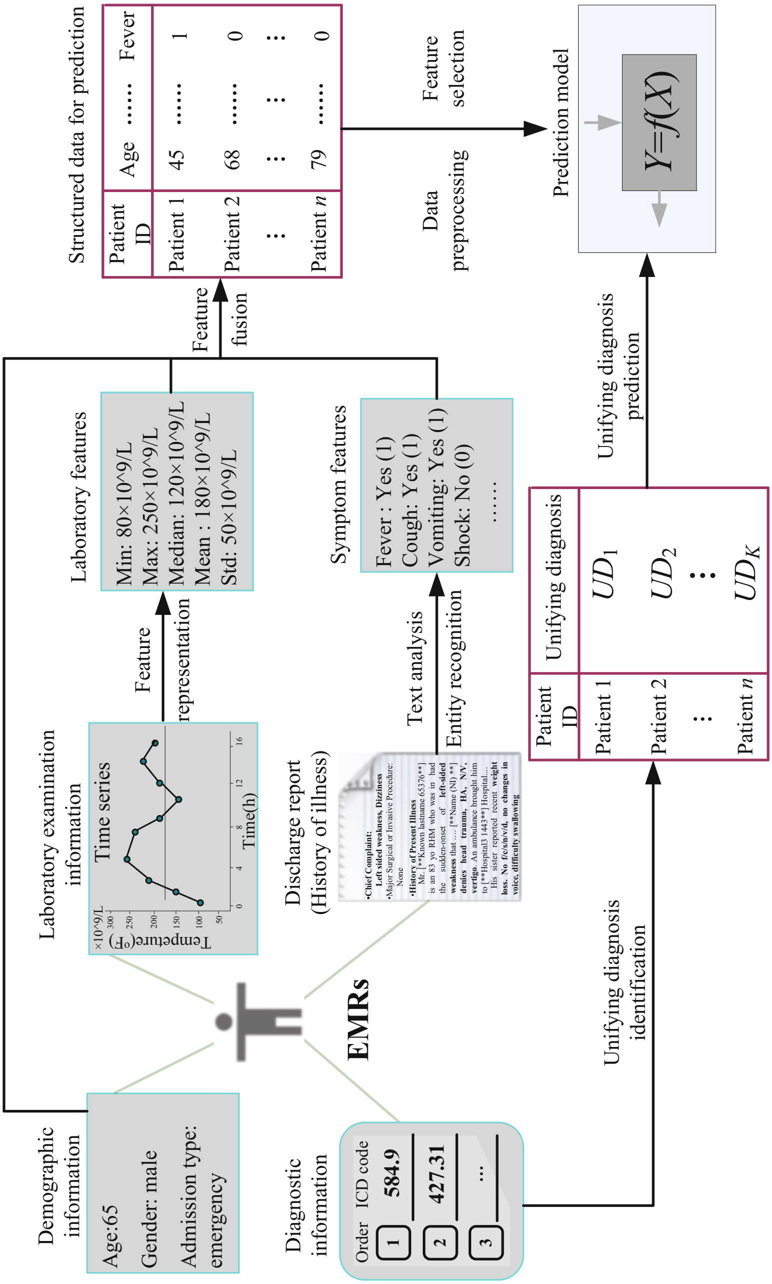

Fig. 2.15 Prediction of typical diagnosis pattern

categories of features using time series feature representation and text analysis methods were fused into structured data for further prediction. Then after data preprocessing and feature selection, all patients were labeled with a UD. Finally, some classical prediction models were adopted to perform the UD prediction task.

2.2.4 Evaluating and Recommending Typical Treatment Patterns

Before recommending typical treatment patterns (TTP) to patients, how to evaluate their effectiveness is also one of the most challenging problems, since the treatment outcome is affected by a lot of factors, and for different patient cohorts, the most effective typical treatment patterns may be different. Sun et al. (2016, 2021) presented a general framework with three stages to address this challenge shown in Fig. 2.16. First, according to demographic information, laboratory indicators, diagnostic information, and outcomes of all patients, we divide patients into different groups by a decision tree model. The patients in the same leaf node are defined as a patient cohort. Then, for a specified patient cohort, we observe how many typical treatment patterns have been used on the patients in this cohort, and further figure out which treatment pattern can result in the highest effective rate. Finally, we can recommend the best typical treatment pattern for each patient cohort.

In addition, Chen, Guo, et al. (2018) and Chen, Sun, et al. (2018) proposed a brief evaluation and recommendation framework. First, we use treatment outcomes to

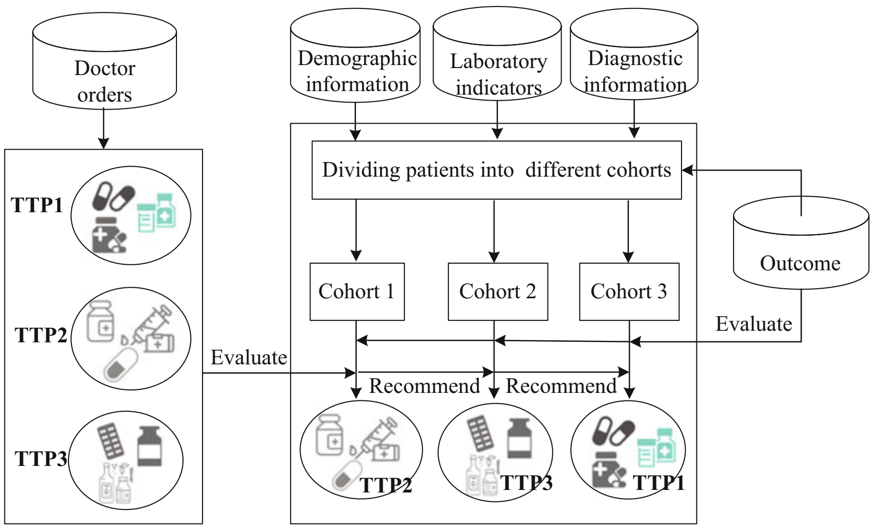

Fig. 2.16 Evaluation and recommendation of typical treatment patterns

evaluate the effectiveness of the extracted typical treatment patterns, such as treatment efficacy and treatment efficiency. Then, we also analyze demographic information, laboratory indicators, diagnostic information of each pattern, and identify some representative characteristics. Finally, for a specific patient cohort with these representative characteristics, we can recommend the most effective typical treatment pattern for new patients.

2.3 Typical Diagnosis Pattern Mining for Clinical Research

This section provides a clinical case of data-driven typical diagnosis pattern mining and predicting (i.e., UDIPM) from EMRs in our previous studies (Chen et al., 2022). In clinical practice, the reasonable classification of a large number of distinct diagnosis codes can clarify patient diagnostic information and help clinicians to improve their ability to assign and target treatment for primary diseases. Thus, the accurate identification and prediction of the UD from a large number of distinct diagnosis codes and multi-source heterogeneous patient admission information in EMRs can provide a data-driven approach to assist in better coding integration of diagnosis. Chen et al. (2022) proposed a research framework for data-driven UDIPM from EMRs, as shown in Fig. 2.17.

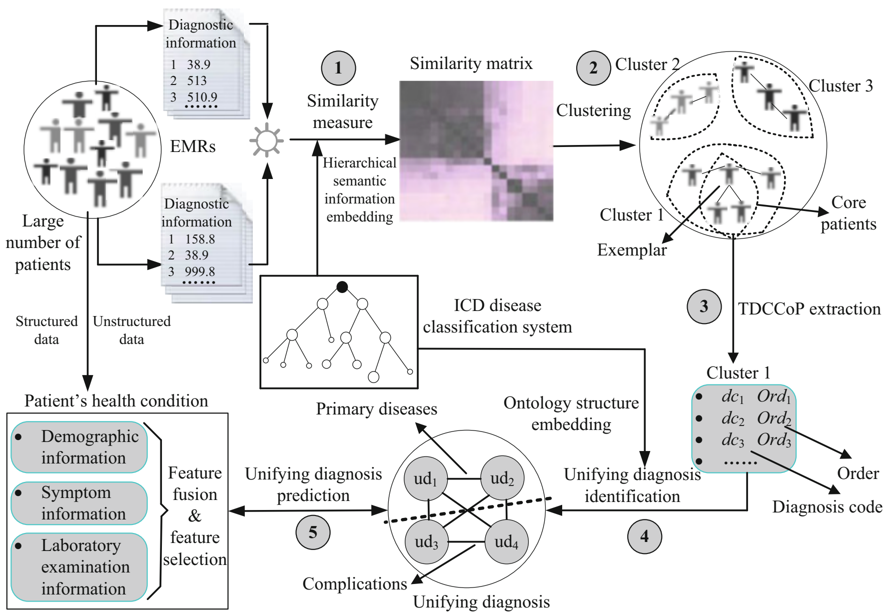

Fig. 2.17 Research framework for applying the proposed UDIPM to EMRs

This study adopted diagnostic information to identify the UD and used demographic information, symptom information, and laboratory examination information to predict the UD. First, a set of similarity measure methods was applied to a large number of patients by embedding the semantic relation of the ICD classification system (Task 1). Second, a clustering algorithm was adopted to divide patients into different groups, and further obtain the exemplar and core patients of each cluster (Task 2). Third, the typical diagnosis code co-occurrence patterns (TDCCoPs) were identified from each cluster by defining a threshold and a sorting function (Task 3). Fourth, the visual analysis and conditional co-occurrence matrix (CCoM) were combined to extract the UD by selecting the optimal segmentation (Task 4). Finally, after obtaining the health condition of the patient admitted to the hospital, a UD prediction using multi-class classification methods was achieved (Task 5).

After applying the AP clustering algorithm, we first divided the 4418 sepsis patients into two clusters, where clusters 1 and 2 contained 1391 and 3027 patients with the support of 31.48% and 68.52%, respectively. After obtaining TDCCoPs, we visualized all the TDCs in the ICD-9 ontology structure and obtained the LCA co-occurrence pattern (LCoP), as is shown in Fig. 2.18. Then we calculated the $CCoM_2$ of the $LCoP_2$ based on the diagnostic information of 800 core patients in cluster 2, as described in Table 2.1. Thus, diseases of the respiratory system (460–519, order: 3) and diseases of the circulatory system (390–459, order: 5)

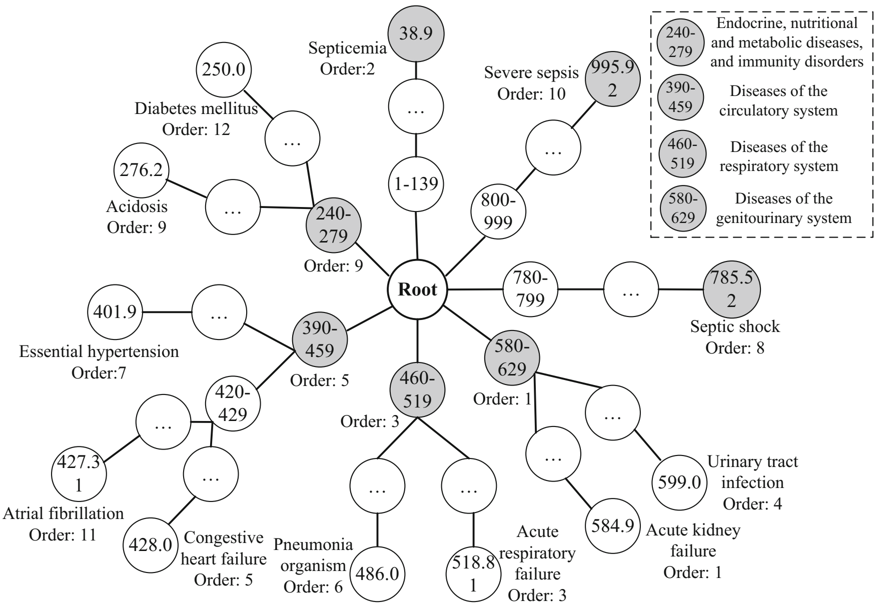

Fig. 2.18 *$LCoP_2$* identified using the visualization of *$TDCoP_3$* in the ontology structure

Table 2.1 CCoM obtained based on the result of LCoP in Fig. 2.18

$p_2(d_j/d_i)$	580-629	38.9	460-519	390-459	785.52	240-279	995.92
785.52 (8)	0.99	0.60	0.65	0.93	**0.73**	0.60	0.97
240-279 (9)	0.74	0.63	0.67	0.91	0.71	**0.61**	0.94
995.92 (10)	**0.74**	**0.61**	**0.66**	0.92	0.75	0.61	**0.94**

Note Values in brackets are the orders of the seven diseases, and bold values on the master diagonal denote the occurrence probabilities of the seven diseases

were likely to be the optimal segmentation between primary diseases and complications, and the first three diseases were considered to be the UD (UD_2) of cluster 2.

Further, we applied feature fusion and feature selection using the IG method and performed five classifications to predict a UD based on patient admission information and identify important features for the constructed prediction models. Figure 2.19 shows the classification performance of the proposed UDIPM, including the area under the ROC curve (AUC), accuracy (Acc), precision (Pre), recall (Rec), and F1-score (F1).

The experimental results indicated that the proposed UDIPM achieved better prediction performance, where the AUC values were all above 0.8, except for the decision tree method. Similarly, the best Acc, Pre, Rec, and F1 among all classifications were XGBoost, at approximately 80%, followed by random forest, SVM, and logistic regression, whereas the decision tree was last, at approximately 66%. Consider the random forest as an example. We obtained the feature importance results to better understand the prediction model. First, we found that demographic information (i.e., age) and laboratory examination information were more important than symptom information. Then some disease severity indicators were very important, such as SAPS and SAPS-II. Finally, the variance distribution (i.e., Var) of the laboratory examination indicators was more important than the mean, median, minimum, and maximum values. To summarize, the proposed UDIPM not only identified a UD from patient diagnostic information but also predicted a UD based on the health condition of a patient admitted to the hospital.

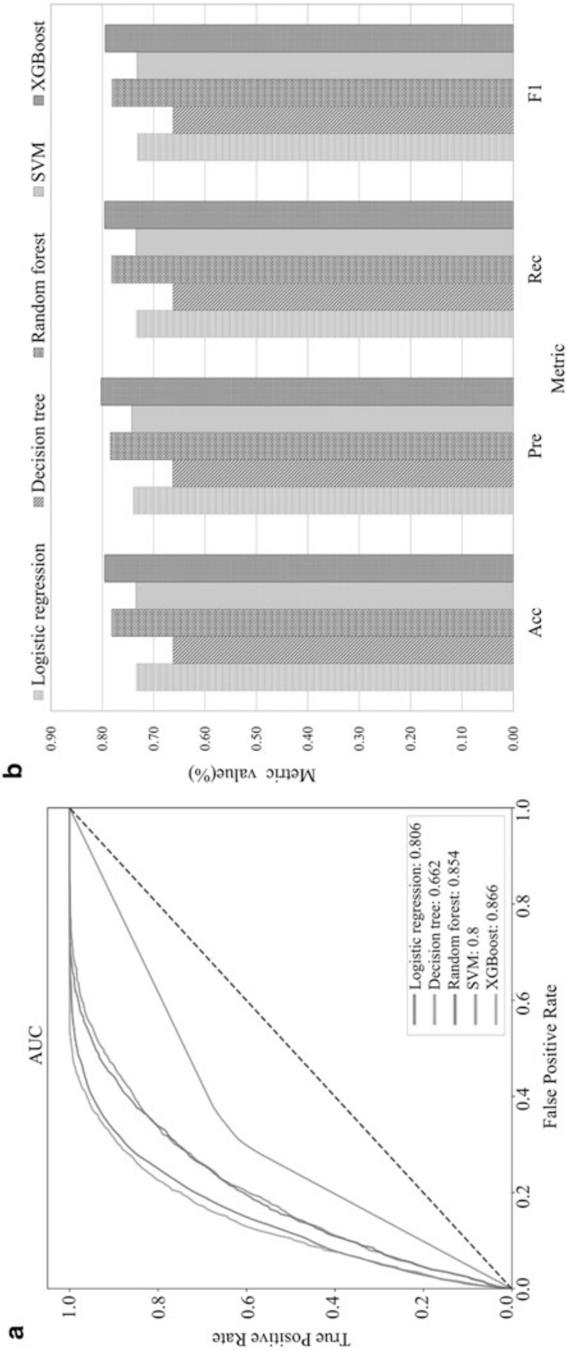

Fig. 2.19 Classification performance of the proposed UDIPM. (**a**) AUC. (**b**) Acc, Pre, Rec, and F1

2.4 Typical Treatment Pattern Mining for Clinical Research

This section provides three clinical cases of data-driven typical treatment pattern mining from different views in our previous studies (Chen et al., 2020; Chen, Guo, et al., 2018; Chen, Sun, et al., 2018; Sun et al., 2016, 2021). The first case proposes a data-driven typical treatment regimen mining approach from a doctor order content view, which is published in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (Sun et al., 2016) and Transactions on Knowledge and Data Engineering (Sun et al., 2021). The second case designs a data-driven typical drug use pattern mining approach from a doctor order duration view, which is published in proceedings of the 19th International Symposium on Knowledge and Systems Sciences (Chen, Guo, et al., 2018) and *Journal of Systems Science and Systems Engineering* (Chen et al., 2019). The third case discusses the context of clinical pathways and presents a data-driven typical treatment process mining approach from a doctor order sequence view in the *Journal of Biomedical Informatics* and our work can provide managerial guidance for clinical pathway redesign and optimization (Chen, Sun, et al., 2018). The fourth case proposes a fusion framework to extract typical treatment patterns based on the multi-view similarity network fusion method in Artificial Intelligence in Medicine (Chen et al., 2020). Furthermore, all proposed methods have been validated on real-world EMRs of the cerebral infarction dataset and MIMIC-III dataset (Johnson et al., 2016). In addition, a typical treatment regimen, typical drug use patterns, and typical treatment process can be regarded as one of the typical treatment patterns according to different research questions. Thus, both cases are in the context of rational drug use, and the methods we proposed can contribute to achieving the "5R" goal, namely right patient, right drug, right dose, right route, and right time.

2.4.1 Typical Treatment Regimen Mining from Doctor Order Content View

A typical treatment regimen usually refers to a series of doctor orders with a high frequency of occurrences (i.e., typical doctor orders) in a group of patient treatment records, and each typical doctor order also includes the drug name, delivery route, daily dosage, frequency, start and end time. Sun et al. (2016, 2021) presented a research framework of data-driven typical treatment regimen mining from doctor order content view shown in Fig. 2.20. This process has been discussed in Sect. 2.2, except for the similarity measure methods. In this work, we developed a novel method that can compute the similarity between two doctor orders by an orderly combination of a drug name, delivery route, and dosage-per-day, and further proposed a complex set similarity measure method for computing the similarity between two treatment records.

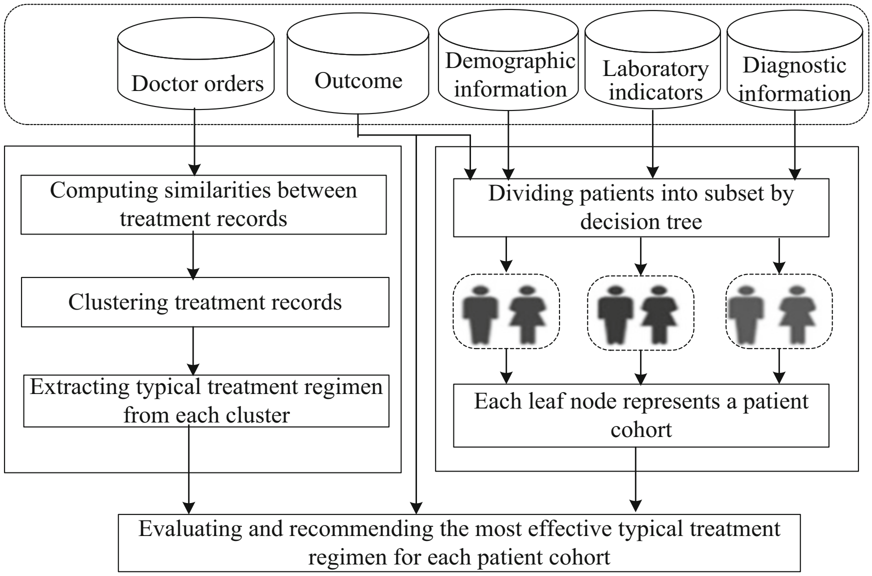

Fig. 2.20 The research framework of data-driven typical treatment regimen mining

After clustering treatment records, we extracted typical treatment regimens from each cluster. For instance, Fig. 2.21 shows the extraction results of typical treatment regimen 2, where each bar denotes a typical drug. Concretely, the support of typical treatment regimen 2 is 15.5%, and the most typical drugs are Shuxuetong, Ozagrel, Cinepazide, and Aspirin. The usages of four medicines in different periods are also different. Further, taking the third period (4–7 days) for example, each pie denotes the different usage manners of the typical drug with its support, such as "IV/160/4" of Ozagrel refers to that the delivery route is an intravenous injection (IV), the daily dosage is 160 units, four days are used during the third period, and the support is 52%.

Next, after extracting typical treatment regimens and dividing the patients into homogeneous cohorts by the decision tree method, we can evaluate and recommend the most effective typical treatment regimen for each patient cohort. For instance, Fig. 2.22 shows the evaluation and recommendation for two patient cohorts. Specifically, for Case 1 (leaf node 2 with 4035 patients), most of the patients are cured and improved. Typical treatment regimen 4 (Patient-T4) is the best regimen with the highest cure rate and improved rate, but only 0.37% of patients in this cohort used this regimen. Typical treatment regimen 3 (Patient-T3) with higher support of 25.97% is regarded as the most effective treatment regimen because it can obtain a higher cure rate and lower ineffective and dead rate than a typical treatment regimen 1 (Patient-T1) and 2 (Patient-T2). Similarly, we can recommend typical treatment regimen 2 to the patient cohort with leaf node 17.

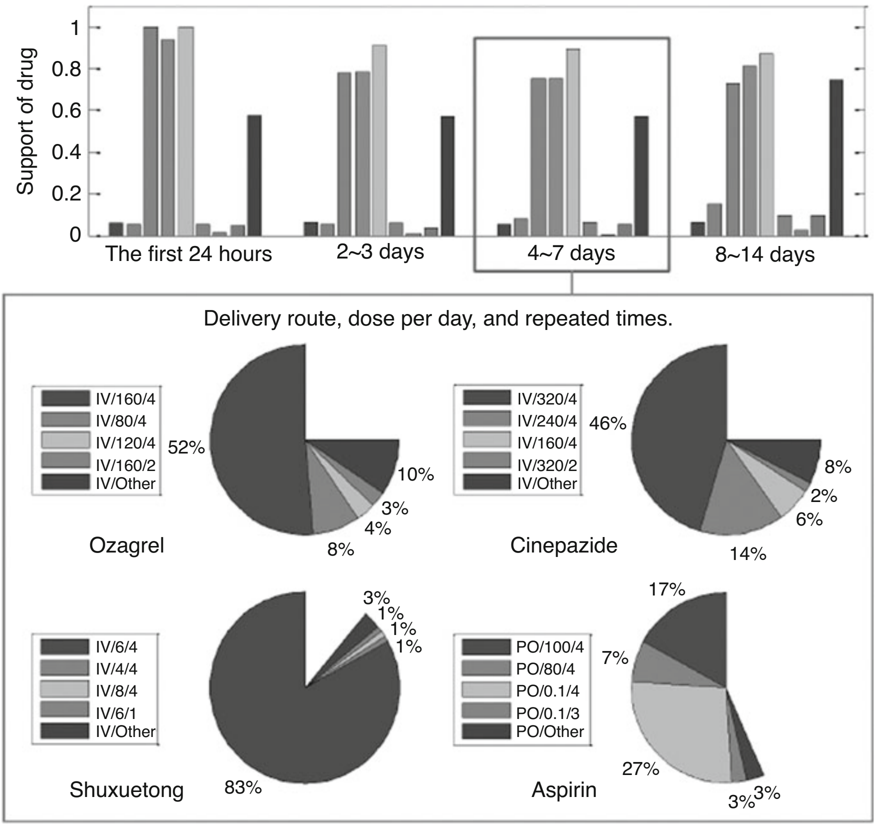

Fig. 2.21 The extraction results of the typical treatment regimen

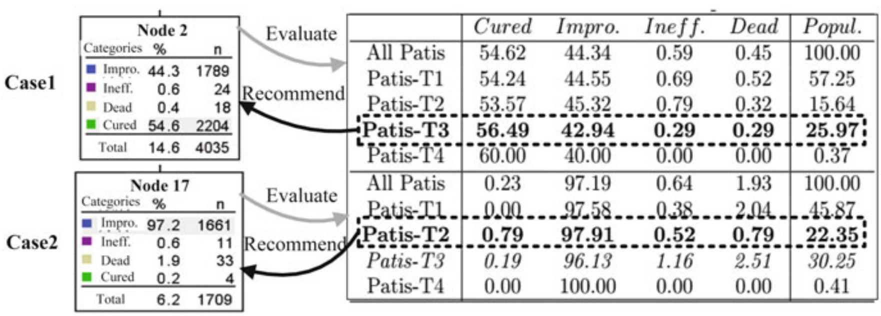

Fig. 2.22 Evaluate and recommend typical treatment regimens for two patient cohorts

2.4.2 Typical Drug Use Pattern Mining from Doctor Order Duration View

Rational drug use also requires that patients receive medications for an adequate period of time. The adequate duration time of medications not only improves the therapeutic effect of medicines but also reduces the side effects and adverse reactions of medicines. Chen, Guo, et al. (2018) and Chen et al. (2019) proposed a research framework of data-driven typical drug use pattern mining from the doctor order duration view shown in Fig. 2.23. The main process has been also discussed in Sect. 2.2, except for the representation of the drug use distribution feature vector (DUDFV) from doctor orders and the similarity measure methods. In this work, in order to analyze the duration time characteristic of medications, we first defined the drug use distribution feature with a quintuple for each drug, including the mean, the variance, the lasting days, and the first and last day of drug use. Then we represented the DUDFV of each patient by the ordered combination of DUDFs for all drugs and further used the Euclidean distance to measure the similarity between pairwise DUDFVs.

After clustering DUDFVs, we extracted three typical drug use patterns (i.e., pattern 1, pattern 2, and pattern 3). For instance, Fig. 2.24 shows the extraction results of pattern 2, where each black bar in Fig. 2.24 (1) and Fig. 2.24 (2) denotes a drug and drug use day, respectively; each white bar in Fig. 2.24 (1) and Fig. 2.24 (2) denotes a typical drug and effective drug use day when exceeding a threshold defined aforehand, respectively; and the curve in Fig. 2.24 (2) is the effective drug use days and DUDF of Heparin. Concretely, the support of pattern 2 is about 55% with 19 typical drugs, and the support of each typical drug is different. For Heparin

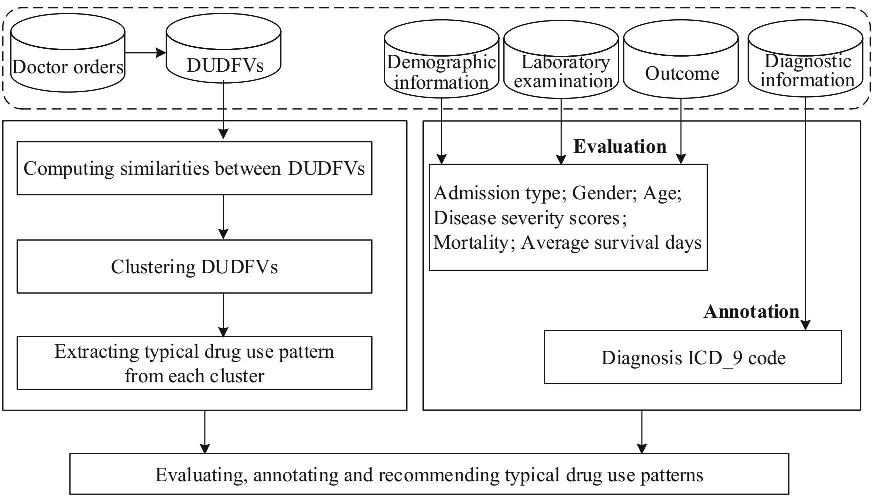

Fig. 2.23 The research framework of data-driven typical drug use pattern mining

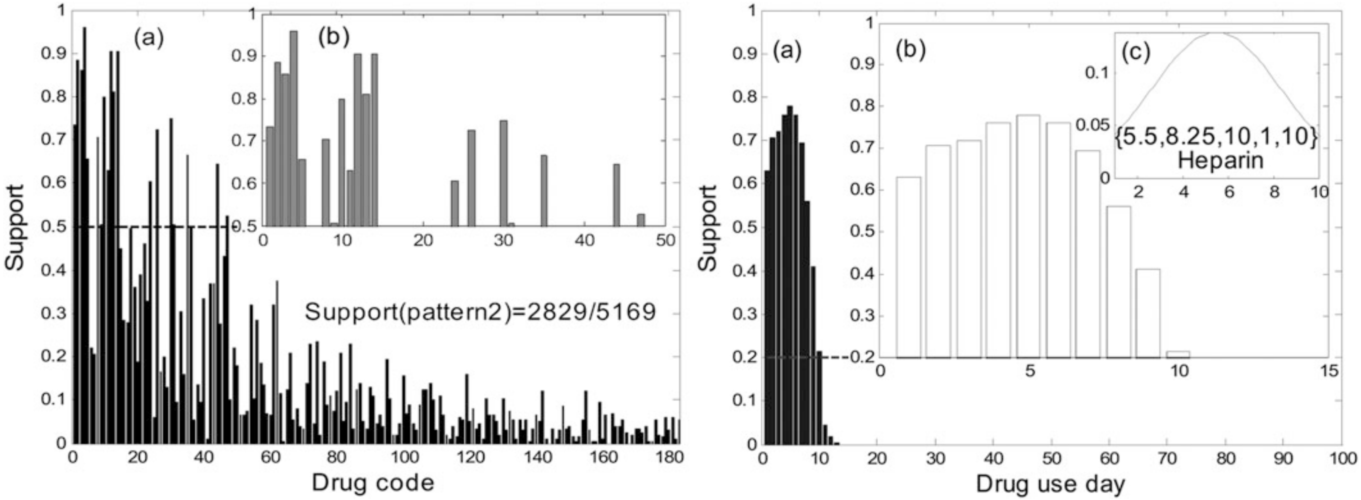

Fig. 2.24 The extraction results of pattern 2. (1) Typical drugs of pattern 2. (2) Effective drug use days and DUDF of Heparin

selected from pattern 2, the DUDF is {5.5, 8.25, 10, 1, 10} indicating that the mean, the variance, the lasting days, and the first and last day of Heparin use are 5.5, 8.25, 10, 1, and 10. Similarly, we can also obtain the DUDFs of all typical drugs and provide clinical guidance for the duration time of drug use.

Then, we further evaluated the extracted typical drug use patterns based on demographic information, laboratory examination and outcome, annotated diagnosis codes for each typical drug use pattern according to diagnostic information, and proposed a recommendation work for the patients with the same patient condition and disease types shown in Fig. 2.25. In Fig. 2.26, we deem patterns 2 and 3 to be the

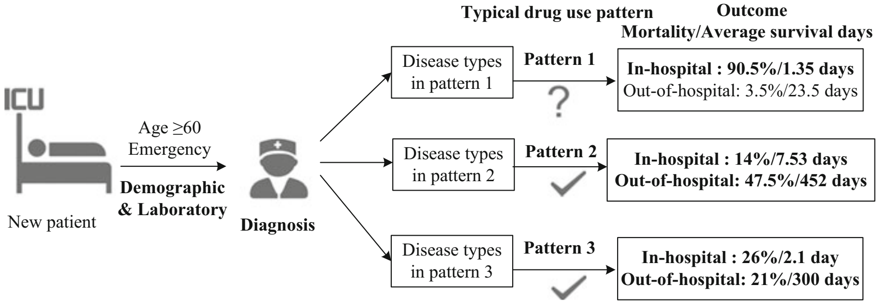

Fig. 2.25 Recommendation of typical drug use patterns

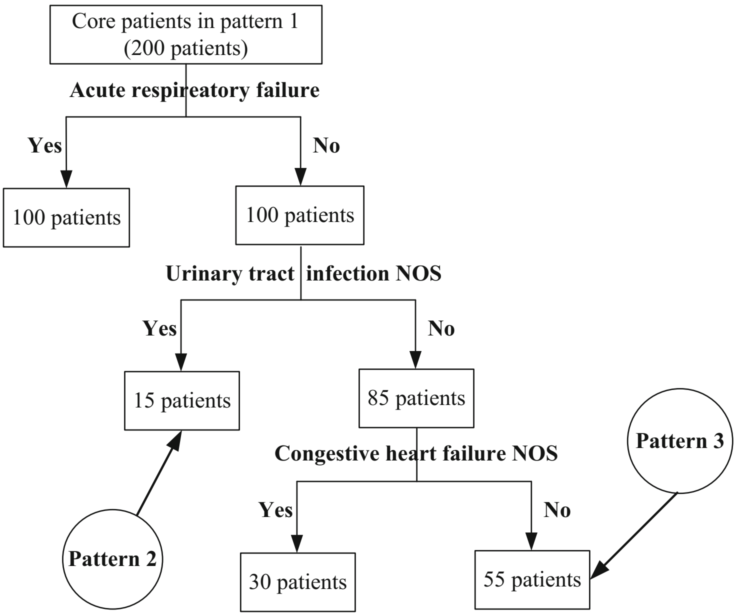

Fig. 2.26 Recommendation for the patients in pattern 1

effective typical drug use patterns because of lower in-hospital and out-of-hospital mortality and a longer average survival time than that of pattern 1. Thus, for patients in pattern 1, we further analyze their disease types and recommend pattern 2 and pattern 3 to the seventy patients in Fig. 2.26, which can effectively improve their treatment outcomes.

2.4.3 Typical Treatment Process Mining from Doctor Order Sequence View

A clinical pathway (CP) defines a standardized care process for a well-defined patient group, aimed at improving patient outcomes and promoting patient safety (Huang et al., 2015). Figure 2.27 shows the process of CP design and implementation. However, in clinical practice, creating such a pathway from scratch is demanding for medical staff as it involves multidisciplinary medical team collaboration, plan-do-check-act-related techniques, and optimal EBM (Chen, Sun, et al., 2018). In addition, due to the difference in disease severity, complication, multi-pathogenesis, and reaction to therapy, the variation of CPs often occurs when implementing them for patients.

In order to build CPs from EMRs, Chen, Sun, et al. (2018) proposed a research framework of data-driven typical treatment process mining from the doctor order sequence view shown in Fig. 2.28. This process has been also discussed in Sect. 2.2, except for the representation of doctor order set sequence (DOSS) from doctor orders and the similarity measure methods. In this work, considering the treatment courses in clinical practice, we divided treatment into different periods and defined DOSS, then generated a set transition matrix sequence from DOSS based on Markov chain theory, and further adopted Manhattan distance to compute the similarity between two treatment records.

After clustering all DOSSs, we can extract the typical treatment process from each cluster. For instance, Fig. 2.29 shows the extraction result of typical treatment processes from dataset 3 (i.e., patients in critical condition), where each circle denotes a typical drug, and each line represents the transition probability of two doctor orders in the adjacent period. Specifically, we identified four categories of typical treatment processes with seven drugs for cerebral infarction patients in the critical condition. For typical treatment process 1, we can extract a high-frequency typical treatment process (HF-TTP: support $\in$ [0.7,1), black thin line), namely, {Admission, {Lum, GBEP, Asp}, {Lum, GBEP, Asp}, {Lum, GBEP, Asp}, {Lum, GBEP, Asp}, Discharge}, which can be contribution to build CPs. Similarly, we can also extract some HF-TTPs from the typical treatment processes 2, 3, and 4.

Next, we further evaluated the treatment efficacy and efficiency, analyzed demographic and diagnosis information of typical treatment process, and discussed a recommendation work for the patients with the same patient condition and disease severity. Figure 2.30 shows the recommendation of typical treatment processes,

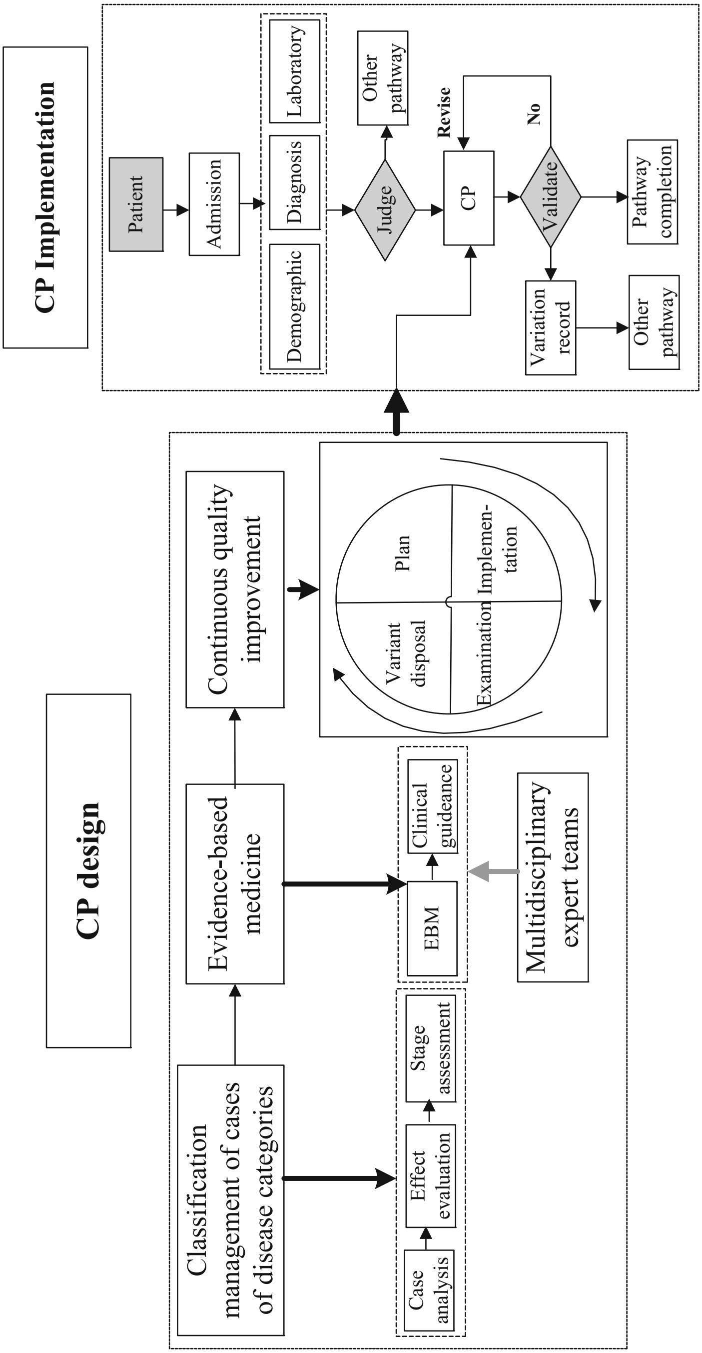

Fig. 2.27 The process of CP design and implementation

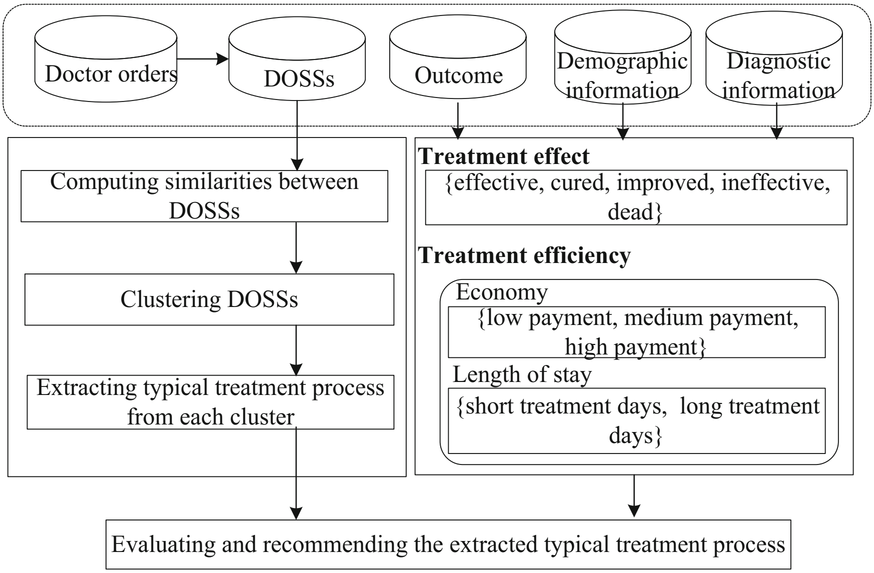

Fig. 2.28 The research framework of data-driven typical treatment process mining

where F-TTP, S-TTP, and C-TTP denote the extracted typical treatment processes from dataset 1 (patients in fair condition), dataset 2 (patients in serious condition), and dataset 3 (patients in critical condition), respectively. For instance, when a new patient is admitted to hospital A, and diagnosed with cerebral infarction in fair condition after demographic information and laboratory examination by clinical doctors, the F-TTP1 can be recommended for this patient, and treatment outcome is predictable, such as the cured rate is as high as 74%, the probability of payment [￥4000, ￥24,000] is 86%, and the probability of length of stay less than two weeks is 78%. Similarly, we can recommend the best treatment for different patients according to Fig. 2.30.

2.4.4 Typical Treatment Pattern Mining from Multi-View Similarity Network Fusion

In clinical practice, rational drug use means that patients receive medications appropriate to their clinical needs, in doses that meet their own individual requirements, for an adequate period of time, and at the lowest cost to them and their community (World Health Organization, 2012). Thus, the goal of rational drug use is to achieve the "5Rs": "right drug," "right dose," "right route," and "right time" for "right patient." However, due to diseases with multiple similar treatment stages, various symptoms, and multiple pathogeneses and clinical experience and

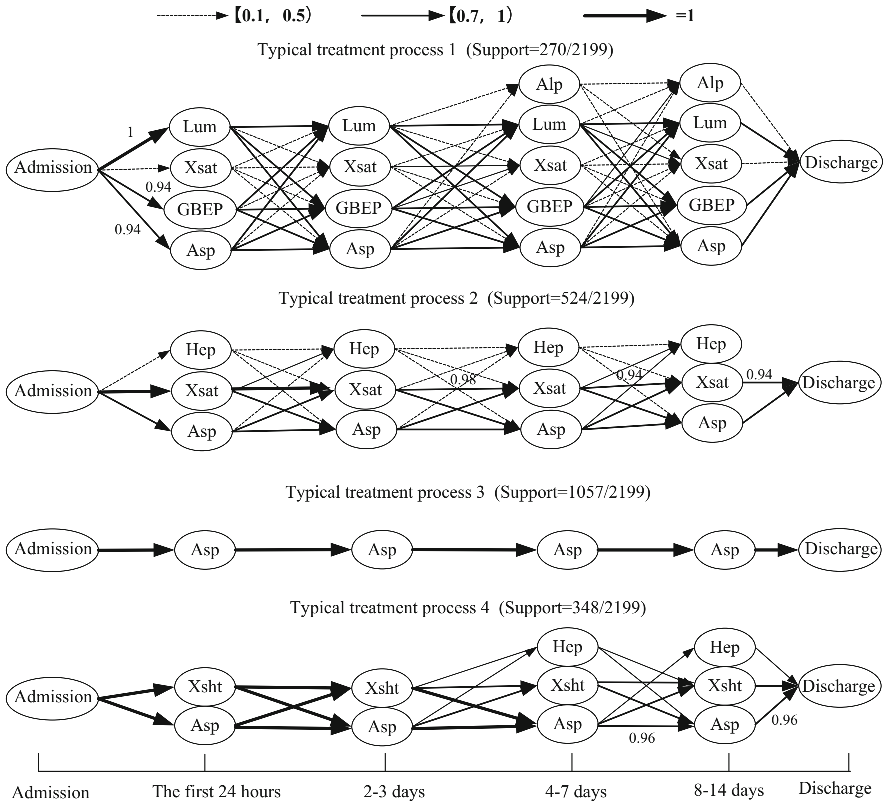

Fig. 2.29 The extraction result of the typical treatment process from dataset 3

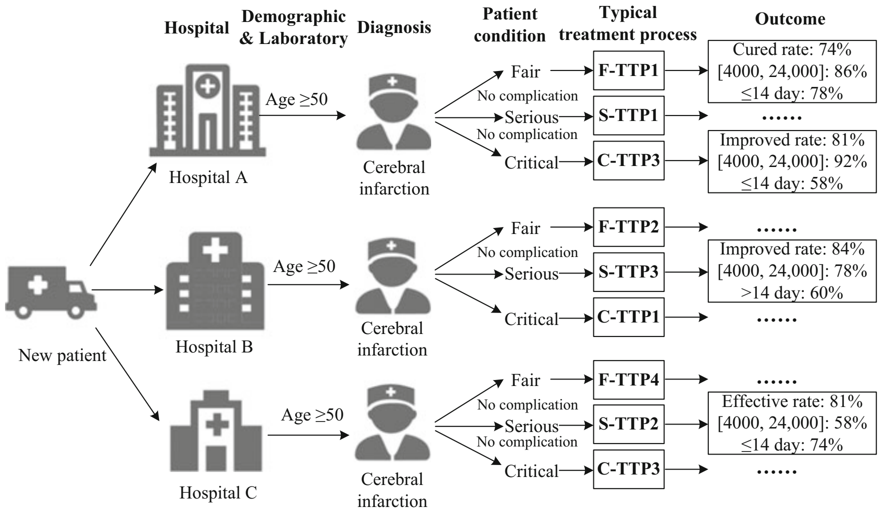

Fig. 2.30 Recommendation of typical treatment processes

knowledge with the characteristics of inadequate communication, experience exchange, and cooperation between young and senior doctors, it is difficult to achieve the "5Rs" goal in an accurate and efficient manner (Chen, Guo, et al., 2018; Chen, Sun, et al., 2018).

Therefore, Chen et al. (2020) analyzed the characteristics of doctor orders, formulate new patient representations and compute the corresponding patient similarity from three views (i.e., an improved doctor order content view patient similarity measure, a doctor order sequence view patient similarity measure, and a novel doctor order duration view patient similarity measure), and applied a multi-view Similarity Network Fusion (SNF) method to fuse three kinds of patient similarity for typical treatment pattern extraction. Figure 2.31 illustrates the fusion framework of a typical treatment pattern extraction in this chapter. The fusion framework mainly consists of four steps: (1) terms and definitions, (2) patient similarity measure methods, (3) the multi-view SNF method, and (4) the typical treatment pattern extraction method.

Real-world EMR data of cerebral infarction patients used in our experiment were collected from three Traditional Chinese Medicine (TCM) hospitals, which are

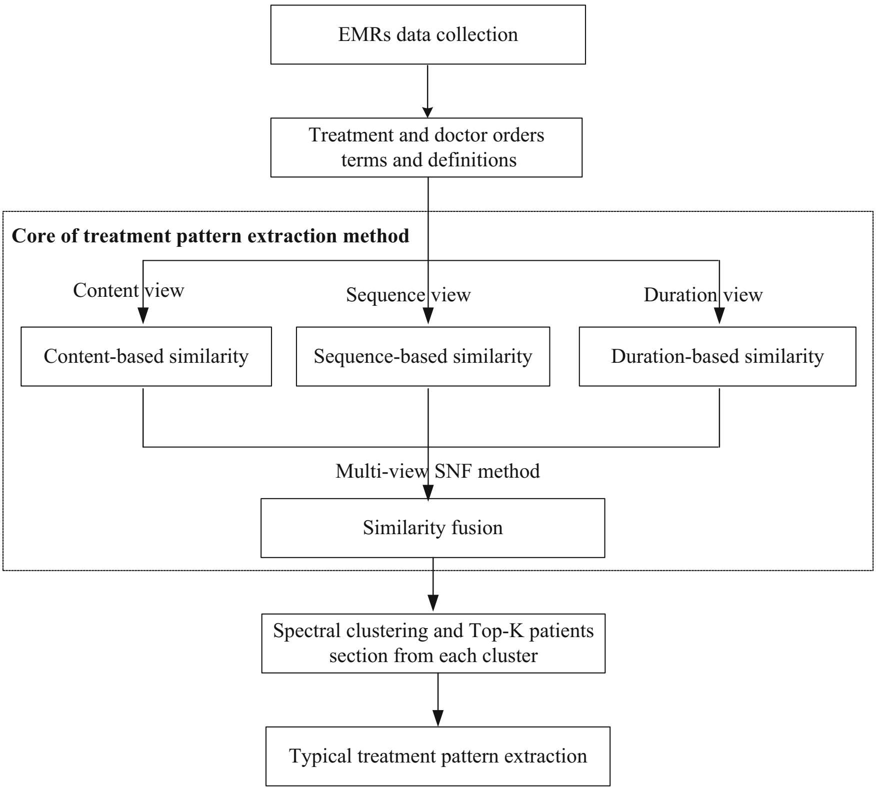

Fig. 2.31 The research framework of data-driven typical treatment pattern mining

located in three cities in China. After evaluating the performance of the multi-view SNF method, we first discussed the selection of the number of clusters and then use the proposed fusion framework to extract typical treatment patterns, including the distribution of typical drugs in different periods, delivery routes, doses per day, and repeated times in different periods from the content view, the transition of typical drugs in different periods from the sequence view, and the duration distribution of typical drugs from the duration view.

From the content view, Fig. 2.32 describes the distribution of typical drugs in four periods for TTP3. First, with the exception of Mannitol (78) in the fourth period (i.e., 8–14 days), most drugs are widely used in four periods, where Aspirin (133) has the largest support of 92%, followed by Xuesaitong (114), Ozagrel (36), and Heparin

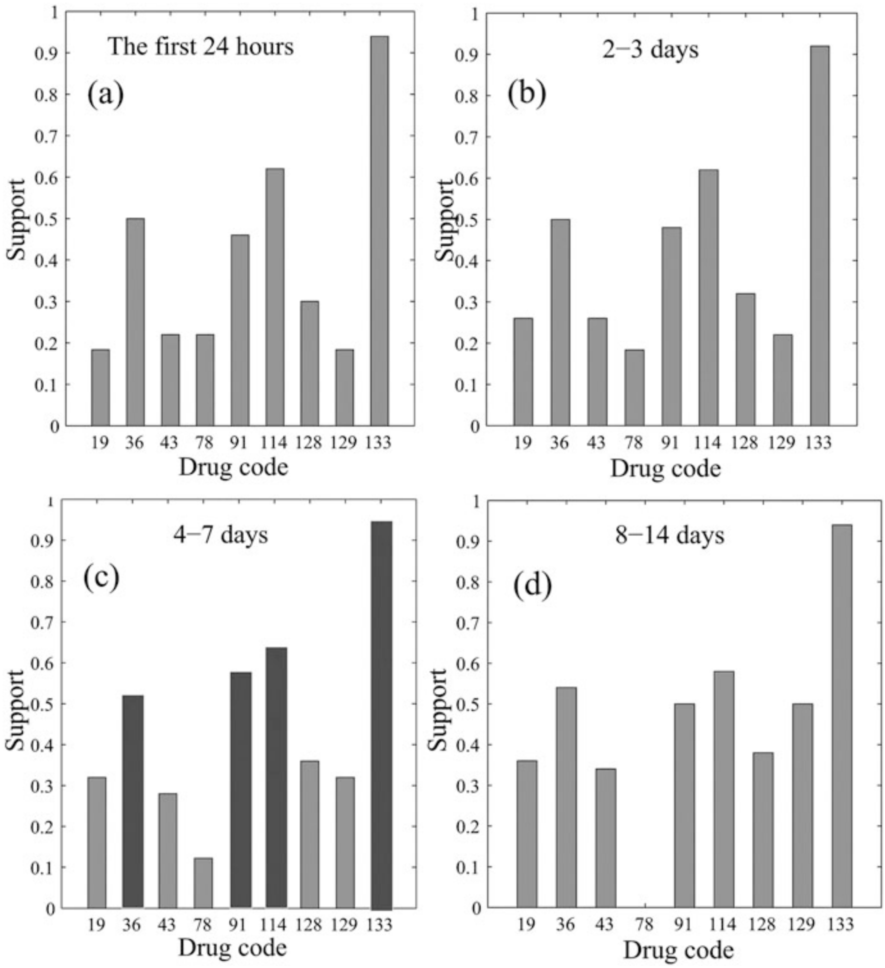

Fig. 2.32 The distribution of typical drugs in different periods for TTP3

(91). Second, Mannitol (78), as a hypertonic antihypertensive drug, is commonly used in clinical rescue, especially in the treatment of brain diseases with the characteristics of rapid and accurate antihypertensive effects to reduce intracranial pressure. Thus, along with the extension of the treatment period, the support gradually decreases from 22% to 0%. Finally, the support of Alprostadil (19), Yindanxinnaotong capsules (128), and Ginkgo biloba extract powder (129) gradually increases from the first 24 h to 8–14 days post-infarction, while other drugs remain unchanged. Additionally, we selected Ozagrel (36), Heparin (91), Xuesaitong (114), and Aspirin (133) as four representative drugs in the third period (i.e., 4–7 days post-infarction) to further analyze how these typical drugs are used.

Figure 2.33 shows the usage manners of the four representative drugs used in the third period for TTP3, including their drug efficacy, delivery route, dose per day, and repeated times. Overall, each drug has multiple usage manners with different supports, and fewer drugs have the same usage manners. Specifically, for Ozagrel (36), the most widely used manner is "IV/80/4" with a support of 28%, followed by "IV/60/4" with a support of 10%, where "IV/80/4" indicates the delivery route is Intravenous Injection, the daily dose is 80 units, and the duration is 4 days in the third period. Heparin (91) is an important anticoagulant drug to treat cerebral infarction and has three distinct usage manners, where "ST/other" ranks first with

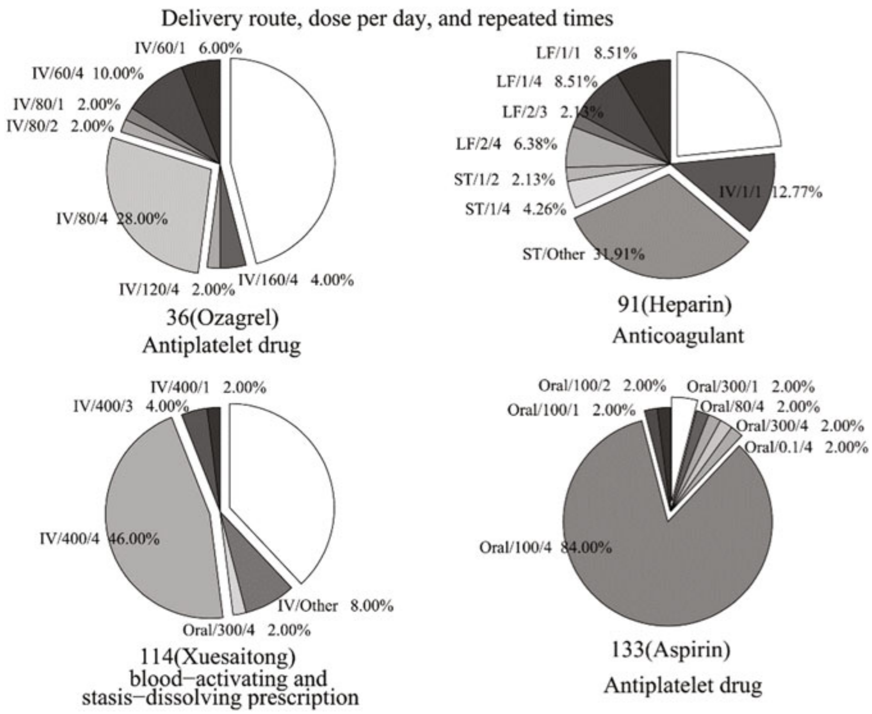

Fig. 2.33 The usage manners of four representative drugs used in the third period for TTP3

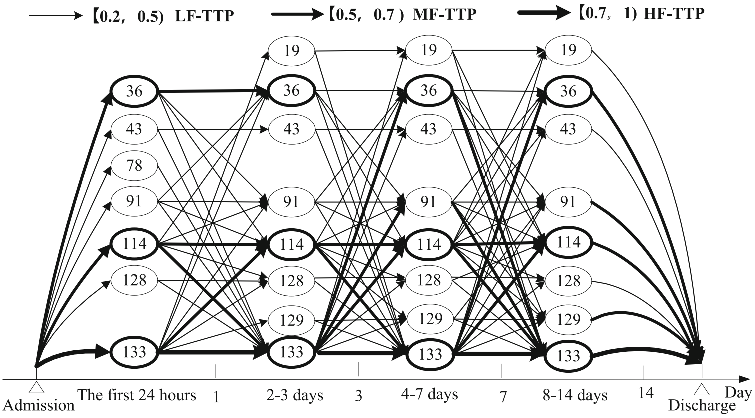

Fig. 2.34 The transition between typical drugs in four periods for TTP3

the support of 31.91%, followed by "IV/1/1," "Lock Flush (LF)/1/4," and "LF/1/1." "ST/other" denotes the delivery route is Subcutaneous Injection, but the daily dose data are missing. For Xuesaitong (114) and Aspirin (133), the most popular usage manners are "IV/400/4" with a support of 46%, and "Oral/100/4" with the support of 84%, respectively.

From the sequence view, Fig. 2.34 shows the extracted transition patterns for TTP3, including an HF-TTP ({Admission, Aspirin (133), Aspirin (133), Aspirin (133), Aspirin (133), Discharge}, an MF-TTP ({Admission, {Ozagrel (36), Xuesaitong (114)}, {Ozagrel (36), Xuesaitong (114)}, {Ozagrel (36), Xuesaitong (114)}, {Ozagrel (36), Xuesaitong (114)}, Discharge}, and some LF-TTPs. In general, the HF-TTP and MF-TTP can be used as important guidance to build different levels of CPs.

From the duration view, Fig. 2.35 shows the duration distribution of the four representative drugs used in TTP3, the mean usage day and dispersion degree of these drugs are similar to distribution intervals [6.9, 7.4] and [15.3, 16.1], while the durations are greatly different, the shortest is Heparin (91) with 7.9 days, while the longest is Aspirin (133) with 12.35 days. Additionally, the start and end times of the four drugs are different. For example, Ozagrel (36) is started on approximately the second day and is ended on the twelfth day, Heparin (91) is started on approximately the third day and is ended the eleventh day, and Xuesaitong (114) is started on the seventh day and is ended on the fifteenth day, and Aspirin (133) is started on the first day and is ended on the fourteenth day.

2.4.5 The Examination of Typical Treatment Pattern Mining Approaches, Limitations, and Open Issues

As discussed in Sections 2.2 and 2.4, four kinds of typical treatment pattern mining approaches mainly include similarity measure method, clustering algorithm, and

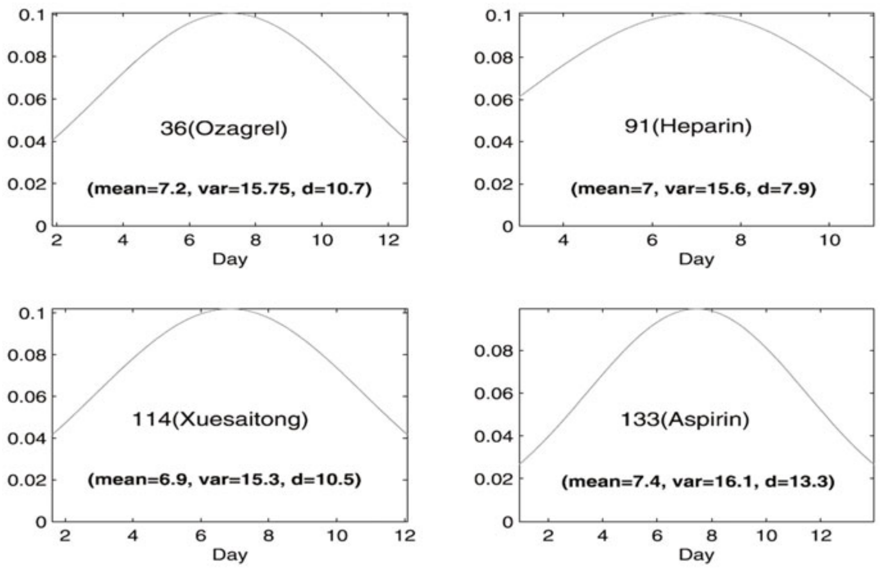

Fig. 2.35 The duration distribution of the four representative drugs used in TTP3

typical treatment pattern extraction method; thus it is an unsupervised learning approach and can be used the clustering results to examine the performance. Concretely, for the experimental setting, the labeled clinical dataset is essential, which requires patients with the same label have similar characteristics, such as patient condition, complication, treatment days, total payment, hospital code, and treatment efficacy. For evaluation criteria, clustering accuracy and normalized mutual information can be used to examine the clustering results (Chen, Sun, et al., 2018; Sun, Guo, et al., 2017). For the baselines of the similarity measure method, we can select the LDA with cosine distance, vector space model weighted by TF-IDF with cosine distance, and edit distance (Chen et al., 2016; Chen, Sun, et al., 2018; Guo et al., 2018). For the clustering algorithm, we can select AP clustering, K-center, and DPC. Chen, Sun, et al. (2018) have demonstrated that the typical treatment pattern mining approach we proposed achieved the highest clustering performance among different clustering algorithms.

In addition, there are still some limitations in our studies. Firstly, fixed intervals for treatment periods may not be the most optimal split due to the complex and varying length of treatment records (e.g., the four periods in the first two weeks), thus a new solution for future studies could involve splitting varying-length treatment records based on significant changes in prescription indications (Hoang & Ho, 2019). Secondly, in the experimental setting, some parameters need to be manually defined aforehand, such as the weights of different treatment periods, the threshold of typical drugs, the definition of the core area for a treatment cluster, and so on. Finally, the labeled clinical dataset is essential to examine the performance of typical treatment pattern mining approaches, while in our experiment, only a small amount of the clinical dataset is manually annotated, which may be a lack of sufficient evidence to demonstrate the advantages of our approaches.

Furthermore, abnormal activities occur frequently in clinical practice; thus abnormal diagnosis and treatment patterns mining from mass EMRs is also a crucial issue for improving clinical diagnosis and treatment level, optimizing the existing clinical guidelines, and identifying healthcare insurance fraud incidents.

2.5 Conclusions

The advance of big data analytics in healthcare is accelerating the transformation of the medical paradigm. This chapter is an extension of our previous work (Guo & Chen, 2019), firstly discussed the research background of big data analytics in healthcare, summarized the research frameworks of big data analytics in healthcare, and analyzed two types of medical processes to highlight the important role of data-driven diagnosis-treatment pattern mining in clinical guidance. Then for three challenges, we investigated how to measure similarity between diagnosis and treatment records, how to extract typical diagnosis-treatment patterns from EMRs, and how to predict, evaluate, and recommend typical diagnosis-treatment patterns. Further, five clinical pieces of research have been provided to demonstrate the important role that data-driven diagnosis-typical treatment pattern mining can contribute to achieving the "5R" goal in UD identification and predication, rational drug use, and CP redesign and optimization. Finally, we also discussed the examination of typical diagnosis-treatment pattern mining approaches, limitations, and open issues.

Although big data analytics and artificial intelligence technology are promoting the automatization, informatization, and intellectualization of healthcare service, several challenges have been widely recognized as major barriers to the successful implementation of big data in healthcare. First and foremost, the security and privacy concerns surrounding big data in healthcare have become increasingly urgent in recent times, primarily due to the sensitive nature of diagnosis and treatment records. To address these concerns, one approach is to enact and enforce the laws and regulations of data sharing and exchange by the government such as the health insurance portability and accountability act (HIPAA) and the health information technology for economic and clinical health (HITECH) Act in the United States; another is to accelerate technological developments in data privacy protection by the technology of data masking, encryption, and de-identification.

In addition, with the increasing popularity of intelligent diagnosis and treatment machines in clinical practice, how to determine their ethics and the legal liability among clinicians, intelligent machines, and producers for medical accidents are becoming the subject of attention. Nowadays there exists a consensus that clinicians are the leader of human-machine relationships, and intelligent diagnosis and treatment machines cannot replace them completely, but assist them to make better clinical decisions. Thus, clinician intelligent diagnosis and treatment machine integration is an effective pathway to enhance the efficiency of healthcare service. In the future, considering high integration and interdisciplinary cooperation of technologies, ethics, laws, and regulations, it is possible to embed ethics and laws into intelligent diagnosis and treatment machines and determine their status as liability subjects.

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Chapter 3
Knowledge Discovery from Online Reviews

Jiangning Wu and Tong Yang

3.1 Overview of Online Reviews Mining

Given the popularity of online reviews, scholars in various industries and disciplines have focused on exploring business opportunities through mining online reviews, such as tourism, hospitality, manufacturing, etc. Regarding the research topics, it is easy to find a wide range of involvement. Mainstream topics include product ranking systems, user preference analysis, review usefulness analysis, and product competitive analysis.

3.1.1 Product Ranking System Based on Online Reviews

To support consumers' decision-making in choosing products, many studies in recent years have focused on constructing product ranking models based on online reviews or user-generated content (UGC). As per the theories and methods, these studies could be classified into two categories, namely mathematical programming-based methods and multi-attribute decision-making-based methods (Bi et al., 2022). The first methods aim at both optimizing consumer utility and minimizing search costs. By constructing such mathematical programming models, the results are obtained in such a way that the optimization objectives are satisfied as much as possible. For example, Ghose et al. (2012) proposed a mathematical programming model to rank products using user-generated content and crowdsourced content. In this method, the authors posited that the products providing higher surplus (also called consumer utility) should be ranked first. By collecting online surveys, the

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validity of the proposed model was validated. Similar to Ghose et al.'s (2012) work, Rianthong et al. (2016) constructed a stochastic programming model, which improved the efficiency of product ranking. The authors considered optimizing utility and reducing search costs, while also considering consumer preferences.

The second category of studies considers both product information and consumer preferences to calculate the ranking values. Based on the ranking values, multi-attribute decision-making methods are utilized to determine the optimal results. This method is currently more popular. For example, Tayal et al. (2022) proposed a new multi-criteria decision-making (MCDM) method for the personalized ranking of products based on multiple dimensions. Specifically, the authors first determined customer preferences as input for decision-making. Then aspect-level sentiment analysis was utilized to calculate attribute performance. This model subtly included customer preferences by mapping different customer preferences to Plithogenic degrees of modeling linguistic uncertainty in online reviews to create a personalized product ranking using Plithogenic aggregation. The comparisons with existing MCDM methods have demonstrated its superiority. Essentially, this approach is carried out based on the calculation of aspect-level sentiment in online reviews, and thus the accuracy of sentiment calculation would influence the ranking effectiveness. For this concern, Fu et al. (2020) constructed deep learning models to accurately identify the sentiment orientation embedded in online reviews and then extracted the feature-opinion pairs. Especially, the authors utilized the interval-valued Pythagorean fuzzy-weighted Heronian mean operator to aggregate the attribute information based on the interrelationship between product attributes. Subsequently, product ranking was achieved, and a case study was experimented with to validate the proposed model. Overall, studies on product ranking based on online reviews are gaining attention.

3.1.2 User Preference Analysis

With the rapid development of information technology and social media, more and more consumers are posting their products/services using experiences online, which incorporate rich consumption perceptions and consumers' attitudes to products/services. Such data are characterized by massive, real, insightful, and passionate. Importantly, sentiments embedded in online reviews mirror consumers' preference for products/services. Therefore, numerous scholars from various fields have conducted research on mining online reviews to capture consumer preferences, such as tourism, manufacturing, and hospitality. These studies posit that online reviews are embedded with consumers' detailed perceptions of multiple aspects, and these positive or negative opinions directly reflect consumers' preferences. Hence to enhance customer satisfaction, managers and practitioners should extract consumers' preferences from massive online reviews. For example, Zhang et al. (2021) constructed an aspect-level sentiment analysis model to identify hotel customers' preferences. Vu et al. (2019) presented a method that utilized online restaurant reviews and text-processing techniques to investigate tourists' dining behaviors. Regarding the manufacturing field, Xiao et al. (2016) explored how to measure mobile phone users' preferences based on the Kano model, and the results demonstrated the superiority of the proposed models.

Similar to the above preference analysis studies based on online reviews, there are also studies that focus on understanding consumer satisfaction through mining online reviews. Customer satisfaction is the compared results of subjective expectations and the actual performance of a product/service. When the actual performance is higher than expectations, consumers are satisfied; otherwise, consumers are unsatisfied. For example, Guo et al. (2017) explored hotel customers' satisfaction by mining sentiment information in online reviews, and the results demonstrated the efficiency of such data. Aiming at revealing why consumers are satisfied, Kim et al. (2022) investigated user opinions via online restaurant reviews. Similarly, Liu, Song, Sun, et al. (2020) analyzed the relationship between food quality and consumers' dining satisfaction using online reviews from a perspective of negative bias. Regarding the tourism field, Park et al. (2020) focused on the asymmetric relationship between attribute performance and customer satisfaction and unveiled the asymmetric effects of online airline reviews. Satisfaction analysis research can also be easily found in the manufacturing field. Imtiaz and Islam (2020), for instance, identified the influential features of smartphones on consumer satisfaction from online reviews and validated how these features determine satisfaction.

3.1.3 Review Usefulness Analysis

Consumers are used to reading online reviews to understand the products before making purchase decisions. But not all online reviews are useful for consumers; especially in the face of massive amounts of data, consumers need to know exactly which reviews are useful and which are not. As per the theory of reasoned action, trust in sellers is one of the determinants of online consumption intention, and such behaviors of consumers are influenced by existing online reviews. In this regard, online reviews could influence product sales and thus are of great importance for sellers and businesses (Choi & Leon, 2020). Especially, useful information might diffuse faster among consumers (Pavlou, 2003), and thus useful online reviews could be efficiently identified to help build consumer trust. For this concern, a lot of academic efforts have been devoted to the usefulness analysis of online reviews.

In general, these studies focus on two aspects of review usefulness, namely reviews and reviewers. Review factors include review content, length, ratings, sentiments, etc.; reviewer factors involve the reviewer's expertise, identity, ranking, etc. Specifically, some scholars investigate how review extremity influences review usefulness. For instance, Siering and Muntermann (2013) explored the relationship between extremity and review usefulness using online reviews from Amazon and found a negative effect; in contrast, Cao et al. (2011) found a positive relationship based on online reviews from CNET. Moreover, many studies have confirmed the fact that longer reviews reflect more useful information. Regarding the reviewer factors, most studies have reported a positive relationship between reviewers' expertise and review usefulness; as Choi and Leon (2020) explained, experienced reviewers have more knowledge and are more likely to discuss the product both positively and negatively, so other consumers will find such reviews more useful.

3.1.4 Product Competitive Analysis

Product competitiveness is the combined ability of two or more products in the competition. Traditional competitiveness analysis studies were typically conducted by surveys and questionnaires. In recent years, scholars have started to focus on online reviews for competitiveness analysis. These studies argued that the competitiveness of a product (service) could be reflected by its consumers' satisfaction level, and the sentiments hidden in online reviews, as we mentioned above, mirror consumers' satisfaction. More importantly, consumers may make a purchase decision by reading online reviews, and thus such data are very important for merchants to evaluate the market performance of their products (services). Therefore, numerous studies have analyzed product (service) competitiveness using online reviews. In terms of the areas of these studies, both service and manufacturing industries are relevant. For example, in the hospitality literature, Gao et al. (2018) proposed a comparative opinion mining method to identify the competitors of the target restaurant, and the results revealed which attributes of the target restaurant performed worse than others. Similarly, Wang et al. (2017) also utilized the comparative opinion mining algorithm to extract consumers' opinions of the restaurants and clearly pointed out the restaurant's comparative strengths and weaknesses. As for the manufacturing field, Liu et al. (2021) mined the product competitiveness of smartphones by fusing multisource online information and tested how different factors influence product competitiveness. Liu, Jiang, and Zhao (2019) proposed a supervised learning method to identify competitors from user-generated content and aspect-level sentiment analysis to assess consumers' sentiment attitudes.

3.2 Online Reviews Information Mining Techniques

With the development of e-commerce platforms and online reviews, as well as the emergence of natural language processing and deep learning, techniques for processing online reviews have been boosted. Overall, frequently used online review mining techniques include information extraction, sentiment analysis, text categorization, etc.

3.2.1 Information Extraction Technique

Information Extraction (IE) is an important subtask of natural language processing (NLP), which is the process of extracting useful structured information from unstructured data. Nadeau and Sekine (2007) defined IE as “the extraction of instances of predefined categories from unstructured data to construct a structured and explicit representation of entities and their relationships.” It takes as input a collection of documents such as research papers, logs, and online reviews and generates a representation of relevant information that satisfies different predefined categories. IE techniques efficiently analyze different forms of texts by extracting the most valuable and relevant information from unstructured data. Thus, its ultimate goal is to identify particular facts from texts to enrich the database or knowledge base.

IE includes different subtasks, namely, named entity recognition (NER), relationship extraction, event extraction, and significant fact extraction. NER is a very important task for extracting descriptive entities in the IE. It identifies generic or intra-domain entity objects such as organization, business name, location, disease, etc. The relationship extraction task can help in completing the annotation of data by extracting the relationships between different entities. The immediate goal of the event extraction task is to identify specific types of events and to determine the elements of the events that hold a given role. From the perspective of theoretical development, event extraction helps us gain insights into the mechanism of machines to understand data and the world, as well as our own cognitive mechanism; from the perspective of the application, event extraction techniques can help us solve many real-world problems, such as the automatic processing of massive amounts of information mentioned earlier.

3.2.1.1 Named Entity Recognition

The named entity recognition (NER) task is the process of identifying and mapping entities to predefined categories. Its main application scenarios include question-and-answer systems, machine translation, information retrieval, opinion mining, and knowledge base populating. Therefore, the efficiency and accuracy of NER are crucial.

Traditionally, NER uses rule-based approaches, learning-based approaches, or hybrid approaches. Rule-based NER systems rely on manually set rules, which are generally designed based on domain-specific dictionaries and syntactic-lexical patterns. Rule-based NER systems can achieve good results when the dictionary size is limited. Due to the domain-specific nature of the rules and the incompleteness of the dictionaries, such NER systems are characterized by high accuracy and low recall, and similar systems are difficult to migrate to other domains (domain-based rules are often not generalized and require reformulation of rules for new domains and different domain dictionaries). Learning-based methods include unsupervised and supervised learning methods. A typical unsupervised learning approach is clustering, where named entities are extracted from clusters based on semantic similarity, and the core idea is to use lexical resources, lexical models, and statistics obtained from a large corpus to infer the class of named entities. In the supervised learning approach, NER is converted into a multi-categorization or sequence labeling task. Based on the labeled data, researchers apply domain knowledge and engineering skills to design complex features to characterize each training sample, and then apply machine learning algorithms to train the model to make it learn the patterns of the data. Many machine learning algorithms have been applied in supervised NER. With the development of information technology, deep learning algorithms have also been applied in NER (Che et al., 2019). NER utilizes the deep learning nonlinear relationship fitting capability to be able to learn more complex features from data. At the same time, deep learning does not require overly complex feature engineering and is able to learn features from data automatically.

3.2.1.2 Relationship Extraction

Relationship extraction is another subtask of information extraction, which aims to identify the relationships of entities in the text. Relationship extraction is important for knowledge base construction and understanding of the text and plays an important role in application scenarios such as question and answer, text understanding, etc. According to the complexity of the task, relationship extraction can be divided into simple relationship extraction and complex relationship extraction. The purpose of simple relationship extraction is to identify the relationship between two entities from the text. For example, a binary relationship can be extracted from the sentence "Tsinghua University is located in Beijing, the capital of China," i.e., "Tsinghua University (Entity) is located in Beijing (Entity)." The current methods of simple relation extraction can be divided into supervised, semi-supervised, and weakly supervised methods. The supervised learning-based simple relation extraction method uses high-quality labeled sample data to train learning, which is obtained through manual labeling or crowdsourcing. With the development of deep learning techniques in recent years, many new models of neural network-based relationship extraction have emerged, such as the graph-based neural network model C-CGNN (Zhang et al., 2018), the pre-training-based method EPGNN (Zhao et al., 2019), and the capsule network-based method (Zeng et al., 2018). However, in many specific domains, it is difficult to obtain high-quality labeled data, yet there is a large amount of unlabeled data available. To be able to utilize a large amount of unlabeled data in the training phase, semi-supervised learning-based relationship extraction models attempt to learn from both labeled and unlabeled data together (Luo et al., 2019). Complex relationship extraction is an emerging research direction that attempts to extract more complex relationships involving multiple entities or under specific constraints. Therefore, some scholars have proposed joint extraction methods (Yuan et al., 2020; Zheng et al., 2017) to extract such complex entity relations. However, at present, there is still relatively more room to explore this method.

3.2.1.3 Event Extraction

Event extraction can be divided into open-domain-based event extraction (Liu, Huang, & Zhang, 2019) and closed-domain-based event extraction (Sheng et al., 2021). Open-domain event extraction refers to acquiring a series of events related to a specific topic, which usually consists of multiple events. As to the closed-domain event extraction, its task is to find words belonging to a specific temporal pattern that reflect a change in the action or state that occurred, such as time, person, place, etc. In the open domain event extraction task, events are usually some descriptions related to a certain topic, which can be achieved by clustering or classification. In either task, the purpose of event extraction is to capture the types of events from a large number of texts and present the essential arguments of the events in a structured form.

3.2.2 Sentiment Analysis Technique

3.2.2.1 Sentiment Dictionaries

As an automated, unsupervised sentiment analysis method, sentiment dictionaries have attracted a great deal of interest from academics and businesses. Companies attempt to mine user reviews and social media content to understand users' sentiments and opinions about their products and services. This approach uses constructed lexicons that contain words marked as positive, negative, or neutral (sometimes with values that reflect the intensity or strength of the sentiment). The lexicon can be constructed in different ways, such as manually; using a corpus of automatically associated words with known seed words; or semi-automatic acquisition of sentiment values based on WordNet.

The advantage of the sentiment dictionary approach is that it does not require manual annotation of the data. With the proliferation of product review sites with user reviews and ratings, the Internet has seen a large number of domain-specific unlabeled online reviews, so sentiment analysis methods based on sentiment dictionaries can be useful. At the same time, however, there are some problems with this approach, such as the fact that words may have multiple meanings, and meanings that are common in one domain may not be common in another. In addition, words that are not usually considered emotionally charged may also be emotionally charged in a given context. Finally, and the biggest problem, this kind of method has limited accuracy.

3.2.2.2 Machine Learning

Online reviews are often poorly structured and have large amounts of data, which makes manual processing very difficult. Among natural language processing and text mining approaches, machine learning is often used to process unstructured data

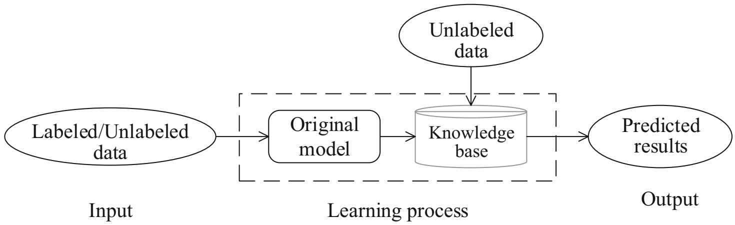

Fig. 3.1 Machine learning method flowchart

and has been widely used to mine the sentiment of online reviews. Machine learning uses information technology to learn patterns from past experiences and then accurately predict existing and future data. The term "experience" refers to past data, which is used to build classification models, which may come from online open platforms, or questionnaire data.

The classical machine learning method flow is shown in Fig. 3.1.

The input to this flow is labeled data or unlabeled data, representing supervised and unsupervised machine learning, respectively. The original model is trained using the input data, and the knowledge base holds the completed trained model and its parameters. The new unlabeled data is then predicted, and the output is the prediction result. Machine learning algorithms can usually be classified into two types: supervised learning and unsupervised learning. Supervised learning refers to the training of classification or prediction models using prior knowledge from the input data. This type of input data is usually labeled datasets. The purpose of supervised learning is to obtain the desired output based on the input data. Common supervised learning models include logistic regression, random forest, and decision trees. In unsupervised learning, model building and training do not require the use of labeled datasets. The purpose of unsupervised learning is to perform dimensionality reduction and exploratory analysis on data with high-dimensional features. Commonly used unsupervised learning models include clustering algorithms such as *K*-means, SOM, and some optimization algorithms. As shown in Table 3.1, we sort out some common machine learning algorithms used in sentiment analysis.

3.2.2.3 Deep Learning

Traditionally, sentiment analysis based on machine learning algorithms requires first modeling the comment texts to extract features. One commonly used approach is the bag-of-words (BoW) model; however, the BoW model ignores the semantic and word order features of the review texts, which is the core of the texts. Another approach to feature extraction is the N-gram approach, which overcomes the shortcomings of BoW but also creates the new problem of over-sparse high-dimensional vectors. All of these are problems inherent to traditional machine learning, which requires features to be extracted from the data in order to train the model. Unlike machine learning, deep learning solves these problems through deep neural

Table 3.1 Commonly used machine learning algorithms in sentiment analysis

Type	Algorithm name	Description
Supervised	LR (logic regression)	Logistic regression assumes that the data obeys the Bernoulli distribution (0-1 distribution) and uses the gradient descent method to solve the parameters by the method of the great likelihood function for the purpose of dichotomizing the data (Rafeek & Remya, 2017)
	Decision tree	Classification of data into predefined classes according to the "Yes" or "No" rule (Mullainathan & Spiess, 2017)
	SVM (support vector machine)	Determining multidimensional boundaries that separate data points belonging to different classes (Srivastava and Bhambhu 2010)
	Random forest	A "forest" classifier built based on decision tree integration with a typical training process of "bagging" strategy (Probst et al., 2019)
	NB (Naïve Bayes)	Predicting the classification of the output by calculating conditional and prior probabilities using Bayes' theorem (Jensen & Nielsen, 2007)
Unsupervised	K-means	It divides the set of samples into k subsets, which constitute k classes, and assigns n samples to k classes, each with the minimum distance to the center of the class to which it belongs (Vashishtha & Susan, 2021)
	KNN (K-nearest neighbor)	A sample belongs to a class if most of its k most adjacent samples in the feature space belong to that class and it has the characteristics of samples in that class (El Mrabti et al., 2018)
	Association rules	Association rule mining finds associations or interconnections between sets of items in the data (Jiang et al., 2018)

networks. The depth of a deep learning model is the number of neural network layers between the input and output layers. While shallow neural networks extract abstract features of the data, as learning advances, deep neural networks can extract certain features that are meaningful in the data. This approach is based on pre-trained word vectors, such as W2V (Rong, 2014), GloVe (Glove, 2014), and fastText (fasttext, 2016), which can transform input text into high-dimensional word vectors. Unlike machine learning, which requires manual extraction of data features, deep learning can automatically extract data features. Thus, deep learning can learn and make intelligent decisions on its own.

For the task of sentiment classification, the types of applications of deep learning algorithms are divided into two main categories, namely, convolutional neural networks (CNNs) and recurrent neural networks (RNNs). The convolutional neural network is a feed-forward deep neural network that was originally applied in the field of image processing. Due to its excellent local feature extraction capability, it has also been used in recent years for text sentiment analysis tasks. CNNs consist of an input layer, a convolutional layer, a pooling layer, a fully connected layer, and an output layer. The convolutional layer extracts local features of the input data, and different convolutional layers can extract different local features, and then the

Table 3.2 Commonly used deep learning algorithms

Type	Algorithm name	Description
Feed-forward	NN (neural networks)	Neural networks reduce the error between truth and prediction by adjusting the weights between neurons (Yang & Sudharshan, 2019). They can be further extended as a multilayer perceptron, back-propagation neural network, and Hopfield network
	CNN	Convolutional neural networks can effectively extract local features from the data (Liu et al., 2015)
Back-propagation	RNN	Recurrent neural networks can learn dependencies in the data (Mikolov et al., 2010)
	LSTM	A special type of recurrent neural network (RNN) that learns long-term dependencies in data (Sherstinsky, 2020)
	GRU	A special type of recurrent neural network (RNN) that learns long-term dependencies in data with less "forget gate" and easier convergence than LSTM (Liu, Wang, Zhu, et al., 2020)
	BiLSTM	A sequence processing model consists of two LSTMs: one receiving input in the forward direction and the other in the reverse direction (Xu et al., 2019)

pooling layer reduces the dimensionality of the features. The feature extraction capability of CNN depends on the number of convolutional and pooling layers. The feature data is then passed into the activation function, Rectified Linear Unit (ReLU), or sigmoid, and the model is trained using a loss function to evaluate the learning process, and the above steps are cycled through.

Unlike feed-forward CNNs, RNNs are back-propagation networks. In addition to the current input, it also considers the previous input. RNNs can process data with sequential relationships with the help of internal memory. It is designed on the principle that humans do not start thinking from zero every time, and therefore need to store and remember prior knowledge. Therefore, RNNs can predict subsequent words based on previous words. Commonly used RNNs include the LSTM (Long Short-Term Memory) model and GRU (Gate Recurrent Unit) model, both of which are extensions of RNNs. LSTM can perform long-term memory storage, which overcomes the gradient disappearance problem of classical RNNs. Unlike LSTM, GRU has a more streamlined structure and does not include a "forget gate," so the model training can converge faster. We summarize the commonly used deep learning algorithms for sentiment analysis tasks, as shown in Table 3.2.

The main application scenarios of sentiment analysis include analysis of online reviews of products (to understand user satisfaction, develop targeted marketing strategies, competitor analysis), analysis of online reviews of special products such as movies (to adjust uptime and marketing strategies), etc.

3.2.3 Text Categorization Technique

Text categorization techniques can be classified into three categories: traditional methods, fuzzy logic-based methods, and deep learning-based methods. In the following, we briefly describe these three methods.

3.2.3.1 Traditional Methods

As mentioned above, text categorization is an important part of text mining. Classifying text from online reviews can help consumers reduce the cost of retrieving information and also help e-commerce platforms obtain effective information. Many studies have been conducted on text categorization using traditional methods (Abrahams et al., 2012; Lan et al., 2009; Liu, Wang, Fan, et al., 2020). A deeper understanding of the feature extraction methods and the correct method of classifier evaluation can ensure the effective operation of traditional text categorization methods. Common feature extraction methods used in text categorization tasks include word frequency analysis, inverse document frequency analysis, *N*-gram, and other word-embedding models. Many methods have been shown to reduce the complexity of the text categorization process, such as principal component analysis, and information gain. And there is a wide range of classifiers to choose from, such as Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Logistic Regression (LR), Multilayer Perceptron (MP), etc.

3.2.3.2 Fuzzy Logic-Based Methods

As a subtask in the field of NLP, text mining inevitably faces the fuzzy nature of natural language. This phenomenon may lead to the misclassification of texts. Therefore, the task of text categorization based on fuzzy logic is born. This approach has been proposed decades ago (Zadeh, 1965) for the study of uncertain knowledge. Unlike traditional mathematics that classifies elements explicitly to a certain set, this approach uses the concept of affiliation for element classification, i.e., fuzzy sets. Fuzzy sets describe the fuzzy concepts embedded in linguistic features, such as "cold" and "a little cold" to describe the weather. Fuzzy logic operates by mimicking the human brain's processing mechanism for uncertain events. In addition, fuzzy logic can be used to convey knowledge and is also good at building uncertain boundaries, the basic structure of which is shown in Fig. 3.2. In view of these

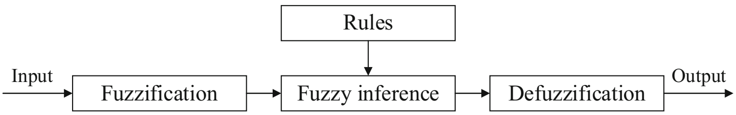

Fig. 3.2 Fuzzy logic diagram (Zadeh, 1965)

advantages of fuzzy logic methods in knowledge representation, it has received increasing attention from researchers in text categorization problems. This approach has been developed in many fields, such as software development, NLP, and cybernetics.

3.2.3.3 Deep Learning-Based Methods

Deep learning-based text categorization methods differ from traditional neural networks in that their core lies in the size of the hidden layers between the input and output layers; the larger the number of hidden layers and the more nodes, the better the fitting ability of the deep learning model. There are many deep learning models applied to text categorization, such as the classical deep neural network model (DNN), recurrent neural network model (RNN), long short-term memory network model (LSTM), convolutional neural network model (CNN), BERT, etc. Neural network models were initially applied to image processing and pattern recognition tasks, and then gradually applied to NLP, including text categorization tasks, due to their excellent feature extraction and autonomous learning capabilities. A deep learning model is trained using a dataset with category labels, and the model automatically learns and extracts features related to the labels from the data and saves the parameters, and then performs category prediction on new text data.

Traditional machine learning methods require explicit data features, and then the classifier learns from the data. But deep learning does not need to specify data features, and it can learn from data automatically. At the same time, deep learning methods are faster and more accurate. As a result, deep learning is now being applied in a wider range of contexts for text categorization.

3.3 Commercial Value Discovery of Online Reviews

This section focuses on the commercial uses of online reviews. Three cases are provided below which cover the topics of product ranking, relationships between retail prices and online reviews, and personalized online reviews ranking.

3.3.1 Word-of-Mouth Ranking of Products by Using Online Reviews

Online reviews play an important role as electronic word-of-mouth (eWOM) for potential consumers to make informed purchase decisions. However, the large number of reviews poses a considerable challenge because it is impossible for customers to read all of them for reference. Moreover, there are different types of online reviews with distinct features, such as numeric ratings, text descriptions, and comparative words, for example, such heterogeneous information leads to more complexity for customers.

To help consumers compare alternative products, there are some studies that describe methods to extract opinions and sentences from text reviews. Some of these studies focus on mining and summarizing customers' opinions and text sentiments from text reviews, whereas other studies directly mine comparative sentences and relationships from text reviews. However, comparative sentences are very rare in text reviews, and they are usually not sufficient to evaluate competitive products comprehensively because there are a limited number of comparisons for some products and even no comparison for many (if not most) products.

To compare multiple products, some websites provide rankings of products according to simple criteria such as the average numeric rating; however, these rankings do not fully consider the voice of customers, such as the text sentiments and comparative sentences. Hereafter, a novel method that integrates heterogeneous information including text sentiments, numeric ratings, comparative sentences, and comparative votes (Yang et al., 2016) is presented. In detail, heterogeneous information is divided into two categories: descriptive information and comparative information. Descriptive information consists of text sentiments and numeric ratings to describe one specific product. Comparative information comes from comparative sentences and online comparative votes that compare more than one product. The flowchart of the proposed method is shown in Fig. 3.3. At first, a crawler is implemented to collect product data from Zol.com.cn. The dataset is from the mobile phone category and comprises three types of consumer reviews: numeric ratings, text reviews, and comparative online votes. By mining text reviews, the sentiment of reviews and comparative sentences can be obtained. Then two types of information can be derived, i.e., descriptive information including numeric rating and sentiment of reviews, and comparative information including comparative sentences and votes.

To consider descriptive information and comparative information simultaneously, a graph structure is applied in which the nodes are the given products, the weights of nodes are derived from descriptive information, and the edges represent pair-wise comparative relationships. A benefit from the graph structure is that the integrated eWOM score can be calculated and an overall ranking of the given set of products can then be generated.

The sentiment embedded in the textual content can be classified as positive or negative. The positive and negative terms in text reviews are assigned explicit polarity values 1 and -1, respectively. For example, given a product i at time t (denoted as P_{it}) and a text review about P_{it} (denoted as TR_{it}), the text review is labeled with a set of sentiment terms, i.e., $\mathrm{TR}_{it} = \{\mathrm{tr}_{it1}, \mathrm{tr}_{it2}, \ldots, \mathrm{tr}_{itn}\}$. The overall sentiment score of P_{it}, denoted as $\mathrm{T\_Score}(P_{it})$, can be computed as follows:

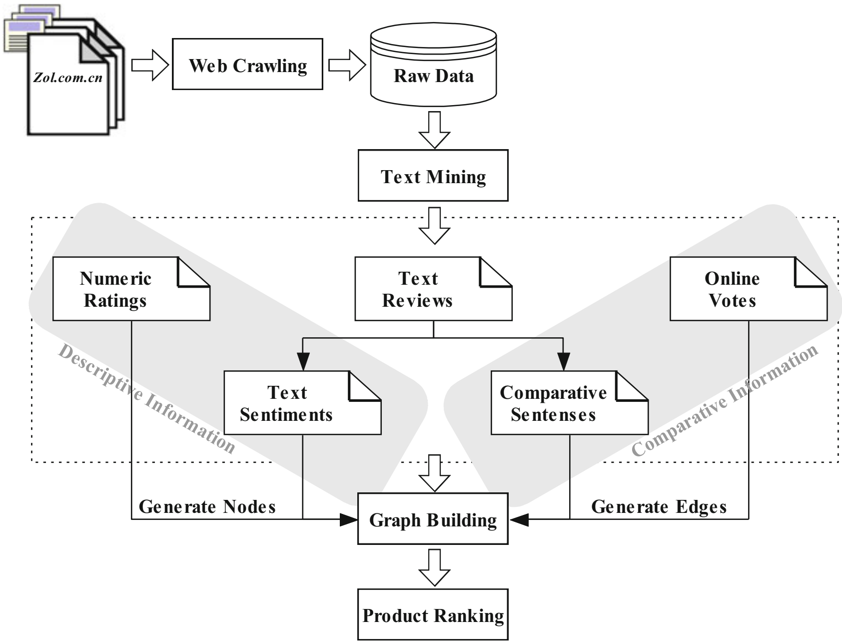

Fig. 3.3 The flowchart of products eWOM ranking

$$T\_\mathrm{Score}(P_{it}) = \frac{\mathrm{PO}_{it}(\mathrm{TR}_{it}) - \mathrm{NO}_{it}(\mathrm{TR}_{it})}{\mathrm{PO}_{it}(\mathrm{TR}_{it}) + \mathrm{NO}_{it}(\mathrm{TR}_{it})} \tag{3.1}$$

where the prefix T of $T\_\mathrm{Score}(P_{it})$ indicates that the score is calculated from a text review, PO_{it} is the number of occurrences of positive terms in all text reviews for P_{it}, and NO_{it} is the number of negative terms.

In addition to the implicit scores in textual contents, another form of the score is readily available, i.e., the ratings in numeric values following each piece of text review. For product i at time t with a set of numeric ratings, denoted as $\mathrm{NR}_{it} = \{\mathrm{nr}_{it1}, \mathrm{nr}_{it2}, \ldots, \mathrm{nr}_{itm}\}$, the average score rating for P_{it}, denoted as $R\_\mathrm{Score}(P_{it})$, can be calculated by

$$R\_\mathrm{Score}(\mathrm{P}_{it}) = \frac{\sum_{j=1}^{m} \mathrm{rate}\left(nr_{itj}\right)}{m} \tag{3.2}$$

where prefix R of $R\_\mathrm{Score}(P_{it})$ means that the score is obtained from a rating value, and $\mathrm{rate}(\mathrm{nr}_{itj}) \in \{r_{\min}, \ldots, r_{\max}\}$ is a discrete rating value within the range of $r_{\min}$ and $r_{\max}$. The numeric ratings are usually on a 1 ~ 5-star scale on most review websites, i.e., $r_{\min} = 1$ and $r_{\max} = 5$, wherein a 1-star rating shows the least satisfaction, and a 5-star rating indicates the most satisfaction.

The T_Score from text review, with a range of $[-1, 1]$, will be integrated with the R_Score from numeric rating; however, a problem is that they do not share the same scale. To facilitate the integration, T_Score is scaled up to the range of 1 to 5. For example, if the originally obtained T_Score value is $x = -0.5$, the value transformed into [1, 5] is calculated by $f(x) = 2x + 3 = 2$. For the product without reviews, the sentiment score is set to be a neutral score of 3 by default. The $f(x)$ function is designed from min-max normalization:

$$f(x) = \frac{x - \min}{\max - \min}(\text{new\_max} - \text{new\_min}) + \text{new\_min} \tag{3.3}$$

where min and max are the original minimum and maximum values of an attribute x. Min-max normalization maps a value by $f(x)$ into the new range [new_min, new_max]. In addition to min-max normalization, there are other methods for data normalization, such as z-score normalization and normalization by decimal scaling. However, certain normalization schemes can change the original data quite a bit, particularly the z-score normalization and normalization by decimal scaling. The min-max normalization is the preferred method that preserves the relationship among the raw data values.

The overall score of P_{it}, denoted as Score(P_{it}), is calculated by combining T_Score(P_{it}) and R_Score(P_{it}):

$$\text{Score}(P_{it}) = \alpha T\text{\_Score}(P_{it}) + (1-\alpha)R\text{\_Score}(P_{it}) \tag{3.4}$$

where $\alpha \in (0, 1)$ is an adjustment factor to balance the effects of T_Score and R_Score.

Comparative information can be expressed as comparative sentences extracted from text reviews, which are identified via comparative keywords, sentence semantics, and sentence structure, as well as fuzzy linguistics. Given a set of sentences comparing two products P_i and P_j, denoted as $S = \{s_1, s_2, \ldots s_h\}$, the information of a comparative relationship derived from one text sentence $s_k \in S$ is described as a quadruple

$$T\text{\_Relation}_{ij}(s_k) = \left(P_i, P_j, \text{Vote}^T{}_k\left(P_i|P_i, P_j\right), \text{Vote}^T{}_k\left(P_j|P_i, P_j\right)\right)$$

where the prefix T indicates that the information is obtained from text reviews. $\text{Vote}^T{}_k(P_i|P_i, P_j)$ equals 1 if the product P_i is commented on as better than P_j in sentence s_k; otherwise, it is 0. For example, if there is a comparative sentence $s_k =$ *"mobile phone A is less than mobile phone B,"* the corresponding quadruple T_Relation$_{ij}(s_k)$ can be written as (A, B, 0, 1). When considering all the comparative sentences, the overall $\text{Vote}^T(P_i|P_i, P_j)$, which denotes the total number of sentences in S preferring P_i to P_j, is computed as follows:

$$\mathrm{Vote}^T\left(P_i|P_i,P_j\right)=\sum_{k=1}^{h}\mathrm{Vote}^T{}_k\left(P_i|P_i,P_j\right) \tag{3.5}$$

The comparative votes can supply direct comparative relationships, also denoted as a quadruple:

$$V\_\mathrm{Relation}_{ij}=\left(P_i,P_j,\mathrm{Vote}^V\left(P_i|P_i,P_j\right),\mathrm{Vote}^V\left(P_j|P_i,P_j\right)\right)$$

where the prefix V means that the information is derived from votes, and $\mathrm{Vote}^V(P_i|P_i, P_j)$ is the number of votes preferring P_i to P_j when comparing both of them.

Roughly speaking, T_Relation focuses more on local comparisons because the limited descriptive words usually concentrate on a few products with some detailed feelings or judgments. V_Relation can provide global information because the comparison is made among a large number of candidate products. The limitation of T_Relation is partially caused by the fact that writing comments are very time-consuming. In contrast, it is much more convenient and simpler to click a button to vote for your favorite products.

The two sorts of comparative information, T_Relation, and V_Relation can be combined to provide a more comprehensive description of the relationships between different products. The combined relationship is denoted as follows:

$$\mathrm{Relation}_{ij}=\left(P_i,P_j,\mathrm{Vote}\left(P_i|P_i,P_j\right),\mathrm{Vote}\left(P_j|P_i,P_j\right)\right)$$

where $\mathrm{Vote}(P_i|P_i, P_j)$ is the full-scale information measuring the preference for P_i to P_j, calculated by

$$\mathrm{Vote}\left(P_i|P_i,P_j\right)=\begin{cases}\dfrac{\mathrm{Vote}^T\left(P_i|P_i,P_j\right)+\mathrm{Vote}^V\left(P_i|P_i,P_j\right)}{\mathrm{Vote}^T\left(P_i|P_i,P_j\right)+\mathrm{Vote}^V\left(P_i|P_i,P_j\right)+\mathrm{Vote}^T\left(P_j|P_i,P_j\right)+\mathrm{Vote}^V\left(P_j|P_i,P_j\right)}, i\neq j,\mathrm{Vote}^T\left(P_i|P_i,P_j\right)\neq 0\\ \quad\text{or}\,\mathrm{Vote}^V\left(P_i|P_i,P_j\right)\neq 0\,\text{or}\,\mathrm{Vote}^T\left(P_j|P_i,P_j\right)\neq 0\,\text{or}\,\mathrm{Vote}^V\left(P_j|P_i,P_j\right)\neq 0\\ \dfrac{1}{2}, i\neq j,\mathrm{Vote}^T\left(P_i|P_i,P_j\right)=0,\mathrm{Vote}^V\left(P_i|P_i,P_j\right)=0,\mathrm{Vote}^T\left(P_j|P_i,P_j\right),\mathrm{Vote}^V\left(P_j|P_i,P_j\right)=0\\ 0, i=j\end{cases} \tag{3.6}$$

Now, both descriptive information and comparative information are ready to be integrated by a directed and weighted graph structure. The graph structure is formally defined as a quadruple, $G = (V, E, W^V, W^E)$, where V is the set of vertices or nodes, E is the set of directed edges (i.e., the ordered pairs of vertices), W^V is the weight associated with each node, and W^E is the weight labeled on each directed edge. The weight for node P_i is normalized from $\mathrm{Score}(P_i)$:

$$W^V(P_i) = \frac{\mathrm{Score}(P_i)}{\sum_{k=1}^{n} \mathrm{Score}(P_k)} \tag{3.7}$$

and the weight on a directed edge from P_j to P_i is normalized from Vote($P_i|P_i$, P_j):

$$W^E\left(P_i|P_i, P_j\right) = \frac{\mathrm{Vote}\left(P_i|P_i, P_j\right)}{\sum_{l=1}^{n} \mathrm{Vote}\left(P_l|P_l, P_j\right)} \tag{3.8}$$

where n is the total number of candidate products under comparison and P_l is the product that has a comparative relationship with product P_j.

Benefiting from the structure of the weighted digraph, a scalar overall eWOM score is developed with which to rank products. The overall eWOM of each product consists of two elements: inherent eWOM derived from its overall score of the product, and extrinsic eWOM accumulated from its comparative relationships with other products.

Roughly speaking, whether a product P_i should be ranked high is affected by three conditions:

- If a product has a high score from descriptive information (i.e., Score(P_i) is high), it should be ranked high.
- If a product P_i has many votes from other products, P_i should be ranked high.
- If a product P_i has more votes than P_j whose ranking is high, P_i should be ranked even higher.

Based on the above analysis, the overall eWOM score of product P_i, W_Score (P_i), can be calculated by

$$W\_\mathrm{Score}(P_i) = (1-\beta) W^V(P_i) + \beta W\_\mathrm{Score}^C(P_i) \tag{3.9}$$

where $\beta \in (0,\ 1)$ is an adjustment factor to balance the effects of $W^V(P_i)$ and W _ Score^C(P_i), and W _ Score^C(P_i) can be calculated by

$$W\_\mathrm{Score}^C(P_i) = \sum_{j=1}^{n} W\_\mathrm{Score}\left(P_j\right) W^E\left(P_i|P_i, P_j\right) \tag{3.10}$$

where $W^V(P_i)$ measures the inherent eWOM, whereas W _ Score^C(P_i) denotes the extrinsic eWOM. By incorporating Eq. (3.10) into Eq. (3.9), the overall eWOM score W_Score(P_i) can be derived as

$$W\_\mathrm{Score}(P_i) = (1-\beta) W^V(P_i) + \beta \sum_{j=1}^{n} W\_\mathrm{Score}\left(P_j\right) W^E\left(P_i|P_i, P_j\right) \tag{3.11}$$

Ranking generation is a calculation of the eigenvector of the matrix to compute the $W\_\text{Score}(P_i)$ value by using Eq. (3.11). The equation can be expressed as the following matrix function:

$$W\_\text{Score} = (1-\beta) \times W^V + \beta \times \boldsymbol{A} \times W\_\text{Score} \tag{3.12}$$

where $W\_\text{Score} = [W\_\text{Score}\,(P_1), W\_\text{Score}\,(P_2), \ldots, W\_\text{Score}\,(P_\text{n})]^\text{T}$, $W^V = [W^V(P_1), W^V(P_2), \ldots, W^V(P_i)]^\text{T}$, and $\boldsymbol{A}$ is a $n \times n$ comparison relationship adjacent matrix:

$$\boldsymbol{A} = \begin{pmatrix} 0 & W^E(P_1|P_1,P_2) & \cdots & W^E(P_1|P_1,P_n) \\ W^E(P_2|P_2,P_1) & 0 & \cdots & W^E(P_2|P_2,P_n) \\ \vdots & \vdots & & \vdots \\ W^E(P_n|P_n,P_1) & W^E(P_n|P_n,P_2) & \cdots & 0 \end{pmatrix}.$$

Based on the presented method, rich and more experiments have been conducted on three types of products (mobile phones, laptops, and digital cameras) in Yang's work (Yang et al., 2016). The results demonstrate that with more information integrated, the ranking method can return better performance. In particular, comparative votes, which have attracted little attention in previous studies, contribute significantly to the ranking quality. An effective system is also demonstrated to help customers make informed choices when comparison shopping and assist manufacturers to maintain awareness of the exact positions of their products and to target implicit problems underlying the data.

3.3.2 Mining Relationships Between Retail Prices and Online Reviews

Marketing tools price is an important decision variable in marketing for a product and can affect customers' cognition, feelings, purchase decisions, and post-purchase satisfaction. Some research found that the price could affect consumer reviews. Online retailers are able to adjust their prices more frequently and easily compared to physical retail stores. A survey estimated that Amazon changes retail prices more than 2.5 million times daily for its millions of products.

In this vein, a fundamentally important question to ask is as follows: What effects can be observed regarding the volume and valence of consumer reviews after increasing or decreasing the retail price for a specific product? Here, volume measures the total amount of reviews posted on a product and is an important cue for product popularity. Valence captures the positive or negative nature of reviews, which contains evaluation information on product quality. To answer this question, computable models for describing relationships between prices and volume/valence of reviews should be built.

A GP (genetic programming) method is introduced to exploit functional relationships between retail prices and consumer reviews from a large and unique data set (Yang et al., 2021). In the experiment, a data set is obtained from an online retailer that comprises 321 types of products with retail prices and corresponding reviews. According to statistics, prices change 5431 times during the period of data collection, and 1,738,114 pieces of reviews are crawled in the same period. Experimental results show that for the relationships between retail prices and the volume of reviews, three types of models demonstrate the best performance: the linearly decreasing, asymmetric U-shaped, and asymmetric inverted U-shaped models. For the relationships between retail prices and the valence of reviews, the promising models are the linearly decreasing, asymmetric inverted U-shaped, and linearly increasing models.

Nevertheless, none of the models dominates all the others on the basis of three evaluation metrics: fitness, complexity, and coverage. For example, for the relationships between retail prices and the volume of reviews, the linearly decreasing models feature high coverage, low complexity, and low fitness, whereas the asymmetric U-shaped model features low coverage, high complexity, and high fitness. Instead of simply suggesting the model, comprehensive evaluations have been conducted to examine the performance of each candidate model in various categories of products to show its comparative advantages and disadvantages. The experimental results provide detailed references for the application of relationship models, such as which model is more suitable for a product or how to choose another model to complement this model when it does not model the relationship under a certain metric.

3.3.2.1 Model Building

To find a good model, a classic method is to perform the Generate/Test Cycle by designing alternatives and testing them against constraints (see Fig. 3.4). The traditional Generate/Test Cycle explicitly determines the models by human researchers on the basis of their hypothetical solution space, which becomes an obstacle when discovering the model from the solution space with sheer size. For example, in the relationship between price and reviews in this research, there are many potentially applicable candidate models. The models should be tested with

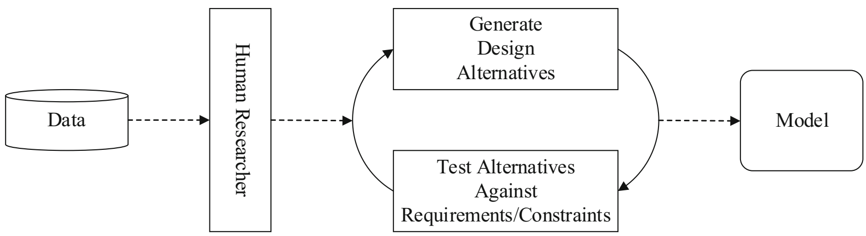

Fig. 3.4 Traditional generate/test cycle

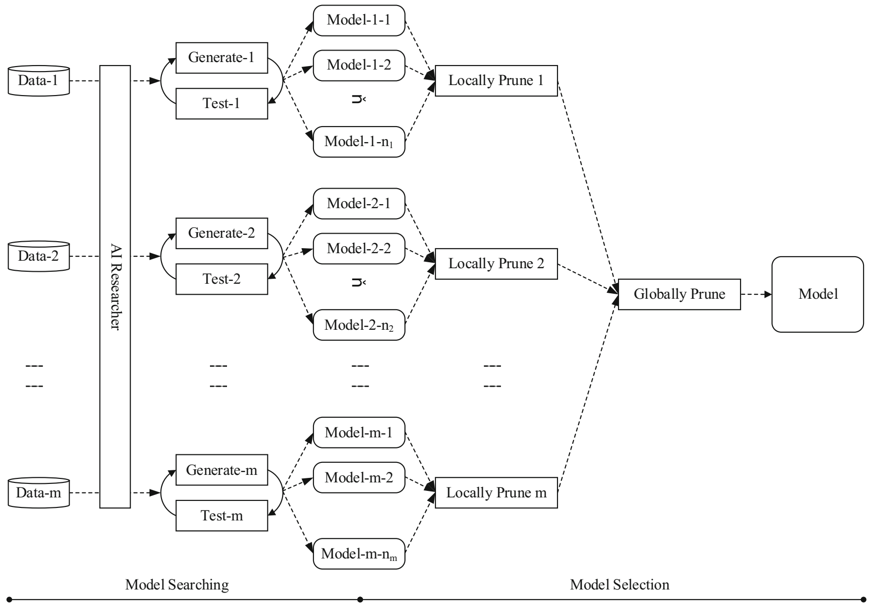

Fig. 3.5 New generate/test cycle

many products associated with frequent price changes and a huge amount of reviews on the selected retail website. Thus, generating and testing many candidate models by human researchers would be time-consuming.

To overcome the above obstacle, a new approach is proposed to the Generate/Test Cycle by incorporating an artificial intelligent (AI) researcher (see Fig. 3.5). Human experts do not have to perform the cycle to determine the proper models, and the AI researcher automatically suggests alternatives to describe the relationships hidden in data. The new approach has two processing stages: model searching and model selection. In the model searching stage, it generates and tests the model by using GP for each subset of data corresponding to one product. In the model selection stage, it first selects the Pareto optimal models for the given products at the individual level, namely, local pruning. Next, it discovers the models with high coverage for all types of products at the group level, namely, global pruning.

The intelligent data-driven generating/testing approach can search for promising models from an extremely large solution space by means of its two-phase operations. The core of the approach is evolutionary algorithms GP with easy transferability, which identifies meaningful analytical links and distills free-form models from data.

To reveal the relationships between price changes and the volume/valence of reviews, GP is adopted to automatically discover the mathematical model. The functional form expresses the nature of the relation, and the substantive meaning could be concretely made by some linear or nonlinear mathematical models. Following Bass's recommendation of simplicity to describe a pattern, the fundamental relationship in terms of reviews and price is defined as follows:

$$\text{REVIEWS} = f\ (\text{PRICE}) \tag{3.13}$$

Identifying fundamental relationships is a critical pursuit of research. Such a model is more likely to be generalizable and provides a starting point for further replication and extension of research.

Based on the basic model (3.13), the volume and valence of reviews have been seriously considered in the study, and their functional relationships with prices are represented by the following formulas (3.14) and (3.15) respectively.

$$R_{it}{}^{vo} = f_{it}{}^{vo}\ (P_{it}) \tag{3.14}$$

$$R_{it}{}^{va} = f_{it}{}^{va}\ (P_{it}) \tag{3.15}$$

where P_{it} denotes the price for a product i for t period; $R_{it}{}^{vo}$ and $R_{it}{}^{va}$, respectively, denote the volume and the valence of reviews regarding the P_{it}.

3.3.2.2 Model Searching by Using GP

GP is the variant of the genetic algorithm with tree structure encoding and could be applied as a function discovery approach to analyze a multivariate dataset. GP explores the solution space by combining building blocks from a set of mathematical operators and operands (e.g., variables and constants) and searching the space of the mathematical expressions to find the model that best fits a given dataset.

In GP, a candidate solution is encoded as a tree structure. The flowchart of GP is shown in Fig. 3.6. There are several procedures. First, initialize the population; a set of primitive functional operators and variables is selected to integrate into the mathematical models to express the intrinsic relationship. The functional operators commonly used in relationship models include addition (+), subtraction (−), multiplication (×), exponential (*exp*), natural logarithm (*ln*), variable and constant. Second, calculate the fitness of the model until the terminal condition is satisfied. The fitting accuracy of the corresponding model is measured by the *R*-squared value. Last, the structures and parameters of models are evolved by genetic operators, such as reproduction, crossover, and mutation (see Fig. 3.7). Reproduction is used to select better individuals for the next generation directly. Crossover is used to exchange parts of two individuals and generate two new individuals. The mutation is used to alter a small portion of one individual randomly. Genetic operators generate new individuals. The configuration of the GP used for function discovery is in Table 3.3. The computational time in our research is 1000 s; at this point, the results have converged.

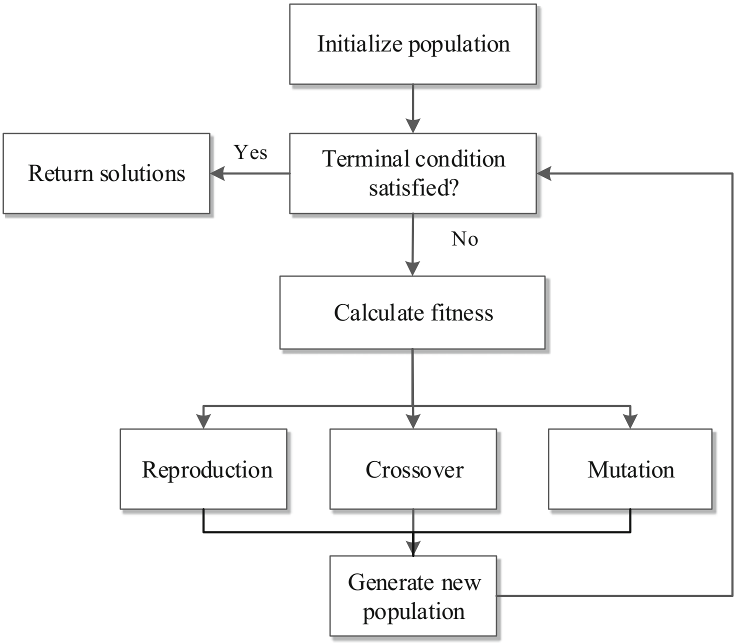

Fig. 3.6 Flowchart of GP

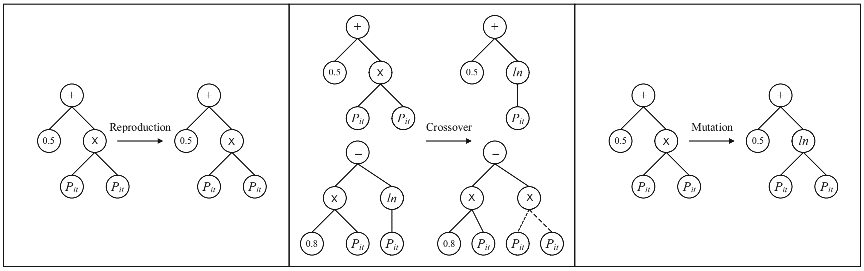

Fig. 3.7 Genetic operations in symbolic regression

Table 3.3 Components of function discovery using GP

Components	Values
Terminals	P_{it}
Functional operators	+, −, ×, exp, ln
Fitness function	*R*-squared
Genetic operators	Reproduction, crossover, mutation

3.3.2.3 Model Selection

Because GP returns a huge number of candidates, model selection plays a key role in pruning the less-promising candidates. Two steps for pruning are designed: local pruning and global pruning. The main principle of local pruning is to select the Pareto optimal models by considering their complexity and fitness based on Occam's razor, and global pruning considers the coverage of the selected models. After pruning, the models with low complexity, high fitness, and coverage remain for further analysis.

The local pruning is performed by that for a specific complexity level, and only the model with maximal fitness is selected:

$$\min(\mathrm{erro}, C) = \min\left(\left(1 - R^2\right), C\right) \tag{3.16}$$

Such a selection leads to a limited number of models for the tradeoff between error and complexity on a Pareto front.

Global pruning is performed to eliminate the less frequently appearing model when considering the whole data set, and each data set corresponds to one product in this study. After local pruning, all the Pareto optimal models can be collected, and the coverage value of each model structure can be counted. By ranking all the models by coverage, the top k models are selected for further analysis. The coverage of model i, denoted by Cove_i, indicates the proportion of the products that the corresponding model fits and is measured by

$$\mathrm{Cove}_i = \frac{n_i}{m} \times 100\% \tag{3.17}$$

where m is the number of products, and n_i is the number of products that model i is selected for.

Based on the proposed approach, a considerable number of experiments on different types of products have been done in Yang's paper (Yang et al., 2021). From a unique dataset, various free-form relationship models with their own structures and parameters have been discovered. Through the comprehensive evaluations of candidate models, a guided map was offered to understand the relationship between dynamic retail prices and the volume/valence of reviews for different types of products. Practitioners could refer to the guide map and choose a proper response model for specific products according to the models provided by this research. If the practitioner wants to acquire more consumer reviews, it should be effective for most products by lowering the price. The experimental results also show that a higher price does not always lead to a decreased number of reviews. If a commercial practitioner wants to boost the average rating, he/she can adjust the price according to the suggestions in this study. For example, for high-involvement products, it is more effective to lower the price.

3.3.3 Personalized Online Reviews Ranking Based on User Preference

With the rapid development of the “customer first” service concept and big data technology, personalized services are flourishing day by day. In order to achieve personalized review ranking, consumer preference must be considered. The so-called consumer preference refers to the degree to which the individual prefers the product’s different features; apparently, consumers are willing to read objective reviews that concretely describe the features of their interests. Taking the hotel as an example, consumers may pay different degrees of attention to various features of the hotel (such as facility, service, location, etc.), and accordingly, a review ranking list matching their preferences is supposed to be shown. How can we measure the matching degree between consumer preference and a review ranking list? In which way can we obtain the ranking list with the maximal matching degree? This study tries to work out these issues.

In the study, a mechanism is designed at first to acquire consumer preferences (Luo & Wu, 2019). And then the matching degree between a review subset S and the consumer preference is defined as the product of the usefulness score of S and the cosine similarity between the feature distribution vector of S and the consumer preference vector. By taking account of potential consumers’ behaviors while reading reviews, a ranking list’s matching degree to the preference could be defined. Thus, the ranking issue is formulated as an optimization problem, whose objective is to maximize the expected matching degree. Due to the NP-hardness of the problem, using exact methods to search for the optimal ranking list is generally infeasible in practice. Hence, a heuristic algorithm for solving the consumer preference-based review ranking (CPRR) problem, denoted as CPRR(α), is proposed. The proposed algorithm selects reviews iteratively to add to the ranking list until an approximately optimal result is produced. In the experiment research, the data of all 79,781 pieces of reviews on hotels in Dalian, China, are collected from Meituan.com up to May 2018, and plenty of experimental results have witnessed the outperformance of the proposed method compared to the other baseline methods. In a word, the main contribution of this study is to present a review ranking algorithm based on consumer preference, which could provide consumers with personalized review ranking lists to support their purchasing decisions more effectively and efficiently.

To formulate the consumer preference-based review ranking (CPRR) problem, a research framework is designed as shown in Fig. 3.8. First, some concepts like the matching degree $M(P, S)$ between the given consumer preference P and a review subset S depends on the similarity $sim(P, FD_S)$ between P and S’s feature distribution (FD_S) and S’s usefulness (U_S) are defined. Next in the phase of problem modeling, by introducing the probability distribution of breaking positions Pro as the weighting factor, the expected matching degree $\exp M(P, L)$ between P and a ranking list L could be calculated. At last, the algorithm named CPRR(α) aiming to maximize the expected matching degree is conducted to obtain the final ranking list.

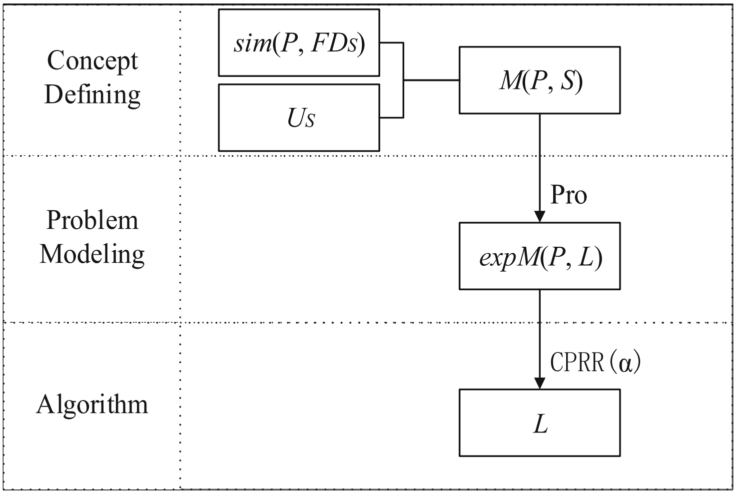

Fig. 3.8 Research framework

3.3.3.1 Concept Defining

As mentioned above, existing consumer preference mining methods always have the problem of cold start; hence a mechanism is designed to obtain consumer preferences directly. Suppose the given product has m features, the interest degree in each feature could be reflected on a five-point Likert-type scale (1 = strongly uninterested; 5 = strongly interested). While doing experiments, the consumer preferences could be generated randomly in the way, so that 5 m preferences can be obtained as the input of the algorithm, which ensures the universality of the experimental results. When applied in real life or user study, consumers can select their preferences on a radio button group.

In order to measure the matching degree between reviews and consumer preferences for different features, it needs to deeply mine the distribution of features in reviews and represent each review as a feature distribution vector. Given a category of products and their relevant reviews, domain feature dictionary $F = \{f_1, f_2, ..., f_m\}$ can be built using the available feature extraction method, where f_i denotes a type of feature words including several nouns or noun phrases with similar or related meanings. It is worth mentioning that the feature dictionary could be more accurate by mining as many reviews as possible. Therefore, given a product, its set of reviews $R = \{r_1, r_2, ..., r_m\}$ and corresponding domain feature dictionary $F = \{f_1, f_2, ..., f_m\}$, a review r, $r \in R$, can be denoted as a feature distribution vector $r = \left(r^{f_1}, r^{f_2}, \ldots, r^{f_m}\right)$, where r^{f_i} represents the number of feature words in r belonging to f_i.

In reality, consumers are concerned about not only whether a review mentions the feature they are interested in, but also whether the description of the feature in the review is informative and objective. Therefore, in addition to feature distribution, the usefulness of a review should also be considered as a weight coefficient reflecting its relative significance in matching degree. Review usefulness is online consumers' subjective perception of whether the review information published by previous reviewers is helpful for them to make purchase decisions, which could be influenced by many factors, such as ratings, sentiments of reviews, reviewers' member levels, etc. To measure it, a family of functions could be applied to map a specific review r to a real-numbered usefulness score U_r in the interval [0, 1]. Through model training and predicting using some machine learning methods, such as linear regression, U_r could be derived easily.

Given a product and its set of reviews $R = \{r_1, r_2, ..., r_n\}$, where $\mathrm{r_i} = \left(\mathrm{r_i^{f_1}}, \mathrm{r_i^{f_2}}, \ldots, \mathrm{r_i^{f_m}}\right)$, for a set of reviews $S \subseteq R$, the feature distribution vector of S can be denoted as

$$\mathrm{FD}_S = \sum_{r \in S} r = \left(\sum_{r \in S} r^{f_1}, \sum_{r \in S} r^{f_2}, \ldots, \sum_{r \in S} r^{f_m}\right) \triangleq \left(S^{f_1}, S^{f_2}, \ldots S^{f_m}\right) \tag{3.18}$$

Given a consumer preference vector $P = \left(P_{f_1}, P_{f_2}, \ldots, P_{f_m}\right)$, where P_{f_i} denotes the consumer's preference degree towards feature f_i, the cosine similarity between P and FD_S in an m-dimensional vector space can be calculated as follows. It can be seen from the formula that whether to normalize P and FD_S or not does not change the result, so for the accuracy of calculation, normalization is not necessary here.

$$\cos(P, \mathrm{FD}_S) = \frac{P \cdot \mathrm{FD}_S}{\| P \| \times \| \mathrm{FD}_S \|} = \frac{P_{f_1} \times S^{f_1} + P_{f_2} \times S^{f_2} + \ldots P_{f_m} \times S^{f_m}}{\sqrt{P_{f_1}^2 + P_{f_2}^2 + \ldots P_{f_m}^2} \times \sqrt{S^{f_1 2} + S^{f_2 2} + \ldots S^{f_m 2}}} \tag{3.19}$$

Thus, the matching degree between P and S can be defined as

$$M(P, S) = U_S \times \cos(P, \mathrm{FD}_S) \tag{3.20}$$

where U_S is a weight coefficient in the interval [0, 1], denoting the average usefulness score of reviews in S.

3.3.3.2 Problem Modeling

Given a review ranking list $L = (r_{l_1}, r_{l_2}, \ldots, r_{l_n})$ for the given product, where r_{l_i} denotes the ith review in the list, consumers always read the reviews in sequence and may break at any position. If the consumer stops after reading the ith review, the set of reviews he has read consists of the top i reviews, denoted as $S_i = \{r_{l_1}, r_{l_2}, \ldots, r_{l_i}\}$. The information that he obtains from S_i can match his preference P in a degree, which is denoted as $M(P, S_i)$, expressing the matching degree between P and S_i.

In reality, the number of reviews that a consumer will read is related to his behavior habit, the task at hand, and other environmental factors. The probability distribution of breaking positions Pro $= (p_1, p_2, \ldots, p_n)$, where p_i denotes the probability that a consumer stops after reading the ith review, could be observed by eye-tracking, log file analysis, and other various technologies.

Therefore, all cases should be considered while forming a review ranking list L, in which any subset of the list, i.e., S_i, $i = 1, 2, ..., n$, may be read by consumers. Thus, the expected matching degree between P and L can be calculated as

$$\exp M(P, L) = \sum_{i=1}^{n} p_i M(P, S_i) \tag{3.21}$$

Then the consumer preference-based review ranking problem could be formally defined as follows:

Problem: The consumer preference-based review ranking (CPRR) problem. Given a consumer preference P and an original set of reviews R for a product, rank all these reviews to form a ranking list L such that the expected matching degree between P and L, i.e., exp$M(P, L)$, is maximized.

According to Formula (3.20), the matching degree between consumer preference P and S_i (i.e., the set of the first i reviews in the ranking list L, $i = 1, 2, ..., n$) could be calculated. Hence, the CPRR problem can be mathematically formulated as

$$\begin{aligned} \max\ \exp M(P, L) &= \sum_{i=1}^{n} p_i M(P, S_i) = \sum_{i=1}^{n} p_i U_{S_i} \cos(P, \mathrm{FD}_{S_i}) \\ s.t. S_i &= \{r_{l_1}, r_{l_2}, \ldots, r_{l_i}\}, \quad i = 1, 2, \ldots, n \end{aligned} \tag{3.22}$$

3.3.3.3 Algorithm

The CPRR problem is NP-hard. Since a well-known NP-hard problem, the maximum coverage problem is reducible to it. For example, 24(4!) review ranking lists can be produced among 4 reviews; in this case, it is necessary to calculate their exp$M(P, L)$ respectively and select the one with maximal exp$M(P, L)$ as the resultant ranking list. While the amount of reviews is huge, it cannot be solved using the exact enumeration method in polynomial time; thus approximate methods should be considered. Intuitively, the expected matching degree between consumer preference and the ranking list could be maximized stepwise and iteratively, that is, certain reviews that perform well on the current exp$M(P, L)$ should be preserved in each iteration until all reviews have been added to a ranking list. Based on this heuristic idea, an approximation algorithm named CPRR(α) is proposed, where α is a parameter controlling the accuracy of the algorithm.

The input of the algorithm CPRR(α) includes the given consumer preference $P = \left(P_{f_1}, P_{f_2}, \ldots, P_{f_m}\right)$, the review set $R = \{r_1, r_2, ..., r_n\}$ with each review structured as a feature distribution vector $r = \left(r^{f_1}, r^{f_2}, \ldots, r^{f_m}\right)$ and a usefulness score U_r, the probability distribution Pro $= (p_1, p_2, ..., p_n)$ where p_i denotes the probability that a consumer stops reading at the ith review, and a controlling variable α ($\alpha \in [0, 1]$) to help to control the number of candidate lists in each iteration. At the beginning of the algorithm, an empty ranking list L_0 and its corresponding set that only contains the empty list SL_0 are initialized. In the ith iteration, each list L_{i-1} belonging to the list set SL_{i-1} preserved at the previous iteration is extended with a new review to generate possible list set SL_i. Later, the maximal and minimal expected matching degree values of the lists in the list set SL_i are calculated and denoted as maxValue and minValue respectively. The lists with exp$M(P, L_i)$ greater than maxValue-(1-α) (maxValue-minValue) ($\sum_{j=i}^{n} p_j$) are preserved as the lists for the next iteration, where the sum of probabilities for the remaining positions ($\sum_{j=i}^{n} p_j$) is multiplied to 1-α, for the purpose of further shrinking the number of candidate lists in each iteration. After n iterations, the list in SL_n with the maximal expected matching degree is the resultant ranking list L.

In summary, due to the information overload of reviews and the prevalence of personalized services, the consumer preference-based review ranking (CPRR) problem is raised. The goal of the CPRR problem is to provide a review ranking list L to match with the consumer preference P, which is formulated as maximizing the expected matching degree between P and L. Because of the limitations of the exact solutions in practice, an approximate optimization algorithm named CPRR (α) has been proposed to achieve a ranking list in an efficient manner. Specifically, the parameter α is used to determine the value range of the expected matching degree for controlling the amount of candidate ranking lists in each iteration. After n iterations, the list with the maximal expected matching degree is finally chosen as the resultant ranking list. Furthermore, CPRR(α) has been evaluated with intensive experiments on real data from Meituan.com, whose results demonstrate its sensitivity to different consumer preferences and its advantage compared with other algorithms of concern, especially the default ranking on the website.

3.4 Expected Future of Techniques for Online Reviews

Based on the literature review of online reviews' mining techniques and their commercial value discovery, in this section, we focus on discussing the expected future techniques for online reviews. The first potential topic is deep migration learning within the information extraction field. Subsequently, the processing of multimodal data is also discussed regarding its valuable directions. Then the expected research topics about text categorization are summarized.

3.4.1 Deep Migration Learning

Currently, deep learning is extensively applied in massive NLP tasks, due to the development of neural networks and artificial intelligence. Common techniques include sentiment analysis, relationship extraction, event extraction, etc.; and especially, these advanced methods are investigated in numerous research fields such as tourism, manufacturing, and the hospitality industry using online customer reviews. However, such deep learning-based methods mandatorily require labeled training data, as well as a pretty long training time. In the current e-commerce context, there are an increasing number of unstructured consumer online reviews. How to deal with the low-quality and unlabeled data due to a large amount of noise is one of the main challenges, which has reduced the effectiveness and performance of deep learning and negatively affected a variety of NLP tasks, such as semantic association recognition between entities and terms, extraction of contextually relevant information, data modeling, and structuring of data.

Fortunately, deep migration learning may address the above issues well. Scholars of computer vision first proposed and applied migration learning to cope with the unlabeled data issue (Fang & Tao, 2019), and their results demonstrated desirable accuracy. Recently, some researchers of NLP have also noticed the advantages of migration learning. For example, using online patient reviews, Xie and Xiang (2022) effectively identified the discussed topics. Encouragingly, these studies provide preliminary evidence of the effectiveness of applying transfer learning to online reviews. Overall, there might be several aspects worth exploring for future research as follows.

As we mentioned about NER, supervised NER systems rely on a large amount of annotated data, and the annotation of online review data is a time-consuming and expensive task with quality and consistency issues. In addition, entity nesting is widespread. Therefore, there is a need to develop generic annotation schemes to handle nested entities and fine-grained entities.

Another notable problem to be solved is the migration learning-based relationship extraction. There are many datasets available for relationship extraction, but almost no problem-specific datasets. For example, cross-sentence relationship extraction, where two different entities are mentioned in two different sentences. There are no such datasets available for researchers to analyze.

Besides, the event extraction task is complex and deep learning-based event extraction models can bring better results, but these methods require a large amount of annotated data. Currently, the event extraction task has only a relatively small amount of annotated data, and manual annotation is very costly and time-consuming. Therefore, building an automated approach to annotating event extraction data is the future direction of development.

3.4.2 Multimodal Data Processing

Motivated by the multimodal way of thinking of humans, more and more consumers are posting their products using experiences in complex and diverse forms on online platforms, including text, images, and even videos. Especially, many e-commerce platforms officially encourage consumers' such behaviors, in order to present their products to potential customers more comprehensively. As stated above, existing studies on text reviews have been very extensive, involving multiple mature text mining techniques such as sentiment analysis, opinion mining, topic discovery, etc. On the other hand, numerous studies have investigated the application and techniques of deep learning in image and video processing. Regarding the exploration of multimodal data in online reviews, however, it is still in its infancy, despite many studies emphasizing its importance to e-commerce and consumers. Overall, there might be several future directions to expand the current literature systems.

The first potential area is analyzing multimodal data with text, images, or videos. By fusing or synthesizing different types of data, sentiments, opinions, or emotions in online reviews could be extracted. A simple way to achieve these tasks is separately processing the content in text, images, or videos, and finally fusing the extracted information to output. Despite its simplicity, however, such a method may lose valuable information in online reviews since it ignores the inside associations that existed between different modal data. Therefore, a more robust way is to transform the input features with different forms into an effective vector representation, and then data mining techniques could be employed to extract useful information.

The second valuable research topic might be the handling of class imbalance issues of multimodal data. Typically, multimodal data may face serious data imbalance (skewed) problems. Regarding text mining, there are several mature and standard steps to preprocess the review texts, such as removing stop words and stemming words. However, little is known about the prior knowledge for images or videos to preprocess, and as a result, much noise would be contained in the dataset.

Another issue worth exploring is the attribute space downscaling. Generally, online reviews are pretty massive; meanwhile, deep learning and neural network are also characterized by high dimensionality. In this regard, the application and processing of multimodal data shall require adequate computing resources and equipment. Therefore, to effectively explore the valuable information in such multimodal data, it is urgent to seek out ways of reducing the high dimensionality. In doing so, the subsequent analysis would be more efficient.

3.4.3 Text Categorization Tasks

In the past few years, the development of deep learning and artificial intelligence techniques has led to the rapid development of text categorization. Many novel ideas and models have been proposed by different scholars, such as the Attention Mechanism, Transformer, Bert, etc. Despite the great progress that has been made, the current text categorization task still faces some difficulties and challenges that need to be continued to be explored by later generations. We believe that the solution to these problems will further promote the rapid development of text categorization tasks, and even natural language processing tasks.

First, *the interpretability of deep learning models in text categorization tasks*. Although a variety of deep learning models have achieved good results in different datasets, the interpretability of the parameters and results of these models is still highly problematic. On the one hand, some models perform better on dataset A and worse on dataset B. Why does this result occur? Is it because of the variability of the models or the variability of the datasets? Moreover, what is the meaning of the parameters of the trained deep learning models? Is there any correlation with the characteristics of the data? In addition, is the larger the structure of the deep learning model, the better? If not, how large should the model structure be set in order to achieve similar classification results? While attention mechanisms have provided some insights to answer these questions, detailed studies of the underlying behavior and dynamics of these models are still lacking. A deeper understanding of these questions could help researchers better design and build deep learning-based text categorization methods.

Second, *the approach of data annotation*. While plenty of large-scale datasets have been collected for common text categorization tasks in recent years, new datasets are still needed for more challenging tasks, such as QA for multi-step inference and text categorization of multilingual documents. Having large-scale labeled datasets for these tasks can help accelerate progress in these areas. The annotation of large-scale data is not very realistic to be achieved manually, so there is a need to promote further development of automatic data annotation techniques.

In addition, *small sample learning techniques*. Most deep learning models are supervised models, which require a mass of domain labels. When the data is relatively small, the effectiveness of deep learning-based text categorization methods is limited. In fact, it is expensive to collect such labeled data for each new domain. Small-sample learning technique is a deep learning technique that can be used empirically on a specific task to classify text using a small amount of labeled data. This problem is not contradictory to the previous one but is an attempt to solve the "big data dependency" problem of deep learning from two perspectives. A solution to either of these two problems will advance the development of deep learning-based text categorization methods.

Finally, *incorporating prior knowledge into deep learning algorithms*. Integrating a priori common-sense knowledge into deep learning models has the potential to significantly improve model performance, just as humans use common-sense knowledge to perform different tasks. For example, QA systems equipped with a common-sense knowledge base can answer questions about the real world. In the absence of information, common sense can also help solve problems. Using people's general knowledge of everyday objects or concepts, AI systems can reason like humans, based on "default" assumptions about the unknown.

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Chapter 4
Machine Learning for Solving Unstructured Problems

Wen Zhang

4.1 Online Deceptive Review Identification Based on Generative Adversarial Network

4.1.1 Introduction

With the rapid development of e-commerce and the surge in the number of online reviews, a large number of deceptive reviews are prevailing on online e-commerce platforms (Hu et al., 2011). Online deceptive reviews are deceptive information posted by fraudulent reviewers who are employed by online vendors to increase product sales or suppress competitors (Zhang et al., 2018). On the one hand, positive deceptive reviews can improve the merchant's reputation and product sales. On the other hand, negative deceptive reviews could discredit competitors and damage their reputations (Wu, 2019). Because consumers cannot easily identify deceptive reviews from their experience, the misleading information in deceptive reviews would influence consumers' purchase decisions (Kugler, 2014). Therefore, deceptive review identification is crucial to protect consumer rights and maintain the normal order of e-commerce. For this reason, more and more scholars are conducting studies on the identification of deceptive reviews (Jindal & Liu, 2008; Ott et al., 2011; Xu & Zhao, 2012; Yoo & Gretzel, 2009).

The development of machine learning techniques has improved the accuracy of online deceptive review identification. However, machine learning models lack a sufficient amount of labeled data for model training. For online deceptive review identification, there are insufficient review data labeled as either deceptive or truthful reviews to train machine learning models to detect online deceptive reviews. Therefore, this study proposes a review dataset expansion method called GAN-RDE

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(GAN-Review Dataset Expansion) based on generative adversarial networks (GAN), to solve the problem of data scarcity in model training of deceptive review identification. Specifically, we divide the initial review data into the truthful review dataset and the deceptive review dataset. The GAN is trained with the two datasets, respectively, to generate vectors that conform to the feature distribution of the truthful reviews and the deceptive reviews. Secondly, we combine the generated vectors by GAN and the initial review dataset to augment the training data. Finally, the multi-layer perceptron (MLP) and support vector machine (SVM) are used as the basic classifiers to study the performances of deceptive review identification with data expansion. Experimental results show that the classifier with the GAN-RDE method performs better than the classifier with the unexpanded dataset in deceptive review identification.

4.1.2 Generative Adversarial Network

Generative adversarial network (GAN) is an emerging framework for training generative models. It is a special process in which discriminator and generator networks compete and counterbalance each other. The basic idea of GAN is derived from the non-cooperative game equilibrium in response theory (Goodfellow et al., 2014). Since the introduction of GAN, a large number of scholars have started to study GAN and propose its improved models and optimization methods (Goodfellow et al., 2014; Mirza & Osindero, 2014; Radford et al., 2016). For instance, Goodfellow et al. (2014) proposed a generative adversarial network model and showed that GAN can simulate the output of more truthful data samples than other generative models by learning the numerical distribution features in truthful data samples.

Mirza and Osindero (2014) proposed conditional generative adversarial networks (CGAN). Based on GAN, the CGAN model introduces conditional variables in the modeling of generators and discriminators to guide the training process, resulting in a more stable GAN and solving the collapse problem of the GAN when training the model. Radford et al. (2016) proposed deep convolutional generative adversarial networks (DCGAN), which also aims to make GAN training more stable. DCGAN combines the CNN (supervised learning method) with the GAN (unsupervised learning method). Here, the generator uses a neural network model that is similar to deconvolution, and the discriminator uses a convolutional neural network model. The specific rules are given for network design and activation functions to make DCGAN more stable in the training process.

Compared with traditional machine learning methods, the primary advantage of GAN is that it is an unsupervised learning method rather than a supervised learning method. The ability of GAN to transform unsupervised learning into supervised learning allows it to play an indispensable role in the field of unsupervised and semi-supervised learning. When the training data is small, the generator can generate diverse "truthful" data through the input noise, and the data generated by the generator will eventually reach a high degree of similarity with the training set during the GAN training process. Therefore, GAN can expand the initial review dataset by the data generated by the generator and thus solve the problem of insufficient training data in deceptive review identification. In this regard, it is practical to introduce GAN in deceptive review identification.

For online deceptive reviews, it is time-consuming to label the review data manually, which also lacks reliability. Experiments by Ott et al. (2011) on the Spam dataset show that the accuracy of manual discrimination of deceptive reviews does not differ from that of random guessing. To overcome these difficulties, Jindal and Liu (2008) simply used duplicate reviews as spam reviews for deceptive review identification studies. In addition, Li et al. (2011) used heuristics to build benchmark datasets for deceptive review identification. However, the current stage of research has not truthfully addressed the problem of insufficient model training data in deceptive review identification. In this study, we utilize the limited labeled review dataset in the machine learning process and generate vectors that match the distribution of the labeled review data by learning the distribution features of the labeled review data through a generator in GAN. This can be used to expand the model training data and improve the efficiency of deceptive review identification. Unlike traditional deep learning models, the most important trait of GAN is the introduction of the adversarial mechanism. Specifically, GAN discriminates between the truthful data from the training set and the data generated by the generator. Moreover, the generator learns how to simulate the data that is closer to the distribution of the truthful data samples, and the discriminative power of the generator is also improved.

4.1.3 Feature Extraction from Textual Reviews

As a key technology for text classification, feature extraction plays an important role in natural language processing, and the quality of text features obtained through the feature extraction model will directly affect the effectiveness of the classification model. For online deceptive review identification, the feature extraction model would have a direct impact on the performance of machine learning algorithms. Therefore, different feature extraction models have different experimental effects on online deceptive review identification. This study mainly uses two feature extraction models as the N-gram model and the TF-IDF model to extract text features from review datasets. Both methods will be used to extract textual features from reviews, and the one with better performance will be assigned as the input data to train the generative adversarial network.

N-gram is one of the common methods to extract and transform text features into numerical features. The basic idea of the N-gram is to treat the length of N bytes as a unit and traverse the sentence. In addition, each byte fragment is called a gram, and the frequency of occurrence of all grams is counted. According to a pre-defined threshold, the N-gram model filters a textual review and forms a list of key grams and a vector feature space of the review. Each gram in the list is a feature vector dimension, and all the text features of grams are extracted as vectors. When N takes different values, we could obtain different feature information due to different fragment lengths. Generally, N takes values of 1, 2, and 3, which correspond to the Unigram, Bigram, and Trigram features in the N-gram model, correspondingly.

Text classification techniques based on N-gram features are validated as effective in detecting deceptive reviews. For instance, Ott et al. (2011) used the N-gram models, including Unigram and Bigram models, to extract features with machine learning to identify deceptive reviews. They combined the N-gram features and the psycholinguistic features extracted by the LIWC software to train the SVM classifier and Naïve Bayes classifier. In this study, the experiments use the Unigram model and the Bigram+ model to extract text features to train the classifier, where the Bigram+ model contains both the Unigram and Bigram features. The combination of these two features could retain more information and boost performance.

The term frequency-inverse document frequency (TF-IDF) model is a numerical statistical method that measures the importance of a word in a document (Salton & Buckley, 1988). In this study, we use TF-IDF to evaluate the importance of a word in a review. The basic idea of the TF-IDF model is that, if a word or phrase occurs in a review with high frequency (TF, term frequency) and low inverse document frequency (IDF), it is important for the review. Therefore, the common "a," "the," "of," and other high-frequency crowns, prepositions, and conjunctions that do not have any meaning in the sentence are semantically unimportant in the review. However, the keywords and central words that indicate the semantics and sentiment of a review will only appear in a few or a particular review.

Using the two indices of word frequency TF (Eq. (4.1)) and inverse document frequency IDF (Eq. (4.2)), the word frequency-inverse document frequency TF-IDF can be calculated (Eq. (4.3)). Specifically, for the feature word $w_i^{r_j}$ in a review r_j, the word frequency of the feature word $w_i^{r_j}$ in the review r_j is denoted as $\mathrm{TF}\left(w_i^{r_j}, r_j\right)$, and the distribution of the feature word $w_i^{r_j}$ in all reviews is denoted as $\mathrm{IDF}\left(w_i^{r_j}\right)$. Thus, the final TF-IDF of the feature word $w_i^{r_j}$ can be calculated by TF and IDF.

$$\mathrm{TF}\left(w_i^{r_j}, r_j\right) = \frac{\left|w_i^{r_j}\right|}{\sum_{i=1}^{n}\left|w_i^{r_j}\right|} \tag{4.1}$$

$$\mathrm{IDF}\left(w_i^{r_j}\right) = \log \frac{|R|}{\left|w_i^{r_j} \in X^{r_j}; r_j \in R\right| + 1} \tag{4.2}$$

$$\text{TF-IDF}\left(w_i^{r_j}, r_j\right) = \frac{\mathrm{TF}\left(w_i^{r_j}, r_j\right) \times \mathrm{IDF}\left(w_i^{r_j}\right)}{\sqrt{\sum_{w_i^{r_j} \in X^{r_j}} \left[\mathrm{TF}\left(w_i^{r_j}, r_j\right) \times \mathrm{IDF}\left(w_i^{r_j}\right)\right]^2}} \tag{4.3}$$

Here, $\left|w_i^{r_j}\right|$ denotes the number of occurrences of the feature term $w_i^{r_j}$ in the reviews r_j, and $\sum_{i=1}^{n}\left|w_i^{r_j}\right|$ denotes the total number of occurrences of every feature term $w_i^{r_j}$ in the review r_j. The inverse document frequency IDF measures the information content of a feature term. That is the importance of the feature term for all reviews R in the corpus. X^{r_j} denotes the feature set of the review r_j, that is, $X^{r_j} = \{w_1^{r_j}, w_2^{r_j}, \ldots, w_n^{r_j}\}$. The importance of a feature word $w_i^{r_j}$ in the TF-IDF model is proportional to the number of times $|w_i^{r_j}|$ that it appears in the reviews r_j. Meanwhile, $w_i^{r_j}$ also inversely proportional to the number of times $\sum_{i=1}^{n} |w_i^{r_j}|$ that it appears in all reviews containing the word. The TF-IDF model removes high-frequency, low-weight words from the corpus reviews and allows the model to retain more valuable information. In this regard, the IDF model can retain more useful information compared to the N-gram model.

4.1.4 Online Deceptive Review Identification

A large number of deceptive reviews and deceptive information emerge on e-commerce platforms, such as Amazon.com and Tripadvisor.com. To better manage these online deceptive reviews, researchers used features such as review data, product content information, and reviewer behavior information to construct models to identify deceptive reviews. Based on the review dataset, they proposed classification methods of deceptive review identification and obtain good results (Jindal & Liu, 2008). For instance, Yoo and Gretzel (2009) collected 40 truthful reviews and 42 deceptive reviews through online hotels and used statistical methods to distinguish between truthful and deceptive reviews based on the linguistic approach. By this method, the differences between truthful reviews and deceptive reviews are pointed out. Ott et al. (2011) used a manual annotation method to identify deceptive reviews and the results showed that the identification rate of manual annotation for deceptive reviews was low. Therefore, the practice of collecting data from existing reviews by manual annotation was undesirable. To this end, they collected data from the first standard dataset of positive reviews, which included 400 deceptive reviews and 400 truthful reviews data from 20 hotels in Chicago. It provided a good dataset basis for studies related to deceptive review identification. Subsequently, many scholars have conducted a series of studies based on their work (Ott et al., 2013; Sun et al., 2013).

Xu and Zhao (2012) used the standard dataset constructed by Ott et al. (2013) and proposed a new method of feature extraction based on sentence structure. They trained a maximum entropy model as a classifier by exploring high-level linguistic features in deceptive reviews and achieved better classification results. Sun et al. (2013) found a method to generate synthetic deceptive reviews from truthful reviews, and they proposed a general framework to detect machine synthesized deceptive reviews by capturing semantic coherence and smoothing in their study. Ott et al. (2013) collected 400 deceptive negative reviews and 400 truthful negative reviews based on a crowdsourcing service platform provided by Amazon and a web crawler approach. They constructed the first standard dataset (1600 reviews) in the field of deceptive review identification based on the standard dataset constructed in 2011. Subsequently, they used the same model to identify deceptive reviews and

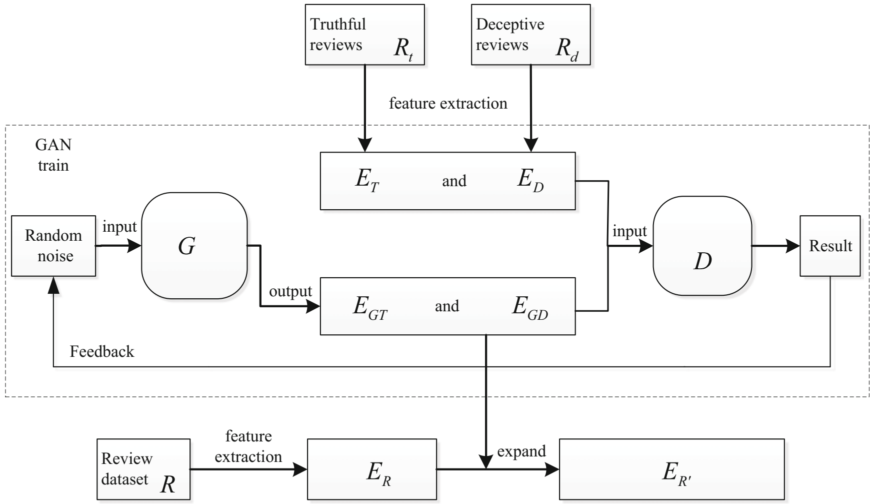


Fig. 4.1 Process of the proposed method GAN-RDE

found that machine learning models could significantly enhance the performance of deceptive review identification after expanding the dataset.

4.1.5 The Proposed Method GAN-RDE

This study proposes an online deceptive reviews method called GAN-RDE based on GAN. The overall framework of the proposed method GAN-RDE is shown in Fig. 4.1. Specifically, the two feature extraction models (N-gram and TF-IDF models that are proposed in the feature extraction method) are used to extract text features from 600 truthful reviews R_t (including 300 truthful positive reviews and 300 truthful negative reviews) and 600 deceptive reviews R_d (including 300 deceptive positive reviews and 300 deceptive negative reviews).

The results of the feature extraction model are used as the input data of the generative adversarial network training. That is, the input contains the feature word vector matrix $E_\mathrm{T} = [e_{w_1}, e_{w_2}, \ldots, e_{w_i}]$ of the truthful review dataset R_t and the feature word vector matrix $E_\mathrm{D} = [e_{w_1}, e_{w_2}, \ldots, e_{w_j}]$ of the deceptive review dataset R_d. The feature word vector matrix E_T of the truthful review dataset R_t and the feature word vector matrix E_D of the deceptive review dataset R_d are used as the input of the generative adversarial network to train the GAN. Algorithm 4.1 illustrates the GAN training process.

After the GAN training, the feature word vector matrices $E_\mathrm{GT} = [e_{t_1}, e_{t_2}, \ldots, e_{t_m}]$ of the truthful reviews and the feature word vector matrices $E_\mathrm{GD} = [e_{d_1}, e_{d_2}, \ldots, e_{d_n}]$ of the deceptive reviews are output. The text features are extracted from the dataset of 1200 reviews (including 300 truthful positive reviews, 300 truthful negative reviews, 300 deceptive positive reviews, and 300 deceptive negative reviews) using the feature extraction method to obtain the feature word vector matrix $E_R = [e_{w_1}, e_{w_2}, \ldots, e_{w_i}, \ldots e_{w_j}]$ of the review dataset. Then, the GAN-generated feature word vector matrix E_G (including E_{GT} and E_{GD}) is merged with the feature word vector matrix E_R of the review dataset R to obtain the feature word vector matrix $E = [e_{w_1}, \ldots, e_{w_i}, \ldots, e_{w_j}, e_{t_1}, \ldots e_{t_m}, e_{d_1}, \ldots e_{d_n}]$ of the augmented dataset R'. Finally, the classifier is trained with the augmented dataset R', and the four evaluation metrics in machine learning, including Accuracy, Precision, Recall, and F-Measure, are used to compare the identification effect of deceptive reviews before and after the augmentation of the review dataset by the GAN-RDE method. In this regard, the results are compared to determine whether GAN can be used to augment the review dataset and improve the accuracy of deceptive review identification.

Algorithm 4.1 GAN Training Procedure for Online Deceptive Review Dataset Expansion

Input:

D– All samples in the training set
M– Number of samples
θ– Parameters of the Generator network
φ– Parameters of the Discriminator network
K– Number of training iterations of the network
N– Total number of iterations of adversarial training

Output:

Generator$G(z, \theta)$;

Procedure:

1. Random initialization of generator parameters θ and discriminator parameters φ;
2. for 1 to N do
3. for 1 to K do
4. Collect M samples from the train set D; $\{x^{(m)}\}$, $1 \le m \le M$;
5. Collect M samples from $p_z(x)$; $\{z^{(m)}\}$, $1 \le m \le M$;
6. Using stochastic gradient ascent to update θ, and the gradient is
$$\frac{\partial}{\partial\varphi}\left[\frac{1}{M}\sum_{m=1}^{M}\left(\log D\left(x^{(m)}, \varphi\right) + \log\left(1 - D\left(G\left(z^{(m)}, \theta\right), \varphi\right)\right)\right)\right];$$
7. End for
8. Collect M samples from $p_z(x)$; $\{z^{(m)}\}$, $1 \le m \le M$;
9. Using stochastic gradient ascent to update θ, and the gradient is
$$\frac{\partial}{\partial\theta}\left[\frac{1}{M}\sum_{m=1}^{M} D\left(G\left(z^{(m)}, \theta\right), \varphi\right)\right];$$
10. End for

4.1.6 The Dataset

Ott et al. (2011) collected the first standard dataset of positive reviews in 2011, which consisted of 400 truthful positive reviews and 400 deceptive positive reviews for 20 hotels in Chicago, USA. Moreover, they collected the first standard dataset of negative reviews in 2013, which consisted of 400 truthful negative reviews and 400 deceptive negative reviews (Ott et al., 2013). In this study, we select 300 truthful positive reviews and 300 truthful negative reviews to constitute the truthful review dataset R_t. In addition, we select 300 deceptive positive reviews and 300 deceptive negative reviews to constitute the deceptive review dataset R_d. The 1200 reviews constitute the training and testing experimental dataset for machine learning in this study, and the review dataset expansion experiments are based on the datasets R_t and R_d.

4.1.6.1 Preprocessing of Review Data

For the processing of the initial review data, the 1200 review data were first divided into 600 truthful reviews and 600 deceptive reviews. We use NLTK library to remove stopwords (i.e., "the," "am," "a," "is," "at") from the review dataset. Compared with other words, because stopwords do not give any information that can help the data model and have no practical meaning, we remove these stopwords. Scikit-learn provides many methods for text feature extraction, and the Scikit-learn library is used as the feature extraction tool for the TF-IDF and N-gram models in this experiment. When using the N-gram model for feature extraction, two models (Unigram and Bigram+) are selected to extract features as vectors. For the TF-IDF model, we use TfidfVectorizer class and set parameters as smooth_idf = Truthful, use_idf = Truthful. In addition, the N-gram model is based on CountVectorizer class. The feature dimensions entreated by TF-IDF, Unigram, and Bigram+ are shown in Table 4.1.

As we can see from Table 4.1 that the dimensions of the features extracted with the above feature extraction models are large, and this means an increase in the difficulty of training for deep neural networks. Therefore, we use the feature selection method SelectKBest in Sklearn to reduce the dimensionality in our experiments to facilitate the GAN training experiments. Although there is information loss after dimensionality reduction of numerical features, it does not affect the result of this study to improve the accuracy of SVM. The dimensionality of the TF-IDF model after dimensionality reduction is 500, and the dimensionality of features extracted by the N-gram model is 2000.

Table 4.1 Feature dimensions

Feature extraction model	Dimensions
TF-IDF	7658
Unigram	7651
Bigram+	20,132

4.1.6.2 Feature Extraction

This study uses the SVM classifier to compare the effect of two feature extraction models on deceptive review identification. The differences in vector dimensions and features obtained in TF-IDF and N-gram models can lead to different classification results. This experiment uses k-fold cross-validation to verify the classification results. Specifically, the dataset data is divided into five folds, where four subsets of the dataset are used as the training set to train the SVM model and one subset of the dataset is used as the validation set for model validation, and the performance metrics of the model are calculated by the validation set. The optimal tuning parameters of the model are sought using a Scikit-learn grid search. When the model is fitted to the dataset, each parameter of the model is set in a certain interval, and all possible combinations of parameter values are evaluated to calculate the best combination.

When the SVM is trained using the N-gram model to extract the features of the training dataset, the SVM classification model has an accuracy rate of 0.83, a recall rate of 0.87, and an F1 value of 0.85 for deceptive review identification; for truthful review identification, SVM classification model has an accuracy rate of 0.89, a recall rate of 0.86, and an F1 value of 0.87, and the overall identification accuracy of the model is 0.86. When the SVM is trained using the TF-IDF model to extract the features of the training dataset, the accuracy of the SVM model for deceptive review identification is 0.89, the recall rate is 0.84, and the F1 value is 0.86; for truthful review identification, the accuracy rate is 0.83, the recall rate is 0.88, and the F1 value is 0.86, and the overall identification accuracy of the model is 0.86. The results of deceptive review identification results are shown in Fig. 4.2.

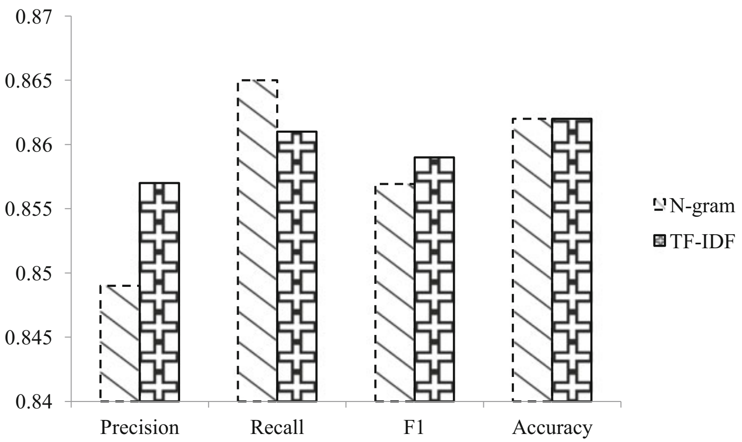


Fig. 4.2 Deceptive review identification results for the SVM model with different feature extraction models

4.1.7 Experiment Setup

When we design the generator model, we first set the dimensionality of the input layer of the generator to the same value as the dimensionality of the random noise, and let the noise pass through a fully connected layer neural network to obtain the processed result. Second, the processed result is reshaped through the Reshape layer, and the output is fed into the next layer of the 1D convolutional neural network. Specifically, the design of the convolutional neural network omits the traditional pooling step and uses the ReLU function as the activation function, and the output of 1D convolution is flattened by Flatten layer, then fed into the fully connected layer. Third, the dimensionality of the output layer is kept consistent with the feature dimensionality in the training set, and the ReLU function is used as the activation function in the output layer. Therefore, the data features of the feature extraction model can be fitted better.

When designing the generator model, the input layer is used to receive the real data and the generated data from the output layer of the generator. In addition, the input layer dimension of the discriminator model is set to be consistent with the generator output feature dimension. The tanh activation function is chosen as the function of the intermediate fully connected layer after several trials to ensure that the GAN network will not collapse during training, thus making the training process more stable. In the discriminator, we also use the one-dimensional convolutional neural network. However, unlike the generator model, the Dropout training technique is used in the convolutional network to put randomness into the network training process to prevent overfitting problems. The 1D convolution results are flattened to one-dimensional data by Flatten layer, and the results are dichotomized based on the sigmoid activation function. In addition, we set the dimension of the output layer as 2 and obtain the classification results. According to the above steps, we connect the designed generators and discriminators and built the generative adversarial network model to run the experiments in this study.

4.1.8 Experiential Results

Due to the small amount of initial review data, the accuracy of the MLP and SVM for deceptive review identification would decrease. However, the generator in GAN can well capture the distribution of review features to generate vectors that match the distribution of truthful and deceptive review features. In this regard, GAN-RDE could expand the amount of training set data based on the GAN training using truthful review dataset and deceptive review dataset and thus improve the accuracy of MLP and SVM for deceptive review identification. This method was also used in the study of Zheng et al. (2017). They proposed a data augmentation method and used the original data to train the GAN. The extended data obtained from the GAN-RDE model is used for SVM and MLP training. In addition, the trained

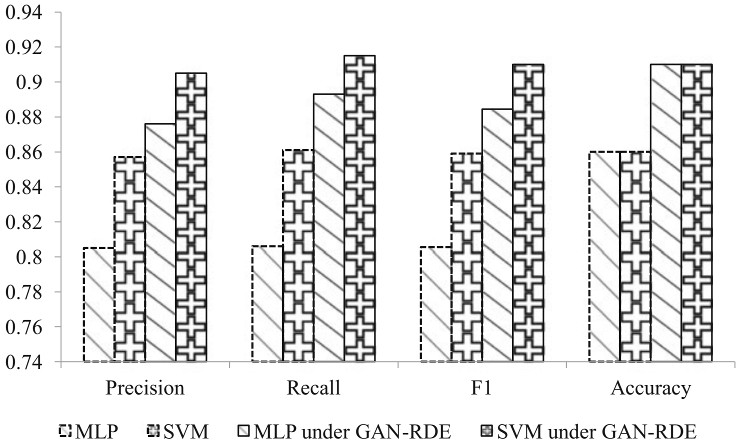


Fig. 4.3 The comparison of the deceptive review identification results of SVM and MLP

GAN-RDE generator in the experiment generates some vectors that match the distributions of truthful and deceptive review features, and we use these vectors to expand the initial review dataset.

This study trains MLP and SVM models and uses a Scikit-learn grid search to find the optimal tuning parameters for the models. The optimal kernel function of SVM model is linear function and the optimal parameter of penalty coefficient C value found by grid search in [0.001, 0.01, 0.1, 1, 10] is 1; the optimal parameter of gamma value found by grid search in [0.001, 0.01, 0.1, 1] is 0.001. The MLP model was constructed with three hidden layers, and the number of nodes in the hidden layer was set to 200, 400, and 200, respectively. In addition, the activation function was set to tanh, and we selected stochastic gradient descent to optimize the weights. The maximum number of iterations was 800, and the initial learning rate was set to 0.001. The comparison of the deceptive review identification of SVM and MLP with data augmentation by the GAN-RDE method is shown in Fig. 4.3.

As we can see from Fig. 4.3, the accuracy of MLP and SVM is improved in deceptive review identification from 85.92% to 91.14% after these two models used the GAN-RDE method to expand the review data. The deceptive review identification results of these two methods have improved after the data expansion. The recall and F1 values of MLP are increased by 13.28% and 13.32% by augmenting the review data with the GAN-RDE method. In addition, the recall and F1 values of SVM increased by 11.17% and 6.08%, respectively. Compared with the identification results of truthful reviews before the data expansion, the accuracy, recall, and F1 values of MLP under the GAN-RDE method increased by 16.82%, 8.16%, and 8.21%, correspondingly. After the data augmentation, the accuracy and the F1-value of SVM are increased by 12.14% and 2.08%, respectively.

To verify the performance of the proposed GAN-RDE method in solving the data-scarcity problem in online deceptive review identification, this study uses the classifiers as Naïve Bayes (Ott et al., 2011), MLP (Ramezanian et al., 2019), and

Table 4.2 Performance comparison of different deceptive review identification methods at different training ratios

Identification method	0.5	0.6	0.7	0.8	0.9
Naïve Bayes	73.25	74.88	74.03	73.31	74.69
Naïve Bayes under GAN-RDE	74.13	75.28	75.16	75.56	75.22
MLP	81.38	85.63	81.46	80.63	82.53
MLP under GAN-RDE	88.33	88.02	87.08	90.21	88.33
SVM	80.38	84.37	83.96	85.08	83.13
SVM under GAN-RDE	87.67	87.19	86.94	89.38	89.25

SVM (Zhang et al., 2019) to study the differences in deceptive review identification before and after using the GAN-RDE method. Naïve Bayes assumes that the effects of individual attributes on the classification results are independent of each other, and this independence assumption greatly reduces the computational complexity of the classifier. MLP is a deep learning-based deceptive review identification method, and SVM is the most popular supervised learning model. These methods are widely used in text classification (Pourhabibi et al., 2020) and deceptive review identification (Ott et al., 2011). They all have good performance in the classification task. Table 4.2 shows the comparison of the deceptive review identification results of the above three models on different training ratios before and after using the review dataset expansion method GAN-RDE.

As shown in Table 4.2, after augmenting the data by the GAN-RDE method, there is a significant improvement in the accuracy of deceptive review identification by the Naïve Bayesian, MLP, and SVM at different training ratios. The results indicate that the trained generative adversarial network learns the feature distribution of the initial review set, and the vectors generated by GAN can augment the review dataset, which makes the above methods improve the effectiveness of deceptive review identification. Therefore, the proposed GAN-RDE method in this study could improve the performance of deceptive review identification models.

4.1.9 Concluding Remarks

This study attempts to use the generative adversarial network to augment the online review dataset to solve the problem of insufficient model training data in online deceptive review identification. By training the generative adversarial network, we provide the deceptive review identification model with a sufficient amount of labeled review data for model training and thus improve the accuracy of deceptive review identification. The contributions of this study can be summarized in two ways.

First, this study proposes the GAN-RDE method to generate more review data with the goal of expanding the training data by merging the feature word vector matrix generated from GAN and the feature word vector matrix of the initial review dataset. The GAN-RDE method can solve the problem of insufficient model training data in the current deceptive review identification method. Second, based on the standard review dataset, we augment the dataset with the help of a generative adversarial network to improve the accuracy of deceptive review identification. Therefore, we believe that GAN can be introduced to the field of online deceptive review identification.

However, this study does not use a complicated neural network structure in the generator and discriminator of GAN. Recently, GAN has gained wide attention in the field of deep learning, and many scholars have conducted research on GAN and derived complicated models. These models have been applied in the field of image and text identification. Network models such as DCGAN and WGAN have also been proposed to extend the applications of GAN. In the future, we will use a more complicated neural network structure in GAN to improve the accuracy of online deceptive review identification.

4.2 Fine-Grained Bug Localization Based on Word Vectors

4.2.1 Introduction

A software bug is an error, fault, or flaw in a computer program or system that causes it to operate in an incorrect or unexpected way (Zhao et al., 2017). The existence of software bugs will lead to software products that cannot meet the needs of users to some extent. In the process of software project development, some bug tracking systems are often used to manage software bugs, such as Bugzilla,[1] JIRA,[2] Mantis,[3] and so on. These bug tracking systems are used to manage the entire life cycle of bug reports in software project development, such as submission, confirmation, distribution, fixing, and closure (Wu et al., 2011). For a large software project, a large number of software bug reports submitted by users are incoming every day, and fixing these bugs takes a large amount of time and labor for developers. For example, nearly 200 bug reports are submitted to the Eclipse bug repository per day before its release. Similarly, nearly 150 bug reports are submitted to the Debian bug repository every day (Zhang et al., 2016). According to Jeong et al. (2009), in the PostgreSQL project, most bugs take 100–200 days to be fixed and even 50% of reported bugs take nearly 100–300 days to be fixed. According to the observation on the Tomcat 7 project, most of the bugs are fixed within 40–200 days, 10% of the bugs can be fixed within 10 h and 5% of the bugs would take nearly 2 years to be fixed.

Once the software bug report is identified by the bug manager and assigned to the developer for resolution, the assigned bug fixer needs to locate the bug, that is, to find out the code snippets that should be modified to resolve the bug (Lukins et al.,

[1] Bugzilla: https://www.bugzilla.org/

[2] JIRA: http://www.atlassian.com/ software/jira/

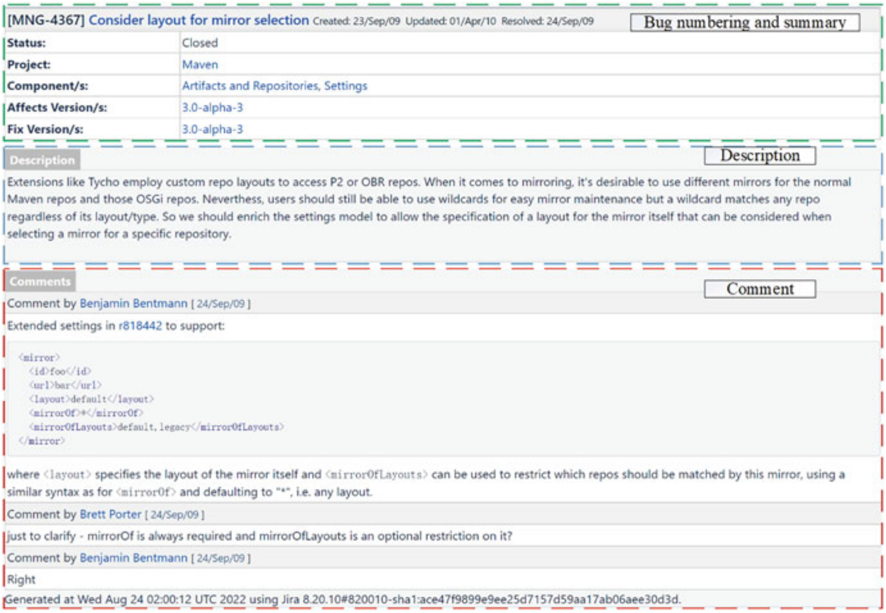
[3] Mantis: https://www.mantisbt.org/

2010). For software developers, in order to fix a software bug, they need to fully understand the relevant information about the bug. Inevitably, software developers need to read a large number of software source codes to decide the location of the bug. When there are a large number of bug reports and source code files, bug localization would be a very time-consuming and labor-consuming task. If a bug cannot be localized in the correct location for a long time, then the time for a bug fixing will also increase, resulting in an increase in the maintenance cost of the corresponding software project and a decrease in user satisfaction with the software product.

Recently, a series of software bug localization methods were proposed by researchers to assist bug fixers to locate software bugs and reduce their workload in fixing bugs. Typical software bug localization methods can be divided into two categories as static bug localization and dynamic bug localization. The former is based on software bug reports, source code, and static information about the development process to locate software bugs (Binkley & Lawrie, 2010; Dilshener et al., 2016; Wong et al., 2014; Youm et al., 2015). The latter is based on techniques such as staking techniques, execution monitoring, and formal methods for software runtime state tracking to speculate where software bugs are likely to occur (Abreu, 2009; Chilimbi et al., 2009; Liblit et al., 2005). These bug localization methods assist software bug fixers to narrow the range of bug locations and reduce staff time locating bugs. However, existing bug localization methods, for both static and dynamic methods, locate bugs at the file level. In other words, the existing bug localization techniques assist the bug fixer to find the source code files containing the bug. However, it requires further debugging and testing of software maintainers to decide the detailed location of the bug in the source code file (i.e., the specific method in which the bug occurs).

Different from the existing methods of locating software bugs at the file level, we propose a method-level fine-grained approach, called MethodLocator, to assist software bug fixers in bug localization. Specifically, the proposed MethodLocator approach treats each bug report as a query and each method body in the source code as a query object. Moreover, the proposed MethodLocator approach uses a revised vector space model (rVSM) (Zhou et al., 2012) for the textual representation of bug reports and method bodies in the source code. Then, the cosine formula is used to measure the similarities between the bug reports and the method bodies. In natural language preprocessing on the method bodies, considering that the text contents of method bodies are much shorter than that of bug reports, the proposed MethodLocator approach expands the method bodies according to the similarities between them.

The remainder of this chapter is organized as follows: Section 4.2.2 gives a problem description of software bug localization. Section 4.2.3 proposes the MethodLocator approach for method-level fine-grained bug localization. Section 4.2.4 gives specific steps on the vector representation and expansion of the method body. Section 4.2.5 describes the method for calculating the similarity of bug reports and method bodies. Section 4.2.6 conducts experiments. Section 4.2.7 provides a comparison of the proposed MethodLoactor method with the baselines. Section 4.2.8 concludes the research and indicates future work.


[MNG-4367] Consider layout for mirror selection Created: 23/Sep/09 Updated: 01/Apr/10 Resolved: 24/Sep/09

Status:	Closed
Project:	Maven
Component/s:	Artifacts and Repositories, Settings
Affects Version/s:	3.0-alpha-3
Fix Version/s:	3.0-alpha-3

Description

Extensions like Tycho employ custom repo layouts to access P2 or OBR repos. When it comes to mirroring, it's desirable to use different mirrors for the normal Maven repos and those OSGi repos. Neverthess, users should still be able to use wildcards for easy mirror maintenance but a wildcard matches any repo regardless of its layout/type. So we should enrich the settings model to allow the specification of a layout for the mirror itself that can be considered when selecting a mirror for a specific repository.

Comments

Comment by Benjamin Bentmann [24/Sep/09]

Extended settings in r818442 to support:

```
<mirror>
  <id>foo</id>
  <url>bar</url>
  <layout>default</layout>
  <mirrorOf>*</mirrorOf>
  <mirrorOfLayouts>default, legacy</mirrorOfLayouts>
</mirror>
```

where <layout> specifies the layout of the mirror itself and <mirrorOfLayouts> can be used to restrict which repos should be matched by this mirror, using a similar syntax as for <mirrorOf> and defaulting to "*", i.e. any layout.

Comment by Brett Porter [24/Sep/09]

just to clarify - mirrorOf is always required and mirrorOfLayouts is an optional restriction on it?

Comment by Benjamin Bentmann [24/Sep/09]

Right

Generated at Wed Aug 24 02:00:12 UTC 2022 using Jira 8.20.10#820010-sha1:ace47f9899e9ee25d7157d59aa17ab06aee30d3d.

Fig. 4.4 An example of a bug report for a Maven project

4.2.2 Problem Description

Figure 4.4 shows an example of a bug report for the Maven project.[4] At the top of the bug report are the numbering and a summary of the bug. The middle of the bug report is a detailed description of the bug made by the bug submitter, which mainly includes the software running context information when the bug occurred. Below the detailed description are comments from software project developers who are interested in this bug. The bug tracking system will automatically record the commenter and the comment time. In the case of difficult software bugs, there can be dozens of comments on the bug report.

For a software project, assume there are n bug reports $\mathrm{BR} = (\mathrm{br}_1, \mathrm{br}_2, \ldots, \mathrm{br}_n)$, where br_i indicates one of the bug reports. When fixing the bug corresponding to a bug report br_i, the modified files set is represented as $f(\mathrm{br}_i) = \left\{ f_1^{\mathrm{br}_i}, f_2^{\mathrm{br}_i}, \ldots, f_{|\mathrm{f}(\mathrm{br}_i)|}^{\mathrm{br}_i} \right\}$ ($f_{\mathrm{j}}^{\mathrm{br}_i} \in F$, Findicates the set of all source code files for the

[4] Big report of the Maven project: https://issues.apache.org/jira/si/jira.issueviews:issue-html/MNG-4367/MNG-4367.html

Table 4.3 Examples of modified files and methods for repairing MNG-4367

Modified file	Number of methods	Modified method	Localization results
DefaultMirrorSelector.java	5	Mirror getMirror()	3
		boolean matchesLayout()	6
		boolean matchesLayout()	9
MirrorProcessorTest.java	14	Mirror newMirror()	4
		void testLayoutPattern()	1
		void testMirrorLayoutConsideredForMatching()	10

software project, $|f(\mathrm{br}_i)|$ indicates the number of elements in the set $f(\mathrm{br}_i)$). In fact, when a bug fixer modifies a file $f_i^{\mathrm{br}_i}$, she or he modifies only one or more method bodies in the file. These modified method bodies are represented as $m\left(f_i^{\mathrm{br}_i}\right) = \{m_1, \ldots, m_p\}$ $\left(m\left(f_i^{\mathrm{br}_i}\right) \in \mathrm{MALL}\left(f_i^{\mathrm{br}_i}\right), \mathrm{MALL}\left(f_i^{\mathrm{br}_i}\right)\right.$ denotes the set of all methods in file $\left.f_i^{\mathrm{br}_i}\right)$. For the traditional software bug localization approach, software bug localization can be described as how to use the bug report br_i to pinpoint the file set $f(\mathrm{br}_i)$ that needs to be modified from F. In this research, we aim at using use the bug report br_i to pinpoint the file set $f(\mathrm{br}_i)$ and its corresponding method set $m\left(f_i^{\mathrm{br}_i}\right)$.

Table 4.3 shows examples of the specific files and methods involved in the Maven project for fixing bug MNG-4367 (see Fig. 4.4 for details). The total number of the Maven project source code files is 898. In order to fix the bug described in the bug report MNG-4367, it is necessary to modify six methods in two source code files. The "DefaultMirrorSelector.java" file contains a total of five methods, three of which actually need to be modified. The "MirrorProcessorTest.java" file contains a total of 14 methods, three of which actually need to be modified. The specific methods that need to be modified are shown in Table 4.3.

Thus, we describe the problem of locating software bugs at the method level as follows: according to the description of bug report MNG-4367, find 2 files to modify (including DefaultMirrorSelector.java and MirrorProcessorTest.java) from the Maven project's all source code files, and further, find the 6 methods that need to be modified in these 2 files.

4.2.3 The Proposed MethodLocator Approach

We propose a fine-grained software bug localization method MethodLoactor, which takes the bug report br_i (including the summary content, description content, and comment content in the bug report) as the query, and $M = \{m_1, \ldots, m_k\}$ (M denotes the set of all methods in the source file, and m_j denotes one of the methods) as the query object. We use the revised vector space model (rVSM) (Zhou et al., 2012) to

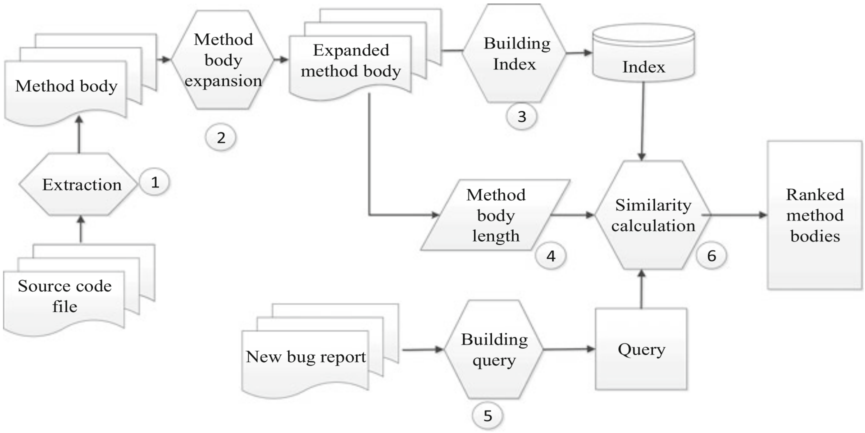


Fig. 4.5 The overall structure of MethodLocator

vectorize the content of bug reports and source code method bodies and use the cosine similarity to calculate the similarity between bug reports and source code methods. Table 4.3 gives the localization results of the proposed method in this chapter for bug report MNG-4367, and it can be seen that the six modified methods appear in the 3rd, 6th, 9th, 4th, 1st, and 10th positions of the ranking results, respectively.

Figure 4.5 shows the overall architecture of the proposed MethodLocator approach. As shown in steps 3–6 in Fig. 4.5, when a new bug report is submitted, MethodLocator first treats it as a query and calculates the cosine similarity between each method in the source code repository and the bug report. Afterward, MethodLocator returns the ranking of the related located methods from the query of the source code method bodies. Finally, MethodLocator ranks the returned methods in descending order of similarity value to locate the method that may the methods that may cause the bug.

Considering that the content of the method body (including the method name and the content of the method body) is shorter than the bug report, it often brings the problem of sparsity in query matching. Based on the investigation of the research results on the topics of short text expansion and query expansion in recent years (Chen et al., 2011; He et al., 2011; Ma et al., 2016; Phan et al., 2008; Quan et al., 2010; Yang et al., 2016), we propose a short text expansion approach for method body expansion. According to the similarity between method bodies, we expand a specific method with similar method bodies. MethodLocator can be divided into two stages, namely method body expansion and similarity calculation. The details can be found in Sects. 4.2.4 and 4.2.5.

4.2.4 Method Body Vector Representation and Expansion

Figure 4.6 gives a detailed description of step 1 (i.e., method body extraction) and step 2 (i.e., method body expansion) in Fig. 4.5. Part I of Fig. 4.6 shows the preprocessing of the method content. First, the method bodies are extracted from the source code files, where the parsing of the source code file is realized by an abstract syntax tree. A method body extracted from the source code file is denoted byMethod_i ($1 < \ = i < \ = n$, $n$is the total number of method bodies in the source code). Then, text preprocessing is performed for each method body, including separating the English words from the method names according to the Java programming hump naming rules, removing stopwords, removing Java reserved keywords, and removing various symbols. The pre-processed method is expressed as $\text{Method}_i^{'}$. Finally, the TF-IDF value of $\text{Method}_i^{'}$ is calculated and the corresponding results are stored in Method_i^{*}. The calculation procedure for the TF-IDF value is as follows.

We first analyze the lexical item frequency TF and inverse text frequency IDF of each lexical stem and then calculate the vector value of each method body. We use $\{x_1, x_2, \ldots, x_n\}$ to denote the lexical stems extracted from the method body$\text{Method}_i^{'}$, where n denotes the total number of stems. Then the representation vector Method_i^{*} of the ith method body is shown in Eq. (4.4).

$$\text{Method}_i^{*} = [\text{tf}(x_1) \times \text{idf}(x_1), \text{tf}(x_2) \times \text{idf}(x_2), \ \ldots, \text{tf}(x_n) \times \text{idf}(x_n)] \tag{4.4}$$

The tfand idf in Eq. (4.4) are calculated as Eq. (4.5).

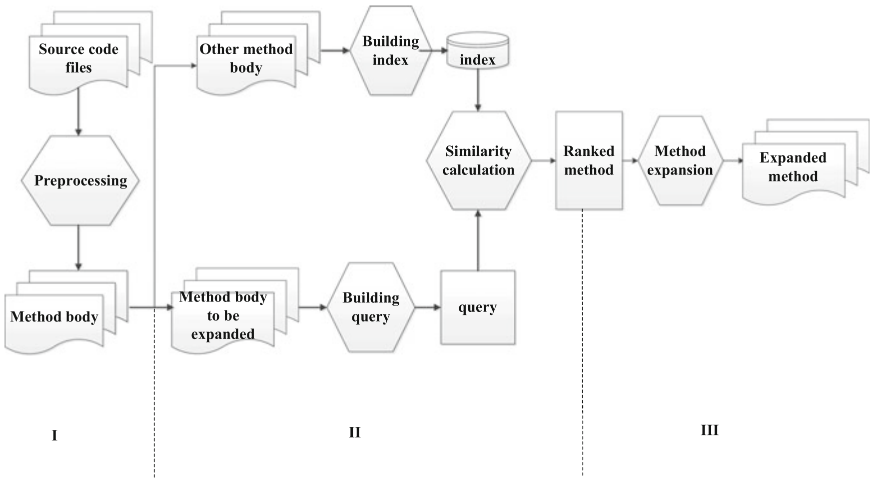


Fig. 4.6 Method body expansion

Fig. 4.7 Method body expansion algorithm

```
Algorithm: Method body expansion
Input:  Method*K
        M : Method*1、 Method*2...Method*N-1(0<i<n)
        s :s1、 s2…sn-1(0<i<n)
        θ
Output: FMK: FinalMethodK
Process
Begin: FMK.tfidfm=FMK.tfidfm(0<m<M)
       for si in s
           if  si> θ
           FMK.tfidfm=FMK.tfidfm+εi*Mi.tfidfm(0<m<M)
       return FMK
End
```

$$\mathrm{tf}_d(t) = \log(f_{td}) + 1, \quad \mathrm{idf}(t) = \log\left(\frac{d}{d_t}\right) \tag{4.5}$$

Here,f_{td} refers to the frequency of stem t in document d. d_t is the number of documents containing the stem t.

As shown in part II in Fig. 4.6, we take the Kth method as a query, and then use other methods as indexes to get a sequence of size $n - 1$ by computing their similarities using vector space model (VSM). Finally, we will compute each method to get n sequences of size $n - 1$. The expansion of the method body is carried out in part III of Fig. 4.6. The specific steps are as follows.

Taking the Kth method as an example, assume that the text similarities between it and the other $n - 1$ methods are denoted as $S_1, S_2, \ldots, S_n$.

$$S_i = \cos(\mathrm{Method}_k, \mathrm{Method}_i) = \frac{\mathrm{Method}_k^* \cdot \mathrm{Method}_i^*}{|\mathrm{Method}_k^*| \times |\mathrm{Method}_i^*|} \tag{4.6}$$

$$\theta = \left(\sum_{i=1}^{n-1} S_i\right) / (n-1) \tag{4.7}$$

As shown in Eqs. (4.6) and (4.7), theθparameter can be derived by calculating its average value. For method$i$, if $S_i > \theta$, the content of method i is expanded to the$K$th method. In order to keep the original method body content dominating the method representation, we add a heuristically weight in the expansion process and uses S_i as the weight. In order to simplify the whole bug localization process, we directly expand the $\mathrm{tf} - \mathrm{idf}$ value of each word in the method body, i.e., $\mathrm{Method}*_i$ is expanded and the expanded result is called $\mathrm{FinalMethod}_i$. Figure 4.7 shows the specific flow of the method body expansion, where M is the total number of words in Method$*_i$.

4.2.5 Bug Report and Method Body Similarity Calculation and Ranking

On the basis of Sect. 4.2.3, the bug report content is processed with the same vocabulary and TF-IDF calculation as the method body, and the processed bug report is denoted as $\text{BugReport}_\text{i}$. It should be noted that we collect the summary, description, and comments in a bug report for vectorization according to previous experience and manual observation. After the above processing, we use all the processed methods FinalMethod_i as indexes and the bug reports BugReport_i as queries. Then, we use the rVSM (Zhou et al., 2012) method to calculate the similarity, and all FinalMethod_i are sorted in descending order according to the results of rVSM calculation. The reason for applying rVSM (Zhou et al., 2012) for similarity calculation is that although the lengths of expanded method bodies tend to converge, there are still differences. The effect of the length of the document code on bug localization was also mentioned in the study of Zhou et al. (2012). Therefore, we chose the rVSM method proposed by Zhou et al. (2012) for the similarity calculation. After getting the method body vector representation $\text{FinalMethod}_i$and the bug report vector representation Bugreport_i^* (the representation process is shown in Eq. (4.4)), the calculation steps of rVSM follow the formulas in the BugLocator of Zhou et al. (2012), as shown in Eqs. (4.8) to (4.11).

$$\cos(\text{Method}, \text{Bugreport}) = \frac{\text{FinalMethod}_i \cdot \text{Bugreport}_i^*}{|\text{FinalMethod}_i| \times |\text{Bugreport}_i^*|} \tag{4.8}$$

$$\text{rVSMscore}(\text{Method}, \text{Bugreport}) = g(\#\text{term}) \times \cos(\text{Method}, \text{Bugreport}) \tag{4.9}$$

$$\text{g}(\#\text{term}) = \frac{1}{1 - e^{-N(\#\text{term})}} \tag{4.10}$$

$$N(x) = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{4.11}$$

In essence, the rVSM method introduces the function g (i.e., Eq. (4.10)) based on the VSM calculation method. The introduction of the function g makes the difference in document length useful when locating bugs. It works by giving a higher score to the longer length of the method body when ranking, where Eq. (4.10) uses the normalized value of (#term) as the input to e^{-x}. The method of normalization is shown in Eq. (4.11), where the x is a set of data, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of this dataset, respectively.

4.2.6 Experiments

4.2.6.1 Building the Benchmark Dataset

In this chapter, four open-source software projects, namely ArgoUML, Ant, Maven, and Kylin, are selected to verify the effectiveness of the proposed fine-grained software bug localization method MethodLocator. Moreover, we collected the change information of the source code files and bug reports from these projects, and the specific data collection process is described below.

1. Get the source code files.

   The purpose of this step is to get the source code files required for the experiment from the open-source project code repositories. For the ArgoUML and Ant projects, we utilize the SVN tool to get the source code data. For the Maven and Kylin projects, we adopt the Git tool to get the source code data.
2. Create dataset of file changes caused by bug fixes.

   First, we use SVN or Git to collect the logs of all the .java files from the source code version control system. For each .java file, we extract the bug ID from its logs using the SZZ algorithm (Sliwerski et al., 2005). Then, we get the version number of the .java file corresponding to the bug ID from the log. We find out all the previous versions of the bug ID from the log (ordered by modification timestamps from closest to farthest). Next, we use the diff command to compare the previous version with the current version and select the most recent previous version with changes as the base version. By comparing the diff result between the current version and the base version, we can obtain the code changes caused by fixing the bug. Then, we use the AST abstract syntax tree to parse each base version source file and the then-current version source file and find the method to which the diff result lines belong. Finally, we gather the bug ID, the modified Java file, the modified lines of code, and the modified method to create a dataset.
3. Get the bug reports.

   In this research, we extract the historical bug reports from the bug tracking system of each software project. Combining previous experience and manual observation (Wu et al., 2011), the three fields of summary, description, and comment of the bug reports are selected for natural language description. In order to ensure the repeatability and verifiability of the experiment, these bug reports with good traceability of bug change records are selected from all bug reports as experimental data, i.e., we can accurately trace the bug report and source code modification record according to the bug ID. Table 4.4 shows the basic information of the experimental datasets from four software projects.

Table 4.4 Basic information of the experimental software projects

Project name	Number of documents	Number of method	Number of bug reports	Bug report time
Argouml	1870	12,176	1128	2001/1–2014/10
Ant	1233	11,805	265	2000/1–2014/1
Maven	898	6459	637	2004/8–2016/10
Kylin	996	7744	356	2015/2–2016/8

Table 4.5 Standard experimental dataset

Project name	Number of documents	Number of method	Number of bug reports	Bug report time
Argouml	1870	12,176	715	2001/1–2014/10
Ant	1233	11,805	230	2000/1–2014/1
Maven	898	6459	392	2004/8–2016/10
Kylin	996	7744	323	2015/2–2016/8

4.2.6.2 Experimental Setup

In the collected dataset, some files and methods corresponding to bug reports were deleted after the version upgrade, and some bugs cannot be located in the corresponding method body, resulting in the number of located methods being smaller than the number of located files. These data can introduce errors in the accuracy of the experiments, so they are excluded from the validation experiment. In this chapter, we call these newly obtained datasets as the standard dataset, and the experiments are conducted on the standard dataset. The data information for each project is given in Table 4.5.

4.2.6.3 The Baselines

In order to validate the performance of MethodLocator in bug localization, we select two baseline methods for comparison experiments, including BugLocator (Zhou et al., 2012) and BLIA v1.5 (Youm et al., 2016). The Buglocator method proposed by Zhou et al. (2012) is a typical and widely accepted file-level bug localization method. Since the focus of this research is on the method level software bug localization, we adjust the granularity of the BugLocator method from the original file-level to the method-level. In terms of method-level static bug localization based on information retrieval, only the BLIA v1.5 method proposed by Youm et al. (2016) can be accessed for comparison experiments. Therefore, we chose BLIA v1.5 as another baseline method to verify the effectiveness of MethodLocator. In the BLIA v1.5, the method-level bug localization is completed by first obtaining the ranking of the files, then selecting the higher ranked files, and analyzing the methods in such files.

4.2.6.4 Evaluation Metrics

In order to verify the effectiveness of the proposed bug localization method, four metrics, namely top N rank, mean average precision (MAP), mean reciprocal rank (MRR), and the amount of code (TAC), are selected for evaluating the experimental results. Assume that the ith bug report of a project is denoted as br_i. The method body set that actually modified to fix the bug is denoted as $m\left(f_i^{br_i}\right)$. We evaluate the performance of MethodLocator and baseline techniques using the positions of actually modified method bodies that appear in the recommended methods list.

1. Top N rank

   For a software bug report, the bug localization is considered successful if the first N ($N = 1,5,10$) method bodies given by the proposed methods contain at least one method related to this bug. The higher the value of top N rank, the higher the performance of the method for bug localization.
2. Mean average precision (MAP)

   MAP represents the average accuracy of source code localization for all bug reports. The higher rank of the source code method body to be modified retrieved by the bug localization method, the higher the MAP. Conversely, if the bug localization method does not retrieve the source code method body to be modified, the accuracy rate defaults to 0. The average accuracy of a single bug (denoted as AvgP) is shown in Eq. (4.12).

$$\mathrm{AvgP} = \frac{1}{|R|}\sum_{k=1}^{|R|}\frac{k}{\mathrm{rank}_k} \tag{4.12}$$

   where R denotes the set of source code methods that can be correctly located in one bug localization, $|R|$ denotes the number of correctly located source code method bodies, and rank_k denotes the ranking of the k-th correct source code method. The MAP for all bug reports is shown in Eq. (4.13).

$$\mathrm{MAP} = \sum_{j=1}^{|Q|}\frac{\mathrm{AvgP}_j}{Q} \tag{4.13}$$

   Here, Q denotes the set of bug reports, $|Q|$ denotes the number of bug reports, and AvgP_j denotes the average precision value of the jth bug report.
3. Mean reciprocal rank (MRR)

   MRR represents the average of the inverse of the position of the relevant source code method, and the higher the MRR, the higher the accuracy of the algorithm. MRR is calculated as follows:

$$\mathrm{MRR} = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{\mathrm{rank}_i} \tag{4.14}$$

where Q is the set of bug reports, $|Q|$ denotes the number of bug reports, and rank_i denotes the position of the ith bug report related to the most forward ranking of the method body located. The higher the MRR value, the higher the accuracy of bug localization.

4. The amount of code (TAC)

TAC is a metric defined in this chapter to evaluate the average number of code lines need to be read by developers for a bug fixing. It reflects the capabilities of method-level and file-level bug localization methods in reducing the amount of code that developers need to read during bug fixing. The lower the score of this metric, the less the amount of code that the software maintainer needs to read. The calculation formula is as follows:

$$\mathrm{TAC} = \frac{\mathrm{Avgnum}}{\mathrm{MAP}} \tag{4.15}$$

Here, Avgnum denotes the average amount of code, i.e., the number of lines of code in the file or method body to be modified, and MAP is the mean average precision value of the method.

4.2.7 *Experiment Results and Analysis*

This section provides the evaluation of the proposed MethodLocator approach in bug localization. We evaluate the effectiveness of the MethodLocator by answering three research questions and comparing its performance with existing bug localization baselines based on information retrieval as introduced in Sect. 4.2.6.

Question 4.1 Is there any improvement in accuracy when MethodLocator is applied to file-level bug localization compared to traditional bug localization methods (Buglocator)?

The difference between MethodLocator and Buglocator for file-level bug localization is that MethodLocator uses the method body to build an index and then proceeds to further operations. Using the method body to build the index is more helpful for bug locating because the method body contains fewer disturbing factors than the source file.

Figure 4.8 shows the experimental results of MethodLocator and Buglocator on the four software projects on file-level bug localization. By comparing the TOP-N, MRR, and MAP three evaluation metrics, we can see that MethodLocator produces better performance than Buglocator. The results illustrate that decomposing the source file into method bodies can reduce the influence of some disturbing factors

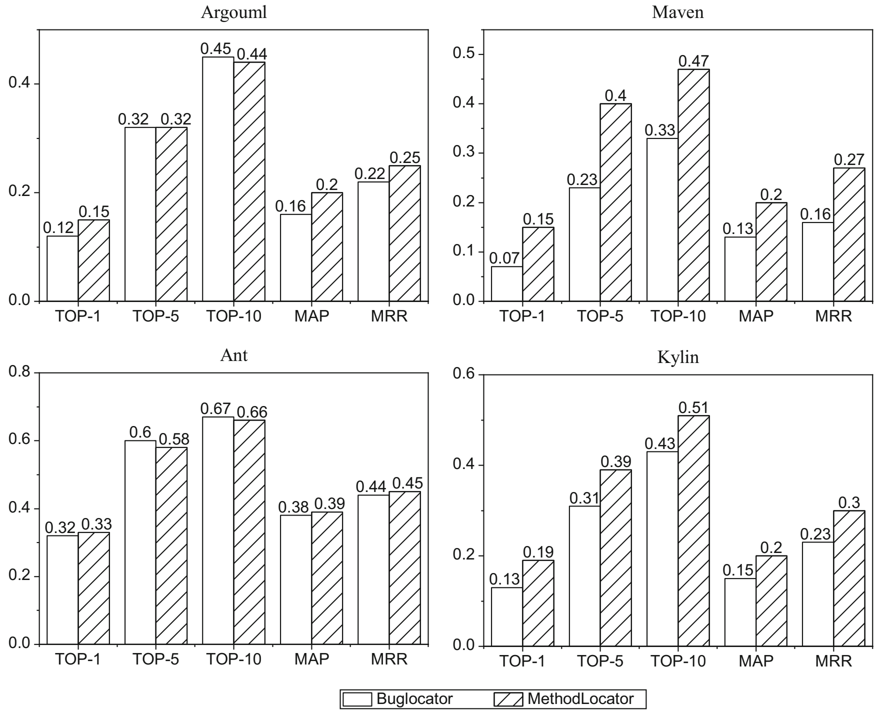


Fig. 4.8 Comparison of experimental results of MethodLocator and Buglocator in file-level bug localization

(such as the content of referenced files within the source file, code comments, etc.) on bug localization and help improve the accuracy of bug localization.

Question 4.2 Does MethodLocator reduce the amount of code read by bug fixers and increase the efficiency of fixing compared to traditional file-level bug localization methods (Buglocator)?

Figure 4.9 shows the experimental results of MethodLocator and Buglocator on the four software projects. Although MethodLocator has lower values than Buglocator in two evaluation metrics of MAP and MRR, we consider it acceptable. There are two factors that affect this result. On the one hand, for a given bug, it may only need to be fixed by modifying one file, but it may need to be fixed by modifying multiple method bodies. We counted the number of source files and the number of method bodies associated with the bug reports. Figure 4.10 shows the average number of source files and method bodies that need to be modified to fix a bug in the four projects. It can be seen that the number of method bodies is significantly higher than the number of source files. The more results that meet the retrieval goal, the lower the MAP value. This can also be seen in the calculation formula of MAP (see Eq. (4.13)). On the other hand, as shown in Table 4.5, the total number of method bodies is much higher than the total number of source files. It can be calculated that

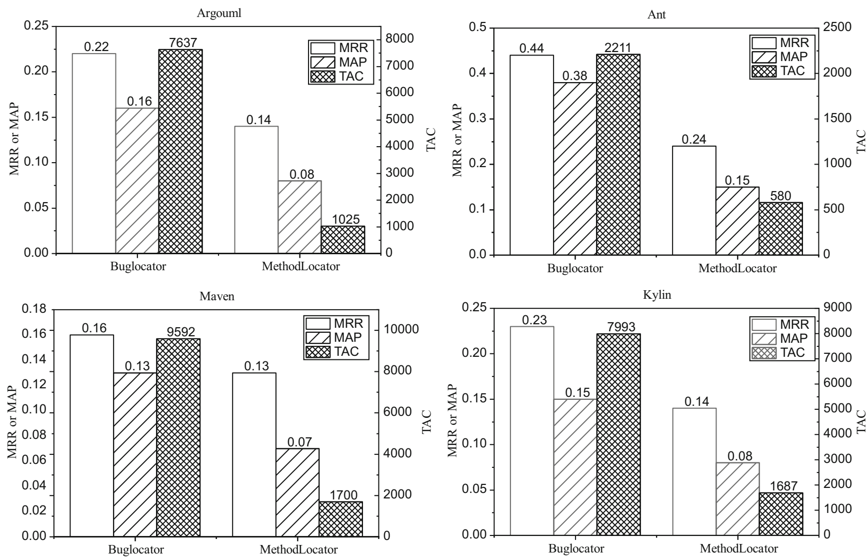


Fig. 4.9 Comparison of MethodLocator and Buglocator experimental results

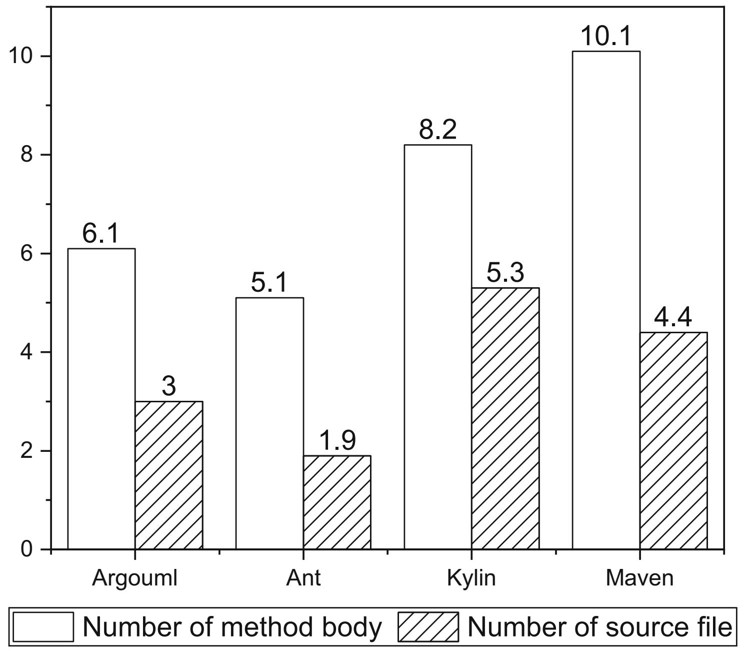


Fig. 4.10 The average number of source files and method bodies that need to be modified to fix a bug

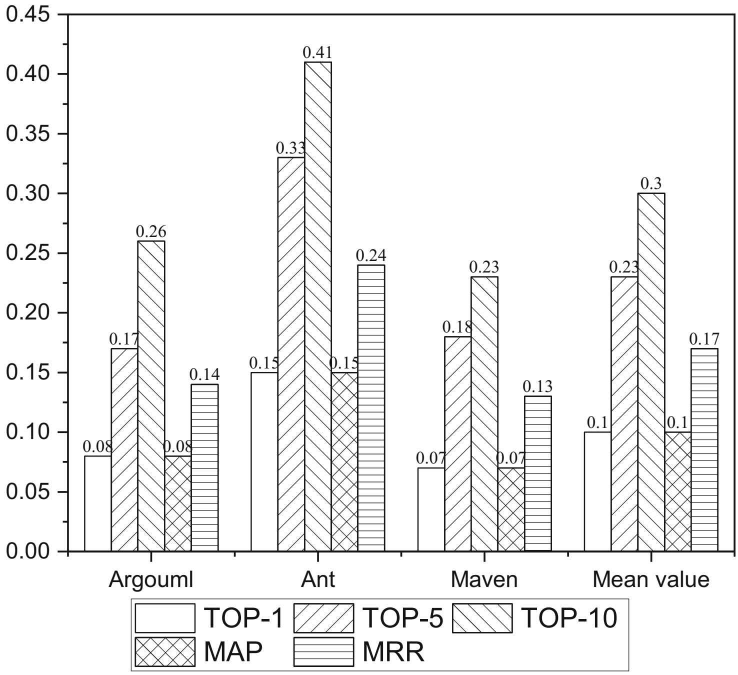


Fig. 4.11 Experimental results of MethodLocator method

the number of methods is 7.64 times the number of source files. From the point of view of information retrieval, the expansion of retrieval scope will reduce the accuracy of retrieval, that is, the accuracy of bug localization is reduced with the number of method bodies increases.

Although the MAP value of the proposed MethodLocator approach is smaller than that of Buglocator, it still seems that MethodLocator achieves a good result from the TAC metric. Across the four projects, the Buglocator method fixes a bug with an average code read of 6558.25 lines, while the MethodLocator method has an average code read of 1248 lines, a difference of more than 5310 lines or nearly 5.3 times.

In terms of code reading, the time to fix a bug using the file-level method is 5.3 times longer than that of the method-level method. The above experimental results show that MethodLocator can significantly reduce the code reading of bug fixers and improve bug fixing efficiency. The study of method-level bug localization methods has positive implications for bug localization and resolution.

Question 4.3 How is the performance of the proposed MethodLocator approach on method-level bug localization compared to existing method (BLIA v1.5)? Figures 4.11 and 4.12 show the experimental results of MethodLocator and BLIA v1.5 on their respective datasets. Table 4.6 shows the basic information of the three software projects used in the evaluation of BLIA v1.5. In order to make the

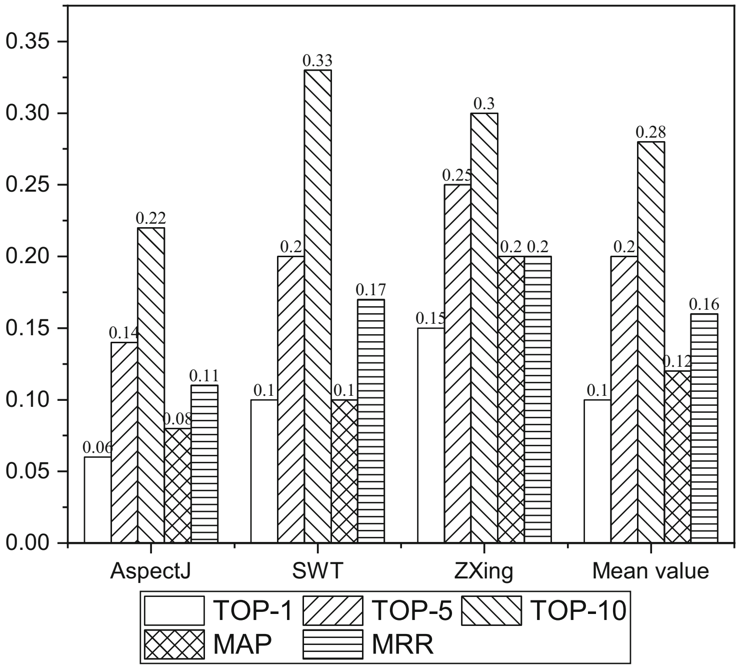


Fig. 4.12 Experimental results of BLIA v1.5 method

Table 4.6 Standard experimental dataset of BLIA v1.5 method

Project name	Number of files	Number of bug reports	Bug report time
AspectJ	5188	284	2002/12–2007/7
SWT	738	98	2002/4–2005/12
ZXing	391	20	2010/3–2010/9

comparison more authentic, we select the same number of software projects in the validation of MethodLocator to make the experimental conditions as identical as possible, i.e., Argouml, Ant, and Maven. The three projects used to validate the performance of MethodLocator are close in time to the projects selected in BLIA v1.5 (Kylin is a new project in 2016 and may be different from the previous projects. Thus, in order to reduce these possible effects, the data of Kylin is not selected in this part for comparison).

From Fig. 4.11 and 4.12, we can see that the mean value of MAP produced by MethodLocator is 0.1, while BLIA v1.5 is 0.12. From the comparison of Tables 4.6 and 4.4, we can find that the data sizes of the SWT and ZXing projects in BLIA v1.5 are small. The ZXing project has only 20 bugs, and its number of source files is merely 391. The smaller size reduces the difficulty of bug localization, which naturally improves the MAP value. On TOP-1, the outcomes of MethodLocator and BLIA v1.5 are nearly equal. On TOP-5, TOP-10, and MRR, MethodLocator shows a significant improvement over BLIA v1.5. Overall, it shows that MethodLocator is effective in locating bugs at the method level.

4.2.8 Concluding Remarks

For any software project, the occurrence of software bugs is inevitable. When faced with a bug, it is a time-consuming and labor-intensive task for software developers to find the position where the bug occurs and fix the bug. To help software developers locate bugs quickly, we propose MethodLocator, a method-level bug localization approach based on information retrieval. We demonstrate the effectiveness of the proposed MethodLocator approach by conducting comparative experiments in four real-world software projects. The experimental results demonstrate that the proposed method achieves desirable performance on both file-level and method-level bug localization. However, we ignore the differences between bug reports (i.e., bug reports from different sources, which may be submitted by ordinary users or professionals), and the differences between method bodies (such as the complexity of the method body and the role of the method), in order to obtain a generally applicable method. In future work, we will take all the above factors into consideration to locate bugs in order to produce better outcomes.

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Chapter 5
Qualitative Modeling to Extract Knowledge for Problem Structuring

Xijin Tang

5.1 Introduction

By simple understanding, problem structuring refers to exposing, finding, or searching structures or threads from collected information about the concerned unstructured problem so as to adopt or go exploiting available methods or models for structured problems during the practical problem-solving process. The unstructured problem also refers to the "wicked" problem discussed by Rittel and Webber (1973) who formally proposed 10 properties typical of "wicked problems," denoting the numerous problems widely existed in planning, management, and policy-making and stood in sharp contrast to the problems of engineering and sciences. Regarding the structuredness of decision problems, Simon (1977) distinguished 2 extreme situations the programmed and the nonprogrammed while the latter is novel, noncurrent, of such poor structures, and then difficult to be solved directly using a simple computer program without human intervention. As more and more complex decision contexts had been confronted, while traditional operational research (OR) models were not to be leveraged for the expected optimal solution to those complex contexts, systems rethinking aroused. Many relevant studies from different perspectives were undertaken worldwide, while some representative results were reported at one meeting held at the International Institute of Applied Systems Analysis (IIASA) in August of 1980. The consequence of the meeting showed "a coherent, interlocking, set of ideas considered as the foundations on which we may describe the subject as a science in its own right," or can be regarded as new insights toward operational research and systems analysis (Tomlison & Kiss, 1984). Among

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those thoughts, Checkland (1981)'s soft system methodology (SSM) which prefers issues to problems in systems practice and engages to construct a conceptual model instead of a mathematical model for desirable and feasible changes toward real-world situations actually distinguished clearly the soft system approaches or soft OR from the hard ones. As summarized by Mingers and Rosenhead (2004), those "nontraditional systems methodologies, also known as "problem structuring methodologies" in the literature appear to have stabilized following a period of rapid growth from the mid-1980s through the 1990s. Till today ramifications of soft approaches for diverse situations (Flood & Jackson, 1991; Rosenhead & Mingers, 2001) have been spread worldwide except in North America where "the more positivist techniques currently employed in systems engineering practice and discussed primarily in the U.S. literature such as Needs Analysis, Hierarchy of Objectives, or Strategies to Tasks".

Blair et al. (2007) noticed eastern systems scholars' work besides those problems structuring methodologies. They addressed that a methodology of "meta-synthesis" founded on Eastern philosophy discussed by Gu and Tang (2005). "The meta-synthesis approach is designed to address unstructured problems using a combination of soft and decision support methods attempting to synthesize experts, knowledge databases, and computers via networking". Besides those western methodologies referred to by Blair et al. (2007), the meta-synthesis approach (MSA) is the only one proposed by eastern scholars, i.e., the famous systems scientist Xuesen Qian and his colleagues officially in 1990.

In this chapter, we first briefly review MSA to indicate the central ideas of different approaches toward similar problematic situations. Three terms, the unstructured problem, the wicked problem, and the open complex giant system problem, can be regarded as of similar meanings and then those methodologies and tools originally proposed for one category of problems can be adopted by problem-solving for another category. Then we address further conducting qualitative meta-synthesis to problem structuring and introduce support technologies or algorithms to practice qualitative meta-synthesis for exposing, finding, or searching structures or threads from the collected information and knowledge. Two situations are considered. One situation refers to context with a small-scale size of available information toward the concerned problem. Under this context, we illustrate the application of two technologies, CorMap and iView, for qualitative meta-synthesis for idea or assumption generation for further verification and validation. Another situation refers to context with open and complex systems problems, such as various societal problems widely discussed and spread across online media. We describe qualitative modeling by outlining the complex problem-evolving process and provide two approaches for storyline generating. For both situations, visualized perspective toward the concerned problems reflected by the texts is emphasized.

5.2 Qualitative Meta-Synthesis for Problem Structuring

Meta-synthesis approach is proposed based on successful systems practice by Qian and Yu on national policy-making on financial subsidies policy of agricultural products by leverage of price and wages in the mid-1980s as China was transferring from a planning economy to a market economy.[1] Domain experts working for the government had been heavily involved in the modeling process, especially to provide individual opinions toward economic development trends as the relevant parameters for the models. Those opinions or expert judgments are qualitative, while the programmers of those algorithms are of science and engineering background. Based on the successful practice by researchers in natural sciences and engineering toward nation's macroeconomic problems, Qian et al. (1990) proposed a new classification of systems taking the open complex giant system (OCGS) as the most difficult system while the social system as the most difficult OCGS and MSA was forwarded to emphasize right system methodology to deal with OCGS problems with which reductionism methods have difficulties to tackle. "From confident *qualitative hypothesis* to rigorous *quantitative validation*" serves as a simplified working philosophy of MSA toward OCGS problem-solving. In 1992, Qian proposed the term Meta-synthetic Engineering, as "a development of systems engineering" for solving OCGS problem, while "Hall of Workshop for Meta-Synthetic Engineering" (HWMSE) as a platform to apply MSA (Qian, 2001; Wang et al., 1996). By Qian's original idea, HWMSE is composed of three systems: human expert system, machine system, and knowledge system. The concept of HWMSE reflects the emphasis on utilizing the breaking advances in information technologies to harness the *collective knowledge* and *creativity* of diverse technical groups of experts by synthesizing data, information, quantitative models, knowledge, and experiences into an interdisciplinary problem-solving process from proposing hypothesis to quantitative validating. Yu and Tu (2002) addressed three types of meta-synthesis for the first time using their successful system practice in macroeconomic policy-making. The three types of meta-synthesis denote qualitative meta-synthesis, qualitative–quantitative meta-synthesis, and meta-synthesis from qualitative understanding to quantitative validation, which roughly indicate the working process of MSA to complex problem-solving. Tang (2016) discussed typical approaches or frameworks for complex problem-solving from different disciplines to explain the working philosophy of MSA. Those include two decision-making models for decision support systems (DSS) development (Simon's 3-phase model and Courtney's framework), two problem structuring approaches for strategic decision-making, i.e., strategic assumption surfacing and testing—SAST) (Mason & Mitroff, 1981), and the Wisdom process proposed by UK researchers (Mackenzie et al., 2006). Here Courtney's framework is briefly reviewed for a better understanding of the MSA working philosophy.

[1] Yu's Talk at systematology seminar. In: Jiang L (ed), Collective Essays of Xuesen Qian on Systems Science. Science Press, pp147-155 (2011) (in Chinese)

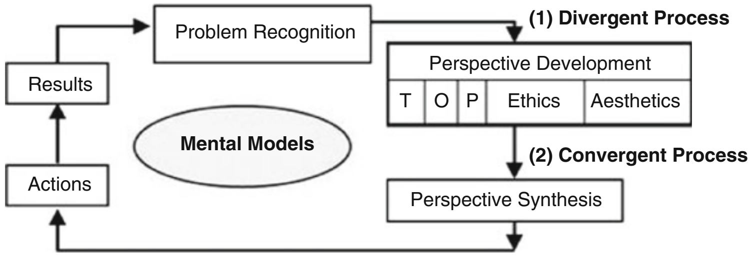

Fig. 5.1 A decision framework for DSS by Courtney (2001) with annotations by Tang (2007)

5.2.1 *Courtney's DSS Framework for Wicked Problem-Solving*

Compared with the traditional decision-making models such as the intelligence-design-choice 3-phase model in a DSS context, the salient feature of Courtney's framework (as shown in Fig. 5.1) lies the step of developing multiple perspectives during problem formulation phases, where besides the technical (T), organizational (O), and personal (P) perspectives (Mitroff & Linstone, 1993), both ethical and esthetic perspectives are required to be considered.

Before actions, the procedure on perspective development and synthesis may be understood as divergence and convergence of individual/group thinking. From problem recognition to the perspective development indicated as (1) in Fig. 5.1 is a divergent thinking process for idea generation and creative perspectives toward unstructured issues. The transfer to the synthesis of perspectives as indicated as (2) is a convergent process for acquiring alternatives for choices or actions. The mental models may be regarded as problem structuring methods or cognitive models of decision-making. If such a process is a collective problem-solving process, the mental models may refer to collective mental models. The transition from a divergent process to a convergent process is defined by the mental model(s). Both (1) and (2) together with the mental models clearly illustrate the working process of MSA toward unstructured problem-solving, while qualitative meta-synthesis (one of the three types of MSA) usually happens to the perspective development phase.

Courtney (2001) adopted "wicked problems" in addressing Fig. 5.1's framework despite the term unstructured problem being more popular in traditional DSS studies. While Rittel had already proposed issued-based information system (IBIS) to enable groups to decompose problems into questions, ideas, and arguments to better deal with wicked problems, illustrating the problem structuring process for unstructured problems. The term "wicked" problem has also been referred to by the Advanced Concept Group (ACG) founded at the Sandia National Lab after the 911 crisis. The mission of ACG is to "harness the collective knowledge and creativity of a diverse group to solve perceived future problems of importance to the national security." There is a report on a summer experiment on computer-mediated group

Table 5.1 Problems, disciplines, and paradigms for problem-solving (Tang, 2016)

Terms for problems	Disciplines	Problem-solving frameworks/methodologies	Support tools
Unstructured problems	Management sciences; OR	Simon's decision-making model; soft OR methods or their synthesis, e.g., wisdom process	DSS, GSS, etc.
Wicked problems	Social sciences	Courtney's framework; IBIS, etc.	DSS, GSS, etc.
OCGS problems	Systems science	Meta-synthesis systems approach	HWMSE

brainstorming at Sandia just showing those ACG scientists undertook serious experiments on the best way to solve wicked problems (Sandia, 2007).

The above brief review is to address that the essential ideas of different approaches toward similar problematic situations are of similar foci. The terms, unstructured problem, wicked problem, and open complex giant system problems can be regarded as of similar meanings and then those methodologies and tools originally proposed for one category of problems can be adopted by problem-solving for another category. The common grounds among those approaches infer to adopt or integrate those relevant methods and technologies by meta-synthetic engineering which is an effective way to develop HWMSE. Table 5.1 lists a brief summary of such an understanding.

As listed in Table 5.1, HWMSE is regarded as an advanced state of a DSS, while humans are elements of HWMSE and play primary roles even as machine systems (with traditional DSS) provide intensive support. Next, more details about MSA are given.

5.2.2 A Working Process of MSA

Gu and Tang (2005) discussed how to achieve three types of meta-synthesis by a synchronous–asynchronous–synchronous process, while each type of meta-synthesis is achieved at a different phase. Activities in Synchronous Stage I denote to achieve qualitative meta-synthesis, i.e., perspective development or hypothesis generation for meta-synthetic modeling. Divergent group thinking is the main theme at that stage. Methods oriented to acquire constructs or ideas toward the concerned problems are considered as qualitative meta-synthesis methods. Thus, problem structuring methods can fulfill qualitative meta-synthesis. Those methods or the technologies such as IBIS define normative frameworks followed by the users. Then the outputs (such as ideas and options) are given directly by users; no further computational analysis is conducted toward those logic-based deliberation processes such as Dialog Mapping or Cognitive Mapping.

The aforementioned problem structuring and relevant tools help to apply MSA and the construction of HWMSE. Tang (2007) discussed the relationship between HWMSE and the knowledge creation ba proposed by Nonaka and Takeuchi (1995).

Ba is defined as a platform where knowledge is created, shared, and exploited; the most important aspect of *ba* is *interaction*. The knowledge-creating process is also the process of creating *ba* (Nonaka et al., 2001). Considering the basic ideas of HWMSE, we suppose HWMSE is the right *ba* for idea generation and wisdom emergence for creative solutions to complex issues (Tang, 2007).

Next, two supporting technologies, CorMap and iView, for hypothesis generation during the problem structuring process for further quantitative validation are addressed to illustrate the integration of multiple technologies and their versatile applications to practice qualitative meta-synthesis.

5.3 Supporting Technologies for Qualitative Meta-Synthesis

Both CorMap analysis and iView analysis aim to implement qualitative meta-synthesis for confident hypothesizing. The structure metadata for both technologies is <*topic, userID, text, keywords, time*>. Such metadata indicate the corresponding participant *userID* submits one piece of *text* (e.g., one comment, one blog, the title of a paper, a reply to one question) with a set of *keywords* under the *topic* at the point of *time*. By word segmentation and filtered feature keywords used in text summarization, or even human's judgment, ideas and opinions can be transferred into a structured representation. Labels or tags of one blog can be the keywords for a blog. The keywords are articulated as attributes of the *userID* or the *text*.

5.3.1 Basic Ideas of CorMap and iView Technologies

Figure 5.2 shows the essential analytics of both technologies. Tang (2008, 2009b) and Tang et al. (2008) presented the mechanisms of both analytical technologies in detail.

The CorMap analysis denotes a technology of exploratory analysis of textual data. By conducting a series of algorithms as listed in Fig. 5.2, CorMap analysis actually helps to expose the group thinking structure from one perspective. Such kind of analysis can be applied to any combination of the concerned participants and may help to "drill down" into those community thoughts to detect some existing or emerging micro-community. If applied to an individual, CorMap analysis may help to unravel personal thinking structure. Luo and Tang (2010) adopted the self-organizing map into idea clustering as another new perspective during the idea structuring process.

The iView analysis exposes the group or individual thinking structure from another perspective. The central concept of iView analysis is the iView network which denotes 3 kinds of networks, *keyword network*, *human network,* and *text*

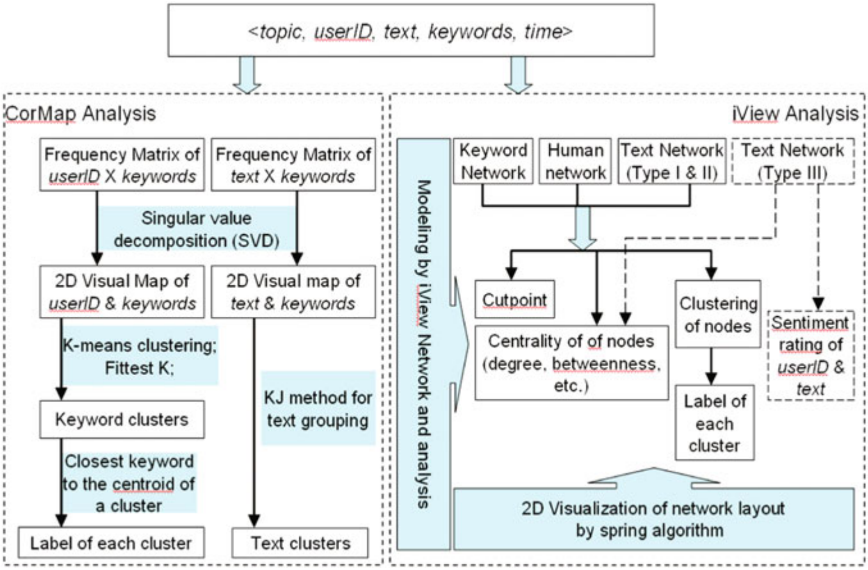

Fig. 5.2 The analytics of CorMap and iView technologies

network. In a keyword network for iView analysis, the link between the vertices (keywords) denotes the co-occurrence of keywords among all *texts*. Such a network is referred to as an *idea map* contributed by all participants. This topological network is a weighted undirected network where the weight of the edge denotes the frequency of co-keywords. In a human network, the link between vertices denotes keyword-sharing (or text-sharing) between participants. The strength between the two participants indicates the number of different keywords or the total frequencies of all the keywords they share. Three types of text networks are built during the iView analysis. All are directed networks. The text network Type I denotes the directed link from text *j* to text *i* indicating text *j* cites one keyword originally appeared in text *i*. In the text network Type II, the link denotes to cite the latest text including the concerned keyword. In the text network Type III, the semantic meaning of link expands to a variety of attitudes, e.g., oppose, support, etc. instead of the citation of keywords in both Type I and II text networks. Text networks may help to show how ideas grow and spread. Different algorithms are applied to the text network Type III due to the different semantic meanings of the link. As a matter of fact, the iView network may be regarded as the different projections of a tripartite (text-participant/author-keyword) network. After the projection, we get a 1-mode network and apply graph theory and social network analysis (SNA) to exploratory analysis.

5.3.2 Features of CorMap and iView for Qualitative Meta-Synthesis

Either CorMap or iView analysis exposes different perspectives toward the same set of data based on different mechanisms and with the same aim to acquire constructs of the problems from those textual data for one topic. Both analytical technologies share common features:

- Expose the hidden structure by a variety of transformations of original textural data.
- Visualize the analyzing process to facilitate human understanding.
- Adopt a series of algorithms or methods instead of applying an individual one.
- Support a problem structuring process: (i) give a rough image of the issue; (ii) draw a scenario of the issue using clustering analysis to detect the structure; (iii) extract concepts from clusters of ideas. Thus, a category of concepts instead of a mess of diverse ideas is acquired step by step.
- Facilitate man–machine collaboration. Each step leaves room to facilitate analysts' direct manipulations and results visualization.

Both technologies can be applied to qualitative meta-synthesis during the problem structuring process. Due to the different mechanisms of each technology, one may be more effective for human understanding at one time. It is the human to make appropriate use of each technology during the discovery process.

5.3.3 Applications to Mining of Community Opinions

Both CorMap and iView technologies have been applied along with research toward demonstrating the feasibility of MSA toward wicked problems. Tang (2016) illustrated some representative scenarios for those applications, including group thinking process mining, conference mining and online conferencing ba (OLCB), expert knowledge mining, and community mind mining, all of which are relevant to community opinion mining. Here we present more cases to illustrate both technologies in acquiring knowledge from community opinions for assumption generation for further studies.

5.3.3.1 Societal Risk Perception by Community Opinions Collected by Survey

Tang (2009a) depicted one application of both technologies to societal risk perception before the 2008 Beijing Olympic Games, exhibiting the potential of both technologies for social psychological study.

Fig. 5.3 CorMap of the people of 4 classes of ages and their associated words on societal risks (Tang, 2009a)

When social psychologists study societal risks, initially they may carry out a small-scale word association test to acquire images and perceptions of a set of impressive social concerns. They design questionnaires to carry out large-scale investigations and explore causal effects among risk factors by constructing structure models. Processing of data collected from those word association tests often needs to manually encode those associated words into societal risk events. Some hypotheses had to be thought of for the design of the questionnaire. To facilitate the processing of the word association test, both iView and CorMap were conducted to the analysis of a small-scaled word association test on societal risk in the Beijing area by social psychological researchers from the Institute of Psychology, Chinese Academy of Sciences in the Fall of 2007 (Zheng et al., 2009). The data with 321 valid subjects contributing 542 associated societal risk phases (i.e., events) in the word associate test were processed. Figure 5.3 shows a CorMap of the subjects with 4 class of ages and their associated phases about societal risk.

Obviously the label “age_above50” locates far away from the other three age labels in Fig. 5.3. As the mapping to 2D space accounts for over 80% of the total variation, 2D spatial relations are reliable and the distances between those different age categories indicate there are cognitive differences of perceptions toward societal risks between the public at different ages. The CorMap provides a basic or possible association between the subjects and their thoughts represented by those 542 phases. As socio-psychologists encoded those 542 phases (events) into a 30-category of societal hazards, CorMap analysis was conducted by replacing those 542 events with

Fig. 5.4 CorMap of the people at different ages and their societal risk encoded words (4 clusters of words while all words are of 30 categories, Tang, 2009a)

their encoded hazard word. The result is as shown in Fig. 5.4. As only 30 keywords appear among all data records, the correspondence mappings shown in Figs. 5.3 and 5.4 are different. However, “age_above50” still locates far away from the other three groups. Labels “age_30_39” and “age_25_29” come closer. As “age_below24” and “age_above50” separate in both CorMap, the assumption of risk perception difference between ages is expected to be validated during the next round of large-scale investigation.

Other CorMap analyses of different topics were also taken, such as words and people of different professions. Besides, the iView analysis of those 542 phases identified 58 cutpoint phases which cover all those 30 hazard words, while the shared words between those cutpoint phases and the top 40 phases with the highest betweenness values account for 21 words that also belong to those 30 categories. The iView analysis shows the potential to improve the efficiency of manual encoding for domain researchers.

Social psychologists perceive social attitudes under microlevels by conducting surveys which is always time-consuming with problems of data quality. As Internet technology advances provide ways to record and disseminate fresh community ideas and thoughts conveniently, detecting topics or emotions from online public opinions is becoming a trend or one supplement way to overcome those data acquisition problems. Tang (2013) discussed one approach to online societal risk perception using hot search words and BBS posts with the 7 major societal risk classes including nation’s security, economy and finance, public morality, daily life, societal stability, government management, and resources and environment. Such a trial aims to provide another way to societal risk perception different from those in traditional socio-psychology studies. Next, we address more about acquiring emerging perspectives toward the concerned issue from the public opinions expressed via online media.

5.3.3.2 Mining Community Opinions from the Online Media by CorMap

People express personal opinions easily via online media where aggregated opinions of communities involved in one concerned issue can refer to an open group discussion process. Jia and Tang (2017a) made a trial to apply CorMap analysis to one live broadcast on April 28, 2016, organized by the famous news portal sina.com for the 30th anniversary of the Chernobyl nuclear disaster. During the live program, one facilitator and one nuclear expert were involved in the program introduction and comments, while the public submitted their questions and comments. Even after the live, posts and even interactions among the netizens still continued.

Figure 5.5 shows the CorMap analysis of the utterances at the Live Room as well as comments posted by the public. By the interactive CorMap visualized analysis, we find that different people hold diverse opinions based on their roles or social identities, e.g., the guest expert in the Live Room explained the national and international factors that caused the explosion and the rescue activities; foreign students studying in China referred the resettlement that the government had been done for the local victims; some general participants commented more on the Fukushima nuclear accident happened in 2011 and the status of nuclear power development in China. Obviously, one hazard event is easily associated with other

Fig. 5.5 CorMap of the participants and their utterances within one Sine Live program on the 30th anniversary of the Chernobyl nuclear disaster organized by sina.com

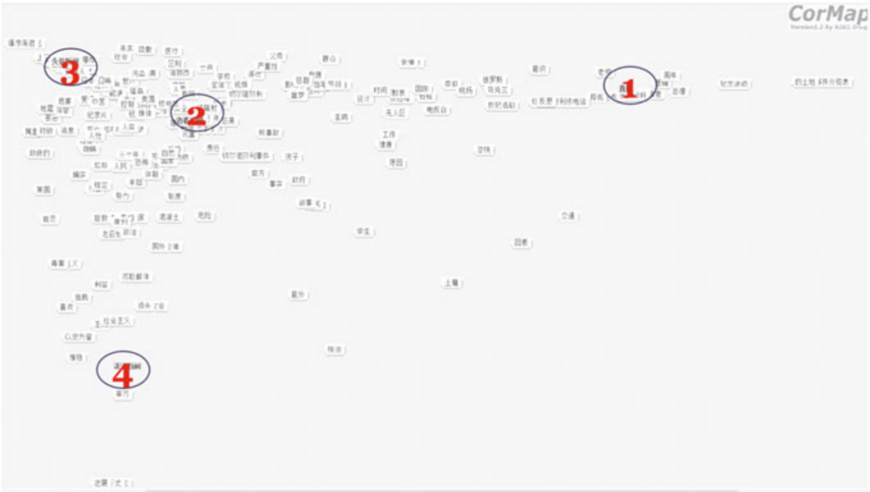

Fig. 5.6 CorMap view of the opinion structure of different online communities (1) Live Room, (2) Live Room Comments, (3) Toutiao, (4) The Paper, Jia & Tang, 2017a)

similar hazard events and arouses more concerns of the public toward those possibilities of similar hazards during online discussions. Such kind of live broadcast program helps knowledge diffusion and systems thinking toward disasters, while subjective opinions from the public also incur more debates.

Unlike the small-sized group discussion, for those open discussions that emerged via online media, applying CorMap analysis directly to the individual's utterances may not make sense, especially with posts (opinions) from different platforms. Jia and Tang (2017a) further collected comments on the same topic on the 30th anniversary of the Chernobyl nuclear disaster but issued by 2 different certified accounts ("Toutiao" and "The Paper") at weibo.com and launched CorMap analysis toward the posts from 4 major communities from different online media, the first one is Live room, the second one is Live room comments, the third is Toutiao Weibo's comments, and the fourth is The Paper's Weibo comments, with results as shown in Fig. 5.6.

The Live room (as labeled 1 in Fig.5.6) locates far away from the other 3 as the main utterances from both the guest expert and the selected participants concentrate on the 30th-anniversary memorial ceremony live broadcast. The Live room comments (as labeled 2) locates between the other 3 communities. The distance between Label 3 and Label 4 may reflect the differences between the followers between the two Weibo accounts. The location of "Toutiao" is in Beijing, while "The Paper" is in Shanghai. The diverse opinions together with their holders are visualized to exhibit the common grounds and differences among the public toward the same topic by CorMap analysis.

5.3.3.3 Perceiving Online Community Concerns by iView Analysis

Baidu is the biggest Chinese search engine worldwide. During the early period, the news portal of Baidu presented 10–20 hot query news words updated every 5 min automatically, as shown in Fig. 5.7. A specific Web crawler was developed to download hot news search words (HNSW) list hourly from news.baidu.com since March of 2011 (Wu & Tang, 2011). Each hot news phase was given one score ranged 1–20 according to its hourly rank. One daily list normally including around 30–70 HNSW was acquired, together with their frequencies and accumulated scores during the past 24 h.

Each hot news search phase can be regarded as one utterance by the community. The Baidu Hot News Vision was developed to show the daily or weekly news word map by iView analysis. Figure 5.8 shows the iView map of 7-day phases aggregated from March 11 to 17, 2011. The hot news words toward the major concerned events may bring one bigger component due to aggregation of more similar words. The cutpoint words (square nodes) may indicate the key players (e.g., Japan and China) or major relevant risk factors or events (earthquake, tsunami, nuclear radiation, rescue, stock market, slump, etc.). Such a map illustrates the major public concerns during the given period while does not expose either causal or temporal relations among the events.

Above we present the applications of both CorMap and iView to community opinions to help implement qualitative meta-synthesis for problem structuring. The

Fig. 5.7 Hot news search words updated on the Baidu news portal (Tang, 2013)

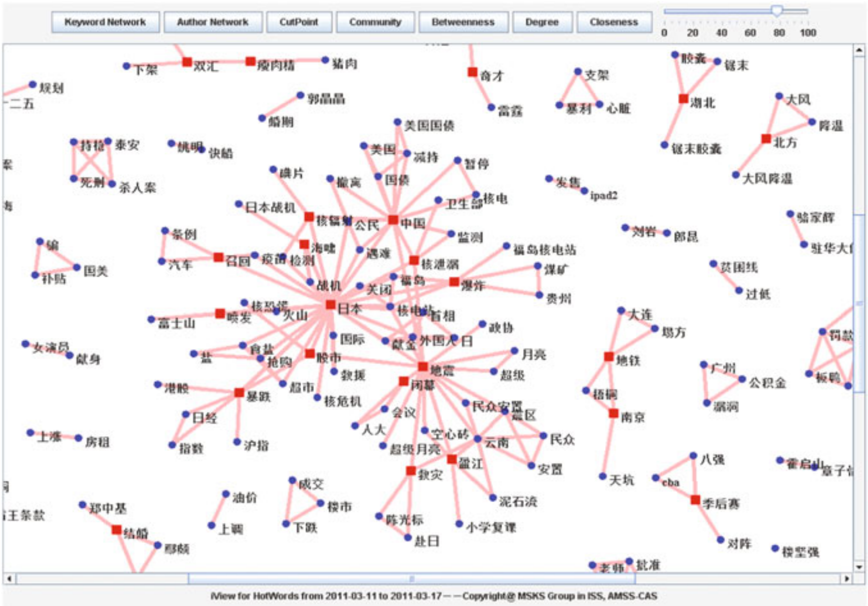

Fig. 5.8 Partial iView map of Baidu hot news search words aggregated during March 11–17, 2011

community size ranges from small groups limited to one discussion to open online forums. While both technologies may not be effective to expose the evolution of those public concerns, especially with a large amount of corpus. Under such a situation, a storyline is required for the evolution of public concerns. Next, we present two approaches to illustrate the storyline generation for problem structuring.

5.4 Generating Storyline for the Big Picture of the Public Concerns

To deal with the issue highly concerned while widely spread across online media, quickly drawing a rough picture of public concerns is a necessity and can also be regarded as the task of qualitative meta-synthesis, especially for a critical event. Topic modeling has become a powerful tool for "extracting surprisingly interpretable and useful structure without any explicit 'understanding' of the language by computer" (Blei & Lafferty, 2007). If we need to investigate the evolving process of the critical event, by another saying, to identify and track dynamic topics from time-stamped textual data, topic models also have been applied. According to discrete or continuous time, topic models can be generally divided into three categories. The first is the basic topic model, the Latent Dirichlet Allocation (LDA) model, which treats documents as bags of words generated by one or more topics (Blei et al., 2003). This model is applied to the whole document to induce topic sets and then classify the subsets according to the time of documents (Hall et al., 2008). The second kind, such as dynamic topic models (DTM) (Blei & Lafferty, 2006) and Online LDA (OLDA) model (AlSumait et al., 2008), marks documents according to the discrete-time before the generative process. The third kind includes the Topics over Time (TOT) model which captures both word co-occurrences and localization in continuous time (Wang & McCallum, 2006), and the continuous dynamic topic model (cDTM) which replaces the discrete state space model of the DTM with its continuous generalization, Brownian motion (Wang et al., 2008).

When facing the flood of the UGC, especially during the critical event evolving, not only topics are to be extracted but the structure of the evolving topics is also barely expected (Marcus et al., 2011). Automatically generating the storyline is of value. Generating the storyline of the concerned issue based on public concerns is related to TDT (Topic Detection and Tracking) (Aiello et al., 2013). The tasks in TDT include story segmentation, topic detection, new event detection, link detection, and topic tracking (Allan, 2002; Bao et al., 2015). LDA and its extensions which model a topic as word distribution are widely used, and these methods belong to the Bayesian analysis (Blei & Lafferty, 2006; Diao et al., 2012; Krishnan & Eisenstein, 2016). In the research of TDT, different natural language processing approaches have been developed to monitor news stories, spot news events, and track the development of hot events (Yang, Carbonell, et al., 2002a; Yang, Zhang, et al., 2002b). Prior research pays less attention to interpreting or modeling the relationships or associations between different events (or topics) (Yang et al., 2009). However, mining such relationships is desirable particularly at event granularity since the public is often concerned about the evolution of news events.

Naturally, the events and the event evolution can be represented as a graph structure. Many researchers apply graphs to depict event evolution (Leskovec et al., 2005; Yang et al., 2009). Here we present two approaches to storyline generation based on different mechanisms.

5.4.1 Generating Storyline as Multi-View Graph by Dominating Set

Wang et al. (2012) adopted the concept of dominating set and the Steiner tree to generate the storyline by greedy algorithm (Charikar et al., 1999; Lin et al., 2012; Raz & Safra, 1997). The Star clustering algorithm was utilized to get the representative tweets for some clusters (Lv et al., 2014). It is easy to know that obtaining the minimum-weight dominating set (MWDS) solved by the greedy algorithm is similar to the star algorithm. While previous studies did not take temporal information into account when detecting representative tweets. Jia and Tang (2017b) expanded those methods. The MWDS greedy algorithm is used to obtain the representative posts to explain what the public focus on at different periods. A storyline is to be generated by using the maximum spanning tree algorithm over the graph including both undirected edge and directed edge to show the evolution of the public concerns. More details are given as follows.

5.4.1.1 The Framework of Generating Storyline Using Dominating Set

Given a set of posts toward the concerned issue, generating a storyline is to pick some representative posts from different periods and connect them to a tree map to exhibit the public attention evolution. Each node of the tree denotes one key post or some key posts; the directed edge of the tree implies the time relationship between the two nodes. The tree is generated by four steps: (1) the undirected consistency graph construction, (2) the representative posts identification, (3) the graph including both undirected edges and directed edges building, and (4) the tree generation. During the undirected consistency graph construction, we view the posts as vertices and use both content consistency and temporal consistency to build an undirected graph. Step 2 applies the greedy minimum-weight dominating set algorithm to the undirected graph to get the dominating set in which the posts are viewed as representative posts. Then, the temporal information is used to build the undirected graph and the content information is used to build the directed graph on the representative posts. Finally, one storyline toward the public concerned issue is generated by using the directed maximum spanning tree algorithm on the graph built by Step 3. Figure 5.9 shows the storyline generation framework.

5.4.1.2 Consistency Graph Construction

Selecting representative posts has a great effect on the quality of the result. The length of one post varies from a few words to several thousand. The *tfidf* is applied to represent the posts. Each pair of posts is written as p_i and p_j, their published timestamps are t_i and t_j, and the corresponding *tfidf* vectors are v_i and v_j. The cosine similarity $sim(v_i, v_j)$ is used to measure the content coherence of p_i and p_j. The time consistency of p_i and p_j is determined by the distance between t_i and t_j. It decays exponentially with the increase of time. The consistency score $S_{i,\,j}$ is defined as:

$$S_{i,j} = e^{-\frac{|\Delta t|}{T_w}} * sim\left(v_i, v_j\right) \tag{5.1}$$

where $\Delta t = |t_i - t_j|$ and T_w is a parameter about the time window size. If Δt is too large, the consistency score of two posts is close to zero. We view one post as a vertex and join the vertices by one edge if and only if the coherence score of two posts is greater than the threshold. We view the sum weight of the edges joined to the vertex as the vertex hotness. The vertex hotness is to measure if one post can be the representative post. The vertex weight is $1-$ the regularized (with maximum value)

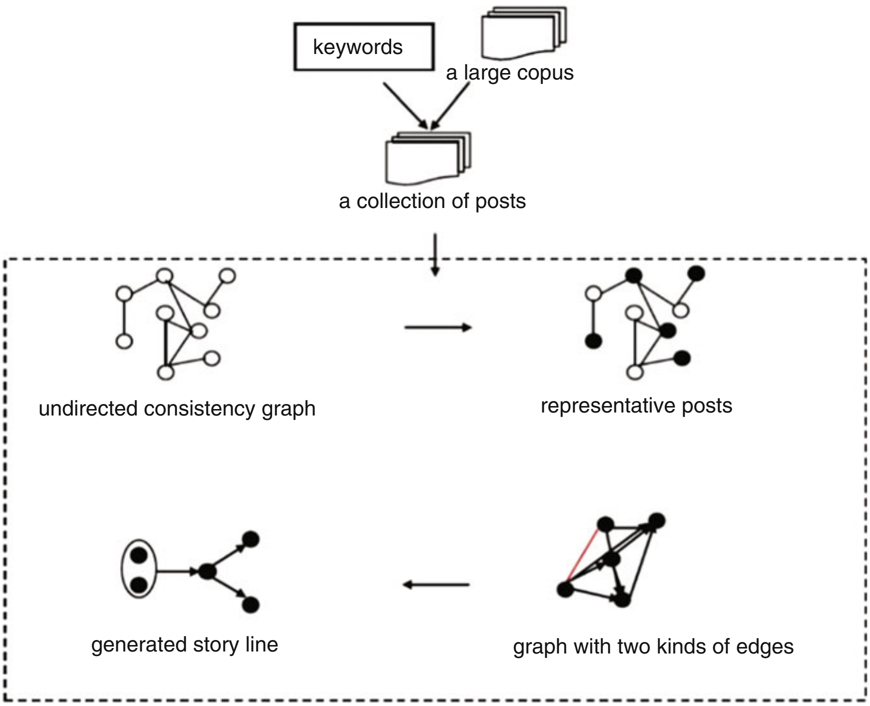

Fig. 5.9 The framework of generating storyline (Jia & Tang, 2017b)

hotness. The vertex weight is used to discover the hottest one at different periods while removing the duplicate ones simultaneously.

5.4.1.3 Minimum-Weight Dominating Set (MWDS)

A vertex u is dominated by another vertex v or vertex u dominates vertex v in an undirected graph if they are neighbors. A subset S is called dominating set if each vertex of the undirected graph is either in the set S or dominated by the vertex in the S. The minimum-weight dominating set is a dominating set whose total vertex weight is the smallest in a weighted undirected graph. Finding the minimum-weight dominating set in an undirected graph is an NP-hard problem. Here we adopt the greedy algorithm used by Wang et al. (2012) and Lin et al. (2012) while with some differences. The set S is generated by adding the vertex which has the smallest weight evenly averaged by the new neighbors, not in the dominating set step by step. The $w(v)$ is the weight of the vertex.

5.4.1.4 The Directed Maximum Spanning Tree

Once the most representative posts are acquired, we go to generate the storyline by connecting those representative posts.

We view the representative posts as vertices to construct a graph *G(V, U, D)*. *V* is the set of representative posts. *U* is the set of undirected edges and *D* is the set of directed edges. For each pair of posts, there is a directed edge induced by time while the weight of the edge is the content coherence $sim(v_i, v_j)$. We select some directed edges by the directed maximum spanning tree algorithm which is simplified to find the largest incoming edges in the graph and merge them since there is no cycle in the graph. As there are some similar posts in the same period, we bring another parameter β to merge these posts into a node to get a concise storyline. The time stage *T* is a resolution parameter deciding the storyline displaying granularity. If two posts denoted as vertices v_i and v_j are published in the same time stage and their content coherence $sim(v_i, v_j)$ is more than β, v_i and v_j are linked by an undirected edge. The connected undirected graph is regarded as one node that probably contains several posts. Thus, we get the storyline. The posts in the same branch of the tree belong to the same topic and the directed edges indicate the evolution of the topic.

5.4.1.5 One Experiment toward the Evolution of the Public Concerns from BBS

The experiment is conducted in the case of Chinese athlete LIU Xiang's story that happened around the London Olympic Games. Liu Xiang is a Chinese hurdler. In the 110-meter hurdles on August 7, 2012, at the London Olympic Games, he fell down from the start and hopped the full 110-meter stretch with his injured Achilles tendon. Some people thought Liu Xiang was a hero, while others wondered why Liu Xiang chose to participate in the game in spite of his injury.[2] Therefore, widely intensive discussions emerged across online media. We study the public opinion evolution on this event as an illustrative case. We use the keywords "刘翔" and "翔飞人" and search for the relevant original posts with the keywords in the titles in the large corpus including all posts from Tianya Club[3] since 2010. We find that almost all posts are published from August 1 to October 31 in 2012. The experiment is then conducted on those 1437 posts within that period. 15 posts are selected into the dominating set using Algorithm 5.1.

[2] https://en.wikipedia.org/wiki/Liu_Xiang_(hurdler)#cite note-36.

[3] http://www.tianya.cn/

Algorithm 5.1 Greedy MWDS Algorithm
Input
$G = (V, W, E)$: Vertex-weighted undirected graph.
W: The maximum number of vertices in dominating set S.
Output
Dominant set S.

1. $S = \emptyset, T = \emptyset$
2. while $|S| < W \& \& T != V$ do
3. $v* = nil$
4. for $v \in V - T$ do
5. $s(v) = \|\{v^{'} |(v^{'}, v) \in E\} \backslash T\|$
6. end for
7. $v* = argmin_v \frac{w(v)}{s(v)+1}$
8. $S = S \cup \{v^*\}$
9. $T = T \cup \{v^{''} |(v^{''}, v^*) \in E\}$
10. end while
11. return S

The posts in the dominating set generated by the algorithm are of the following insights:

- The hotter the post, the more easily to be selected into the set S.
- Similar posts could be in the set S simultaneously if they are created at different periods.
- Similar posts published in the same period could be in the set S simultaneously if and only if the posts are very hot.

In order to illustrate the societal risk transfer we use the labeled dataset that comes from Tianya Zatan, one board about normal living within Tianya Club, to generate the societal risk lexicons. In the generating storyline stage, each word in one post has a *tfidf* value. For one post, the words both with high *tfidf* values and belonging to certain societal risk lexicons are chosen as the societal risk feature words. All the posts in the dominating set together with the risk feature words can be tracked by Jia and Tang (2017b).

Figure 5.10 shows the storyline generated. Such a multi-view graph highlights not only the evolution of public concerns but the transfer of societal risks as well. The societal risk at the start of the concerned event was “Daily Life.” Soon the risk of public concerns changed to “Public Morality.” In the end, the societal risks of both “Daily Life” and “Public Morality” remained. From the generated storyline, the public responses toward Liu Xiang’s story in London Olympic Games along with the concerned event evolution can be clearly sensed.

The tree map indicates the start of the event and refers to the root of the tree. It may be useful for a whole picture of one event. While complex issues are often

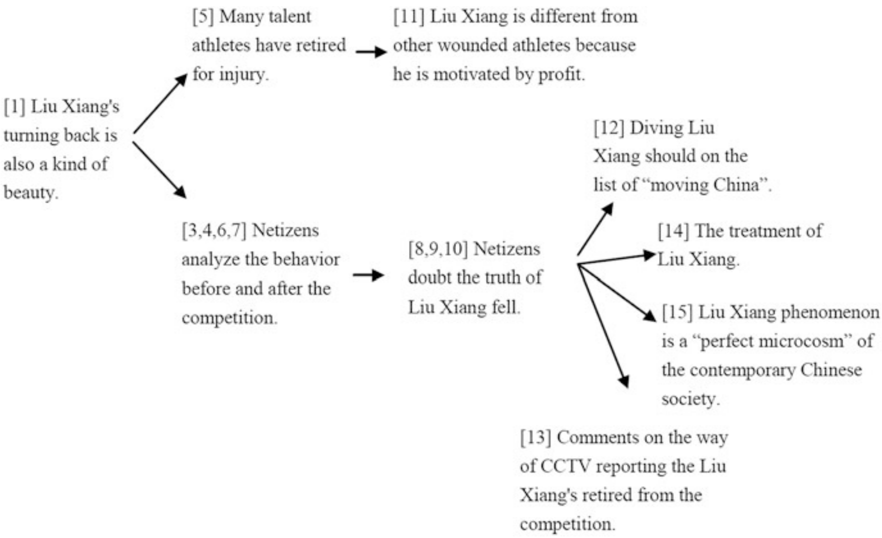

Fig. 5.10 The generated storyline about Liu Xiang's falling down at the 2012 London Olympic Games. Note: The number within each node indicates the label of the post within the dominating set. Nodes with Post 1 and Post 14 are of societal risks in daily life. The node includes Post 5 is risk free. All other nodes are of the societal risk in public morality

with multiple triggers. Complex stories often require a nonlinear structure: stories with branches, side stories, and intertwined narratives. Thus, nonlinear output with different concepts of storylines emerged. Yang et al. (2009) defined an event evolution score function that took the time stamp, content similarity, temporal proximity, and document distributional proximity into consideration to model evolution relationships. There are also other different studies, e.g., Weiler et al. (2014), Kalyanam et al. (2015), Wu et al. (2016), etc. while the coherence of the storyline for complex stories is still to be of further study. Next one approach to generating a storyline for complex stories is presented. The approach also considers tracing the societal risk transfer along with the story development.

5.4.2 Generating Storyline Using Risk Map

Shahaf et al. (2012) proposed a "metro maps" methodology to create structured summaries of stories by considering coherent chains of events generated by taking multiple criteria into account. However, the map generated by the "metro map" represented the evolution of topics by words, instead by events. Xu and Tang (2018) improved the algorithm by Shahaf et al. (2013) to increase the applicability for analysis of actual societal risk events from two perspectives. On the one hand, the algorithm is extended to the event level with events represented by distributed vectors. On the other hand, different clustering methods are implemented to obtain a set of events as the metro stops. The event-level metro map is referred to as a risk map, which consists of nodes and links where nodes are represented by a set of risk events and links denote how events evolve or develop.

5.4.2.1 Concepts of Risk Map

Definition 1 (Risk Maps). A risk map R is a pair (G, Π), where $G = (\mathbb{C}; E)$ is a directed graph and Π is a set of paths in G. We refer to paths as risk lines. Each $e \in E$ belongs to at least one risk event line.

The vertices $\mathbb{C}$ correspond to event clusters (subsets of S) and denote stops (R). Similar to metro maps, three criteria "coherence," "connectivity," and "coverage" of the "risk maps" are, respectively, elaborated and formalized as follows.

5.4.2.1.1 Coherence

Coherence is a measure of the quality of forming a unified whole story. The event clusters, denoted as stops, play an important role in coherence. The coherence of a "risk map" is to measure the similarity between each pair of consecutive event clusters divided into several time stamps along one line.

A variety of clustering methods are tried to obtain event clusters. Obviously, the quality of the cluster is essential for building a good map. The silhouette[4] is chosen to measure the quality of event clustering results. At each time stamp, the best silhouette is selected to generate high-quality clusters.

To get a coherence score, the similarity between each pair of consecutive clusters along the line is computed. The Jaccard similarity coefficient is chosen to measure the coherence. Given a line of clusters, we first score each transition by computing Jaccard similarity which is defined as the size of the intersection divided by the size of the union of the sets:

$$J\left(c_{i(j-1)}, c_{ij}\right) = \frac{\mid c_{i(j-1)} \cap c_{ij} \mid}{\mid c_{i(j-1)} \cup c_{ij} \mid}, j \in \{1, 2, \ldots, n\} \tag{5.2}$$

where c_{ij} denotes jth cluster in ith line, and n denotes the number of clusters one line contains. Then the coherence of line i is calculated as:

[4] https://en.wikipedia.org/wiki/Silhouette_(clustering)

$$line\_coh_i = \frac{\sum_{n-1} J\left(c_{i(j-1)}, c_{ij}\right)}{n-1} \tag{5.3}$$

5.4.2.1.2 Coverage

In addition to coherence, high coverage is ensured for the risk map. On the one hand, the coverage of essential aspects of the story is to be emphasized. On the other hand, diversity is to be expected. Therefore, we consider set-coverage as a sampling procedure: each line in the map tries to cover cluster c with probability $cover_{\Pi}(c)$, defined as the proportion of clusters one line covers over all the clusters. The coverage of c is the probability that at least one of the lines succeeds:

$$cover_{\Pi}(c) = 1 - \prod_{l \in \Pi} (1 - cover_l(c)) \tag{5.4}$$

Thus, if the map includes lines that cover c well, $cover_{\Pi}(c)$ is close to 1. Adding another line that covers c well provides very little extra coverage of c, which encourages picking lines that cover other clusters and promotes diversity.

5.4.2.1.3 Connectivity

The goal of connectivity is to ensure the storylines intersect, rather than stand-alone. To measure the connectivity of a map, we count the number of connected components or the number of vertices that belong to more than one line. We simply formalize connectivity as the number of lines of Π that intersect.

5.4.2.2 Risk Map Generation

With three criteria of the risk map formally defined, we combine them into one objective function. We need to consider trade-offs among three criteria, as maximizing coherence often results in repetitive and low-coverage lines. Maximizing connectivity encourages choosing similar lines, resulting in low coverage as well. Maximizing coverage may cause low connectivity, leading to fewer intersecting lines. As a result, the appropriate objective function is to be found to make trade-offs among the three criteria.

If connectivity is the primary objective, we face a stickier problem that coherent lines tend to come in groups: a coherent line is often accompanied by multiple similar lines. Those lines intersect with each other. Choosing them will maximize connectivity. However, the map acquired will be highly redundant. Thus, we choose coverage as the primary objective. We first maximize coverage, then maximize connectivity over maps that display maximal coverage. Let k be the maximal coverage across maps with $coherence \geq \tau$. τ is the given threshold. Now the problem is formulated as follows:

Problem. Given a set of candidate clusters C, find a map $R = (G, \Pi)$ over C which maximizes connectivity, s.t. $Coherence(C) \geq \tau$ and $Cover(C) \geq k$.

To construct a good map, the first is to pick good lines. We expect to list all possible candidates. However, the number of possible lines may be exponential, and thus it is not applicable to enumerate them all. Restricting the number of lines is needed by restricting the map size R. We choose to restrict R to K lines. Add lines until coverage gains fall below a threshold. The objective function is optimized that prefers longer coherent storylines whenever possible. For this, the greedy algorithm is adopted. At each round, compute the approximate best paths among clusters. Then greedily pick the best one among them for the map. The map obtained may show two forms, linear stories become linear maps, while complex stories maintain their intertwined threads.

Thereafter the "risk map" operates as follows. Firstly, start with a large corpus of texts and one concerned named entity. Secondly, all relevant posts (texts) are extracted and divided into several time stamps. Thirdly, perform vector representations of texts and generate clusters in each time stamp. Finally, compute the scores of those three criteria, respectively, and optimize the objective function under constrained criteria as defined above.

5.4.2.3 One Experiment Toward the Public Concerns from Baidu Hot News Search Words

As Tang (2013) had corresponded Baidu hot news search words (HNSW) to societal risk events, here we select HNSW to explore the evolution of societal risk events and transitions of risks over time using Risk Map.

The HNSW concerned with the "Chinese Red Cross" is chosen as a case study to conduct evolution analysis. In June 2011, the name "Guo Meimei" was very famous on Sina Weibo. The 20-year-old girl who showed off a luxurious lifestyle claimed close relations with the Chinese Red Cross. During that period, there emerged a large amount of HNSW about "Guo Meimei" and the Chinese Red Cross, such as "The survey report of Guo Meimei" and "Chinese Red Cross rebuilt public trust." The "Guo Meimei" incident exerted negative effects on the image of the Chinese Red Cross and a trust crisis started. Compared with the donation during the Wenchuan earthquake that happened in May of 2008, the donation dropped sharply during the Lushan earthquake happened in April of 2013. The foci of public opinion shifted from the case of the "Guo Meimei" incident to the government management.

Besides the original HNSW relevant to "Chinese Red Cross," we also crawled the news whose URLs are listed on the first page for each HNSW. For this study, we collected 82 HNSW including 633 corresponding news texts related to the "Chinese Red Cross" from the corpus of HNSW downloaded since November 2011. The time span of HNSW on the "Chinese Red Cross" ranges from 2011 to 2016.

There are two strategies to divide HNSW into chronological time stamps, i.e., divide HNSW into stamps encompassing either a fixed amount of time or a fixed number of HNSW. The popularity of an event over time varies; there are bursts of intense popularity, followed by long periods of relative unpopularity. As we prefer to have more details during popular times, we use the latter and divide the set of "Chinese Red Cross"-related HNSW into 10-time stamps. Chinese news text segmentation and stopword removal have been performed during preprocessing. To acquire more comprehensive semantic information, the news texts from April 1, 2013, to December 31, 2016, are chosen to learn word vector representations. The parameters are set as follows: the learned vector representations are set to 100 dimensions, and the optimal window size is 5. Furthermore, the top 20 keywords from news text are extracted as the contents of HNSW documents by TextRank (Mihalcea & Tarau, 2004). The vector of one HNSW is represented by averaging its word vectors.

Once clusters are generated by clustering, we compute scores of "coherence," "coverage," and "connective," respectively. Then optimize the objective function to get a risk map.

Figure 5.11 is the Risk Map of the "Chinese Red Cross" and Fig. 5.12 is its English translation. Evaluations are made between Risk Map and Metro Map, while Risk Map performs better (details in Xu and Tang (2018)).

The Risk Map as shown in Fig. 5.12 reveals a rich and intricate structure. The first storyline (in red) and the second one (in blue) are closely intertwined during the early time (on the left side of both lines) because of a series of activities on wealth flaunter by "Guo Meimei," which leads to the trust crisis of the Red Cross. The first one on the left focuses on the trust crisis caused by "Guo Meimei" and the investigation on her by the Chinese Red Cross. The consecutive stops contain the same event "Chinese Red Cross denied misappropriation of funds" because the events with the same corresponding HNSW appear on different days and are divided into two different time stamps. The second line on the left presents the "Guo Meimei" incident, starting with a flame war in Sina Weibo between Guo Meimei and Weng Tao (the chairman of the associated company of Chinese Red Cross) and ending up with "Guo Meimei arrested by the police." The third line (in green, at the bottom) describes the events of donation corruption during the Wenchuan earthquake. The risk map clearly and comprehensively illustrates the evolution of societal risk events. At the start, the risks of the events about the wealth flaunter of "Guo Meimei" are public morality. Later, the police found "Guo Meimei" suspected of gambling. The risks transfer from public morality to social stability. When we mentioned the "Chinese Red Cross" before, the risks of related events are risk-free. Since the show-off incidents of Guo Meimei and donation corruption, the Chinese Red Cross encountered a public trust crisis with a great donation decrease. The societal controversy was so heated that the Chinese Red Cross had to clarify it, and the investigation was carried out. Thus, the risks of events in the Chinese Red Cross transfer from risk-free to government management.

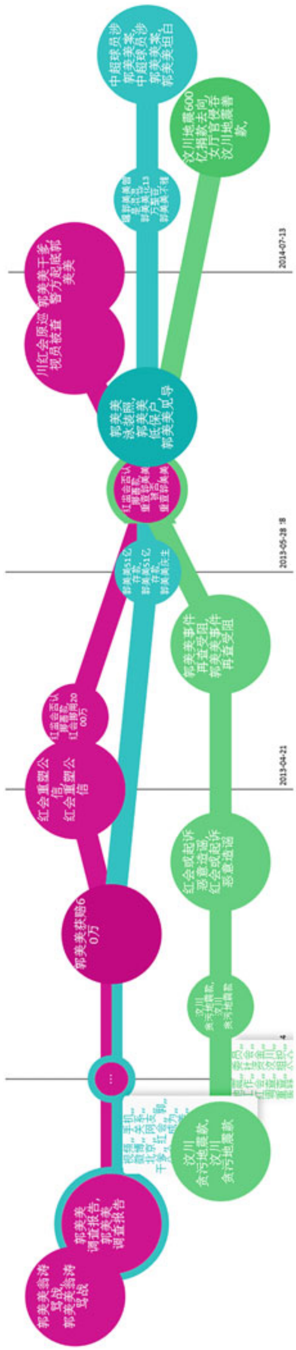

Fig. 5.11 Risk map of Chinese Red Cross events by Xu and Tang (2018)

Fig. 5.12 English Translation of Risk Map of Chinese Red Cross Events (Xu & Tang, 2020)

The above illustrates the generation of the risk map to capture societal risk events evolution and explicitly to show the risk transfer among the HNSW along the story development.

5.5 Summary

In this chapter, we first describe the meanings of the meta-synthesis system approach by diverse paradigms relevant to unstructured or wicked problem-solving. From management science to systems thinking, from problem structuring to knowledge creation, from DSS to knowledge-creating *Ba,* the fundamentals and essentials of MSA are addressed for better understanding. Then it is easily accepted to practice qualitative meta-synthesis using problem structuring methods, such as soft OR or IBIS methodology which also serves as a design rationale to develop technologies for logic-based collaborative deliberation. While those kinds of technologies heavily rely on the defined framework which somewhat hinders wider application. The qualitative meta-synthesis technologies CorMap and iView take another way. Both conduct exploratory analysis toward those topics or ideas created bottom-up by textual computing and enable the facilitation of human–machine interaction by visualizing the analytical process in accordance with the human cognitive process, which reflects the thinking of those “people problems” instead of avoid of them in pursuit of advanced technologies. We illustrate two cases of applications. One is community mind mining with data collected by word association test. Another is to perceive the online community’s concerns with utterances or comments published via online media for one topic. The practical context of both cases is about societal risk events.

To deal with the wicked problem, the unstructured problem, or the OCGS problem, qualitative meta-synthesis is to extract the knowledge from data and information collected during the interactive problem-solving process. Both CorMap and iView find a structure or systemic vision from a group of textual data, draw a scenario using different clustering based on different modeling toward group arguments, and extract concepts from clusters of arguments from multi-perspective. When online media contribute huge information toward critical events, not only topics of those UGCs are required, but complex stories which outline the evolving process are also of study to expose the problem structures. Two approaches for storyline generating are introduced together with respective examples. Again, visualized perspective toward the concerned problems reflected by the texts is emphasized.

Snowden (2002) proposed the Cynefin framework which roughly divides decision contexts into four spaces: known space, knowable space, complex space, and chaotic space. Different decision-making forms are suggested for each space. In complex space, Snowden suggests decision-making as, i.e., *probe, sense, and respond* and in chaotic space, decision-making will be more of the form of *act, sense, and respond* (Kurtz & Snowden, 2003). We say qualitative meta-synthesis to conduct qualitative modeling may serve as one common tool support for those decision-making forms. Those approaches introduced in this chapter may be helpful to extract useful information or knowledge, from discussions either from the closed small-sized group or public via online media and may be the starting point during a collaborative deliberation for decision-making.

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Chapter 6
Agent-Based Simulation of Low Carbon Emissions Product Diffusion

Tieju Ma and Arnulf Gruebler

6.1 Introduction

Complex adaptive systems (CASs) include heterogeneous actors who interact with one another and adapt to the environments they collaboratively create (e.g., Arthur, 1999, 2021). It is difficult to analyze CAS *emergence* (defined as macro-phenomena that arise from micro-level interactions) with traditional methods, and agent-based models (ABMs) are considered to be a powerful tool for investigating such systems as well as their *emergence* (e.g., Farmer & Foley, 2009; Gilbert, 1995). ABM can be used to generate knowledge regarding CASs to expand insights and aid the development of strategic intuition on CASs (Axelrod, 1997).

Amid the increasing effects of global climate change, there have been increasing calls to develop and promote the diffusion of low carbon emissions products (simplified as low emissions products in the rest of this chapter). For example, many countries are trying to develop and promote the diffusion of low emissions vehicles (e.g., China's State Council, 2020; US Department of Energy, 2013). Diffusion of low emissions products is the result of interactions among different heterogeneous actors/agents. For example, for low emissions vehicles, it is a result of interactions among consumers, vehicle producers, governments, and others within the chain of automobile development and sales. Consumers have unique preferences that could be influenced by one another, the availability of different vehicle types, and government policies, and vehicle producers could have diverse technology

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development strategies and adapt research and development (R&D) decisions based on market observations and government policies. Subsequently, the diffusion of low emissions products could be viewed as an *emergence* of a CAS.

This study develops an ABM on the diffusion of low emissions products to generate knowledge on potential diffusion dynamics under different scenarios. The diffusion of low emissions products is associated with technological innovation. No single model can capture all the features of emerging technological innovations and diffusion of low emissions products. The innovative features of the ABM constructed in this chapter include: (1) peer effect among consumers as well as interactions between consumers and producers, (2) producers' technological innovations are path-dependent when developing new products, and (3) actors are influenced by the product's emissions after the industry has been operated for a certain time period. The timing in the entry of the emissions attribute in the simulations denotes that actors do not realize the importance of the emissions attribute at the early stage of product development, and after a certain amount of time passes, actors begin to pay attention to the emissions attribute. In the example of the vehicle industry, at the early stage, actors (including consumers, producers, governments, and so others) do not realize (or pay attention to) the importance of carbon reduction, and actors later start to pay attention to carbon reduction, thus triggering the influence of the attribute of low emissions.

With the ABM, we first simulate how different timing in the entry of the emissions attribute influences the diffusion of low emissions products, then simulating how different peer effects among consumers and social network structure influence the diffusion of low emissions products, and finally, how different government policies influence the diffusion of low emissions products. Simulations using the model can generate more knowledge regarding how the appropriate timing of the emissions attribute, peer effect and social network, and different government policies influence the diffusion of low emissions products. And this knowledge is helpful for producers and governments to develop more effective measures and strategies to promote the diffusion of low emissions products.

The remainder of this chapter is organized as follows: Section 6.2 presents a review of the relevant literature. Section 6.3 details the proposed ABM. Section 6.4 analyzes the simulations on the diffusion of low emissions products under different scenarios. Section 6.5 presents concluding remarks.

6.2 Literature Review

6.2.1 Modeling Innovation and the Diffusion of Low Emissions Products

It has been recognized for decades that both demand-pull and technology-push have important roles in technological innovation (Mowery & Rosenberg, 1979), and interactions occur between demand-pull and technology-push in the process of innovation (Kline & Rosenberg, 1986). Considerable research has been conducted exploring the innovation and diffusion of low emissions products from the supply side (producers) and from the demand side (consumers) as well as from both sides which interact with each other.

From the supply side, it has been observed that numerous companies have launched (or are planning to launch) new low emissions products (e.g., Confente, Scarpi, & Russo, 2020; Dangelico & Pujari, 2010; Padilla-Lozano & Collazzo, 2022). Incentives for developing low emissions products include compliance with emissions regulations, the pursuit of emissions-based competitive advantage, and assuming emissions responsibility (e.g., Dangelico & Pujari, 2010; Delchet-Cochet, Vo, & Akeb, 2015). It has been demonstrated that R&D collaboration with consumers, suppliers, other firms within the same corporate group, and consultants is positively associated with the development of low emissions products (e.g., Pippel, 2015).

From the demand side, researchers have analyzed the factors driving and hindering consumers' adoption of low emissions products, including norms, attitudes, novelty seeking, how innovation attributes are perceived, and other considerations (e.g., Arkesteijn & Oerlemans, 2005; Jansson, 2011). Empirical studies of the diffusion of low emissions products have also demonstrated the importance of peer effects among consumers on the demand side (e.g., Bollinger & Gillingham, 2012; He, Wang, Chen, & Conzelmann, 2014; Rai & Robinson, 2015).

From a system perspective, some general evolutionary models of technological innovation have been developed considering interactions between the supply and demand sides. For example, Adner and Levinthal (2001) developed a computer simulation model that explicitly considers the presence of consumers with different needs and firms with different innovation choices to examine the dynamics of product and process innovation (Utterback & Abernathy, 1975). Ma and Nakamori (2005) developed an evolutionary model of technological innovation that includes producers and consumers and maps design parameters on the supplier side to the performance parameters on the demand side using Kauffman's NK model (Kauffman, 1993). Focusing on innovation and consumer adoption of low emissions products, Janssen and Jager (2002) developed a simulation model of coevolution between firms and consumers to analyze the stimulating effect of diffusion of low emissions products using different tax schemes. Some models on the diffusion of alternative fuel vehicles have been developed considering the interactions among various actors (e.g., Choi, Im, & Park, 2012; Ebrie & Kim, 2022; Ma, Zhao, Xiang, Ya, & Peipei, 2014; Plötz, Gnann, & Wietsche, 2014; Schwoon, 2008; Stephan & Sullivan, 2004; Vooren & Alkemade, 2012). These models including interactions between supply and demand sides are primarily ABMs.

6.2.2 ABMs and Social Influence

ABMs are considered to be powerful tools for capturing details regarding heterogeneous actors and interactions. Numerous ABMs have been developed to examine interactions among heterogeneous and adaptive actors in various contexts, such as the stock market (e.g., Palmer, Arthur, Holland, et al., 1994), dissemination of culture (e.g., Axelrod, 1997), electricity trading (e.g., Bunn & Oliveira, 2001), drivers' route choice (e.g., Dia, 2002), pedestrian walking behavior (e.g., Antonini, Bierlaire, & Weber, 2006), the coevolution of individual behaviors and social institutions (e.g., Bowles, Choi, & Hopfensitz, 2003), the formation of virtual organizations (e.g., Norman, Preece, Chalmers, et al., 2004), the coevolution of parochial altruism and war (e.g., Choi & Bowles, 2007), evacuation from buildings under fire (e.g., Shi, Ren, & Chen, 2009), the diffusion of epidemic diseases (e.g., Beyrer, Baral, Van Griensven, et al., 2012), and technological diffusion (e.g., Delre, Jager, & Janssen, 2007). Bonabeau (2002) classified applications of agent-based modeling and simulations into four categories of flow simulation, organizational simulation, market simulation, and diffusion simulation.

Traditional technology diffusion models, such as the Bass diffusion model (Bass, 1969), commonly describe the macro-level diffusion pattern of new technologies as s-shaped curves. With the development of complexity theories, researchers began to study the process of new technology diffusion as a type of CAS emergence from interactions among heterogeneous actors.

In existing ABMs on technology diffusion, consumer heterogeneity is embodied as individual variations in thresholds for adopting products (e.g., Adner & Levinthal, 2001; Delre et al., 2007), perspectives regarding ideal products (e.g., Kim, Lee, Cho, & Kim, 2011; Ma, Ryoke, & Nakamori, 2002), weighting functions (e.g., Ma & Nakamori, 2005; Malerba, Nelson, Orsenigo, & Winter, 2007; Shafiei, Thorkelsson, Ásgeirsson, et al., 2012; Windrum, Ciarli, & Birchenhall, 2009), and demographic characteristics (e.g., Ma et al., 2014; Shafiei et al., 2012; Stephan & Sullivan, 2004).

Most existing ABMs addressing technology diffusion include social influence among consumers. The mechanisms of social influence in these ABMs can be grouped into four types.

- **Network externalities.** A consumer's utility of adopting a good/service will be influenced by the proportion of consumers who chose the same product (see De Almeida Prado, Belitsky, & Ferreira, 2011; Goldenberg, Libai, & Muller, 2010).
- **Contagious epidemic.** A new product is viewed as a contagious epidemic or a virus transmitted within the society that is modeled as various kinds of networks (e.g., see Delre et al., 2007; Dodds & Watts, 2005).
- **Bandwagon and snob effect.** Some people want to be "in style," whereas others might wish to attain exclusiveness (Leibenstein, 1950). The ABM developed by Safarzyńska and Van Den Bergh (2010) is a good example of modeling this effect.
- **Systematic effect**. Consumer agents may not directly interact with one another, but since they operate in the same system, one consumer's decision will influence

others. ABMs on the co-diffusion of alternative fuel vehicles and their infrastructure (e.g., see Ma et al., 2014; Schwoon, 2007; Stephan & Sullivan, 2004) are good examples of this effect.

The first three constructs in the above list are all related to peer effect, meaning that consumers will be influenced by their (social) neighbors; and the fourth means consumers will experience interactions with other kinds of agents (for example, producers), and then indirectly influence other consumers. The ABM introduced in this chapter includes both the peer and the systemic effects.

Considerable research has examined policies to promote the adoption of low emissions products (e.g., Lehtoranta, Nissinen, Mattila, & Melanen, 2011; Norberg-Bohm, 1999; Riahi, Grübler, & Nakicenovic, 2007; Spaargaren, 2003); however, minimal work has been conducted simulating their effects using models that include interactions among heterogeneous agents. With the ABM introduced in this chapter, we simulate the diffusion of low emissions products with different policies.

6.3 The Agent-Based Model

In this section, we describe the narrative of the ABM, and the mathematical formulations of the model are presented in Appendix.

6.3.1 Agents and Elements in the Model

There are two types of agents in the model, consumer and producer agents. At each simulation step, consumer agents will evaluate producers' products, and producer agents will endeavor to improve products through R&D. Consumer agents' decisions to purchase products will influence producer agents' profits, further influencing the amount of budget that producer agents can use for R&D. Producer agents' R&D budget will influence products' improvement, which will then further influence consumer agents' decisions to purchase products.

Both consumer agents and producer agents are heterogeneous. Different consumer agents apply different weights to function attributes and different thresholds of functional utility when evaluating products. Consumer agents are organized in a small-world social network, in which weights of function attributes are influenced by social neighbors. Different consumer agents have different levels of resistance to neighbors' influence. Different producers offer different initial products, and each producer is initialized with a certain wealth. Producers with poor business are removed from the system when their wealth becomes negative, and there are entries of new producers.

Each product has five function attributes, with values in the range (0, 1), and the higher the value, the better the performance of the function. The first four attributes denote traditional product functions, and the fifth attribute denotes the products' emissions function. For example, if we consider the products to be vehicles, the first four attributes could be *safety*, *elegance*, *power*, and *handling*, and the fifth attribute could be *carbon-free*. In our model, in the beginning, we assume that the fifth attribute is ignored by both consumer agents when evaluating products and by producer agents when improving products. After a certain amount of time passes, consumer agents begin to realize the importance of the fifth attribute, which then becomes one of their criteria for selecting products, and producer agents begin to allocate an R&D budget to improve the fifth attribute.

With the ABM, we will simulate and analyze the effect of the following four kinds of government policies to promote consumers' adoption of low emissions products.

- Educating consumers to emphasize products' emissions performance when adopting products.
- Subsidizing consumers who adopt low emissions products.
- Imposing a carbon tax on using products with higher emissions.
- Subsidizing producers' R&D to improve emission performance.

The detailed behaviors of consumer and producer agents are introduced in the remainder of this section, and mathematical formulations of the model are introduced in Appendix.

6.3.2 Consumer Agents

6.3.2.1 Peer Effect among Consumers

Empirical research demonstrates that social networks are often small-world networks (Watts & Strogatz, 1998). In our model, consumer agents form a small-world social network that is generated with the Watts–Strogatz model using the following process (see Watts & Strogatz, 1998):

- Generate a regular network with N consumers, which is a normal lattice in which every consumer is linked to k neighbors.
- Rewire each link in the regular network randomly with probability β.

Here, $\beta \in [0, 1]$; when $\beta = 0$, the resulting network is a regular network, and when $\beta = 1$, the resulting network is a random network. Increasing β from 0 to 1 will cause the average path length between two randomly selected nodes to rapidly narrow.

Each consumer agent assigns different weights to the five attributes, which are initialized randomly. A consumer agent's functional utility for using a product is calculated as the weighted average of the product's four (and later five) attributes.

Each consumer agent has an independent factor for each attribute, indicating its resistance to neighbors' influence, which is initialized randomly in the range (0, 1).

We define two kinds of peer effects:

- Peer effect 1: A consumer agent's weight for an attribute in the next step is the weighted sum (using the independent factor as the weight) of the agent's weight and all its neighbors' average weight at the current step.
- Peer effect 2: A consumer agent's weight for an attribute in the next step is the weighted sum (using the independent factor as the weight) of its weight and the average weight of those neighbors whose weights are higher than its own at the current step.

We apply the two versions of peer effects on the emissions attribute (i.e., the fifth attribute) to examine any differences.

6.3.2.2 Consumers' Decision to Buy Products

Each consumer agent would like to buy a product at each step, but a consumer agent might not buy a product because none of the existing products reaches the agent's expectations regarding performance (i.e., each consumer has a threshold for functional utility, in which, if all existing products' functional utilities are lower than a consumer's threshold, the consumer will not buy any product). Consumers' threshold is initialized following a Weibull distribution.

In addition to utility, price is another factor that influences consumers' purchase decisions. Each consumer agent has a different sensitivity (or weight, which is randomly assigned) to price. For a product, the lower the price, the higher its attractiveness. If there are products with functional utility higher than a consumer's threshold, the consumer will calculate the scores of these products, which are the weighted sum of each product's functional utility and price attractiveness. The consumer will then purchase the product with the highest score.

When consumers begin to consider the fifth attribute (simplified as A5), the associated weights follow a skewed distribution (a Weibull distribution), with most being quite small, reflecting the fact that most consumers have a low willingness to pay for improved emissions performance (Caird, Roy, & Herring, 2008).

6.3.3 Producer Agents

6.3.3.1 Producers' Entries and Exits

There are initially a number of producers, and each of them is initialized with a unit of wealth. At each step, each producer has a 0.1-unit OM (operation and maintenance) cost, indicating a loss of wealth. Producers will allocate an R&D budget to develop new products, which is another loss of wealth. Producers obtain profits by selling products, which adds to wealth. If a producer is unable to earn enough profits to cover costs, its wealth will finally become negative. If a producer's wealth becomes negative, the producer will be removed from the system. At each step, there is a possibility that a new producer will enter the system, and the more producers, the higher probability of entrance.

Each producer (including initial and new producers) is initialized with a product with attributes that are randomly initialized in a range, and the initial cost of this entry product is the weighted sum of its attribute values.

6.3.3.2 Technological Learning Effect with Cumulative Adoption

A product's cost tends to decrease with the cumulative increase of adoption, which implies accumulating experience in production (the technological learning effect), as shown in Eq. (6.1):

$$c_{t+1} = c_0 {a_t}^{-b}, \tag{6.1}$$

where a_t denotes the cumulative adoption of the product at time step t, c_{t+1} denotes the cost of the product at time step ($t + 1$), and b is the elasticity of cost in terms of cumulative adoption, and it is straightforward to prove that $1 - 2^{-b}$ (called the learning rate) is the proportion of the cost decrease when cumulative adoption doubles. The learning rate is assumed to be 10% (i.e., $1 - 2^{-b} = 10\%$) in our simulations.

The learning effect is assumed to be local, meaning that even when two producers have exactly the same products, indicating that all attribute values are the same, the cumulative adoption of products is only limited to each producer's own selling when Eq. (6.1) is applied to calculate the products' new costs.

6.3.3.3 Price Mark, R&D Budget, and New Products

Producers make profits by implementing a certain price mark for each product (e.g., 20% percent of each product's cost). For products with very low cost (because of the learning effect introduced in Subsection "Technological Learning Effect with Cumulative Adoption"), we assume a bottom price that is half the weighted sum of the product's attribute values.

At each step, each producer will take part of the profit (e.g., 10%) from the previous step as the R&D budget in the current step, which will be allocated randomly to one of the four (and later five) attributes. With R&D, at each step, it is possible (e.g., with a 0.3 probability) that a new product will be developed that improves the selected attribute (on which the budget is spent) with a logistic function (Ayres, 1994).

$$y = \frac{1}{1 + e^{-\alpha(x-\theta)}}, \tag{6.2}$$

where y denotes the attribute value of the new product, and x denotes the cumulative research budget for this attribute. α and θ are two design parameters, in which α controls the speed of y's increase with the increase of x, and θ is the value where the curve has the largest slope.

For a producer, there is a technological spillover between previous products and the new product because the new one actually is an improved version of the previous product. If the new product improves the previous one very slightly, its cost will be similar to the previous one, and if it improves the previous product considerably, then its cost will be higher than the previous product (see Eq. (6.7) in Appendix).

If a producer does not sell out any products in the previous step, then it earns no profit and no R&D budget. In this case, we assume that a knowledge depreciation effect exists, and knowledge (denoted by the amount of cumulative budget) regarding each attribute will decrease by a certain percentage (e.g., by 10%).

6.3.4 Policies for Promoting the Diffusion of Low Emissions Products

We will explore the effects of the following four kinds of policies for promoting the diffusion of low emissions products:

- **Educating consumers to be more environmental-friendly**. With this measure, consumer agents' allocated weights to the fifth attribute are increased little by little at each step before being normalized with weights to other attributes. For each consumer, the growth rate of the weight for the fifth attribute is assumed to be a random value in the range [0, 2σ%], and thus the expected growth rate is σ% at each step.
- **Subsidizing consumers who adopt low emissions products**. With this policy, the lower the emissions of the product a consumer agent adopts, the higher the subsidy obtained. Suppose the subsidy rate is γ%, a consumer agent can receive a subsidy which is $(\gamma \cdot A_5)$% of the price of the adopted product, meaning that when the product adopted is a perfect low emissions (i.e., zero-emission) product, with $A_5 = 1$, a γ% subsidy of the product's price can be obtained.
- **Imposing a carbon tax on high emissions products**. With this policy, the higher the emissions of the product a consumer agent adopts, the higher the carbon tax imposed. Suppose the carbon tax rate is λ%, a consumer agent must pay a carbon tax that is $[\lambda \cdot (1 - A_5)]$% of the price of the adopted product, meaning that when the product adopted is of the highest emissions, with $A_5 = 0$, the consumer agent must pay a carbon tax that is λ% of the product's price.
- **Subsiding producers' R&D to improve emissions performance**. With this policy, producer agents will receive a subsidy for improving the fifth attribute. Suppose the R&D subsidy rate is φ%, a producer agent will obtain a subsidy that is φ% of its own R&D budget. This R&D subsidy will only be used to improve

the fifth attribute, while a producer's own R&D budget can be used to improve other attributes.

6.4 Simulations and Analyses

6.4.1 Initializing the Baseline Simulations

To explore how the diffusion of low emissions is influenced by the inclusion of the fifth attribute, peer effect, and different government policies, we first run a group of baseline simulations. We then run other groups of simulations, varying the timing of the introduction of the fifth attribute, the structure of the social network, and policy implementation. Each group of simulations includes 200 simulations with the same initialization. The group of baseline simulations is called G0. The first three columns of Table 6.1 present a detailed description of the baseline simulations. Each additional group of simulations only changes one of the parameters listed in the first column of Table 6.1, and the fourth column of Table 6.1 presents the values of the parameters in the other groups of simulations.

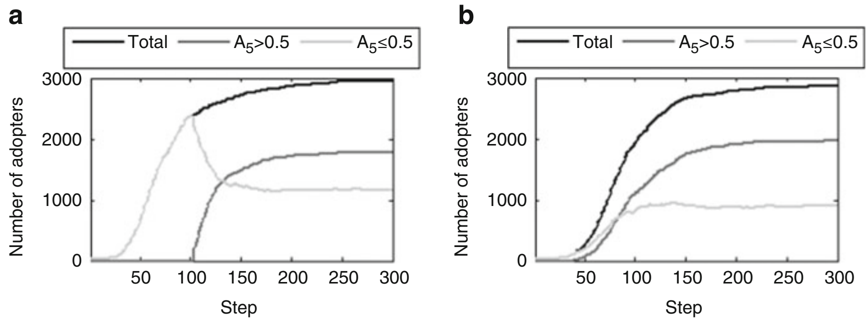
Table 6.1 Baseline simulations (G0)

Parameters	Value	Explanations	Other groups of simulations
A5 timing	100	From the 100th step, producers will begin to improve the fifth attribute	G1–10
Peer effect	1	Consumer are influenced by peer effect 1	G2–peer effect 2 G3–no peer effect
N	3000	There are potentially 3000 consumers	G4–1000 G5–5000
k	8	Each consumer has eight direct neighbors, on average	G6–4 G7–16
β	0.5	Probability of rewiring an edge of a regular network	G8–0.2 G9–0.8
σ	0	Do not educate consumers	G10–1 G11–10
γ	0	No subsidy to consumers	G12–20 G13–50
λ	0	No carbon tax	G14–20 G15–50
φ	0	No subsidy to R&D	G16–10 G17–1000
Whether consumers will prioritize A5	Yes	From the 100th step, consumers will begin recognizing A5	G18

6.4.2 How Different Fifth Attribute Timing Influences the Diffusion of Low Emissions Products

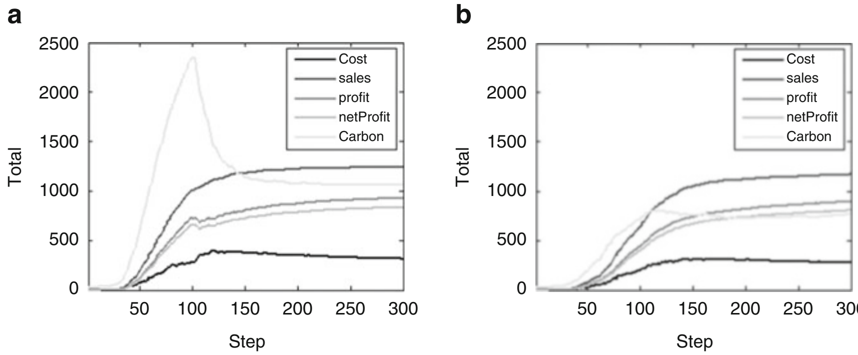
Before the fifth attribute is recognized, it is ignored by consumers and producers, indicating that consumers do not prioritize or do not care about products' environmental impact at the beginning, until they finally do. Figure 6.1 plots the dynamics of the number of adopted products in G0 and G1. In G0, the fifth attribute is introduced at the 100th step, and in G1, it is introduced at the tenth step. The black line in the figure denotes the total number of products adopted by consumers, the dark gray line denotes the number of products adopted with the value of the fifth attribute larger than 0.5, and the light gray line denotes those for which the value of the fifth attribute is not larger than 0.5.

Figure 6.2 plots the dynamics of the total cost, sales, profit, net profit, and carbon factor for G0 and G1, where the total cost does not include R&D expense, profit = sales–cost, and net profit = profit–R&D expense. Carbon is the sum of



A5 is introduced at the 100th step (G0) A5 is introduced at the 10th step (G1)

Fig. 6.1 Number of adopted products in G0 and G1. (**a**) A5 is introduced at the 100th step (G0). (**b**) A5 is introduced at the tenth step (G1)



A5 is introduced at the 100th step (G0) A5 is introduced at the 10th step (G1)

Fig. 6.2 Total cost, sales, profit, net profit, and carbon factor of G0 and G1. (**a**) A5 is introduced at the 100th step (G0). (**b**) A5 is introduced at the tenth step (G1)

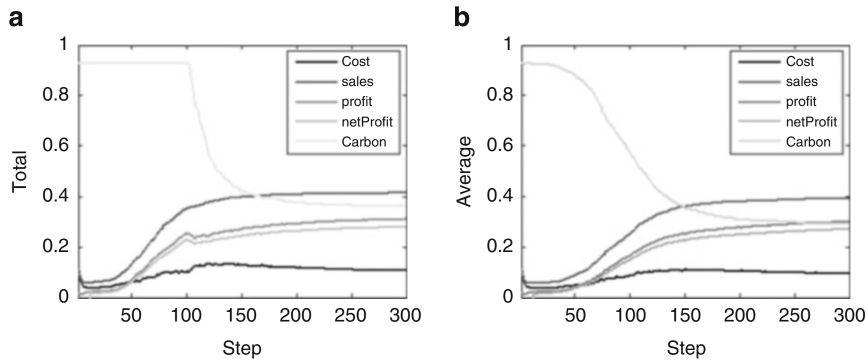


Fig. 6.3 Average cost, sales, profit, net profit, and carbon factor of G0 and G1. (**a**) A5 is introduced at the 100th step (G0). (**b**) A5 is introduced at the tenth step (G1)

$(1 - A_5)$ for all adopted products. Figure 6.3 plots the dynamics of average cost, sales, profit, net profit, and carbon emissions for G0 and G1, which are the values in Fig. 6.2 divided by the total number of adopted products at each step.

Figures 6.1, 6.2, and 6.3 reveal that introducing A5 earlier can stimulate the adoption of low emissions products and slightly decrease carbon emissions when the number of adopted products is stabilized (by around 5%, comparing G1 to G0).

6.4.3 How Different Peer Effect and Network Structure Influence the Diffusion of Low Emissions Products

Figure 6.4 plots the dynamics of the number of adopted products with different peer effects and network structures (G0, G2–G9). Figure 6.5 plots the dynamics of the total cost, sales, profit, net profit, and carbon factor with different peer effects and network structures, and Fig. 6.6 plots the average cost, sales, profit, net profit, and carbon factor.

Figures 6.4, 6.5, and 6.6 reveal that:

- Peer effect 2 will cause more adoption of low emissions products. This is because all consumers' weights to A5 will be converged to the highest weight initialized in peer effect 2, as shown in Fig. 6.7**.**
- Removing the peer effect will slightly diminish the total adoption of products. This is because, without peer effect, consumers remain heterogeneous; thus, it is more difficult for a single producer/product to dominate the system, resulting in less intensive R&D to improve products to reach consumers' thresholds on performance.

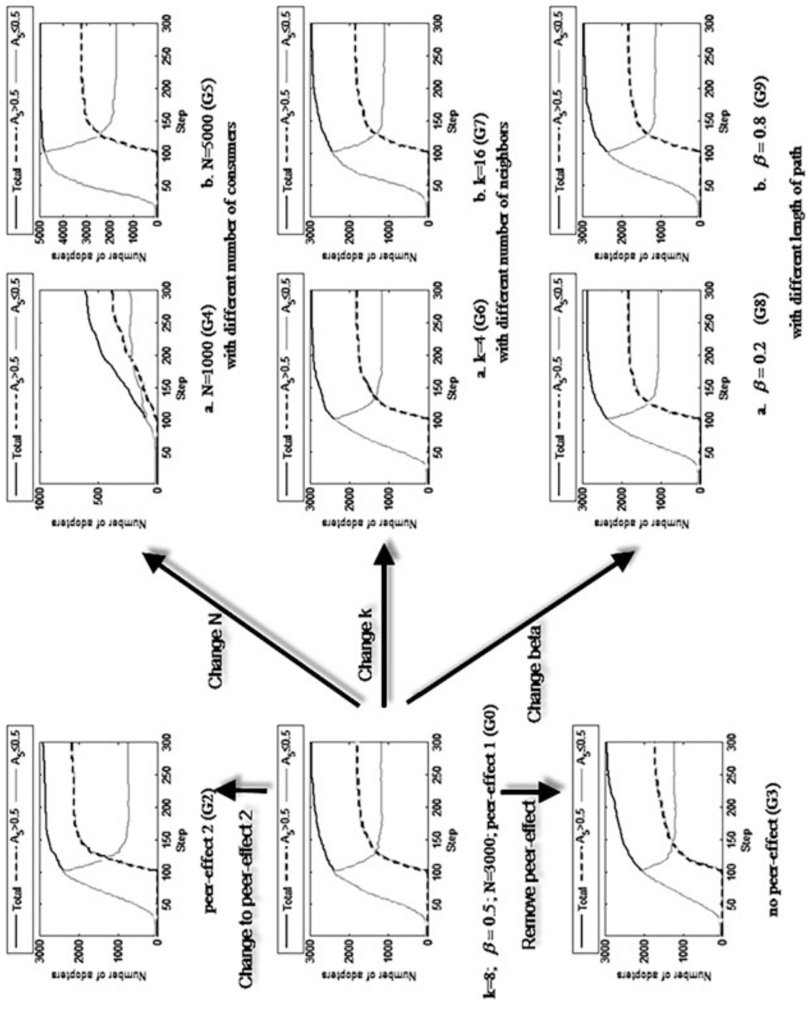


Fig. 6.4 Number of adopted products with different peer effects and social network structures

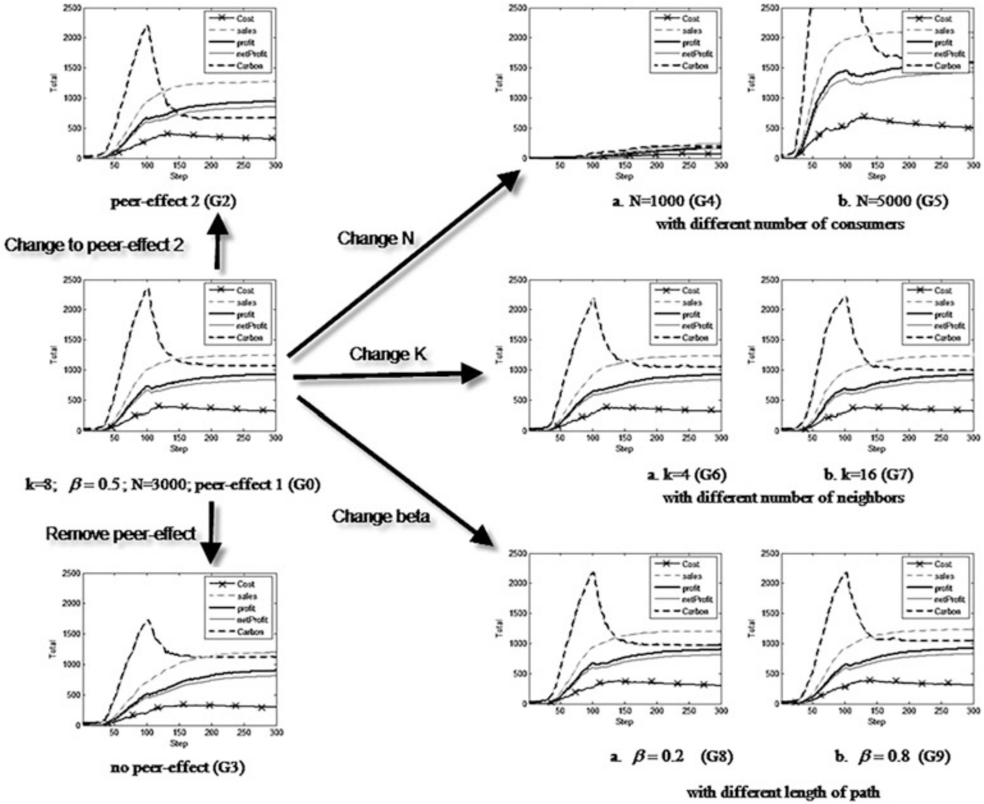


Fig. 6.5 Total cost, sales, profit, net profit, and carbon factor with different peer effects and social network structures

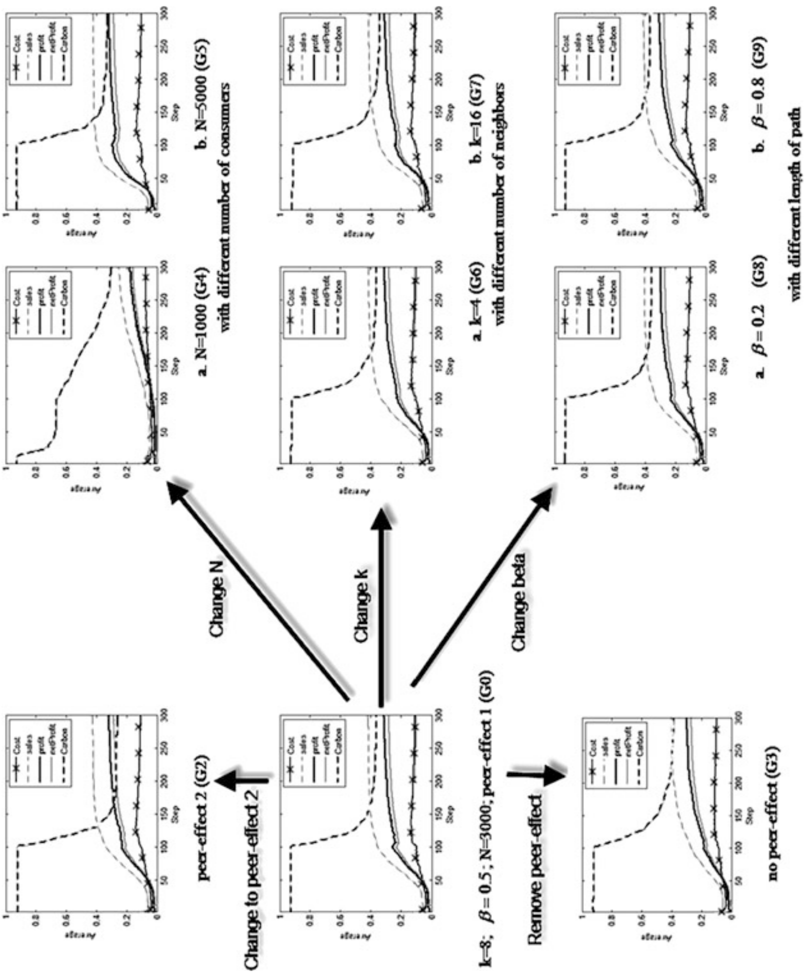


Fig. 6.6 Average cost, sales, profit, net profit, and carbon factor with different peer effects and social network structures

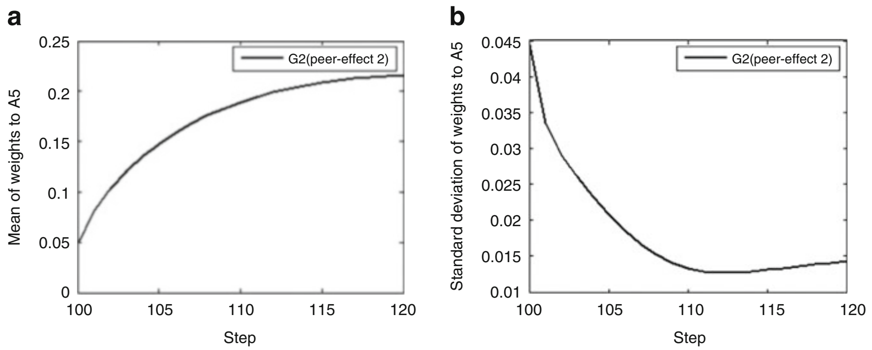


Fig. 6.7 Mean and standard deviations of A5 with peer effect 2 (G2). (**a**) Mean of A5. (**b**) Standard deviations of A5

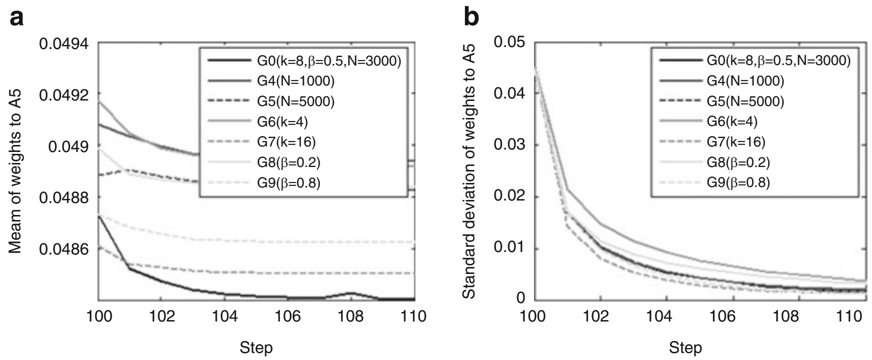


Fig. 6.8 Mean and standard deviations of A5 with peer effect 1 with different social network. (**a**) Mean of A5. (**b**) Standard deviations of A5

- A small market size ($N = 1000$) will result in slow product diffusion because producers will gain minimal profit, resulting in a small R&D budget to improve products, and large market size ($N = 5000$) will result in rapid product diffusion because producers will obtain large profit, resulting in a large R&D budget to improve products.
- Changing the network structure does not have a distinct influence on the diffusion of products, although it will result in different speeds in convergence of consumers weights to A5 (as shown in Fig. 6.8) and other attributes.

6.4.4 How Policies Affect the Diffusion of Low Emissions Products

Figure 6.9 plots the dynamics of the number of adopted products with different policies (G0, G10–G18), Fig. 6.10 plots the dynamics of the total cost, sales, profit, net profit, and carbon factor with different policies, and Fig. 6.11 plots the average cost, sales, profit, net profit, and carbon factor.

Figures 6.9, 6.10, and 6.11 reveal that:

- Consumers' willingness to pay for emissions performance is the most significant factor for accelerating the diffusion of low emissions products. In the simulations educating consumers, agents assign higher weights to A5, demonstrating more effect than other policies. When consumers do not care about A5, low emissions products are not adopted, although they are available in the market through producers' R&D efforts.
- Subsidizing consumers who adopt low emissions products will have a better effect than imposing a carbon tax.

6.5 Concluding Remarks

This chapter developed an ABM on the diffusion of low emissions products. The innovative features of the model include: (1) peer effect among consumers as well as interactions between consumers and producers, (2) producers are path-dependent when developing new products, and (3) the emissions attribute is introduced after the industry has been operated for a certain time period.

With the model, we first simulate how different timing in the recognition of the emissions attribute influences the diffusion of low emissions products. The primary finding is that if the emissions attribute is recognized and introduced earlier, it will accelerate the adoption of low emissions products and slightly decrease the carbon factor when the number of adopted products is stabilized. We then simulate how different peer effects and social network structures influence the diffusion of low emissions products, the main findings are (1) consumers will be more homogenous with peer effect, and thus it is easier for some producers to dominate the market, resulting in more R&D budget for producers to improve products to reach consumers' thresholds on performance; (2) a large market will accelerate product diffusion because producers will gain large profits, resulting in a large R&D budget to improve products; (3) the structure of the network does not have a distinct influence on the product diffusion; (4)the upward peer effect on the low emissions attribute will accelerate the adoption of low emissions products. Finally, we simulate how different policies influence the diffusion of low emissions products, and the main findings are (1) educating consumers to increase their willingness to pay (if this works) for emissions performance has a larger effect than other policies;

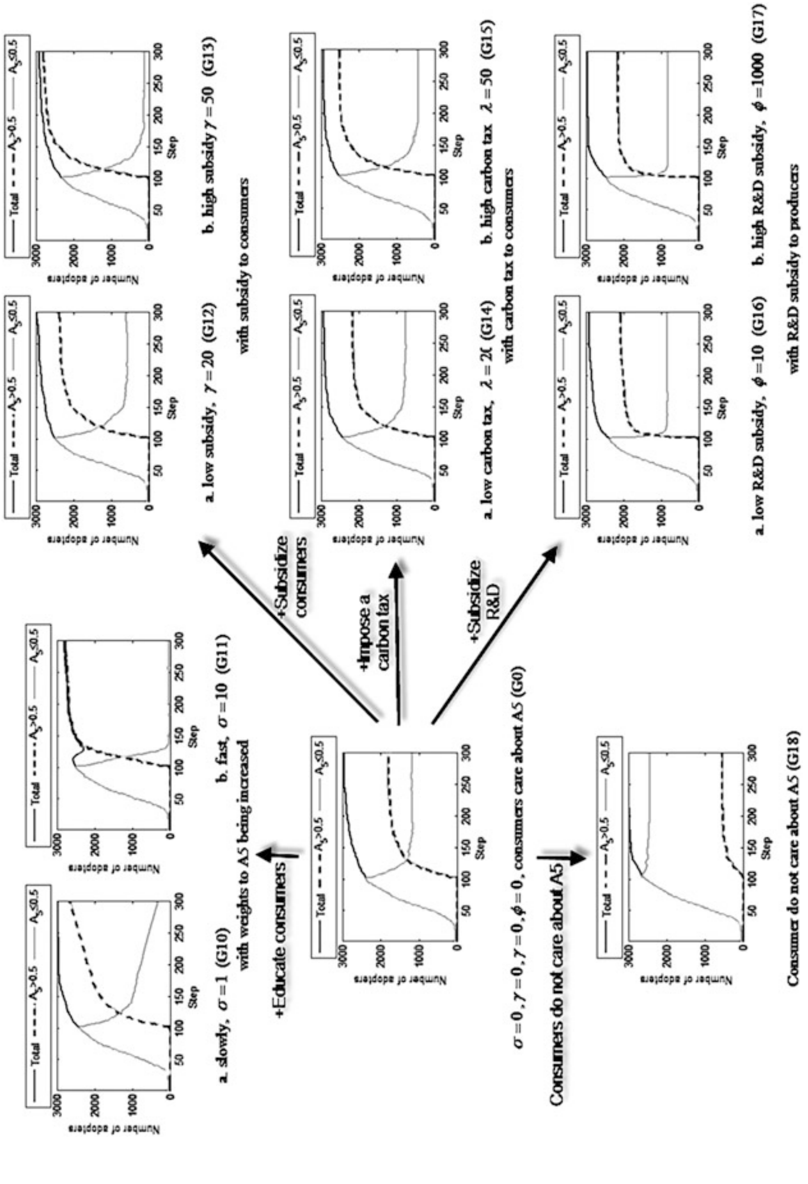


Fig. 6.9 Number of adopted products with different policies

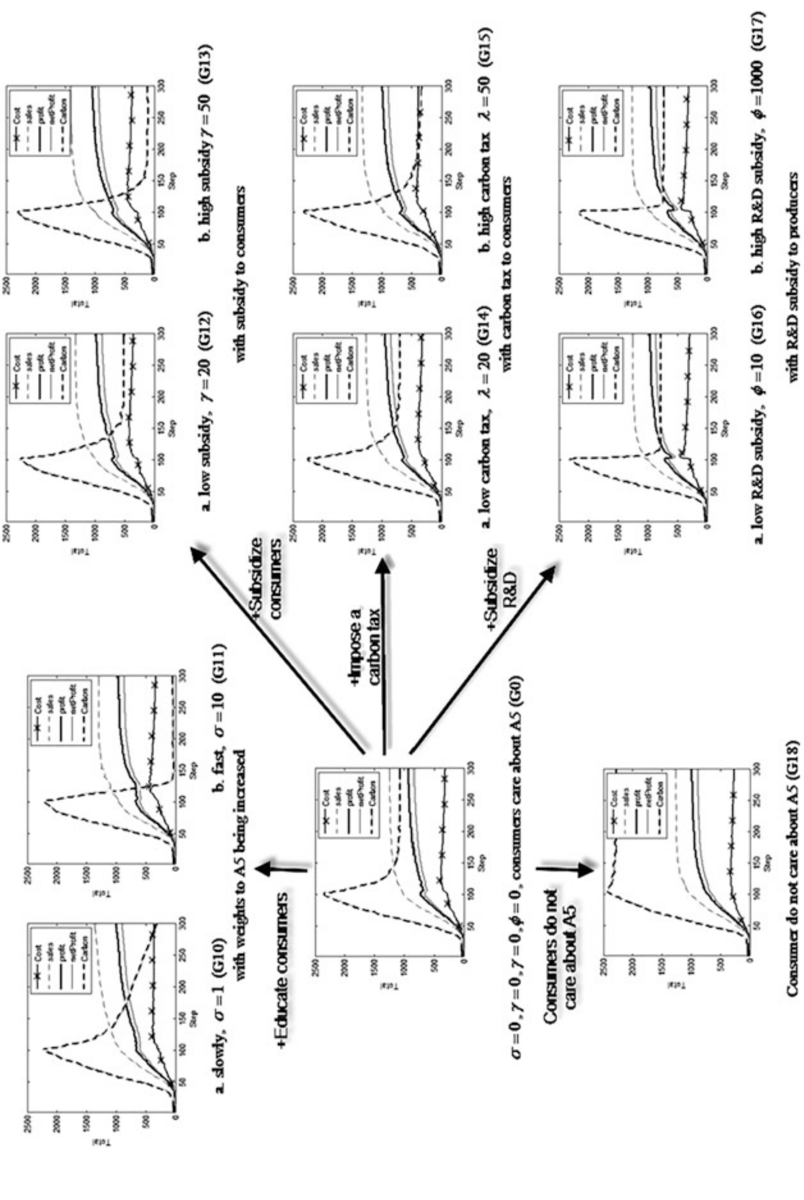


Fig. 6.10 Total cost, sales, profit, net profit, and carbon factor with different policies

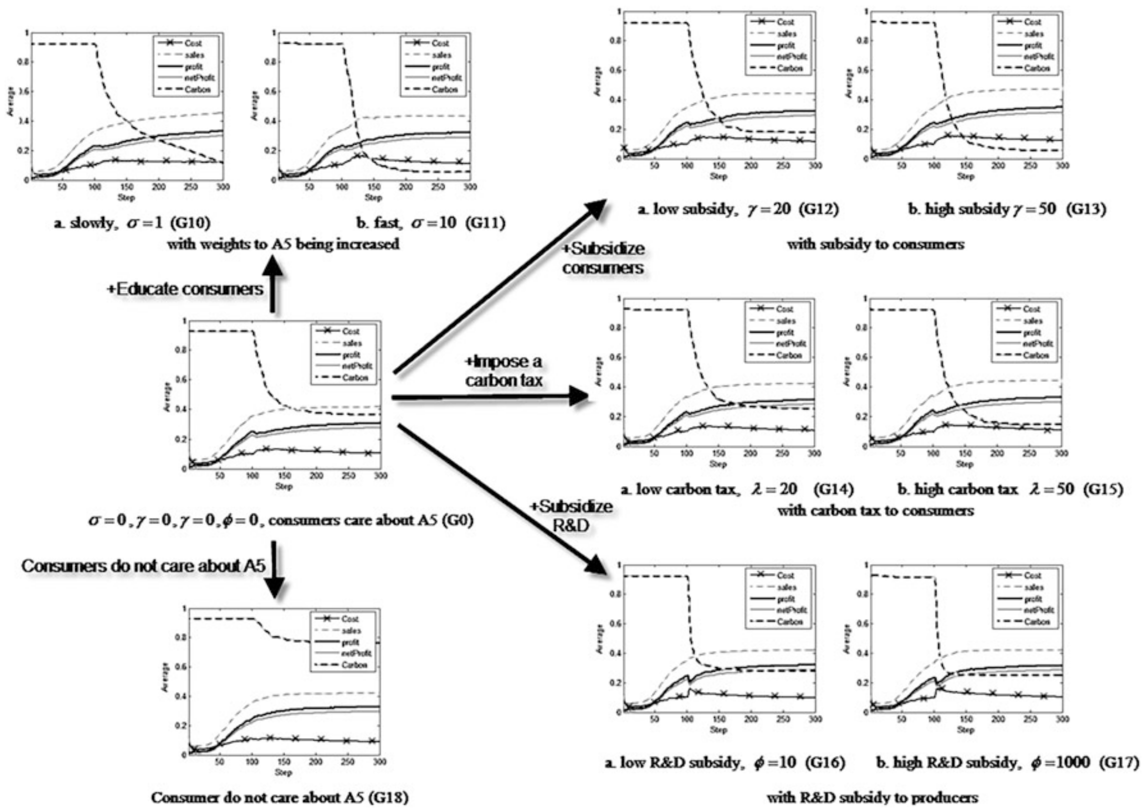


Fig. 6.11 Average cost, sales, profit, net profit, and carbon factor with different policies

(2) subsidizing consumers who adopt low emissions products will have a better effect than imposing a carbon tax.

In future work, we will explore how different combinations of policies influence the diffusion of low emissions products and seek to determine the optimal combination of subsidies to consumers or producers with a limited budget. The model presented in this chapter could also serve as a foundational starting point for constructing further, more complex models to explore how the industry will evolve with collaborations among producers, heterogeneous R&D strategies, and pricing strategies.

No single model can capture all of the dimensions and stylized facts involved in the processes of technological innovation and consumer adoption. The role of simulation in this chapter is not to establish a facsimile of any particular innovation that could be useful for prediction, but to use a relevant simulation to assist in the exploration of the consequences of various assumptions and initial conditions.

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Appendix: Mathematical Formulations of the Agent-Based Model

Producer Agents and their Products

Initial Producers and Products

Suppose there are initially M producer agents. Each producer agent is initialized with a unit of wealth and a product. Each product has five function attributes, denoted with $A_i(i = 1, \cdots, 5)$. Each attribute's value is within the range (0, 1). The fifth attribute is ignored in the beginning; thus, producer and consumer agents do not recognize this attribute, and it will be introduced after a certain step. For each producer, the initial cost of the initial product is the sum of attribute values, as shown in Eq. (6.3):

$$c_0 = \sum_i A_i, \tag{6.3}$$

where $i = 1, \cdots, 4$ before the fifth attribute is introduced, and $i = 1, \cdots, 5$ after the fifth attribute is introduced. With Eq. (6.3), for each producer's initial product, the higher the attribute values, the higher the initial cost.

Initial producers' opening product attribute values are set within the range (0,0.15), indicating the infant stage of an industry, and producers have minimal knowledge of producing high performance products.

There is a fixed OM (operation and maintenance) cost for each producer at each step, which is 10% unit wealth. If a producer is unable to sell any product for the first 10 steps, then wealth will become negative. Once a producer's wealth becomes negative, that producer will be removed from the system.

Selling Products and Making Profit

A product's cost tends to decrease with the increase in cumulative adoption. The more a producer sells out of a product, the lower the cost of producing this product will be; thus, the cost of a product at time step ($t + 1$) is a function of cumulative adoption at step t, as shown in Eq. (6.4):

$$c_{t+1} = c_0 {a_t}^{-b}, \tag{6.4}$$

where a_t denotes the cumulative adoption of a product at time step t, c_{t+1} denotes the cost of the product at time step ($t + 1$), and b is the elasticity of cost in terms of cumulative adoption, from which it is straightforward to prove that $1 - 2^{-b}$(called the learning rate) is the percentage of the decrease in the cost when cumulative adoption doubles.

The learning effect denoted by Eq. (6.4) is assumed to be local, indicating that even when two producers make the same product, meaning that all attribute values are the same when counting the cumulative adoption of the products, it will be limited to each producer's own sales when Eq. (6.4) is applied to calculate the products' new costs.

Depreciation occurs in the possession of productive knowledge. If a producer does not produce anything in one step, the costs of all its products will increase by 10%.

Producers earn profits by implementing a price mark to each product they sell, which is 20% of the product's cost. For products with very low production costs (because of the learning effect introduced above), we assume a bottom price that is half that of the weighted sum of the product's attribute values; thus, the price of a product at step t can be denoted with Eq. (6.5):

$$p_t = MAX\left[(1 + 20\%)c_t, \frac{1}{2}\sum_i A_i\right], \tag{6.5}$$

where c_t denotes the product's cost at step t, and A_i denotes the value of the product's ith attribute.

At each step, each producer's profit will be added to its wealth.

R&D and Discovering New Products

At each step, producers spend 10% of the profits on R&D, which will increase producers' competencies and knowledge, enabling the discovery of new products. At each step, producers allocate an R&D budget to improve one attribute that is selected randomly, with a 0.3 probability that a new product will be discovered. The new product improves the selected attribute with a logistic function, denoted with Eq. (6.6):

$$y = \frac{1}{1 + e^{-\alpha(x-\theta)}}, \tag{6.6}$$

where y denotes the attribute value of the new product, x denotes the cumulative research budget on the attribute, α and θ are two design parameters, α controls the speed of increase of y with the increase of θ, and θ is the value where the curve has the largest slope. In the simulations, by trial and error, we set $\alpha = 0.5$ and $\theta = 100$; thus, it takes around 100 steps for 80% of consumer agents to adopt new products.

For a producer, its productive knowledge regarding previous products can spill over to new product development because the new product actually is an improved version of the previous one. If the new product improves on the previous one very slightly, its initial cost will be extremely similar to the cost of the previous one, and if it improves on the previous one considerably, then its initial cost will be higher than the cost of the previous one. The initial cost of the new product is defined with Eq. (6.7):

$$c_0^{j+1} = \left(\sum_i A_i^{j+1}\right)\left[a\prod_i\left(\frac{A_i^j}{A_i^{j+1}}\right)^2\right]^{-b}, \tag{6.7}$$

where c_0^{j+1} denotes the initial cost of the new product, A_i^{j+1} denotes the value of ith attribute of the new product, A_i^j denotes the value of the previous one, and a denotes the cumulative adoption of the previous product based on which the new type of product is developed.

If a producer does not have an R&D budget at a step (because of no sales in the previous step), there will be depreciation in the knowledge (i.e., the cumulative R&D budget in each attribute), and we assume a knowledge depreciation of 10%. With the depreciation of knowledge, when a producer is conducting R&D to discover new products again, it must cover the depreciated R&D before being able to discover new products.

Exit and Entry of Producers

A producer's initial wealth is 1, at each step, OM (operation and maintenance) cost and R&D budget reduce wealth, and the profit from selling products increases wealth. When a producer's wealth becomes negative, it exits the system.

At each step, it is possible that a new producer will enter the system. The more producers in the system, the higher the probability of new product entrance. At each step, the probability that a new producer will enter is calculated with Eq. (6.8):

$$probability_t = 0.011 M_t - 0.01, \tag{6.8}$$

where M_t denotes the existing number of producers at time step t, and $probability_t$. is the probability that a new producer will enter the system at time step t. With Eq. (6.8), the probability that a new producer will enter at a step is 0.1 when there are 10 existing producers and it is 0.001 when there is only 1 producer.

The new producer's initial product's attribute value is set randomly in the range (0,0.15), and its initial wealth is 1.

Consumer Agents

Social Influence among Consumer Agents

Suppose there are N consumers, and the number of consumers is constant. Consumer agents form a small-world social network which is generated through the following process (see Watts & Strogatz, 1998).

1. Construct a regular ring lattice, comprising a graph with N nodes (consumers), each connected to K (an even integer) neighbors, $K/2$ on each side.
2. For every node $n_i (i = 1, \cdots, N)$, take every edge (n_i, n_j) with $i < j$, and rewire it with probability β. Rewiring is conducted by replacing (n_i, n_k), where k is chosen from all possible values that avoid self-loops and link duplication with uniform probability.

In the simulation, we assume $K = 8$ and $\beta = 0.5$, indicating that each consumer agent has an average of eight neighbors.

Each consumer agent assigns different weights to the four (and later five) attributes. Weights are initialized randomly and are influenced by social neighbors. Each consumer agent has an independent factor for each attribute, ρ_i, indicating whether the consumer is easily influenced by neighbors. ρ_i is randomly set in the range (0, 1). For a consumer agent, suppose at time step t, its neighbors' average weight for an attribute is $\overline{w}_i^t$, then its weight before normalization for this attribute is calculated with Eq. (6.9):

$$w'^{t}_{i} = \rho_i w_i^{t-1} + (1 - \rho_i)\overline{w}_i^t. \tag{6.9}$$

Then, w'^{t}_{i} will be normalized with Eq. (6.10):

$$w_i^t = \frac{w'^{t}_{i}}{\sum_i w'^{t}_{i}}, \tag{6.10}$$

where w_i^t is the normalized weight for attribute i at time step t.

With peer effect 1, $\overline{w}_i^t$ in Eq. (6.9) is all direct neighbors' average weight, and with peer effect 2, $\overline{w}_i^t$ is the average weight of those neighbors whose weights are higher than the consumer's weight.

Consumers' Decision to Buy a Product

A consumer agent's utility for using a product is calculated as the weighted average of the product's four (and later five) attributes, as shown in Eq. (6.11):

$$u = \sum_i w_i^t A_i. \tag{6.11}$$

Each consumer agent has a utility threshold. Each consumer agent would like to buy a product at each step, but if all existing products' utilities are lower than the consumer's utility threshold, then the consumer will not buy any product. Consumers' threshold is initialized following a Weibull distribution. The shape parameter of the Weibull distribution is set to 3, the scale parameter is set to 0.5, and the location parameter is set to 0. Figure 6.12 illustrates the probability distribution of consumer agents' utility thresholds.

In addition to utility, price is another factor that will influence consumers' purchase decisions. Each consumer agent has a different sensitivity (or weight, which is randomly initialized) to price. At each step, a consumer will evaluate all the producers' products and buy the one that has the largest following value:

$$V = w_p(1 - p) + \left(1 - w_p\right)U \tag{6.12}$$

where w_p denotes the sensitivity to price, p is the price of a product (calculated as cost + profit markup), and U is the product's utility for the consumer.

In the beginning, consumer agents ignore the fifth attribute when evaluating products. After a certain step, consumer agents begin to consider it. Consumers' initial weights for the fifth attribute are quite small and also follow a Weibull distribution. The shape parameter of this Weibull distribution is set to 1, the scale parameter is set to 0.054, and the location parameter is set to 0. These parameter

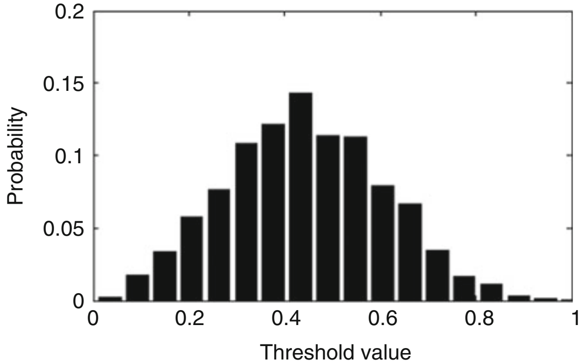
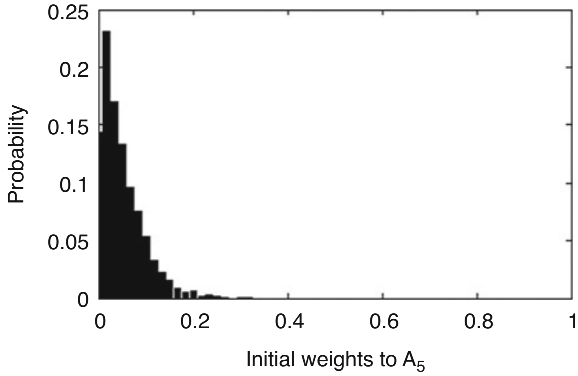


Fig. 6.12 The probability distribution of consumer agents' utility thresholds

Fig. 6.13 Consumers' initial weights for the fifth attribute



values are selected so that around 1% of consumer agents will give higher weights than the average (i.e., 0.2) to the fifth attribute, as shown in Fig. 6.13.

Educating Consumers to Be more Environmental-Friendly

After the fifth attribute is introduced, one of the measures for promoting the adoption of low emissions products is to educate consumers so that they increase their weights for the fifth attribute. At each step, each consumer's weight for the fifth attribute will increase with Eq. (6.13):

$$w'^{t+1}_5 = (1 + 0.01\mu) \cdot w^t_5, \tag{6.13}$$

where w'^{t+1}_5 is a consumer's weight (before normalization) for the fifth attribute at time step $t = 1$, w^t_5 is the consumer's weight for the fifth attribute at time step t, and μ is a random value in (0,1). w'^{t+1}_5 will be normalized with the weights for the other four attributes with Eq. (6.10).

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Chapter 7
Emotional Product Development: Concepts, Framework, and Methodologies

Hongbin Yan

7.1 Introduction

7.1.1 New Product Development

It is widely recognized that effective new product development (NPD) is strategically important in generating long-term organizations since NPD can lead to a core competence that either differentiates an organization from its competitors or provides a threshold competency that is necessary just to survive in fast-changing and innovative industry/service sectors. By definition, NPD could be conceived as "the transformation of a market opportunity and a set of assumptions about the product technology into a product available for sale" (Krishnan & Ulrich, 2001). The NPD process can be generally divided into two building blocks: fuzzy front end (FFE: from knowledge acquisition to idea generation) and back end (from concept definition to product-process engineering) (Yan & Ma, 2015a).

The most critical problem in NPD may be that organizations focus too much on product design and manufacturing but lack consideration and preparation in the market (Schneider & Hall, 2011). One typical example of unsuccessful NPD is the Facebook Phone launched in 2013, which failed to investigate market and consumer perspectives and thus was viewed as merely an Android-skinned device manufactured by HTC. Organizations are thus striving to design and develop products that best satisfy consumer needs at the stage of FFE, which tries to integrate the knowledge acquisition from marketing consumers into the idea generation phase by the engineering department. Such an endeavor definitely requires organizations to combine knowledge of engineering and marketing in the context of NPD, which is perhaps the most challenging and uncertain part of the entire NPD process.

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7.1.2 Emotional New Product Development

Nowadays, it becomes more and more important for organizations to have a consumer-oriented approach to improve the attractiveness of their products, which should not only satisfy the functional requirements of products, defined objectively, but also, the emotional needs, by essence subjective (Petiot & Yannou, 2004; Yan & Li, 2021). Consequently, it is strategically important for organizations to convey consumers' specific emotions to the new products, referred to as emotional product development or emotional product design since positive emotions usually lead to higher market sales.

The concept of emotion could be conceived as the feeling or reaction that people have to a certain event, i.e., a mental state of readiness that arises from cognitive appraisals of events or thoughts (Bagozzi et al., 1999). Consumers' emotional reactions toward products are subjective outcomes of the consumers' evaluation of the targeted products. The Japanese word "Kansei" is the feeling or impression sensitivity and some kinds of emotion (Ishihara et al., 1997), which is an individual subjective impression from a certain artifact, environment, or situation using all senses of sight, hearing, feeling, smell, taste, and sense of balance as well as their recognition (Grimsæth, 2005; Nagamachi, 1995; Schütte et al., 2004). Obviously, the term "Kansei" incorporates the meaning of the following words: sensitivity, sense, esthetics, feelings, emotions, affection, and intuition.

Although Kansei has a broader meaning than emotion, Kansei could be used to conceptualize emotion, since consumers' emotions could be measured by different methods and in terms of different aspects. For example, when seeing a laptop, a consumer uses the word "happy" to express his/her feeling. The consumer's emotional response may be caused by the "esthetics" aspects of the laptop. This means that the consumer's emotion is evoked by the evaluation and can be measured in terms of the "esthetics" aspects. One typical example may be Apple's iMac, which was heralded as an "esthetic revolution in computing," indicating that the esthetics of computers has become a key factor in purchase decisions (Postrel, 2001). In this sense, the term "emotion" will be measured by different aspects and conceptualized as "Kansei," referred to as emotional needs/attributes.

This chapter focuses on emotional product development at the FFE phase, aiming at integrating the emotional knowledge acquisition of marketing consumers into the emotional idea generation phase by the engineering department, i.e., conveying specific consumer emotions in the new products' physical (technical) attributes with a set of technical elements, to design and manage emotionally attractive products intentionally. In line with NPD, emotional product development could be conceived as the transformation of a market *emotional* opportunity and a set of *emotional* assumptions about the product technology into a product, which supports the emotional idea generation phase of the FFE innovation process.

7.1.3 The Concept of Product

It is necessary to clarify the perspective on products. The word "product" originates from the Latin word "productum," meaning the result or gain. During the industrial revolution, it becomes synonymous with industrially manufactured artifacts.

Nowadays, the expression also includes services. Similar to manufacturing a product composed of hundreds or thousands of components, services consist of hundreds or thousands of components; but, unlike a product, service components are often not physical entities, but rather a combination of processes, people skills, and materials that must be appropriately integrated to result in the "planned" or "designed" service (Goldstein et al., 2002). In this sense, artifacts can be connected with services, e.g., delivery and installation of a washing machine.

Originally, emotional product development only focuses on artifacts; recently, it has been employed in the community of new service design/development, where the characteristics of services have to be taken into account (Yan & Li, 2021). In this chapter, the concept of "product" refers to artifacts, services, or combinations, as shown in Fig. 7.1.

7.1.4 Motivations and Outline

The main motivations of this chapter are as follows: First, in the literature, different terminologies have been used in emotional product development, such as "emotion," "mood," "affect," "sensitivity," and "attitude," which may confuse readers to understand emotional product development. Moreover, there are different methodologies for emotional product development in the literature. For example, the Japanese methodology, Kansei engineering (Nagamachi, 2002), can be viewed as a quantitative one, whereas the emotion-driven innovation process (Alaniz & Biazzo, 2019) is in fact a qualitative one. The readers may be confused by the differences between these methodologies for emotional product development. Finally, nowadays emotional product development has received more and more interest in terms of different aspects in the literature, e.g., sensitivity analysis-based emotion extraction/analysis and integration of other models (e.g., Kano and QFD). Nevertheless, such studies only focus on some pieces of blocks related to emotional product development,

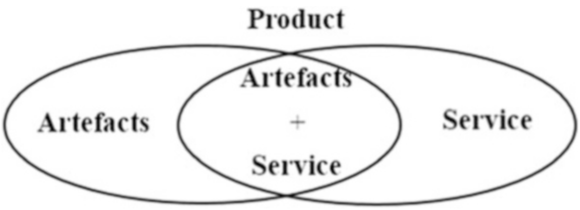

Fig. 7.1 Product definition used in emotional product development (Schütte et al., 2004)

which will confuse the readers to completely understand the essence of emotional product development.

Toward this end, this chapter tries to open up the black box of emotional product development to help readers have a better understanding of how to perform emotional product development in practice. The rest of this chapter is as follows: In Sect. 7.2, conceptualizations and measurements of emotion and Kansei will be discussed. In Sect. 7.3, the frameworks of emotional product development and Kansei engineering will be summarized from the literature. In Sect. 7.4, a physical–emotion–satisfaction framework will be proposed by integrating the Kansei engineering framework into the emotion-driven innovation process. In Sect. 7.5, this framework will be thoroughly discussed based on the recent advancements in emotional product development. Finally, this chapter is concluded with remarks in Sect. 7.6.

7.2 Emotion and Kansei: Conceptualization and Measurement

It is necessary and important to conceptualize what is emotion, since the terms “emotion,” “mood,” “affect,” “sensitivity,” and “attitude” have frequently been used inconsistently in the literature of marketing science and engineering design.

7.2.1 Conceptualization of Emotion

As summarized by Bagozzi et al. (1999), “affect could be viewed as an umbrella for a set of more specific mental processes including emotions, moods, and (possibly) attitudes. Thus, affect might be considered a general category for mental feeling processes, rather than a particular psychological process, per se.” Such a view is also shared by Yan and Li (2021).

The term, “emotion” is a very complicated and multidimensional characteristic reflecting the personality and behavioral traits of humans. By definition in Oxford Dictionary, emotion could be conceived as “A strong feeling deriving from one’s circumstances, mood, or relationships with others.” Moreover, American Psychological Association defines “emotion” as “A complex pattern of changes, including physiological arousal, feelings, cognitive processes, and behavioral reactions, made in response to a situation perceived to be personally significant.” Essentially, the term “emotion” is the feeling or reaction that people have to a certain event. For example, people could use the following words to express their feelings about certain events: “Happy,” “Sad,” “Angry,” and “Fear.”

Especially, the line between emotion and mood is frequently difficult to draw. The main differences between them may be as follows (Bagozzi et al., 1999). (1) A mood is often conceived as being longer lasting and lower in intensity than an emotion. (2) Emotion is typically intentional (i.e., it has an object or referent), whereas the moods are generally nonintentional and global or diffused. (3) The moods are not as directly coupled with action tendencies and explicit actions, which are the results of emotions.

Regarding the term "attitude," it is often considered as an instance of an affect, with the same measures used on occasion to indicate emotions and attitudes (e.g., pleasant–unpleasant, happy–sad, or interested–bored semantic differential items). By definition, Eagly and Chaiken (1993) view an attitude as "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor."

Two often replaceable terms are "emotion" and "sentiment." Nevertheless, sentiment represents a more general idea-polarity of emotion (i.e., positive, negative, or neutral). For example, if someone writes "I am angry," then it is understood that the emotion of a person is "angry" and the sentiment underlying the emotion is "negative." The research of sentiment analysis often uses sentiment to express a consumer's emotion.

In summary, in line with Bagozzi et al. (1999) and Ladhari et al. (2017), the concept of emotion is defined as the mental state of readiness arising from cognitive appraisals of events or thoughts; it has a phenomenological tone; it is accompanied by physiological processes; it is often expressed physically in terms of gestures, posture, and facial features; and it may result in specific actions to affirm or cope with the emotion, depending on its nature and meaning for the person having it.

7.2.2 Measurement of Emotion

There are different ways to measure emotion in the literature. In their seminal work, Bagozzi et al. (1999) indicate that emotions are accompanied by physiological processes and often expressed physically (e.g., in gestures, posture, and facial features).

The words are commonly used to measure emotions in the community of marketing science. On the one hand, most studies conceptualize emotions simply as discrete primary emotions such as "anger" or "happiness." On the other hand, Elfenbein (2007) suggests that cognition (appraisal) and emotion occur together in response to a stimulus. A recent review of emotions in organizations (Elfenbein, 2007) provides an overview of the psychology literature in this domain and attempts to move away from the difficulty of defining whether: (1) a stimulus causes emotions with subsequent cognitive attention to the stimulus or (2) the cognitive appraisal of a stimulus causes the emotions.

Barrett et al. (2007) suggest that to capture people's emotions, one should ask them to relate their experiences in their own words such as "powerless" or "discouraged." In line with this view, Rychalski and Hudson (2017) conceptualize emotions not simply as pure emotions, but based on a mix of cognitive appraisals and emotions, which are registered and felt by individuals subjectively. This view is shared by Barrett et al. (2007), who suggest that to capture the emotions of a person, one should ask them to relate their experience in their own words such as "powerless" or "discouraged."

7.2.3 Conceptualization and Measurement of Emotion as Kansei

Dahlgaard et al. (2008) indicate that Kansei engineering could be used to design and develop products/services that match consumers' emotional and psychological feelings and needs. The term "Kansei" is a Japanese word embedded in Japanese culture and there is no corresponding word in English. Several studies have investigated the conceptualization of Kansei in the literature (e.g., Grimsæth, 2005; Nagamachi, 1995; Schütte et al., 2004). One commonly used definition may be that the term "Kansei" corresponds to feeling or impression sensitivity and some kinds of emotion (Ishihara et al., 1997), which is an individual subjective impression from a certain artifact, environment, or situation using all senses of sight, hearing, feeling, smell, taste, and sense of balance as well as their recognition (Grimsæth, 2005, Nagamachi, 1995, Schütte et al., 2004). In essence, Kansei incorporates the meaning of the words: sensitivity, sense, esthetics, feelings, emotions, affection, and intuition, indicating that Kansei has a broader meaning than emotion.

A stimulus causes emotions with subsequent cognitive attention to the stimulus (Bagozzi et al., 1999). In the literature, there are different ways of measuring Kansei, such as words, physiological responses, people's behaviors and actions, people's facial expressions, and people's body expressions, which indicates that Kansei can also be viewed as accompanied by physiological processes and often expressed physically and may result in specific actions to affirm or cope with the emotions, depending on its nature and meaning for the person having it. It is thus reasonable to interchangeably use "emotion" and "Kansei" to express the subjective outcomes of a new product.

Despite the many different ways to measure Kansei, the most common way of measuring Kansei is through words, which are just external descriptions of the internal Kansei (emotions) within a human's mind (Grimsæth, 2005). This view is consistent with the measurement of emotions in the marketing community by Barrett et al. (2007), who suggest that to capture the emotions of a person, one should ask them to relate their experience in their own words. To differentiate positive emotions from negative emotions, bipolar pairs of Kansei words (referred to as emotional attributes/needs) are often used to represent persons' emotions.

7.3 Emotional Product Development and Kansei Engineering

7.3.1 The Emotion-Driven Innovation Process

Emotional product development aims at conveying specific consumer emotions in the new products. It could be a very complex challenge to generate products with significant emotional features since professionals responsible for designing and developing the new products should be facilitated with techniques and tools to understand consumer emotions. In this section, the so-called framework of emotion-driven innovation (Alaniz & Biazzo, 2019) will be borrowed to illustrate the following three phases: emotional knowledge acquisition, emotional goal definition, and emotional idea generation, as illustrated in Fig. 7.2.

7.3.1.1 Emotional Knowledge Acquisition

This phase aims at supporting the design/development team to create a panorama/dimension of emotions to work with the new product. Such a phase is particularly critical because, to generate emotion-focused new product ideas, professionals involved in the new product project should develop the competence of the new product from the view of emotional granularity. In practice, it is quite a complex challenge to generate products with significant emotional features, since professionals responsible for designing and developing new products should be facilitated with techniques and tools to understand emotions.

7.3.1.2 Emotional Goal Definition

As the core of the emotional development framework, this phase aims at defining the emotional intentions of the new product to be developed. It has been seriously challenged by the following two great difficulties. (1) How to make strategic decisions by selecting the specific emotions that the new product has to evoke;

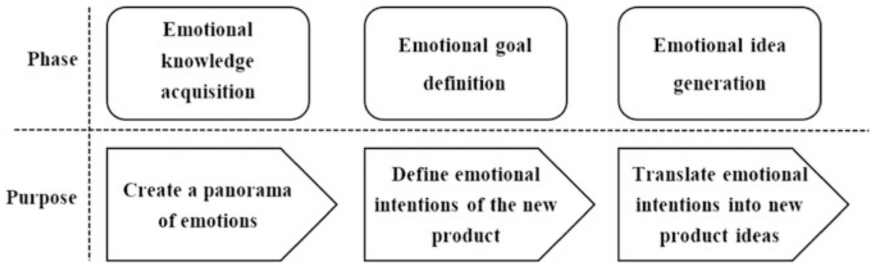

Fig. 7.2 The structure of emotion-driven innovation process (Alaniz & Biazzo, 2019)

such a task needs to quantify emotion and determine the emotional goal of the products to be developed. (2) How to transform the selected emotions into a product development briefly.

7.3.1.3 Emotional Idea Generation

The final phase of the emotion-driven innovation process focuses on translating consumers' emotional intentions into emotion-focused new product ideas, i.e., conveying specific emotions in the new products. Such a phase in fact will generate a set of emotional ideas but does not aim at generating a large number of emotional ideas. Instead, it focuses on delivering a few but strong and meaningful emotion-focused product ideas (thick ideas). The concept of "thick idea" is used here to refer to the product ideas that contain rich details on how the selected emotions will be evoked and make the new product more emotionally attractive.

7.3.1.4 Summary

The above emotion-driven innovation process proposed by Alaniz and Biazzo (2019) has been successfully illustrated by a case study of the visual design of the Filter Game. Nevertheless, such a process is qualitative, which leads us to consider a quantitative methodology for emotional product development.

7.3.2 Kansei Engineering as a Powerful Methodology for Emotional Product Development

As a consumer-oriented product development methodology, Kansei engineering tries to transfer a consumer's ambiguous image of a product into a detailed design (Nagamachi, 2002). In other words, it does not focus on the manufacturer's intention of the product, but rather on the consumers' psychological feelings and needs. Kansei engineering is also referred to as "sensory engineering" or "emotional usability" (Grimsæth, 2005). Since its inception in the 1970s, Kansei engineering has been successfully used in a wide range of physical products (artifacts), such as automotive (Nagamachi, 2002), industrial machinery (Grimsæth, 2005), and traditional crafts (Yan et al., 2017). Recent studies on service design prove that Kansei engineering has a much wider applicability (Yan & Li, 2021).

Kansei engineering is able to build the associated relationships between the physical attributes of products and the emotional needs of consumers (Grimsæth, 2005; Schütte et al., 2004), to convey consumers' specific emotions to the new products. It is thus possible to create a systematic procedure with Kansei (emotional) needs based on the Kansei engineering methodology, which can be generally

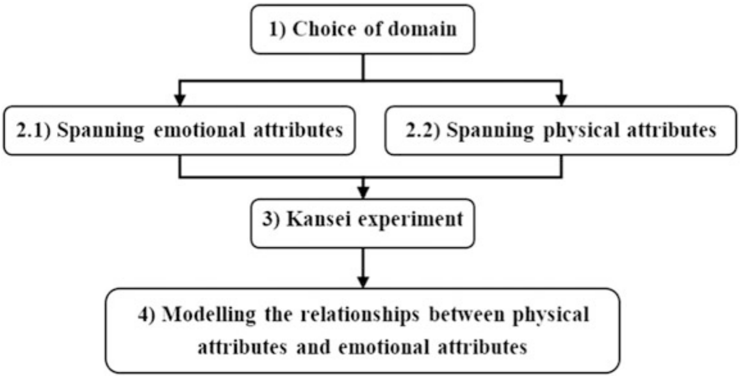

Fig. 7.3 Procedure of Kansei Engineering Methodology

divided into the following four phases: (1) Choice of the domain, (2) spanning attributes, (3) Kansei experiment, and (4) model building, as shown in Fig. 7.3 and described in great detail as follows.

7.3.2.1 Choice of the Domain

Choosing a product domain is usually conducted by selecting a target group, market, and specification of the new product. The product domain should include as many as possible representative concepts and potential solutions that not yet have been developed.

7.3.2.2 Spanning Attributes

Each emotional attribute is defined by a bipolar pair of Kansei words, which can be collected from all available sources including magazines, literature, manuals, experts, and experienced users (Grimsæth, 2005). It is also important to include words from ideas and visions so that potential new solutions may be included. Researchers then have to eliminate duplicate or similar words to find high-level words representing the product domain, by manual methods or statistical methods (e.g., Llinares & Page, 2007). Manual methods include affinity diagrams, designer's choice, and interviews, by which researchers can manually group and summarize the Kansei (Grimsæth, 2005). Statistical methods to eliminate duplicate or similar Kansei words include factor analysis, principal component analysis, cluster analysis, etc., which often need questionnaires to collect data from consumer groups (Grimsæth, 2005). Such a process of spanning emotional attributes is referred to as the "Collection–Selection–Compile" principle.

Similar to the case of emotional attributes, the process of spanning physical attributes is also based on the "Collection–Selection–Compile" principle, which consists of the following two steps (Schütte et al., 2004; Yan & Li, 2021): (1) physical attributes are first collected from technical documents, comparison of competing products/services, pertinent literature, manuals, experts, experienced users, and related Kansei studies and (2) a focus group is then asked to choose desired design attributes based on whether they have influences on emotional attributes.

7.3.2.3 Kansei Experiment

The methodology is based on a Kansei experiment to obtain people's Kansei, central to which is to choose a set of experimental stimuli. In the sector of artificial products, the stimuli are always represented as the product images, which can be easily collected in the marketplace such as websites, producers, catalogs, and magazines (Grimsæth, 2005; Schütte et al., 2004). As for the service sector, the experiment stimuli are always represented as service scenarios, which are derived from different combinations of the possible elements of physical attributes.

A questionnaire is then designed by the semantic differential method, which is currently considered the most powerful quantitative technique available for measuring emotions. The questionnaire consists of listing all the emotional attributes, each of which corresponds to a bipolar pair of Kansei words.

7.3.2.4 Relationship Modeling

The final phase aims at building the relationships between physical attributes and Kansei (emotional) attributes. This phase tries to provide a quantitative method to generate potential emotional ideas so as to convey specific emotions in the new product.

7.3.2.5 Summary

In summary, the processes of spanning physical and Kansei attributes, as well as the Kansei experiment, play the role of acquiring emotional knowledge. The process of modeling the relationships between the physical attributes and the Kansei (emotional) attributes serves the role of generating emotional ideas through quantitative approaches.

7.4 A Physical–Emotion–Satisfaction Framework for Emotional Product Development

Although Kansei engineering can build the relationships between physical attributes and emotional attributes to convey consumers' emotions into the physical elements of the new products, it misses the critical phase of emotional goal definition. In other words, Kansei engineering views emotional knowledge as the goal of emotional product development. This means that the generated emotional idea may be suitable to all organizations in the relevant markets, i.e., all the organizations can use the same solution to improve and/or design their new products. As is well-known, different organizations should have different characteristics and problems. It is essential for the targeted organization to know its strengths and constraints in all emotional aspects of the new product and to compare it with its main competitors.

Moreover, since its inception in the 1970s, Kansei engineering has been widely utilized and revised in terms of different aspects, such as sensitivity analysis-based Kansei engineering, consumer-oriented Kansei evaluation, and integration of the Kano model into Kansei engineering. Nevertheless, such studies only focus on some pieces of blocks related to Kansei engineering or emotional product development, which will confuse the readers to completely understand the recent advancements of Kansei engineering for emotional product development.

Finally, the emotion-driven innovation process (Alaniz & Biazzo, 2019) is qualitative, whereas Kansei engineering is a quantitative methodology. It may be important to integrate these two types of methodologies to have a better understanding of emotional product development. In the sequel, a framework of emotional product development based on the physical–emotion–satisfaction link will be proposed.

7.4.1 The Physical–Emotion Link

The concept of the emotional product plays a key role in product design and development, not only as a core element of the physical design process but also as a means of "concretizing" the nature of the product. The concept of emotional product could be viewed as the emotional prototype for the new product and defined as the "detailed emotional description of what is to be done for the consumer (what emotional needs and wishes are to be satisfied, referred to as WHAT) and how this is to be achieved in terms of physical attributes with a set of design elements (referred to as HOW)."

In emotional product development, the physical attributes trigger emotions and elicit various meanings that extend the use of products for consumers. Thus, the emotional product development indicates that the concept of emotional product not only defines the "WHAT" in terms of emotional needs and the "HOW" in terms of physical attributes, but also ensures the integration between the “WHAT” and the “HOW.”

Such a WHAT–HOW approach is indeed rooted in the marketing-operations strategy. For example, in his seminal work, Heskett (1987) describes the strategic service vision, which consists of identifying a target market segment, developing a service concept to address targeted consumers’ needs, codifying an operating strategy to support the service concept, and designing a service delivery system to support the operating strategy. Lovelock et al. (1999) separate the “service marketing concept” as the benefits to the consumer (i.e., the “WHAT”) and the “service operations concept” as the specification of how the service will be delivered.

With the WHAT–HOW approach, the physical–emotion link for emotional product development could be constructed. In Kansei engineering, such a link is usually built in the phase of spanning physical and Kansei (emotional) attributes.

7.4.2 The Emotion–Satisfaction Link

In the marketing community, it is known that a higher level of consumer satisfaction ultimately leads to a greater consumer loyalty and word-of-mouth recommendations. Previous studies argue that satisfaction judgments are comprised of both cognitive and emotional elements (Bagozzi et al., 1999). Theoretically, the cognitive appraisal theory of emotions stresses that the appraisal of a situation (subjective evaluation of the outcome of product/service usage) causes an emotional response. In other words, emotions are evoked by the evaluation of a specific event (Ladhari et al., 2017). In line with Bagozzi et al. (1999), satisfaction is conceptualized as an evaluative judgment that includes an emotional dimension in this chapter.

Perceived product quality is defined as the evaluation of a specific product, resulting from the comparison of that product’s performance with the consumer’s expectations of how organizations in that industry/service sector should perform. This chapter conceptualizes emotions in terms of bipolar pairs of Kansei words. In this sense, perceived product quality is defined as the cognitive evaluation of the targeted product in terms of emotional attributes/needs, which are expressed with bipolar pairs of Kansei words. Usually, it is necessary to recognize how subjective outcomes (the emotions and the feelings) shape how consumers perceive their product experiences. The above phenomena are referred to as the emotion–satisfaction link in emotional product development.

7.4.3 The Proposed Framework

With the above physical–emotion and emotion–satisfaction links, a comprehensive framework of emotional product development could be formulated by integrating the following three phases of the emotion-driven innovation process: emotional

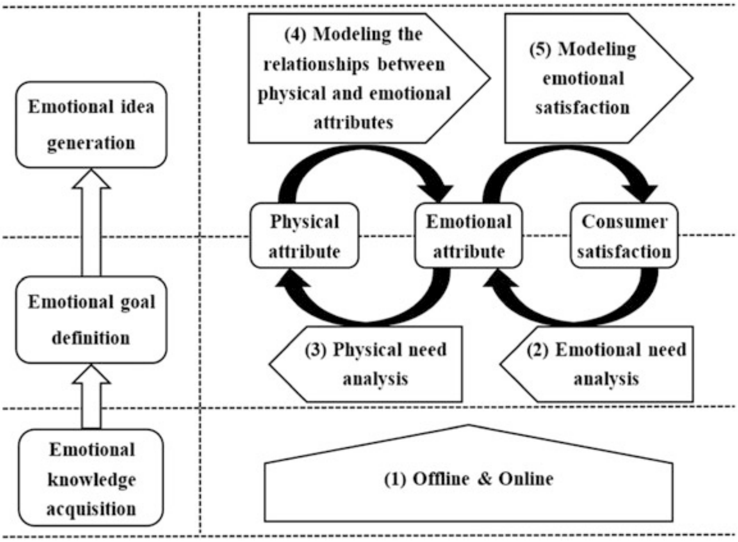

Fig. 7.4 Emotional innovation process based on physical–emotion–satisfaction link

knowledge acquisition, emotional goal definition, and emotional idea generation, as shown in Fig. 7.4. Such a framework consists of two dimensions in terms of three phases of the emotion-driven innovation process and the physical–emotion–satisfaction link.

In the phase of emotional knowledge acquisition, traditional experiment-based methods (referred to as offline) and big data-driven methods (referred to as online) are used to obtain consumers' emotional needs and products' physical attributes with a set of elements. The phase of emotional goal definition is carried out by two tasks: emotional need analysis and physical need analysis. The phase of emotional idea generation is performed by two tasks: modeling the relationships between physical attributes and emotional attributes as well as the ones between emotional attributes and consumer overall satisfaction.

Accordingly, once having acquired the emotional knowledge of the targeted product, the proposed framework of the emotional innovation process is a closed-loop process, it starts with consumer emotional need analysis and ends at best satisfying consumers' emotional needs. In the sequel, this framework will be thoroughly discussed based on the recent advancements in emotional product development.

7.5 Detailed Descriptions of the Physical–Emotion–Satisfaction Framework

7.5.1 Emotional Knowledge Acquisition

The first phase of emotional product development is how to acquire emotional knowledge, which helps professionals involved in the new product project develop the competence of the new product from the view of emotional granularity. The process of emotional knowledge consists of the attribute spanning process and the emotion evaluation data collection process. Here two types of methodologies will be introduced, namely offline and online.

7.5.1.1 Offline Acquisition

Traditionally, the process of spanning physical and emotional attributes is conducted by the "Collection–Selection–Compile" principle, which is a burdensome task for the researchers. Then, an emotional (Kansei) experiment must be conducted to obtain people's emotions toward the targeted products (also referred to as a set of experiment stimuli).

Despite its wide application and efficiency in obtaining consumers' emotional knowledge, such an offline process is still critically challenged by the use of surveys or focus group interviews to gather and identify emotional attributes and emotional evaluation data during the initial procedures of emotional product development. Such a procedure is usually costly, time-consuming, and labor-intensive to use, and the size of the available data set is usually on a small scale.

A typical example may be the work of utilizing Kansei engineering to evaluate subjective real estate consumer preferences in Spain (Llinares & Page, 2007). In their work, the set of stimuli used to develop the field study consists of 112 images of properties. The questionnaire contains 60 adjectives for describing the emotional response of users and professionals in the sector to the city's supply of real estate. A previous pilot study has shown that an interviewee could only reply to a maximum of three questionnaires before losing interest; therefore, each subject evaluates only three stimuli.

In addition, due to the high industry competition and the product customization trend, more and more products are launched to the market in a very short period. Conversely, the number of new products is rapidly increasing and consumer preferences may change from time to time. Finally, the respondents in the Kansei experiments may not be the real consumers of the target products. In this sense, it is possible to acquire emotional knowledge through online methodologies, as introduced later.

7.5.1.2 Online Acquisition

Recently, contemporary consumers are accustomed to sharing their experiences regarding the use of products/services by reviews via the Internet platform including forums, blogs, wikis, social networks, and other web resources. Sentiment analysis, also referred to as opinion mining, is the task of extracting and analyzing people's opinions, sentiments, attitudes, perceptions, etc., toward different entities such as topics, products, and services.

Essentially, consumer online reviews often capture direct, real-time, and honest emotional expressions regarding product/service usage experiences (Liu, 2015). It is thus natural to extract emotional knowledge from online reviews with the help of sentiment analysis, to provide organizations with real-time, direct, and rapid data-driven decision support for emotional product development. Especially, the aspect-level sentiment analysis can obtain more fine-grained results, which could be utilized in emotional product development; the process of which is shown in Fig. 7.5. For a detailed review of aspect-level sentiment analysis from the perspective of emotional product development, the readers may refer to Yan and Li (2022).

With the help of sentiment analysis, some researchers try to extract emotional attributes from online reviews. For instance, Hsiao et al. (2017) have proposed logistics service design for cross-border E-commerce by using Kansei engineering with text-mining-based online content analysis. Chiu and Lin (2018) have utilized text mining and Kansei engineering to support data-driven design automation at the conceptual design stage. Wang et al. (2018) have proposed a Kansei text mining approach to automatically extract and summarize product features and their corresponding affective responses based on online product descriptions and consumer reviews.

However, many of them mainly focus on polarity classification, determining whether the text expresses a positive or negative (or neutral) opinion, which lost the specifics of emotions the text delivered and may thus be insufficient for emotional product development. Thus, Wang et al. (2019) have proposed a heuristic deep learning method to extract emotional opinions from consumer product reviews and then classify them into pairs of emotional words. Kim et al. (2019) have applied a self-organizing map to cluster the collected opinion words and detected 15 categories of affective variables. Li et al. (2020) have clustered adjectives and adverbs into 4 pairs of affective attributes and 5 categories of affective degrees, respectively, and modeled the relationship between review texts and affective responses through regression models.

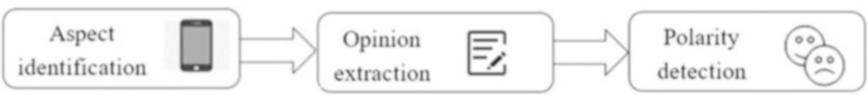

Fig. 7.5 Three phases of aspect-level sentiment analysis (Yan & Li, 2022)

7.5.2 Emotional Goal Definition

With the emotional knowledge acquired, this part aims at answering the following two questions: (1) How to make strategic decisions by selecting the specific emotions that the new product has to evoke, referred to as emotional need analysis. Such a task needs to quantify emotion and determine the emotional goal of the products to be developed. (2) How to transform the selected emotions into a product development briefly, referred to as physical need analysis.

7.5.2.1 Emotional Need Analysis

Generally, the main goal of emotional need analysis is to determine which emotional needs should be considered with higher priorities by the design team for designing and developing the new product. Essentially, the emotional needs in terms of bipolar pairs of Kansei words are obtained from the marketing department, by either offline or online methodologies, which creates the possibility of using marketing methods to analyze the emotional needs. The emotional need analysis may be conducted with the help of the Kano model. The Kano model is an effective tool for understanding consumer preferences, due to its convenience in classifying consumer needs (Kano et al., 1984). Interested readers may refer to Berger et al. (1993) for complete reviews of the Kano model. Here, a brief introduction to the Kano model will be first summarized since it will be used in later parts.

7.5.2.1.1 Brief Introduction to Kano Model

The Kano model (Berger et al., 1993; Kano et al., 1984) classifies consumer needs into six categories: A (Attractive), O (One-dimensional), M (Must-be), I (Indifference), R (Reverse), and Q (Questionable). Figure 7.6 shows the conceptual model of Kano's two-dimensional quality theory.

The A, O, and M types of consumer needs are often used in most studies by removing the types of I, R, and Q elements, as explained as follows.

- Attractive needs (A): Fulfillment of attractive attributes results in a higher level of satisfaction. However, the absence of these needs does not lead to great dissatisfaction, as they are not assumed by consumers.
- Must-be needs (M): Fulfillment of must-be attributes is taken for granted by consumers. However, if they are not fulfilled by must-be attributes, consumers will be very displeased.
- One-dimensional needs (O): One-dimensional needs lead to satisfaction if performance is high and to dissatisfaction if performance is low.

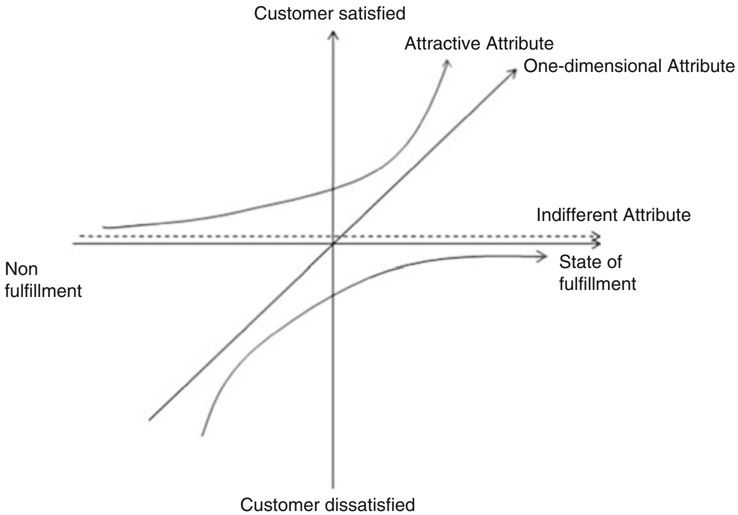

Fig. 7.6 Kano's two-dimensional quality theory: Conceptual model

7.5.2.1.2 Offline Emotional Need Analysis

In the Kano model, the categorizations of consumer needs are identified via a specially designed questionnaire that contains a pair of questions for each characteristic. The question pair includes one functional and one dysfunctional form of the same question. The functional form captures a consumer's reaction if the product/service has a certain characteristic. Conversely, the dysfunctional form describes the consumer's reaction if the product/service does not have that characteristic. The pair of questions may be "If this product/service has this function, how you feel?" and "If this product/service does not have this function, how you feel?"

In Kansei engineering, the function is expressed in terms of a bipolar pair of Kansei words. Thus, the questionnaire will be expressed as "If the product is left Kansei word, how you feel?" and "If the product is right Kansei word, how you feel?" Both forms of the question include five different response options for the consumer to choose from, as shown in Table 7.1. The Kano questionnaire is then distributed to a number of consumers to obtain their feelings for each emotional attribute in terms of left Kansei and right Kansei questions, respectively.

Used together, the answers to both questions provide an understanding of the Kano category for each emotional attribute, as shown in Table 7.2. For example, if a consumer's answer to the right Kansei form of the question is "I like the right Kansei," and her/his answer to the left Kansei form of the question is "I dislike the left Kansei," then the particular Kansei attribute is O type according to the Kano categorization rules. Recently, Yan and Li (2021) have proposed an uncertain Kansei engineering methodology for behavioral service design, where the Kano model is used to screen and weight Kansei/emotional attributes. In this way, the prioritization of emotional attributes could be derived.

Table 7.1 Emotional Kano model: Questionnaire

Kansei Attributes	Bipolar Kansei Words	Assessments				
		S_1: Like	S_2: Must-be	S_3: Neutral	S_4: Live-with	S_5: Dislike
Y_1	Left Kansei: kw_1^-	□	□	□	□	□
	Right Kansei: kw_1^+	□	□	□	□	□
Y_2	Left Kansei: kw_2^-	□	□	□	□	□
	Right Kansei: kw_2^+	□	□	□	□	□
⋮	⋮	⋮	⋮	⋮	⋮	⋮
Y_J	Left Kansei: kw_J^-	□	□	□	□	□
	Right Kansei: kw_J^+	□	□	□	□	□

Table 7.2 Kansei Kano model: Categorization rules

Kansei attribute Y_j		Left Kansei: kw_j^-				
		S_1: Like	S_2: Must-be	S_3: Neutral	S_4: Live-with	S_5: Dislike
Right Kansei: kw_j^+	S_1: Like	Q	A	A	A	O
	S_2: Must-be	R	I	I	I	M
	S_3: Neutral	R	I	I	I	M
	S_4: Live-with	R	I	I	I	M
	S_5: Dislike	R	R	R	R	Q

7.5.2.1.3 Online Emotional Need Analysis

With the help of sentiment analysis, some researchers try to perform emotional need analysis based on the Kano model. For instance, Xiao et al. (2016) have analyzed product online reviews for preference measurement based on a modified ordered choice model and a marginal effect-based Kano model, where product features and the reviewers' sentiment orientations (like or dislike) toward them are extracted from online product reviews. Qi et al. (2016) have developed a product improvement strategy from online reviews to classify product features using the conjoint analysis model and Kano model, where sentiment polarities are used to represent consumers' utilities toward products.

7.5.2.2 Physical Need Analysis

The emotional needs are generally obtained by the marketing department, and the output of this is a list of qualitative emotional attributes such as <Uncomfortable, Comfortable> and < Ugly, Beautiful > for a mobile phone. Conversely, physical attributes trigger emotions and elicit various meanings that extend the use of products. The design team has to make the product specifications satisfy what the consumers really want. The design specifications are based on physical attributes with a set of elements, which is with a quantitative nature, such as "color," "weight," and "shape" for a mobile phone. A conflict between marketing and engineering departments may arise, as they speak different languages.

Moreover, with the WHAT–HOW approach, an emotional product can be deconstructed into the emotional needs and the physical attributes or into its components/elements, allowing product designers to identify various elements of a product concept, check them against consumer emotional needs, and then design and deliver those elements. It is impossible for the design team to consider all the physical attributes due to the constraints on time, budget, or feasible facilities and so on. The design team then needs to make trade-offs while selecting the physical attributes based on their relative impacts on consumer emotional attributes to achieve greater consumer satisfaction, which needs to prioritize the physical attributes.

7.5.2.2.1 Brief Introduction to QFD Model

To perform a quantitative analysis of physical needs, one possible solution may be with the help of the quality function deployment (QFD) model. QFD is one of the very effective consumer-driven quality system tools typically applied to fulfill consumer needs and, more importantly, to improve consumer satisfaction. As defined by Akao (1990), QFD is "a method for developing a design quality aimed at satisfying the consumer and then translating the consumers' needs into design targets and major quality assurance points to be used throughout the production stage." The first stage of QFD, also known as the house of quality (HOQ), is of fundamental and strategic importance. Moreover, the service QFD has been tailored to the employment of the product QFD model (Akao, 1990) in service development, where the characteristics of services have to be taken into account. For example, Yan et al. (2019) have proposed an uncertain target-oriented QFD approach to service design based on service standardization with an application to bank window service.

A full HOQ can consist of as many as 18 elements or concepts (Yan & Ma, 2015b): consumers, WHATs, structuring WHATs, correlation matrix of WHATs, relative importance ratings of WHATs, competitors, competitor assessments, goals for WHATs, sales-point, final importance ratings of WHATs, HOWs, correlation matrix of HOWs, relationship matrix of WHATs vs. HOWs, improving directions of HOWs, technical competitor assessment, goals for HOWs, probability factors, and importance ratings of HOWs. Due to the high difficulty of implementing a HOQ in practice, it is both difficult and unnecessary to include all the eighteen HOQ elements described above. In fact, different users build different HOQ models involving different elements from the above list. The simplest but widely used HOQ model contains only the consumers, the WHATs and their relative importance, HOWs and their relationships with the WHATs, and the importance weights of the HOWs.

When adapted to emotional product development for translating consumers' emotional needs to physical attributes, a revised simple framework is shown in Table 7.3, where the output is the prioritization of all the physical attributes. In

Table 7.3 A simple but widely used QFD framework for emotional product development

Emotional attributes (WHATs)		Physical attributes (HOWs)			
		X_1	X_2	$\cdots$	X_N
Y_1	WY_1	x_{11}	x_{12}	$\cdots$	x_{1N}
Y_2	WY_2	x_{21}	x_{22}	$\cdots$	x_{2N}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
Y_M	WY_M	x_{M1}	x_{M2}	$\cdots$	x_{MN}
		WX_1	WX_2	$\cdots$	WX_N

Table 7.3, an emotional attribute is denoted as Y_m with an importance weight WY_{m}; the relationship between an emotional attribute Y_m and physical attribute X_m is denoted by x_{mn}; the derived priority of physical attribute X_n is expressed as WX_n.

7.5.2.2.2 Physical Need Analysis Based on QFD Model

The QFD model has been widely used in emotional product development. For example, in the context of online reviews, Jin et al. (2015) have proposed a probabilistic language analysis approach to data-driven QFD to link online review sentences with the product design attributes, the implementation of which invokes a deeper understanding of consumer preferences on product features.

Recently, Xu et al. (2022) have integrated data-driven and competitive analysis into QFD for emotional product development. Methodologically, an uncertain online QFD model is proposed based on a sentimental analysis of online reviews. On the one hand, the relationships between consumer needs and technical characteristics are built by the dictionary-based machining learning approaches. On the other hand, the competitive analysis of consumer needs is based on the satisfactory-oriented decision principle, by setting competitors' uncertain performance as targets. An empirical study on three competing mobile phones is conducted to illustrate the efficiency of the proposed models.

7.5.3 Emotional Idea Generation

Central to emotional product development are the relationships among various variables used in the analysis, i.e., the relationships between physical attributes and emotional attributes as well as the ones between emotional attributes and consumer overall satisfaction.

7.5.3.1 Modeling the Relationships Between Emotional and Physical Attributes

Researchers have generally used linear regression models to build the relationships between physical attributes and emotional attributes, which is often achieved with the help of the (Partial) Least Square (PLS) method by minimizing the squared prediction error. Recent research has shown that there exist nonlinearities of Kansei evaluation data, i.e., nonlinear relationships between physical attributes and emotional attributes. Alternatively, there are several nonlinear methods that can be used to analyze emotions. Among these are genetic algorithms, neural networks, and artificial neural networks.

In addition, based on the explanation of the uncertain NPD process (Yan & Ma, 2015b), emotional product development should be an uncertain process due to the following reasons: (1) at the time of the decision, usually only uncertain and incomplete information is available; (2) the competitive environment is marked by uncertainty and rapid changes in technologies and markets; (3) the emotional attributes are always qualitative in nature; and (4) multiple subjects, each with a different perspective, are involved in the process of Kansei experiment.

The accurate relationships may thus be inflexible and inefficient in most cases. Rough set theory has been used to model the uncertain relationships between physical attributes and emotional attributes. However, the Kansei ratings are preferably made on a three-point scale, the interpretation becomes more complex with more grades for each dependent variable (Grimsæth, 2005). Fuzzy set theory is also used, which needs the definition of fuzzy numbers. Recently, Yan and Li (2021) have utilized multinomial logistic regression to build the uncertain and nonlinear relationships between physical attributes and emotional attributes.

7.5.3.2 Modeling the Relationships Between Emotional Attributes and Satisfaction

With the increasing of emotional products, it may become more and more important and quite difficult for consumers to choose their preferred products. The consumer-oriented Kansei/emotional evaluation (Huynh et al., 2010; Yan et al., 2008; Yan et al., 2012; Yan et al., 2017) regards Kansei as one aspect of the quality of products and focuses on the evaluation of existing commercial products based on consumers' emotional preferences.

Accordingly, the consumer-oriented Kansei evaluation may provide decision support to consumers for selecting products based on their emotional preferences and thus would be helpful for marketing or recommendation purposes, particularly important in the era of e-commerce, where recommender systems have become an important research area. On the other hand, in the era of e-commerce, consumers' emotional preferences and preferred products may be discovered from the navigation history with the help of recommender systems. In this sense, by integrating the relationships between physical attributes with a set of design elements and emotional attributes, consumer-oriented Kansei evaluation may provide a decision support for emotional product development, since designers are able to design new products that best satisfy consumers' emotional preferences.

7.5.3.2.1 Decision Analysis Approaches

Individual Emotional Satisfaction

Marketing scholars have studied the effects of emotions on satisfaction in hedonic and utilitarian settings. On the one hand, the positive asymmetric effect of delight on satisfaction is well-established in hedonic settings, where consumers attribute higher weight to positive than negative emotions in their decisions when a product or service exceeds expectations in a surprising and pleasant way (Falk et al., 2010). Positive asymmetry means that the presence of the "delightful" attribute increases satisfaction more than its absence decreases them. Rychalski and Hudson (2017) find positive asymmetries for utilitarian services, but for different, lower arousal emotions than delight. On the other hand, the negative asymmetry in the emotions–satisfaction link also exists. Here, a decrease in emotional quality has a larger negative effect than the positive effect of the same amount of increase in emotional quality.

From the perspective of the Kano model (Kano et al., 1984), as briefly introduced in Sect. 7.5.2.1, the satisfaction function curves of different categories shape in different ways: the A (Attractive) and M (Must-be) types of attributes follow an exponential curve, while the O (One-dimensional) type of attributes follows a linear curve. It is reasonable to model the nonlinear and asymmetric satisfaction functions of emotional/Kansei attributes in terms of the Kano model. Recently, Yan and Li (2021) have proposed a quantitative Kano model to model the asymmetric and nonlinear satisfaction functions reflecting the "gains and losses" effects of positive emotions and negative emotions. Figure 7.7 illustrates the satisfaction functions of three emotional needs (Y_1 <Inconvenient, Convenient>, Y_7 <Traditional, Modern>, and Y_8 <Unsafe, Safe>) in a package delivery service problem.

Multi-Attribute Emotional Satisfaction

The multi-attribute nature of consumers' emotions has led many researchers to study emotional evaluation from the perspective of multi-attribute decision-making. Emotional needs are often expressed in terms of bipolar pairs of Kansei words, i.e., negative-positive pairs of words. Due to the asymmetric nature of individual emotional quality on satisfaction, the satisfaction function of each emotional attribute may be divided into two parts: positive satisfactions and negative dissatisfactions.

Empirical studies (Falk et al., 2010; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) have found that the typical decision maker may value equal magnitudes relative to a reference point differently, depending on whether they are

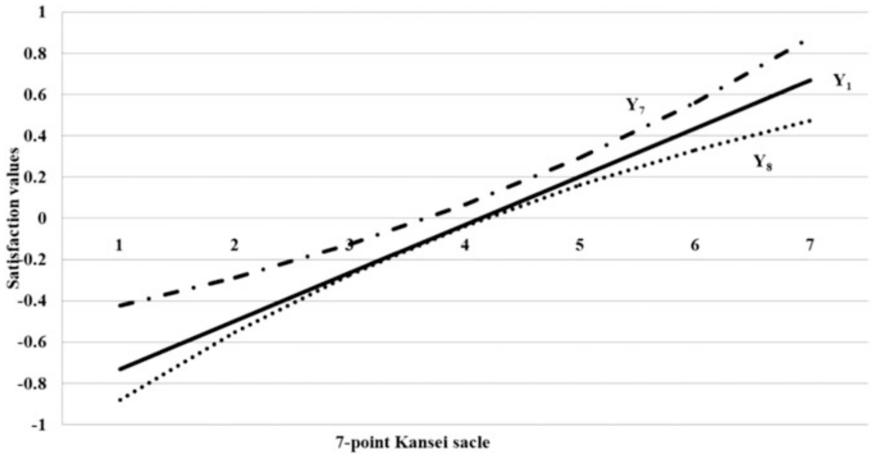

Fig. 7.7 The satisfaction functions of three emotional attributes (Yan & Li, 2021)

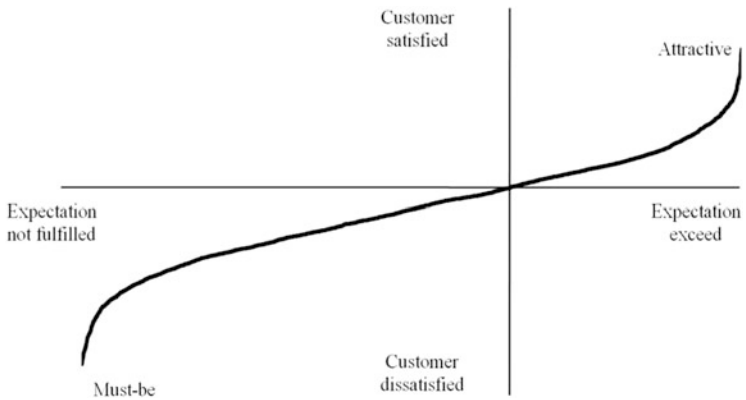

Fig. 7.8 The overall satisfaction function of delivery service (Yan & Li, 2021)

categorized as "gains" or "losses" relative to the reference point. Later, Homburg et al. (2006) proposed that a one-unit decrease in consumer attribute satisfaction has a larger impact on overall satisfaction than an equal amount of satisfaction increase in the same attribute. It is thus necessary to derive the overall emotional satisfaction by distinguishing the positive satisfactions and negative dissatisfactions, separately.

In their pioneering work of behavioral service design based on uncertain Kansei engineering, Yan and Li (2021) have utilized the Prospect Theory to derive consumer overall satisfaction by distinguishing the "gains and losses." Figure 7.8 shows the overall satisfaction function of the delivery service, which is consistent with the cubic response functions with dual thresholds proposed by Finn (2011). Obviously, it combines the decreasing dissatisfactions of the M type of emotional attributes with the increasing satisfactions of the A type of emotional attributes.

There are also some other approaches to consumer-oriented Kansei evaluation. For example, Yan et al. (2008) have proposed a prioritized multi-attribute fuzzy target-oriented decision analysis approach to model the consumers' preferences on Kansei attributes and the prioritization of Kansei targets. Yan et al. (2012) have proposed a group nonadditive multi-attribute consumer-oriented Kansei evaluation model with an application to traditional crafts to quantify mutual dependence among multiple Kansei preferences. Recently, Yan et al. (2017) proposed a stochastic dominance-based approach to consumer-oriented Kansei evaluation with multiple priorities, to eliminate the burden of quantifying consumers' Kansei preferences in terms of fuzzy set.

7.5.3.2.2 Statistical Approaches

In addition to the decision analysis approaches to modeling the relationships between emotional attributes and consumer overall satisfaction, the statistical approaches have been also widely used in the emotion–satisfaction link.

For example, Llinares and Page (2007) have used the PLS method to predict the influence of consumers' emotions on consumer overall satisfaction based on the Kano model. Recently, Rychalski and Hudson (2017) have utilized regression analysis to capture the relationships between negative–positive emotions and consumer overall satisfaction and found positive asymmetries for utilitarian services, but for different, lower arousal emotions than delight.

7.6 Conclusions and Future Work

7.6.1 Summary

The research on emotional product development has made significant efforts to demonstrate the value of emotional knowledge in NPD practices. In this chapter, after conceptualizing and measuring emotion in terms of Kansei, the emotion-driven innovation process and Kansei engineering were summarized from the literature to illustrate the existing frameworks for emotional product development. A physical–emotion–satisfaction link-based framework is proposed for emotional product development, which combines the qualitative emotion-driven innovation process and quantitative Kansei engineering methodology.

The proposed framework consists of three phases. First, there are two types of approaches to emotional knowledge acquisition: traditional offline approaches and emerging sensitivity analysis-based online approaches. Especially, the online approaches may provide organizations with real-time, direct, and rapid data-driven decision support for emotional product development. Moreover, in the phase of emotional goal definition, on the one hand, the Kano model is revised to be integrated into emotional product development to answer the following question:

How to make strategic decisions by selecting the specific emotions that the new product has to evoke, either for offline or online emotional knowledge? On the other hand, the QFD has been adapted to emotional product development to answer the following question: How to transform the selected emotions into a product development briefly, either for offline or online emotional knowledge? Finally, in the phase of emotional idea generation, on the one hand, the nonlinear and uncertain relationships between emotional and physical attributes have been especially highlighted, where the multinomial logistic regression approach seems to be the most suitable one. On the other hand, decision analysis and statistical approaches are often used to model the relationships between emotional attributes and consumer overall satisfaction. Especially, the nonlinear and asymmetric impacts of negative and positive emotions on consumer satisfaction are discussed based on the Prospect Theory and quantitative Kano model. In summary, the proposed framework is a closed-loop process, starting with consumer emotional need analysis and ending at best satisfying consumers' emotional needs.

Generally, this chapter can help readers completely and thoroughly understand emotional product development in terms of three aspects. First, the readers can eliminate the confusion of different terminologies used in emotional product development. For example, the term "Kansei" is often used in Japan and Korea, whereas emotional product development is often emphasized in America and Europe. Moreover, the readers can have a better understanding of the qualitative and quantitative methodologies for emotional product development. Finally, based on the proposed framework with its detailed descriptions, the readers will open up the black box of the three detailed phases of emotional product development.

7.6.2 Future Research Directions

It is obvious that the research within the framework of the physical–emotion–satisfaction link-based emotion-driven innovation process has made significant efforts to promote the development of emotional product development. Nevertheless, there are still several research directions to be thoroughly investigated in the future.

When emotional knowledge is acquired by the offline way, most studies focus on some pieces of blocks within the physical–emotion–satisfaction link-based emotion-driven innovation process, rather than the whole closed-loop process; with the exception of the recent uncertain behavioral service design (Yan & Li, 2021). Such phenomena may be due to the fact that in practice it is time-consuming and complex to utilize the closed-loop process for emotional product development. However, to precisely convey consumers' specific emotions into the new products in practice, a thorough investigation of the closed-loop process is still left for future work.

The challenge of applying the whole closed-loop process in practice is in fact due to the offline way of emotional knowledge acquisition. With the rapid development of sentiment analysis, it is possible to consider online reviews driven emotional product development within the closed-loop process, which may provide organizations with real-time, direct, and rapid decision support as well as greater flexibility and self-improvement mechanism. In fact, several studies have made efforts to investigate some pieces of blocks within the physical–emotion–satisfaction link-based emotion-driven innovation process. Recently, Yan and Li (2022) have conducted a comprehensive review of sentiment analysis from the view of emotional product development, to build a link between sentiment analysis and emotional product development. Nevertheless, the investigation of online reviews driven emotional product development is just at the beginning stage, where several research questions need to be thoroughly investigated.

First, although many different techniques and approaches are proposed in sentiment analysis, most of them focus on sentiment analysis itself; but not from the view of emotional product development, the readers may refer to Yan and Li (2022) for detailed discussions. For example, these studies try to extract product features by mixing product technical features and consumers' emotional perceptions. Therefore, suitable techniques and approaches for emotional product development need to be further investigated.

Moreover, in online reviews, although many consumers can provide their emotional expressions toward products, the consumers evaluated may be on a very small scale. Conversely, each consumer may present his/her opinion regarding different products on different emotional attributes, which is in fact a sparse evaluation matrix. Such a type of data structure is quite different from the one by the offline way of emotional knowledge acquisition. Therefore, the second research direction is to investigate the data-driven methodologies within the physical–emotion–satisfaction link-based emotion-driven innovation process.

Finally, the integration of sentiment analysis in emotional product development may provide us the opportunity of investigating the dynamic mechanisms of consumers' emotions toward products. Taking the mobile phone as a typical example, iPhone 4 was heralded as an esthetic revolution in 2010; at that time consumers' feelings may be "How could a mobile phone be unexpectedly like this way?" Nowadays, more and more similar and competitive mobile phones have appeared in the market; at this time, consumers' feelings may be "A mobile phone must be like this way." Such an example indicates the changes and dynamics of consumers' emotions on the product mobile phone. Thus, the final research direction may be the investigation of emotion dynamics and their impacts on product development.

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Chapter 8
Knowledge Synthesis and Promotion

Yoshiteru Nakamori and Siri-on Umarin

8.1 Knowledge Construction Systems Methodology

This section presents the knowledge construction systems methodology (Nakamori, 2013, 2019) that supports the creation of ideas or new knowledge by synthesizing rational and intuitive knowledge. Since this is a methodology, it cannot be scientifically verified, but it has been getting justification in some application cases. This methodology consists of three components. The first one, the knowledge construction system model, shows the procedures to construct new knowledge. The second one, the knowledge construction diagram, suggests a method to synthesize knowledge. The third one, constructive evolutionary objectivism, provides action guidelines in creative activities. Chapter 1 introduced it as a guide when promoting the processes of the OUEI spiral model. However, this chapter describes constructive evolutionary objectivism as a guide for collecting and constructing knowledge according to the knowledge construction system model.

8.1.1 Knowledge Construction System Model

The knowledge construction system model shown in Fig. 8.1 has five nodes: *Intelligence, Involvement, Imagination, Intervention,* and *Integration.* The first

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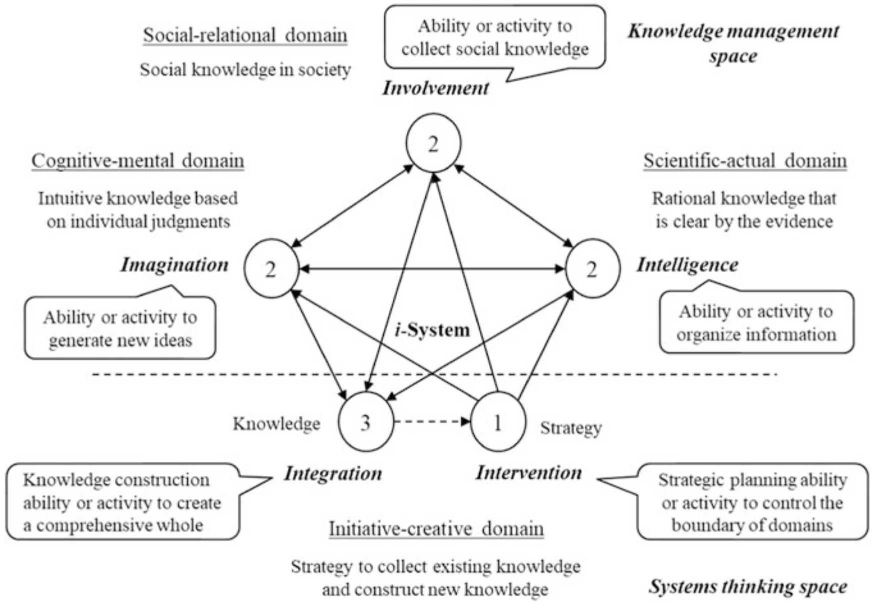

Fig. 8.1 Knowledge construction system model (Nakamori, 2021)

three nodes deal with the knowledge of the *scientific-actual domain*, the *social-relational domain*, and the *cognitive-mental domain*, respectively. The rest two nodes in the *initiative-creative domain* manage knowledge creation activities.

Below is an explanation of the three knowledge domains in the knowledge management space and one knowledge domain in the systems thinking space:

- The scientific-actual domain is the domain of rational knowledge (explicit knowledge) that is clear from evidence such as science and technology, socio-economic trends, academic evaluation, and historical facts.
- The social-relational domain is the domain of social knowledge, such as social norms, values, cultures, power relations, reputations, traditions, fashions, and episodes.
- The cognitive-mental domain is the domain of intuitive knowledge (including tacit knowledge) based on individual judgments, such as judgment criteria, dominant logic, unique concepts, hypotheses, motivations, and hopes.
- The initiative-creative domain is the domain of strategic knowledge, such as ways to collect existing knowledge and validate constructed knowledge. It relates to system intervention and system integration.

The names given to the nodes suggest the abilities or activities required for people to collect and construct knowledge. Below explains the abilities or activities necessary to work in the knowledge domains of the knowledge management space:

- “Intelligence” is the ability or activity to collect and organize existing data and knowledge in the scientific-actual domain, with a sincere attitude to learn and understand things.
- “Involvement” is the ability or activity to collect knowledge in the social-relational domain by conducting social research or utilizing social networks.
- “Imagination” is the ability or activity to generate new ideas in the cognitive-mental domain, utilizing collected data and knowledge.

In the knowledge domain of systems thinking space, two abilities or activities are necessary, which are the essential pair of “creativity”:

- “Intervention” is the ability or activity to create a strategy for knowledge construction. It defines the problem and determines the methods for knowledge construction and principles to evaluate the constructed knowledge. It specifies actions in the knowledge domains of the knowledge management space.
- “Integration” is the ability or activity to integrate or synthesize knowledge from three knowledge domains to construct new knowledge. This knowledge must correspond to a solution to the problem defined in Intervention. If we judge that the constructed knowledge is insufficient according to the evaluation principles, we return to Intervention.

8.1.2 Knowledge Construction Diagram

Nonaka et al. (2013) stated, “Tacit knowledge and explicit knowledge do not exist independently but are interacting continuums. However, because they have contrasting natures, the *dialectical* dynamics of creation are needed in an efficient mutual conversion process.” The knowledge construction systems methodology executes the dialectical knowledge construction using the knowledge construction diagram, shown in Fig. 8.2.

Imagine a situation where we are looking for a solution to a social or business problem. Fill in the knowledge obtained from the three domains in the top three boxes. For example, scientific-actual knowledge is quantitative relationships that affect problem-solving, social-relational knowledge is the possible contributions of problem participants, and cognitive-mental knowledge is people’s feelings and involvement in the problem. Note that the boxes in Fig. 8.2 look smaller due to space limitations, but there is no size limitation.

In the box on the right side of the second row, enter factual-rational knowledge by synthesizing scientific-actual knowledge and social-relational knowledge. To put it exaggeratedly, it means considering the interaction between science and society. The synthesized knowledge is modified scientific-actual knowledge by the constraint condition of social-relational knowledge. Using the terminology in the soft systems methodology (Checkland, 1981), this knowledge includes systemically desirable ideas for problem-solving.

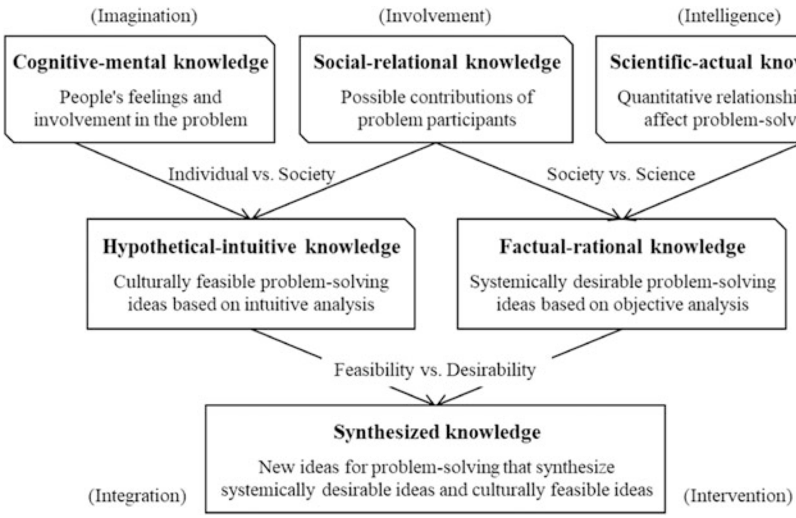

Fig. 8.2 Knowledge construction diagram

In parallel, in the box on the left side of the second row, enter hypothetical-intuitive knowledge, constructed by synthesizing cognitive-mental knowledge and social-relational knowledge. It means considering the interaction between individuals and society. The synthesized knowledge is modified cognitive-mental knowledge by the constraint condition of social-relational knowledge. Using the terminology in the soft systems methodology (Checkland, 1981), this knowledge includes culturally feasible ideas for problem-solving.

Finally, in the bottom box, enter the knowledge that synthesizes the above factual-rational knowledge and hypothetical-intuitive knowledge. It contains problem-solving ideas combining systematically desirable and culturally feasible ideas.

The knowledge construction diagram enables the synthesis of quantitative and qualitative analysis results. For that purpose, it is necessary to document the quantitative analysis results. The scientific-actual knowledge on the upper right of Fig. 8.2 is, for example, the result of simulation or optimization. It is necessary to re-express it in sentences. The social-relational knowledge in the center of the upper row contains a large amount of text and numerical data. We must summarize and document them properly. The original texts in the upper left box contain people's codified tacit knowledge. We need to understand and summarize them in depth.

The knowledge construction diagram realizes the collaboration between knowledge management and systems thinking. The lateral direction corresponds to knowledge management that promotes interactions between various types of knowledge. Intuitive knowledge goes to the left, and rational knowledge goes to the right. The vertical direction represents the system integration in which various details form a comprehensive whole. In this way, this diagram constructs new knowledge by knowledge management enhanced by systems thinking.

8.1.3 Constructive Evolutionary Objectivism

The constructive evolutionary objectivism provides action guidelines when constructing knowledge according to the knowledge construction system model shown in Fig. 8.1. It consists of the following four principles:

- Intervention principle: At the Intervention node, define the problem and choose how to collect and construct knowledge in the three domains of the knowledge management space. Determine the boundaries of the three domains by considering time, cost, personnel, and method. In other words, determine the scope of knowledge to search under restrictions.
- Multimedia principle: Collect necessary knowledge (including data and information) at the three nodes in the knowledge management space using as many media as possible. Utilize not only information technology but also human knowledge carriers. Listen to the ideas of outside experts and the general public.
- Emergence principle: Construct new knowledge by combining existing knowledge (including information and wisdom). Or create it with intuitive inspiration, an unexplained integration of knowledge. To provoke the emergence of such intuitive inspiration, facilitate the interaction of the participants in question in parallel with the systematization of the collected knowledge.
- Evolutionary falsification principle: Verify the effectiveness of a new idea that emerges evolutionarily. If scientific verification is difficult, obtain a subjective consensus among the participants in the problem. In doing so, estimate its robustness in situations that interfere with the idea.

8.1.4 Example 1: Thinking About the Summer Menu of a Sushi Restaurant

Consider the problem of creating summer menu ideas for a restaurant serving sushi on a conveyor belt, which Nakamori (2021) dealt with for illustration. The following are possible actions at the five nodes of the knowledge construction system model.

At *Intervention*, develop an idea creation strategy. Specify the idea creation method at each of the three nodes of the knowledge management space and the integration method for them at the Integration node, as follows:

1. *Intelligence*: Compare the average of each sushi ingredient in the winter and summer for the past three years without creating a mathematical model.

2. *Involvement*: Customers of this restaurant seldom write opinions on the net, so do not perform text mining. Instead, ask about the sushi ingredients they want to eat in the summer through a questionnaire survey.
3. *Imagination*: Bring together restaurant staff to let them discuss ideas for summer menus.
4. *Integration*: Synthesize the ideas created above using the knowledge construction diagram.

At *Intelligence*, use data from the last three years to compare winter and summer sushi sales. Pay attention to the waste loss data and opportunity loss data to explore the demand. As a result, suppose that we obtained the following ideas.

- **Quantitative problem-solving ideas**: Several types of sushi sell less in summer than in winter. Is it because customers' demand has decreased in summer? No, it's not. The opportunity loss happened for some types of sushi. Customer preferences do not change between winter and summer, just that seasonal fish in winter is not prepared enough in summer. It is necessary to import and serve winter fish, even if it is a little expensive. As for the side menu, there is a lot of demand for warm seafood soup and noodles in winter, while vegetable salads and tempura sell well in summer.

At *Involvement*, ask customers to write down what kinds of sushi and services they want in the hot summer. List representative ones from many opinions.

- **Customers' demands**: Many customers want to eat fresh and delicious seasonal fish. In particular, there are many requests for delicious winter fish. But they are happy if it is not so expensive. Some want the side menus such as seafood soup, summer vegetable salad, and seasonal fish and vegetable tempura to be enhanced. Moms want to bring their kids during the summer vacation, but moms want kids to have sushi that they like at a reasonable price.

At *Imagination*, discuss the summer menu between staff according to the organizational knowledge creation model called the SECI model (Nonaka & Takeuchi, 1995). Talk about individual thoughts in the Socialization process, select some concepts in the Externalization process, and create ideas by combining them in the Combination process.

- **Qualitative problem-solving ideas**: The concepts obtained are, for example, children on summer vacation, fresh fish in summer, high-end fish in the winter season, featured dishes that attract customers, and increased profitability. By combining these concepts, it is possible to create the following ideas. Provide sushi sets for children during the summer vacation, including omelets and chicken that children like. Use imported or frozen fish for popular fish. But, even if not having much profit, offer it cheaply. Conversely, provide a large amount of fresh fish with a low purchase price to increase profit margins.

At *Integration*, synthesize ideas by using the knowledge construction diagram. First, combine "quantitative problem-solving ideas" with "consumers' demands" to derive systemically desirable ideas. Second, combine "qualitative problem-solving ideas" with "consumers' demands" to derive culturally feasible ideas. Finally, combine those ideas to create the ideas for the summer menu.

- **Systemically desirable ideas**: In addition to fresh summer fish, import and serve delicious winter fish even if it is a little expensive. Fresh summer vegetable salads, tempura, and seafood soups are also in high demand. It is possible to increase the number of various customers by enhancing the side menu.
- **Culturally feasible ideas**: Create a menu that attracts children during the summer vacation and strengthen promotion. However, be careful not to make it expensive. Conversely, prepare featured dishes that attract adults at low prices. However, promote a large amount of fresh fish with a low purchase price to increase the profit margin.
- **Synthesized ideas**: Offer high-end fish popular with customers throughout the four seasons as recommended dishes. However, keep down its price. Prepare and promote a large amount of fresh summer fish to increase the profit margin. Enhance the side menu such as tempura suitable for summer. Also, develop a set menu that attracts children at an affordable price. Put these ideas into practice and fill the restaurant with guests even in the hot summer.

8.1.5 Example 2: Building a Healthy and Lively Community

Imagine a small city located near a big city. This city has been developing as a commuter town for decades, and more new residents are working in the big city than the original residents. Although rice fields remain in the plain, residential and commercial areas occupy a large part. At the foot of the mountain, there are traditional pottery-producing areas and several hot spring inns. But due to recent lifestyle changes, both industries have entered a period of stagnation. Although the fields are widespread in the mountains, the number of abandoned cultivated land has increased due to the decrease in successors. There are hiking trails along mountain streams and some campsites, but they are less used.

It is a peaceful city, but the mayor is in trouble with the increase of retired workers. The increase in retirees will inevitably reduce tax revenues and increase medical costs. The mayor hopes that retirees will spend their time in good physical and mental health, and he wants to use their power to revitalize the local economy. The mayor plans to care for and utilize retired men, listening to the opinion that retired men lose their physical and mental health more rapidly than women.

At *Intervention*, determine a plan for idea creation as follows:

1. *Intelligence*: Search for successful cases to maintain the physical and mental health of retirees.
2. *Involvement*: Investigate possible health guidance services for men around retirement age and possible economic activities that harness their power.

3. *Imagination*: Listen to the true intentions of men around retirement age. Confirm their will to live their second lives.
4. *Integration*: Synthesize the above ideas into a systemically desirable and culturally feasible plan.

At *Intelligence,* collect the scientific-actual knowledge by using the knowledge of researchers and experienced people. Due to the declining birthrate and aging population nationwide, efforts to care for the mind and bodies of people before and after retirement are beginning to take place. Here, focus on the following two initiatives.

- **Health care for patients with mild diabetes**: There is a report of a social experiment on physical care. A city, a hospital, and a university collaborated to conduct a health care experiment for patients with mild diabetes for three months. The subject patient sends blood glucose value, urine sugar value, steps, weight, and photos of meals of the day to the advisor on a cell phone every night. A university provides biotechnology test kits, and a system developer serves mobile apps. The advisor is a nutritionist from a large pharmacy chain. A hospital compared changes in blood glucose values and others between patients who participated in the experiment and those who did not and reported that the patients who participated showed a statistically significant improvement. This experiment suggests that living with advice may help prevent severe diabetes. They carried out this experiment with a national subsidy, but they have not shifted it to full-scale implementation because of the problem of cost burden.
- **Mental care for pre-retirement men**: There is a report on a social experiment on mental care. A medical school in a university provided pre-retirement men with education on how to plan their second lives. The purpose is to avoid the risk of mental and physical collapse and rapid aging due to the loss of own significance due to retirement. The lectures provide information for affluent living in old age, including positive aging, family management, community participation, etc. After a series of lectures, participants positively design their second lives, present their plans, and evaluate each other. Organizers carry out this series of activities over the weekend for about two months. They implement this project with subsidies from the national and local governments because of instructor fees, classroom rents, and advertising expenses. However, aftercare for participants is an issue, such as preparing a menu for participants to work on social activities together.

At *Involvement*, collect the social-relational knowledge from those involved. The city currently offers the following services:

- **Sending instructors at the request of citizen groups**: At the request of some local women's associations, the city sends health nurses and registered dietitians to the gatherings of local voluntary activities to provide health lectures and exercise guidance. The contents include health promotion, disease prevention, exercise and diet, and child-rearing. Almost all the participants are women. The women's associations cover the venue fee, and the city covers the instructor costs.

- **Providing health-related lectures in collaboration with a university**: The city holds monthly public lectures in collaboration with universities in the neighboring big city. The contents include health care in addition to history and culture. The enthusiastic participants are post-retirement men and housewives who have finished raising their children. The city collects a small entry fee from them and uses it as part of the instructor and venue fees.

There is a potential in this city to implement regional vitalization projects by utilizing the experience and knowledge of retired people. Potential projects include growing vegetables on abandoned farmland, revitalizing shopping streets, the traditional craft industry, and the hot spring town, and running green tourism and healthcare businesses.

By the way, some pharmaceutical companies sell handy health diagnostic devices that make blood tests easy. Test items include glucose metabolism, fat metabolism, liver function, nutritional status, and renal function. We order the test kit from the Internet, and when the test kit arrives, we collect blood and return the sample to the test center. An expert explains the analysis results to us in an easy-to-understand manner. However, the cost for one inspection is nearly 80 dollars.

At *Imagination*, collect the cognitive-mental knowledge from citizens. When asked about the thoughts of male residents before retirement, it seems that they generally think as follows: Since the children are already independent, I think I can live comfortably with my wife for another 20 years with savings and pensions. I will enjoy reading, traveling, and eating while maintaining proper physical fitness. But it doesn't seem that easy. *Health means being satisfied not only physically but also mentally and socially*. Retired people lose their meaning of existence, which leads to mental and physical collapse and rapid aging. To extend healthy life expectancy, they need to feel expectations from the world around them.

What should we do to stay in good physical and mental health for a long time? A pre-retirement man would think:

- One is health management. After retirement, I take out the national health insurance of the local government, receive health consultations at the clinic about once a month, and manage my health through a comprehensive health check once a year. However, if the city raises a community health management system, I would like to participate as much as possible.
- The other is a rewarding and respected activity. I want to join activities where I can make use of my experience. Even if that is not the case, I would like to participate in efforts to achieve results while maintaining good health by moving my body. I don't require much, but I'd be happy if there is any reward for the activity.

At *Integration*, synthesize knowledge using the knowledge construction diagram shown in Fig. 8.2. First, construct factual-rational knowledge by deriving solutions from scientific-actual knowledge with social-relational knowledge as a constraint. It is a systemically desirable problem-solving idea. The city plans to hold a course on life planning after retirement and build a system for preventing lifestyle-related diseases so that retired men can spend their time in good physical and mental health.

- The city will develop its existing instructor dispatch service and hold a monthly post-retirement life planning course for men who will retire within three years. The instructors are experts from nearby universities. Participants will learn how to maintain physical and mental health after retirement and rebuild relationships. Finally, they make plans for how to live after retirement. There is a charge for materials, but the city is responsible for the venue and instructor costs.
- The city will build a diabetes prevention network for pre- and post-retired men by learning a successful health care practice. Participants send the data on weight, the number of steps, and a photo of their meal to the advisor by cell phone every day. They measure the blood glucose level once a week with a simple blood test kit and send it to the advisor. The advisor gives health advice to participants once a week by email. Participants and the city share the costs of implementing the project.

Then, construct hypothetical-intuitive knowledge by deriving solutions from cognitive-mental knowledge with social-relational knowledge as a constraint. It is a culturally feasible problem-solving idea. In response to the desire to be respected and rewarded, the city prepares the following jobs:

- Helping the city's businesses such as guidance on green tourism or management assistance for the health management system.
- Participating in efforts to revitalize agriculture and industries such as cultivation and sale of vegetables by renting abandoned farmland or revitalization of traditional crafts and hot spring industries.

Pre-retirement men want to participate in health courses and health maintenance activities to extend healthy life expectancy, but hopefully, the city will bear the necessary expenses. For example, they want the city to work with a general hospital to build a lifestyle-related disease prevention system, not just diabetes. Participants record daily weight, body fat, blood pressure, steps, photos of meals, and more. They visit the hospital once every three months and have a blood test. They attend a monthly health course and receive advice from a registered dietitian at the hospital based on the data recorded after the lecture. They pay for blood tests at the hospital but want the city to pay for the advisor's labor. This activity will help reduce public spending on medical expenses in the future.

At last, construct the final solution by synthesizing the factual-rational knowledge and the hypothetical-intuitive knowledge as follows:

- The city will hold a mental and physical health management course on the third Saturday of every month for men from 3 years before retirement to just before retirement. Participants will learn how to live after retirement from lecturers from a nearby university and plan their second lives. Participants will pay for training but will get a refund through post-retirement activities. Those who have completed the course will form several groups and hold study sessions to enhance each other. The city provides a place for them to meet.

- The city will build a lifestyle-related disease prevention network for post-retirement men three years before retirement. It prevents not only diabetes but also lifestyle-related diseases in general. Participants will send a drop of blood once every two months using a health checker sent by a pharmaceutical company. The test items are glucose metabolism, lipid metabolism, liver function, nutritional status, renal function, etc. The cost is 50 dollars per year. They must send their advisor the data of weight, body fat percentage, steps, and photos of meals they have. They receive advice from their advisor by email once a month. The participation fee is also 50 dollars per year.
- The city will organize the following projects that leverage the experience and knowledge of retired men: Creation and implementation of revitalization plans at the Traditional Crafts and Hot Springs Industry Revitalization Committee, farming practices on abandoned farmlands, and green tourism business instructor. They are exempt from the above costs if they participate in these projects. For activities beyond that, they receive a share of the revenue.

8.2 Knowledge Synthesis Enablers

The knowledge construction system model assumes that five basic activities, Intervention, Intelligence, Involvement, Imagination, and Integration, realize knowledge construction. This section first examines the validity of the assumption that knowledge management consists of three activities: Intelligence, Involvement, and Imagination. Next, it explores the relationship between five activities using the covariance structure analysis. Nakamori (2022) introduced a simplified version of the following content, but this research is still in its early stages and needs further consideration.

8.2.1 Defining Enablers for Knowledge Synthesis

"Knowledge-Creating Company" by Nonaka and Takeuchi (1995) is a landmark work on knowledge management. However, it is not easy to practice the knowledge creation theory proposed in their book using information technology. Nonaka responded to this as follows. "Knowledge creation is the product of human relationships. If human relations are not good, no matter how good the theory of knowledge creation is, we cannot put it into practice. Knowledge-creating activities do not work well unless we develop, at the same time, the organizational structure, systems, human resources, and the culture they form."

Nonaka published "Enabling Knowledge Creation" (Krogh et al., 2000) with his collaborators. They introduced five key knowledge enablers: instilling a knowledge vision, managing conversations, mobilizing knowledge activists, creating a suitable context for knowledge creation, and globalizing local knowledge. Nonaka argues that *knowledge creation is not information system theory, and knowledge creation is the creation of good relationships*. Thus, his interests are focused on personalization strategy. That is because intensive investment in codification strategy does not always lead to successful knowledge management.

This section explores the knowledge synthesis enablers using covariance structure analysis (see, for example, Werner et al., 2009; Hair et al., 2016). We assume the knowledge construction system model as a structural equation model, set its five nodes as latent variables, and define some observed variables as candidates of knowledge synthesis enablers.

We will introduce queries to give values to observed variables, which become data for analysis. We will prepare data by evaluating several applied systems research projects in which one of the authors, Nakamori, was involved. Since this section considers research projects, it is necessary to modify queries for business projects.

The first purpose of the analysis is to investigate whether the three activities of the knowledge management space, Intelligence, Involvement, and Imagination, are suitable as independent factors. The second purpose of the analysis is to investigate how the activity of Intervention affects Intelligence, Involvement, and Imagination. The third purpose is to explore how Intelligence, Involvement, and Imagination affect Integration. The fourth purpose is to investigate how observed variables in the knowledge management space contribute to knowledge synthesis and research outcomes.

8.2.2 Structural Equation Modeling

The software used for analysis is "R" (Ihaka & Gentleman, 1996; R Core Team, 2016), so the structural equation model is described according to its grammar. Below are the symbols, names, and meanings of the five latent variables corresponding to the five nodes of the knowledge construction system model shown in Fig. 8.1.

(K1) Intelligence: Activities to collect, maintain, and understand existing knowledge and related data/information.
(K2) Involvement: Activities to collect, maintain, and understand external information and implicit knowledge.
(K3) Imagination: Activities to create ideas through systematic knowledge and member interaction.
(S1) Intervention: Activities to define problems, establish research systems including research funding, and clarify research contents.
(S2) Integration: Activities to achieve research goals, publish research results, and then develop research by discovering new issues.

Define the observed variables corresponding to the above five latent variables as follows.

1. Corresponding to the Latent Variable (K1) Intelligence

   (SA1) Intelligence on existing knowledge (Surveying previous and related research)
   (SA2) Intelligence on data and information (Collecting necessary data and information)
   (SA3) Intelligence on knowledge technology (Mastering analytical/modeling methods)

2. Corresponding to the Latent Variable (K2) Involvement

   (SR1) Involvement with stakeholders (Confirming stakeholders' intention)
   (SR2) Involvement with external researchers (Collaborating with external researchers)
   (SR3) Involvement with internal people (Gaining support from the boss and colleagues)

3. Corresponding to the Latent Variable (K3) Imagination

   (CM1) Imagination enhanced by Intelligence (Leveraging codified knowledge)
   (CM2) Imagination enhanced by Involvement (Leveraging knowledge from the network)
   (CM3) Imagination enhanced by discussion (Leveraging personalized knowledge)

4. Corresponding to the Latent Variable (S1) Intervention

   (IC1) Intervention in problem situations (Defining problems and goals)
   (IC2) Intervention in the research process (Establishing a research system)
   (IC3) Intervention in knowledge domains (Determining activities in three knowledge domains)

5. Corresponding to the Latent Variable (S2) Integration

   (IC4) Integration of knowledge from three domains (Constructing new knowledge)
   (IC5) Integration of discoveries by research (Writing academic papers and reports)
   (IC6) Integration of research results and other issues (Discovering new problems)

Below is the list of queries that give observed variables the following rating scores: strong denial = 1, denial = 2, neutral = 3, affirmative = 4, and strong affirmation = 5.

(SA1) Have you collected sufficient existing knowledge from previous research surveys?
(SA2) Have you collected sufficient data and information to promote the research?
(SA3) Have you mastered enough technologies to analyze data and information?
(SR1) Have you communicated well with the government, stakeholders, and users?

(SR2) Have you fully cooperated (or exchanged opinions) with domestic and foreign researchers?
(SR3) Have you established trust relationships with the managers, supervisors, and colleagues?
(CM1) Have you effectively used the systematized data, information, and knowledge?
(CM2) Have you effectively used the knowledge of experts, stakeholders, and policymakers?
(CM3) Have you effectively used the knowledge of group members?
(IC1) Have you been confident in the problem settings?
(IC2) Have you been confident in the research funding and implementation system?
(IC3) Have you been confident in the approach to knowledge collection?
(IC4) Have you synthesized various knowledge and got satisfactory research results?
(IC5) Have you written a satisfactory research report and academic papers?
(IC6) Have you found promising ideas for continuous research development?

The following measurement equations show the relationships between latent variables and observed variables. Here, we read the operator "=~" as "is observed by."

K1 = ~SA1 + SA2 + SA3
K2 = ~SR1 + SR2 + SR3
K3 = ~CM1 + CM2 + CM3
S1 = ~IC1 + IC2 + IC3
S2 = ~IC4 + IC5 + IC6

The structural equations show the influence relationship between variables, using the regression operator "~". Place the objective variable on the left side of this operator and the explanatory variables on the right side, separating them by the operator "+". Here, the following influence relationships are assumed.

K1 ~ S1
K2 ~ S1
K3 ~ S1
S2 ~ K1 + K2 + K3

The first three equations above investigate how strategic planning affects knowledge management activities. The last equation investigates how three types of knowledge management activities affect research outcomes.

8.2.3 Covariance Structure Analysis

Below are 20 past research projects involving one of the authors prepared to obtain the data.

1. Optimal sensor placement for urban air pollution.
2. Simulation of urban air pollution distribution.
3. Evaluation modeling of urban living environment.
4. Development of an interactive modeling support system.
5. Sensibility evaluation of kitchen systems.
6. Agent-based simulation to explore purchasing behaviors.
7. Knowledge sharing using information technology.
8. Modeling to forecast stock price fluctuations.
9. Management of technology in a graduate school.
10. Knowledge management in graduate laboratories.
11. Forecast of fresh food demand in a supermarket.
12. Research on successful cases of regional revitalization.
13. Promotion and evaluation of a biomass town.
14. Sensibility evaluation of traditional crafts.
15. Decision-making methods by multiple experts.
16. Building of product recommendation systems.
17. Life planning of retired men and evaluation.
18. Evaluation of creative environment in a graduate school.
19. Promotion story creation and evaluation.
20. The spillover effect of research institute knowledge.

We refrain from presenting raw assessment data in which one of the authors answered the above 15 queries regarding these projects.

8.2.3.1 Confirmatory Factor Analysis

Below are the results of confirmatory factor analysis to validate the classification of knowledge management into three types of activities. Assuming that the number of factors is 3, this analysis used the maximum likelihood method for estimation and the Promax method for rotation. Table 8.1 shows the factor loadings and uniqueness

Table 8.1 Factor loadings and uniqueness

Observed variables	Factor 1	Factor 2	Factor 3	Uniqueness
SA1	**0.900**	0.138	−0.186	0.205
SA2	**0.784**	0.036	0.112	0.235
SA3	**0.995**	−0.081	−0.113	0.203
SR1	−0.085	**0.834**	−0.001	0.386
SR2	0.068	**0.745**	0.066	0.305
SR3	0.036	**1.038**	−0.158	0.069
CM1	**0.483**	−0.084	**0.317**	0.572
CM2	0.073	**0.443**	**0.409**	0.324
CM3	−0.147	−0.093	**1.126**	0.005
Cumulative contribution rate	0.299	0.584	0.764	3 factors are sufficient

of the nine observed variables in the knowledge management space. Looking at this table, the assumption of the three factors is almost satisfied.

However, the observed variable CM1 is more influenced by Factor 1 than Factor 3. The reason could be that the query for this variable was "Did you make effective use of activities related to Factor 1 in creating ideas?" Also, the observed variable CM2 is slightly more affected by Factor 2 than Factor 3. The reason could be that the query for this variable was "Did you make effective use of activities related to Factor 2 in creating ideas?"

Discussing knowledge management in three parts is not a monopoly patent of the knowledge construction systems methodology. Many thinkers and system theorists have proposed using three areas of knowledge to deepen thinking. Here, we mention the following two:

(A) Linstone (1984) shows how taking three different viewpoints could yield a rich appreciation of the nature of problem situations:

1. (T) Traditional or technical perspective.
2. (O) Organizational or societal perspective.
3. (P) Personal or individual perspective.

These perspectives act as filters to view the system. Each produces insights that are not attainable by other perspectives.

(B) Mingers (1997) argues that any real-world situation is a complex interaction of substantively different aspects:

1. Those that are relatively hard and observer-independent, particularly material and physical processes that we can observe and model.
2. Those that are dependent on cultures, social practices, languages, and power structures that we must share and participate in to understand.
3. Those that are individual beliefs, values, fears, and emotions that we must try to express and understand.

8.2.3.2 Regression Analysis

Figure 8.3 shows the results of estimating the strength of the influence relationships between variables by covariance structure analysis. The coefficients are standardized estimates. The estimates are statistically significant, except for the last regression equation. Figure 8.3 shows that all the coefficients from the latent variables to the observed variables are sufficiently large. Therefore, we can conclude that the introduced observed variables are valid.

The *p*-values for the estimates in Fig. 8.3 are almost zero except for the p-values for the three estimates for S2. The standardized estimates and p-values of the three explanatory variables K1, K2, and K3 for S2 are as follows.

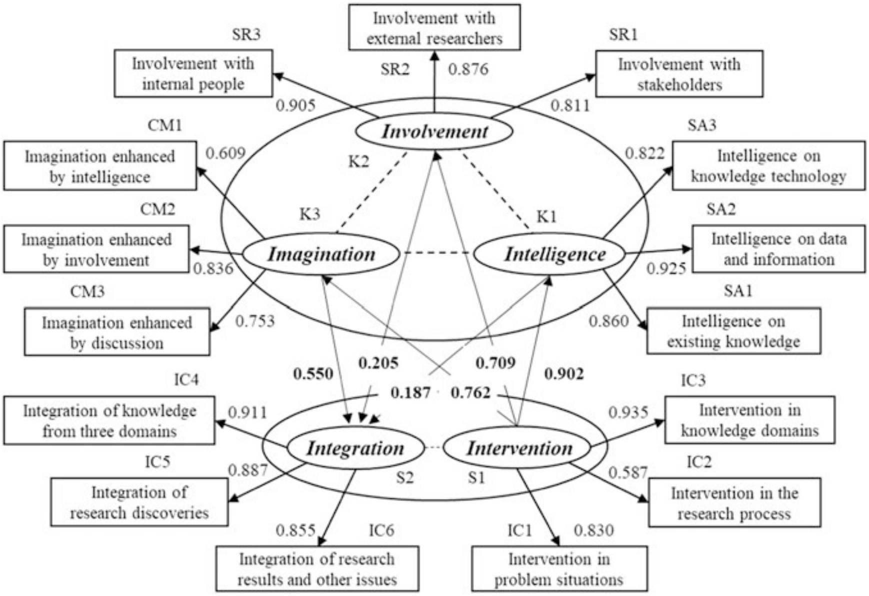

Fig. 8.3 Path diagram with standardized estimates

K1 → S2: Coefficient = 0.187, p-value = 0.439
K2 → S2: Coefficient = 0.205, p-value = 0.507
K3 → S2: Coefficient = 0.550, p-value = 0.133

Figure 8.3 shows that Intervention enhances Intelligence, Involvement, and Imagination. We can see that Intervention influences Intelligence greater than Involvement and Imagination. Also, Fig. 8.3 shows that Imagination influences Integration more than Involvement or Intelligence. Factor Intelligence is considered essential to driving research. However, it seems that Imagination is more important than Intelligence to the success of the author's past research. The regression model that explains Integration by Intelligence, Involvement, and Imagination is less reliable. Nonetheless, it is convincible that no matter how much data, knowledge, or expert opinion we collect, Imagination is crucial for the success of the research.

8.2.3.3 Multivariate Regression Analysis

We should perform path analysis or multivariate regression analysis with all variables, but we do not because the number of cases of the data is too small. However, to investigate the impact of activities related to knowledge management on research results, we perform three multivariate regression analyses:

(Model 1) Objective variables: IC4, IC5, IC6; Explanatory variables: SA1, SA2, SA3

Table 8.2 Standard regression coefficients and p-values

Model 1		Explanatory variables		
		SA1	SA2	SA3
Objective variables	IC4	0.229 ($p = 0.276$)	0.172 ($p = 0.528$)	0.186 ($p = 0.526$)
	IC5	0.275 ($p = 0.296$)	**0.573** ($p = 0.094$)	−0.203 ($p = 0.579$)
	IC6	0.254 ($p = 0.222$)	0.152 ($p = 0.575$)	0.042 ($p = 0.884$)
Model 2		Explanatory variables		
		SR1	SR2	SR3
Objective variables	IC4	−0.082 ($p = 0.687$)	**0.404** ($p = 0.114$)	**0.534** ($p = 0.079$)
	IC5	−0.080 ($p = 0.802$)	0.191 ($p = 0.635$)	**0.683** ($p = 0.152$)
	IC6	−0.135 ($p = 0.518$)	**0.396** ($p = 0.131$)	**0.450** ($p = 0.149$)
Model 3		Explanatory variables		
		CM1	CM2	CM3
Objective variables	IC4	**0.338** ($p = 0.036$)	**0.528** ($p = 0.105$)	0.288 ($p = 0.210$)
	IC5	0.203 ($p = 0.376$)	0.511 ($p = 0.270$)	**0.521** ($p = 0.111$)
	IC6	0.221 ($p = 0.200$)	**0.907** ($p = 0.009$)	−0.096 ($p = 0.696$)

(Model 2) Objective variables: IC4, IC5, IC6; Explanatory variables: SR1, SR2, SR3
(Model 3) Objective variables: IC4, IC5, IC6; Explanatory variables: CM1, CM2, CM3

Table 8.2 shows the standardized regression coefficients and p-values.

There is only one regression coefficient with a p-value below 0.05, and it is difficult to dismiss the null hypothesis that the value is 0 for most regression coefficients. Nevertheless, we make rough reasoning here. We assume that an observed variable with a standard regression coefficient with a p-value less than 0.2 affects the objective variable.

1. The following observed variables may contribute to IC4 (constructing new knowledge):

   - SR2: Collaborating with external researchers.
   - SR3: Gaining support from the boss and colleagues.
   - CM1: Leveraging codified knowledge.
   - CM2: Leveraging knowledge from the network.

   Activities that contribute to synthesizing knowledge are "gaining internal support," "collaborating with external researchers," and "the use of codified knowledge and knowledge from the network." Therefore, we can regard these variables as *knowledge synthesis enablers.* However, although the p-value is 0.21, CM3 (leveraging personalized knowledge) is also considered to contribute to knowledge synthesis. At the level of latent variables, "Imagination" and "Involvement" contribute to knowledge synthesis more than "Intelligence," as shown in Fig. 8.3. As Nonaka pointed out, *human resources are most important for creating knowledge*.

Table 8.3 Correlation coefficients between objective variables and explanatory variables

	SA1	SA2	SA3	SR1	SR2	SR3	CM1	CM2	CM3
IC4	0.614	0.577	0.578	0.535	0.698	0.709	0.597	0.633	0.640
IC5	0.570	0.613	0.451	0.386	0.473	0.540	0.443	0.569	0.623
IC6	0.564	0.513	0.482	0.447	0.635	0.630	0.434	0.627	0.423

2. The following observed variables may contribute to IC5 (writing academic papers and reports):

   - SA2: Collecting necessary data and information.
   - SR3: Gaining support from the boss and colleagues.
   - CM3: Leveraging personalized knowledge.

   Activities that contribute to the writing of papers and reports include "collecting data and information," "gaining internal support," and "discussing with fellow researchers." We must use the ideas of colleagues in addition to data and information to write academic papers.
3. The following observed variables may contribute to IC6 (discovering new problems):

   - SR2: Collaborating with external researchers.
   - SR3: Gaining support from the boss and colleagues.
   - CM2: Leveraging knowledge from the network.

   Activities that contribute to discovering new problems include "gaining internal support," "collaborating with external researchers," and "utilizing knowledge from the network." This inference suggests that ideas for new problems often come up in discussions with others. However, although the *p*-value is 0.2, CM1 (leveraging codified knowledge) may also be necessary for discovering new problems.
4. It is not that other explanatory variables do not contribute to knowledge synthesis, but the result is that they contribute relatively low. Table 8.3 shows the correlation coefficients between objective variables and explanatory variables. The single correlation is not that low for all variables.

Consider three explanatory variables that do not appear in the above analysis. The p-value for SA1 (previous and related studies) is in the 0.2-point range, but we cannot rule out its impact on the objective variables. It should be considered necessary as a basis for conducting research. SA3 (mastering analytical/modeling methods) and SR1 (confirming stakeholders' intention) have little effect on the research results in the research projects evaluated this time. However, this is not always the case with different types of research.

In summary, activities that contribute to knowledge synthesis include the use of codified knowledge, the use of internal support, collaboration with the outside world, and the use of knowledge from networks. This fact suggests that *the networking* *strategy is needed in addition to the codification and personalization strategies to construct new knowledge.*

8.3 Knowledge Promotion Stories

When promoting a synthesized idea, such as claiming a new theory, suggesting a solution, selling a product, etc., it is necessary to appeal to people's sensibilities. This section provides an overview of content marketing and storytelling and then suggests how to create promotion stories using the knowledge construction diagram. To show how it works, we will present a project on story creation at a national research institute in Thailand.

8.3.1 Content Marketing and Storytelling

Entering this century, strategic marketing called content marketing has emerged. It aims to attract customers, maintain relationships with them, and drive buying behavior by communicating the right content related to the product. Traditional advertising is a style of unilaterally delivering what a company wants to convey to consumers. Conversely, content marketing aims to build a two-way relationship between the company and consumers. The company provides content consumers want to know, builds relationships with them, and then gradually explains its products.

For example, suppose you find a web page that says, "As you get older, it is harder for you to lose belly fat." You will see a graph in which basal metabolic rate decreases with age. You are directed to a web page to show content about fat-burning exercises or low-carb diets. You wonder if you cannot do these things, then you will move to a product promotion page that says, "Why don't you try a tablet that reduces belly fat?"

Recently, the myth of content marketing that "if we create good content, users will surely find it" has been shaken. Currently, content marketing is moving to the next evolution. According to Pulizzi and Rose (2017), the era of the audience first will come, and instead of attracting prospects after making a product, a company attracts prospects before making a product.

Storytelling is one of the main methods of content marketing, which is a way to attractively present products and services to consumers (Solomon et al., 2016). Stories ads influence consumer purchase intent more than non-stories ads (Kim et al., 2017). Consider the requirements for a widely accepted story. First, it is factual and needs to include content that solves real problems. This condition is essential to convince consumers of the proposal. However, even if humans make rational decisions, they perform their actions emotionally. Therefore, the story needs to appeal to consumers' sensibilities and emotions. However, unless the storyteller is highly motivated, it is difficult to win the hearts of consumers. Finally, for busy consumers, compelling stories need to be concise.

Therefore, the promotion story must include scientific-actual, social-relational, and cognitive-mental knowledge, which suggests the validity of the knowledge construction system model introduced in Sect. 8.1.1. The knowledge construction systems methodology helps create stories that promote products and services by encouraging people's esthetic sense and evoking their emotions and sympathies. In the following, we focus on creating stories to promote research and projects that do not necessarily pursue profits. By learning the method to be presented, researchers and staff members who are not necessarily familiar with storytelling systematically create promotion stories of their work.

8.3.2 Steps to Create a Promotion Story

We can use the knowledge construction systems methodology in many knowledge creation contexts. For example, we can use it as a framework for creating technology roadmaps and research plans. It is also usable in creating stories to promote products and services. Nakamori et al. (2020) used this methodology to propose a three-stage process for creating promotion stories of research, projects, and organizations:

- Stage 1: Consider a strategy of story creation at Intervention.
- Stage 2: Develop stories at Intelligence, Involvement, and Imagination.
- Stage 3: Create promotion stories at Integration.

Below introduces the tasks at these stages and the templates to execute them.

8.3.2.1 Stage 1: Considering a Strategy for Story Creation at *Intervention*

The template for Stage 1 is shown in Fig. 8.4, followed by a description of the five steps in this stage.

Step 1-1: Narrow down the targets (people) to whom you want to convey your stories. Why is it necessary to clarify the target? Because if you make a story for everyone, it won't reach anyone's heart in the end. It's a good idea to clarify to whom you want to tell your story. Therefore, you need to create as many stories as your targets. Examples of targets are evaluators, stakeholders, managers, business-people aiming for innovation, or young researchers exploring new research.

Step 1-2: Define story factors to highlight in the scientific-actual domain. First, think systematically about what to write. Let us call the subject or keyword of the story a story factor. Here, show the merits of your research or project the target would like to know. Each target has different interests, such as background and purpose, research achievements, awards, acquisition of research funding, academic

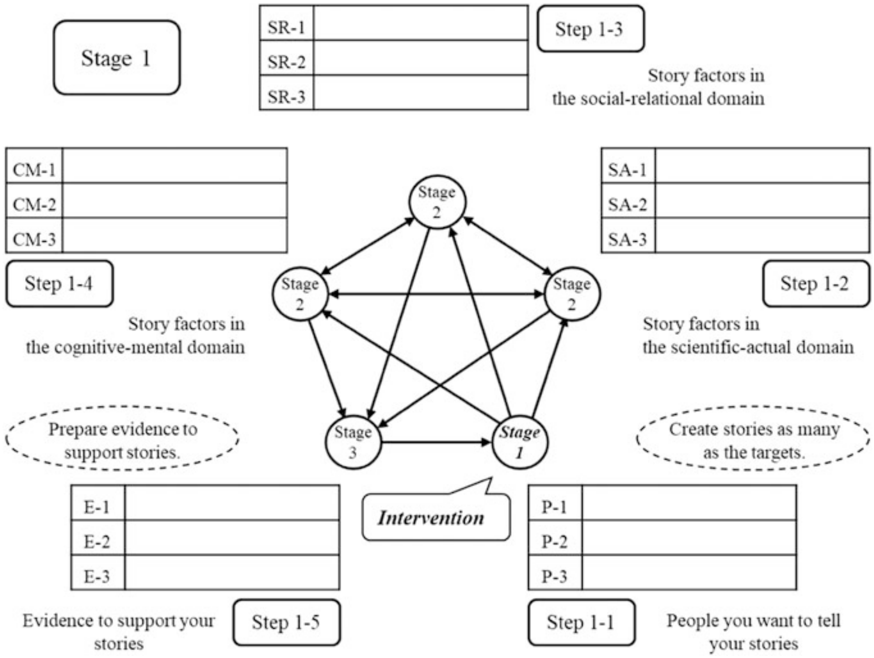

Fig. 8.4 Template of stage 1: Considering a strategy for story creation at *Intervention*

significance, and ripple effects. Evaluators of your research or project are interested in the objective basis of your story.

Step 1-3: Define story factors to show social contribution in the social-relational domain. Summarize the reputation of the research or project you want your target to know. The government and the general public want to know how your research or project can contribute to the country. People are interested in how your research or project will change the future. With these in mind, you can choose the following story elements: invited lectures, joint research, problems expected to be applied, episode, or reputation.

Step 1-4: Define story factors to show your motivation in the cognitive-mental domain. Here, define story factors to convey your motivation or ambition to the target. It is important to choose words that touch the targets' hearts. Examples of factors include personal evaluation, pride, unique concepts and ideas, perspectives, and potential for further development. Evaluators of your research or project are interested in your enthusiasm, seriousness, and ability to execute.

Step 1-5: Prepare outcomes (including planned) that are evidence to support your stories. Since figures have the power to attract people's eyes, you should utilize the concreteness of numbers so that the target has a solid image. Stories with specific numbers are more persuasive. You should show the evidence in every possible way. Depending on the target, you should prepare evidence such as research papers, collaborative research, invited talks, or photos of workshops.

8.3.2.2 Stage 2: Developing Basic Stories at *Intelligence*, *Involvement*, and *Imagination*

Product and service advertisers use exaggerated stories to encourage people to make purchases. However, in promotion stories for research or projects, you should clearly state their social significance so that people desire their success and, in some cases, willingly offer financial assistance. Develop a story for each knowledge domain for each target using the template shown in Fig. 8.5.

Step 2-1: Introduce outstanding achievements at *Intelligence*. Emphasize the novelty and strength of your research or the purpose and usefulness of your project. Since numbers have the power to attract people's eyes, you should utilize their concreteness. If the story gets complicated, use the evidence figures as much as possible.

Step 2-2: Show the benefits to the target at *Involvement*. People are interested in what your research or project will bring to society. You need to appeal to them the merits of your research or project. Even experienced evaluators are not always

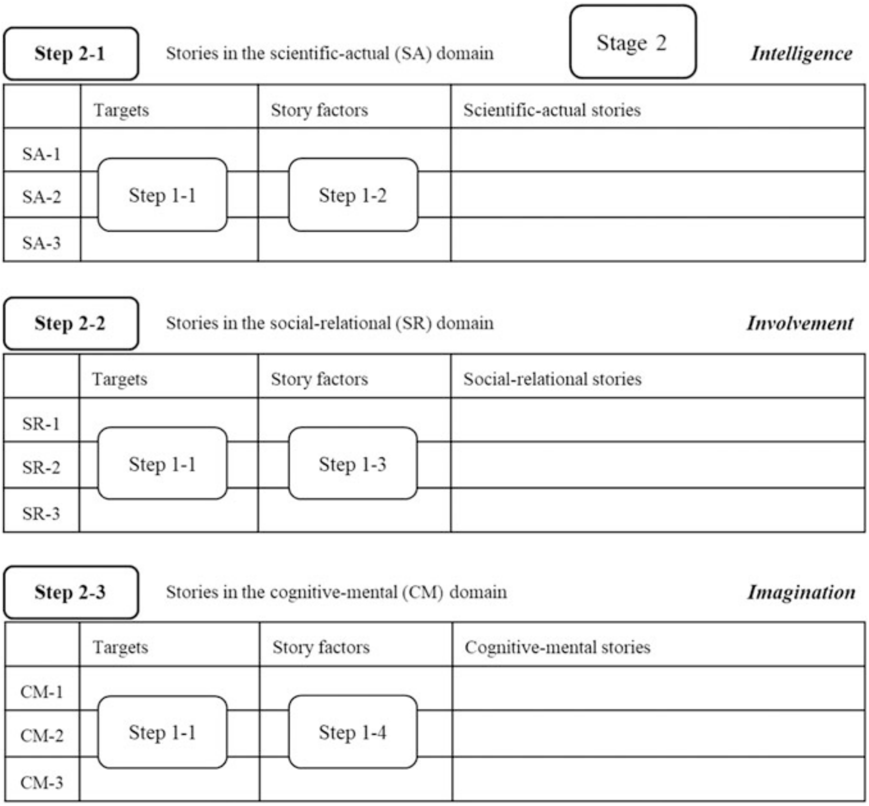

Fig. 8.5 Template of stage 2: Developing stories at *Intelligence*, *Involvement*, and *Imagination*

confident in their evaluation. The evaluators want to know about its reputation. So, tell them positive opinions about your research or project.

Step 2-3: Emphasize your passions and dreams at *Imagination*. Appeal your motivation for the research or project to move the target's mind. If you can successfully stimulate the curiosity of your target, you will get a high evaluation. Convey your dreams without exaggerating the facts. The evaluators want to check your passion, seriousness, and your confidence.

8.3.2.3 Stage 3: Creating Promotion Stories at *Integration*

Follow the steps below to create promotion stories by combining the stories developed in Stage 2. You can add compelling sentences if it is not misleading. Figure 8.6 shows the template for Stage 3.

Step 3-1: Create an intermediate story considering the interaction between science and society. Construct a factual-rational story (FR-*i*) by synthesizing the scientific-actual story (SA-*i*) and the social-relational story (SR-*i*) developed in Stage 2. Here "*i*" indicates a target number or a promotion story number. As you can see from Fig. 8.4 and Fig. 8.5, *i* is 1, 2, or 3 in the sample template. Create a compelling story to get the target's empathy.

Step 3-2: Create an intermediate story considering the interaction between society and individuals. Construct a hypothetical-intuitive story (HI-*i*) by synthesizing the social-relational story (SR-*i*) and the cognitive-mental story (CM-*i*)

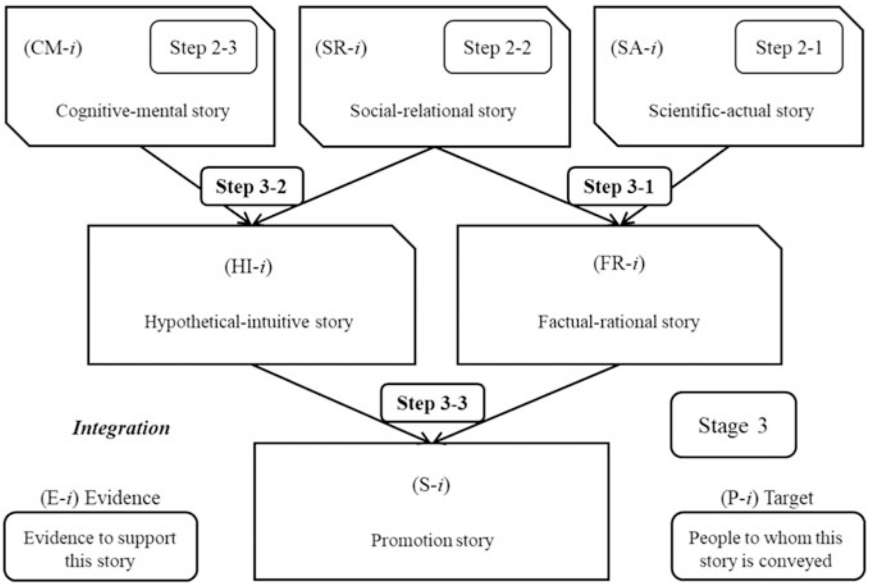

Fig. 8.6 Template of stage 3: Creating a promotion story for each target

developed in Stage 2. If there are good reviews from other people on your research or project, the target will refer to them. At the same time, the target wants to know your real intention and sincerity.

Step 3-3: Create a promotion story considering the interaction between rationality and intuition. Construct a final promotion story (S-*i*) for the target (P-*i*) by synthesizing the factual-rational story (FR-*i*) and the hypothetical-intuitive story (HI-*i*) developed in Steps 3-1 and 3-2. Complete a promotion story that shows the target your honesty and passion.

8.3.3 A Story Creation Project

We implemented a story creation project from August 2018 to February 2019 at the National Electronics and Computer Technology Center (NECTEC) under the National Science and Technology Development Agency (NSTDA), a member of the Ministry of Science and Technology, Thailand. The project was called Collaborative Research on Creating Stories to Appeal Project Significance. Nakamori et al. (2020) introduced the method of promotion story creation and reported this project in detail. Five researcher teams and three staff teams participated in the story creation project. Each created three promotion stories in English and Thai. At the final seminar, they exhibited posters in addition to oral presentations. They received positive reviews from many members of the institute. Below, we introduce a promotion story developed by a staff team.

The leader of this staff team is Umarin, one of the authors of this chapter. They are working to create the brand image of their institute NECTEC. They would like to widely appeal for excellent research at the institute, international exchange, and training of young researchers.

The targets chosen by this team are government and mass media, businesspeople, and researchers or students. In Stage 1, they decided on the story factors as follows.

Step 1-1: People whom they want to convey their story

P-1: Government and national/international mass media
P-2: People in the domestic and international business sector
P-3: Domestic and international researchers and students

Step 1-2: Story factors in the scientific-actual domain

SA-1: Outstanding researchers and national-scale important projects
SA-2: Successful research and projects in collaboration with the industry
SA-3: International-level research in the field of information science

Step 1-3: Story factors in the social-relational domain

SR-1: Voices of praise from the public evaluation committee
SR-2: Appreciation, requests, and expectations from the industry
SR-3: Great trust through international joint research and national projects

Step 1-4: Story factors in the cognitive-mental domain

CM-1: Roadmap to becoming an internationally important research institute
CM-2: Willingness to collaborate with industry to induce innovation
CM-3: Fostering young researchers who can play an active role worldwide

Step 1-5: Evidence to support their stories

E-1: National projects, budget size, awards, and open workshops
E-2: Technology transfer, licensing, and joint research
E-3: International research papers and research projects

This team created promotion stories for each of the three targets. Below introduces the story-making process that appeals to Target 3: researchers and students.

Step 2-1: A scientific-actual story (SA-3)

NECTEC promotes cutting-edge research in informatics, including artificial intelligence, data science, intelligent systems, sensing systems, and communication networks. Researchers are working with the government and private companies to contribute to the innovation of Thai services and products.

Step 2-2: A social-relational story (SR-3)

NECTEC promotes bilateral or multilateral joint research with Asian and European countries and has earned international trust. Researchers are contributing to important national projects in parallel with promoting international cooperation. The Thai government strongly trusts NECTEC and requests a lot of research.

Step 2-3: A cognitive-mental story (CM-3)

NECTEC promotes developing talented young researchers through the dual degree system, the internship system, the postdoctoral program system, etc. Senior researchers want to grow young researchers and students by giving them chances to participate in international collaborative research and national projects actively.

In Stage 3, they completed a promotion story with the help of the knowledge construction diagram.

Step 3-1: A factual-rational story (FR-3)

NECTEC conducts cutting-edge research in the fields such as artificial intelligence, data science, communication networks, etc. and has earned the great trust of the government. It promotes national projects and collaborative research with private companies and contributes to service and product innovation.

Step 3-2: A hypothetical-intuitive story (HI-3)

Young researchers have the opportunity to participate in the international research community together with senior researchers and deepen the research exchange. They also have the chance to grow as researchers by participating in various training programs, international collaborative research, and domestic projects.

Step 3-3: A promotion story (S-3)

Dear young researchers and students.

NECTEC is conducting important international and national research projects and has achieved world-level research results in information technology. NECTEC has earned strong trust from the government for contributing to service and product innovation in Thailand. NECTEC is also working to develop the next generation of talented researchers. We offer you the opportunity to create an impact on Thailand and the international society. Join our family to form a strong research community and open a new future together.

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Chapter 9
Group Decision-Making

Meimei Xia and Jian Chen

9.1 Introduction

In group decision-making (GDM), more than one decision-maker (DM) is involved in doing a joint decision. GDM can consider more relevant aspects of a problem, which is not possible for a single DM (Saaty, 2008). GDM can often yield more accurate outcomes, even if the initial individual DMs' evaluations contain large errors (Galton, 1907; Keck & Tang, 2021), such phenomenon is commonly referred to as the "wisdom of the crowd" (Mannes et al., 2014; Surowiecki, 2005).

Researchers have different opinions about the framework of GDM. Keeney (2013) proposed a general framework for group decision analysis based on individual decision analysis, in which the group expected utility is a weighted sum of the individual DMs' expected utilities for alternatives. Owen (2015) named the GDM as collaborative decision-making, which is not to strive for an optimum, a compromise, or a satisficing solution, but to aggregate the understandings of DMs in order to obtain a significantly more valuable choice than the existing alternatives.

In GDM, DMs may express their preferences using different types of information, so different methods should be suggested to collect different types of preferences of DMs. For example, the Borda method (Borda, 1784) and the Borda–Kendall method (Kendall, 1962) are the most famous methods to fuse the ordinal rankings. The simple additive weighting method (Kirkwood & Corner, 1993) is the widely used one to aggregate the evaluation values of alternatives. In general, there is no aggregation technique for combining individual rankings into a group one without

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violating five natural fairness properties (Arrow, 1963): universal domain, transitivity, unanimity, rank reversal, and non-dictatorship. Many methods have been developed to solve this problem. For example, Keeney and Raiffa (1976) used an interpersonal comparison of preferences in the aggregation.

By integrating the preference information of DMs, a “group decision” can be reached. However, some DMs may refuse to accept the “group decision,” if their preferences are not taken into account sufficiently (Butler & Rothstein, 1987). This implies that such a “group decision” is not a satisfying group decision. To help DMs obtain a satisfying decision, consensus improvement is necessary. Usually, it is hard to obtain a complete consensus, then a soft consensus (Kacprzyk & Fedrizzi, 1988) based on agreement levels is introduced. This process may be an iterative process with several consensus rounds, in which the DMs adjust their preferences following the consensus rules and the consensus levels that are predefined.

In the development of decision-making, researchers have demonstrated that some classical decision-making methods cannot explain many phenomena, such as Allais’s Paradox and Ellsberg’s Paradox in real applications. That may imply that the behavior of DMs may influence the final decision. Therefore, researchers have investigated the decision-making theories based on behavior (Ramos et al., 2014), and many behavioral decision theories have been developed, such as prospect theory (Kahneman & Tversky, 1979), regret theory (Bell, 1982; Loomes & Sugden, 1982), fairness theory (Rabin, 1993), disappointment theory (Bell, 1985), and team reasoning theory (Colman, 2003). These theories can explain the behavior of DMs and can help DMs judge and choose between alternatives in GDM.

This chapter will give a review of the GDM. According to the evolution of GDM, we can classify it as the one based on information fusion, the one based on consensus improvement, and the one based on behavior. These categories are neither exhaustive nor mutually exclusive.

9.2 GDM Based on Information Fusion

In the GDM, each DM has his/her own attitude and motivation, how to reach a collective decision is the key problem. Chakhar and Saad (2014) denote that most of the GDM methods use either input or output aggregation strategies. The input aggregation strategy first aggregates the individual inputs into a collective input and then yields the final results, while the output aggregation strategy first yields the individual results, then aggregates the individual results into the final results. In any strategy, the aggregation function is necessary. According to different types of decision-making information, the GDM based on information fusion can be classified as the one for rankings, the one for evaluations, and the one for pairwise comparison.

9.2.1 Aggregation for Rankings

For the alternatives in GDM, the DMs may compare at least two alternatives and give the complete or partial rankings of them. Borda examined the ordinal ranking problem for choosing candidates in an election and proposed a method to rank candidates according to the sum of ranks (Borda, 1784). Kendall considered it in a statistical framework, which is proved to be equivalent to Borda's method (Kendall, 1962). So, the method is also named as Borda–Kendall (BK) method, which has been widely used due to its computational simplicity.

Definition 9.1 (Borda, 1784; Kendall, 1962) Suppose there are n candidates (alternatives) denoted by $X = (x_1, x_2, \cdots, x_n)$, and m voters (DMs) denoted by $E = (e_1, e_2, \cdots, e_m)$, each voter e_l gives the rank for the candidate x_i denoted as $r_i^{(l)}$, where $r_i^{(l)} \in \{1, 2, \cdots, n\}$, then the Borda–Kendall score of candidate x_i is defined as:

$$BK(x_i) = \sum_{l=1}^{m} \left(n - r_i^{(l)}\right) \tag{9.1}$$

The BK method assumes that the voter gives the full rank for candidates and no tied rankings. It is not possible to distinguish the distances between rankings. Condorcet (1785) proposed the simple majority rule method, whereby x_i should be the winner if most of the voters prefer x_i to x_j. Kemeny and Snell (1962) proposed an axiomatic approach by minimizing the deviation of individual rankings based on the distance between two complete rankings.

Definition 9.2 (Kemeny, 1959; Kemeny & Snell, 1962) The group ranking r^* is defined as:

$$r^* = \arg \min_{r \in Z_n} \sum_{l=1}^{m} d\left(r^{(l)}, r\right) \tag{9.2}$$

where Z_n is the universe of all full rankings. For a given ranking

$$r^{(l)} = \left\{r_1^{(l)}, r_2^{(l)}, \cdots, r_n^{(l)}\right\}$$

of n candidates, the Kemeny–Snell metric $d(r^{(s)}, r^{(l)})$ between any two rankings $r^{(s)}$ and $r^{(l)}$ is defined as

$$d\left(r^{(s)}, r^{(l)}\right) = \sum_{i=1}^{n} \sum_{j=1}^{n} \left(a_{ij}^{(s)} - a_{ij}^{(l)}\right)$$

and

$$a_{ij}^{(l)} = \begin{cases} -1, & r_i^{(l)} > r_j^{(l)} \\ 0, & r_i^{(l)} = r_j^{(l)} \\ 1, & r_i^{(l)} < r_j^{(l)} \end{cases}$$

Barzilai et al. (1986) demonstrated that Kemeny and Snell's model could be equivalently expressed as a generalized network model. Bogart (1975) extended Kemeny and Snell's method to partial orders considering the transitive and intransitive orderings. Cook and Seiford (1982) defined a distance between complete ordinal rankings and proposed a linear programming method by minimizing the total absolute distance to obtain the group ranking. Cook and Kress (1985) and Ali et al. (1986) gave an integer linear programming method to acquire the group ranking based on distance measure for ordinal rankings with the intensity of preferences. Gonzalez-Pachon and Romero (1999) gave further extension and presented a goal programming to aggregate complete and incomplete ordinal rankings, respectively. By maximizing agreement among DMs, Beck and Lin (1983) proposed the maximized agreement heuristic method to obtain a group ranking. Kaur et al. (2016) proposed an integer linear programming model to integrate various rankings.

Data envelopment analysis (DEA) (Charnes et al., 1978) has also been used to aggregate ordinal rankings, which was shown to be equivalent to the BK method in certain special circumstances (Cook & Kress, 1990). Puerto et al. (2000) employed an extreme point approach to aggregate ordinal rankings. For the aggregation of multi-agents' preference orderings, Yager (2001a) proposed an algorithm, which can reflect the majority of the multi-agent preference orderings. Franceschini et al. (2016) presented a generalized version of the algorithm given by Yager, which is adaptable to less stringent input data. Hochbaum and Levin (2006) presented an optimization framework that addresses major shortcomings that exist in current models for group ranking. Fu et al. (2020) proposed a GDM method based on DMs' satisfaction to examine whether a group solution is satisfactory to the DMs or not, in which group satisfaction is constructed from alternative assessment and ranking differences between DMs and the group.

9.2.2 Aggregation for Evaluations

In the GDM with multiple criteria, DMs may give the evaluations of alternatives with criteria. The aggregation operators for evaluations are usually compensative (Zimmermann & Zysno, 1980). In a multi-criteria group decision-making (MCGDM), let $E = (e_1, e_2, \cdots, e_m)$ be the set of DMs, $\lambda = (\lambda_1, \lambda_2, \cdots, \lambda_m)$ the weight vector of DMs, $X = (x_1, x_2, \cdots, x_n)$ the set of alternatives, $G = (G_1, G_2, \cdots, G_g)$ the set of criteria, and $p_{ij}^{(l)}$ the evaluation of alternative x_i under criterion G_j provided by DM e_l, then the decision matrix $P^{(l)} = \left(p_{ij}^{(l)}\right)_{n \times g}$ can be constructed for DM e_l. The weighted mean (Aggarwal, 2015), the ordered weighted averaging (OWA) (Yager, 1988), and the geometric mean have been widely applied in MCGDM to aggregate the evaluations of different DMs. Aggregation based on Archimedean t-conorm and t-norm[1] (Klement & Mesiar, 2005; Klir & Yuan, 1995; Nguyen & Walker, 1997) are generalizations of a lot of existing aggregation operators (Beliakov et al., 2011).

A strict Archimedean t-norm $TN(x, y)$ and t-conorm $TC(x, y)$ can be expressed via the additive generator g as $TN(x, y) = h^{-1}(h(x) + h(y))$ and $TC(x, y) = g(g(x) + g(y))$, where g is a strictly decreasing function $g : [0, 1] \to [0, \infty]$ such that $g(1) = 0$ and $h(t) = \mathrm{g}(1 - t)$.

Definition 9.3 Based on Archimedean t-norm and t-conorm, the group evaluation of alternative x_i under criterion G_j can be expressed by (Beliakov et al., 2011)

$$p_{ij} = h^{-1}\left(\sum_{l=1}^{m} \lambda_l h\left(p_{ij}^{(l)}\right)\right) \tag{9.3}$$

or

$$p_{ij} = g^{-1}\left(\sum_{l=1}^{m} \lambda_l g\left(p_{ij}^{(l)}\right)\right) \tag{9.4}$$

Pasi and Yager (2006) proposed a fuzzy majority approach that can generate the majority opinion in GDM using a linguistic quantifier. Boroushaki and Malczewski (2010) developed a framework for Geographic Information Science (GIS)-based MCGDM using the fuzzy majority approach. The evidential reasoning approach (Yang & Singh, 1994), developed from Dempster–Shafer's evidence theory (Dempster, 1967), can represent incompleteness or ignorance in a decision-making problem. Zhou et al. (2018) employed evidential reasoning to cope with GDM, in which both the weights and reliabilities of criteria and DMs are considered. Fu et al. (2019) employed the evidential reasoning to aggregate the belief distributions and distributed preference relations in an MCGDM problem.

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[1] A function $T : [0, 1] \times [0, 1] \to [0, 1]$ is called a t-norm if it satisfies the following four conditions: (1) $T(1, x) = x$ for all x. (2) $T(x, y) = T(y, x)$, for all x and y. (3) $T(x, T(y, z)) = T(T(x, y), z)$, for all x, y, and z. (4) If $x \le x'$ and $y \le y'$, then $T(x, y) \le T(x', y')$. A function $S : [0, 1] \times [0, 1] \to [0, 1]$ is called a t-conorm if it satisfies the following four conditions: (1) $S(0, x) = x$ for all x. (2) $S(x, y) = S(y, x)$, for all x and y. (3) $S(x, S(y, z)) = S(S(x, y), z)$, for all x, y, and z.. (4) If $x \le x'$ and $y \le y'$, then $S(x, y) \le S(x', y')$.

A t-norm function $T(x, y)$ is called Archimedean t-norm if it is continuous and $T(x, x) < x$ for all $x \in (0, 1)$. An Archimedean t-norm is called strictly Archimedean t-norm if it is strictly increasing in each variable for $x, y \in (0, 1)$. A t-conorm function $S(x, y)$ is called Archimedean t-conorm if it is continuous and $S(x, x) > x$ for all $x \in (0, 1)$. An Archimedean t-conorm is called strictly Archimedean t-conorm if it is strictly increasing in each variable for $x, y \in (0, 1)$.

However, the above-mentioned operators do not consider the interaction among the arguments of aggregation. Choquet integral (Choquet, 1954) is an established aggregation function, which can represent the interactions and can be reduced to the existing operators in some special cases.

Definition 9.4 Based on Choquet integral (Choquet, 1954), the group evaluation of alternative x_i under criterion G_j can be expressed by

$$p_{ij} = \sum_{T' \subseteq T} \lambda_{T'} \bigwedge_{l \in T} p_{ij}^{(l)} \tag{9.5}$$

or

$$p_{ij} = \sum_{T' \subseteq T} \lambda_{T'} \prod_{l \in T} p_{ij}^{(l)} \tag{9.6}$$

where $\lambda_{\phi} = 0$, $\sum_{T' \subseteq T} \lambda_{T'} = 1$, $\forall i \in M$, $\forall S \subseteq M \backslash \{i\}$, $\sum_{T' \subseteq S} \lambda_{T'} \cup \{i\} \geq 0, M = \{1, 2, \ldots, m\}$.$\lambda_{T'}$ measures the interactions of the set of DMs e_l, $l \in T'$. If $\lambda_{T'} > 0$, then the set of DMs e_l, $l \in T'$ has positive interactions; if $\lambda_{T'} < 0$, then the set of DMs e_l, $l \in T'$ has negative interactions; otherwise there is no interactions.

An induced Choquet OWA is proposed in Yager (2004) and is applied in GDM. Fusion Choquet integral, attitudinal Choquet integral, and generalized attitudinal Choquet integral are further developed by researchers (Aggarwal, 2018; Mesiar et al., 2011). Yager (2001b) introduced the power average to provide an aggregation operator which allows arguments to support each other in the aggregation process. The Bonferroni mean originally introduced by Bonferroni (1950) and then generalized by Yager (2009) can also capture the interrelationship between input arguments. Butler et al. (2001) developed a multiple attribute utility theory to aggregate the evaluations considering their interactions of them. Huang et al. (2013) proposed an aggregation for utility-based individual preference for GDM considering the preferential differences and preferential priorities.

In the information fusion process, one important issue is to specify the weights of DMs based on some specific technique (Keeney, 2013). French (1956) used influence relations of DMs to determine their relative importance. An interpersonal comparison can also be used to reflect the weights of the DMs (Keeney & Kirkwood, 1975). Bodily (1979) used the eigenvector method to calculate the weights of DMs. Brock (1980) used Nash bargaining to estimate the weights. Khelifa and Martel (2001) employed the individual outranking indices to derive the DMs' weights. Deviations between DMs have also been used to express their relative weights (Xu, 2008). Dong and Cooper (2016) adopted a Markov chain method to determine DMs' weights. Wu et al. (2017) calculated the weights of DMs according to the strength of the trust relationship between two nodes in the social network. From the point of opinion dynamics, Capuano et al. (2018) obtained the weights of DMs in the social network using trust strength and location operators based on fuzzy ordering. Amenta et al. (2021) proposed a method based on the Frobenius norm to compute coefficients and aggregate individual judgments under the assumption that there is a large dispersion and DMs are unwilling or unable to revise their judgments and the weights are not negotiable.

9.2.3 Aggregation for Pairwise Comparison

The pairwise comparison (PC) matrix (Saaty, 1980) can help DMs in GDM express their information about alternatives by comparing pairs of them. For a set of alternatives $X = \{x_1, x_2, \cdots, x_n\}$, the PC matrix provided by DM e_l can be defined as $A_l = (a_{ijl})_{n \times n}$. where a_{ijl} expresses the degree to which alternative x_i is preferred to alternative x_j. The entry a_{ijl} can be described in different forms according to the preferences of DMs (Saaty, 1980; Tanino, 1984). Cavallo and D'Apuzzo (2009) unified these concepts based on the Abelian linearly ordered group (alo-group for short).

Definition 9.5 Let Q be a nonempty set, $\odot : Q \times Q \to Q$ a binary operation on Q, and $\leq$ a total weak order on Q. Then $\odot$ is called an Abelian linearly ordered group (alo-group for short) if and only if $(Q, \odot)$ is an alo-group and $a \leq b \Rightarrow a \odot c \leq b \odot c$ for $c \in Q$.

For convenience, let $\Omega = (Q, \odot, \leq)$ be an alo-group and $PC_{\mathrm{n}}(\Omega)$ denote the set of all the PC matrices based on alo-group. Let $A_l = (a_{ijl}) \in PC_n(\Omega)(l = 1, 2, \ldots, m)$ be provided by DMs $e_l(l = 1, 2, \cdots, m)$, whose weight vector is $\lambda_l(l = 1, 2, \cdots, m)$.

In the GDM based on PC matrices, in general, one must decide in advance whether to represent a group by aggregating their individual judgments (AIJ) or by aggregating their individual priorities (AIP). Based on the AIJ method, the following approach can help DMs fuse individual PC matrices into a group one.

Definition 9.6 (Xia & Chen, 2015a) Let $A_l = (a_{ijl}) \in PC_n(\Omega)$ $(l = 1, 2, \cdots, m)$, then their group PC matrix defined as $A = (a_{ij}) \in PC_n(\Omega)$ can be constructed as

$$a_{ij} = \bigodot_{l=1}^{m} a_{ijl}^{[\lambda_1]}, i, j = 1, 2, \ldots, n.$$

Many methods have been developed to derive the priority from the PC matrix based on the consistency index (Saaty, 1980; Saaty & Vargas, 1998), and the one based on alo-group can be found in Xia and Chen (2015a). Based on the AIP method, the following approach can be used to derive the group priority of PC matrices based on alo-group.

Definition 9.7 (Xia & Chen, 2015a) Let $(w_{1l}, w_{2l}, \cdots, w_{nl})^{\mathrm{T}}$ be the priority vector derived from A_l and $A = (a_{ij})$ be the collective matrix with the priority vector $w = (w_1, w_2, \cdots, w_n)^{\mathrm{T}}$. Then the group priority vector is defined as

$$w_i = \bigodot_{l=1}^{m} (w_{il})^{[\lambda_1]}, i = 1, 2, \ldots, n.$$

PC matrices are usually used in the AHP method, Saaty (1996) extends AHP to analytical network process (ANP) to deal with the problem in a network instead of a hierarchy. Best-worst method (Rezaei, 2015) is another method to express the relationship of alternatives but needs lesser pairwise comparisons. Ishizaka and Labib (2011) developed the Group AHP ordering method, in which the DMs are incorporated into a level of the hierarchy and the weights are derived by pairwise comparisons. Scala et al. (2016) propose a method for aggregating judgments based on principal component analysis. Saaty and Vargas (2007) introduced a dispersion test for group aggregation. When the judgments fail this test, then the use of the geometric mean would be inappropriate. Huang et al. (2009) developed an MCGDM method based on AHP embracing preferential differences and preferential ranks. Negahban et al. (2017) proposed an iterative rank aggregation algorithm for discovering the priority of PC matrices. The algorithm has a natural random walk interpretation over the graph of objects with an edge present between a pair of objects if they are compared.

Linear programming technique for multidimensional analysis of preference (LINMAP) is one of the classic methods for solving MCGDM problems (Srinivasan & Shocker, 1973), which is based on pairwise comparisons of alternatives given by the DMs and provides the best alternative as the solution that has the shortest distance to the ideal solution. Let $x^* = \left\{p_1^*, p_2^*, \cdots, p_g^*\right\}$ be the positive ideal solution, then the divergence between alternative x_l and the ideal position x^* can be defined as

$$s_l = \sum_{j=1}^{g} w_j \left(p_{lj} - p_j^*\right)^2,$$

where $w = (w_1, w_2, \cdots, w_g)$ is the criteria weight vector. Let $\phi = \{(k, l)\}$ denote the set of orders of alternatives given by DMs. The pair of alternatives $(k, l) \in \phi$ means that alternative x_k is closer to the positive ideal position x^* than alterative x_l. Therefore, $s_l \geq s_k$ consistent with the preference given by decision makers, while $s_l < s_k$ is not.

Let $(\mathrm{s_l} - \mathrm{s_k})^-$ denote the inconsistency index with the pair (k, l), then summing it over all the pairs in ϕ, we can get the total inconsistency index

$$I = \sum_{(k,l)\in\phi} (s_l - s_k)^- = \sum_{(k,l)\in\phi} max\{0, s_k - s_l\}.$$

In the same way, the consistency index is given by

$$S = \sum_{(k,l)\in\phi} (s_l - s_k)^+ = \sum_{(k,l)\in\phi} max\{0, s_l - s_k\}.$$

To determine the weight vector of criteria and the positive ideal solution, the following model is given

$$\begin{aligned} \min \quad & \sum_{(k,l)\in\phi} \max\{0, (s_k - s_l)\} \\ \text{s.t.} \quad & S - I \geq h \\ & \sum_{j=1}^{g} w_j = 1, w_j > 0 \end{aligned}$$

LINMAP model aims to minimize the inconsistency index under the condition that the consistency index is not smaller than the inconsistency index by h, where h is a positive number given by DMs as a priori.

9.3 GDM Based on Consensus Improving

In the context of GDM, due to DMs' different knowledge and experience levels, there may be a diversity of opinions among DMs. Thus, one critical issue is how to help DMs reach an agreement on the final solution. The consensus-reaching process (CRP) is usually employed to achieve a general consensus regarding the selected alternative. Different types of CRPs have been proposed in the literature. We can classify CRPs as the process-oriented one and the content-oriented one, the former focuses on the process of consensus reaching of DMs, and the latter attempts to obtain an optimal or satisfactory solution through establishing models. In CRP, the relationships of DMs may influence consensus improving and should be investigated.

9.3.1 Process-Oriented Consensus Improving

The process-oriented consensus-improving process is an iterative process with several consensus rounds. Take the GDM based on PC matrices as an example, DMs initially express their individual PC matrices, then the consistency levels of PC matrices are calculated. If the consistency levels are lower than a specified threshold, then the individuals are required to revise their PC matrices until the consistency levels are satisfied. After that, the individual PC matrices are aggregated into the group PC matrix by using the aggregation operator, based on which the consensus levels of individual PC matrices are calculated. If the consensus levels of the PC

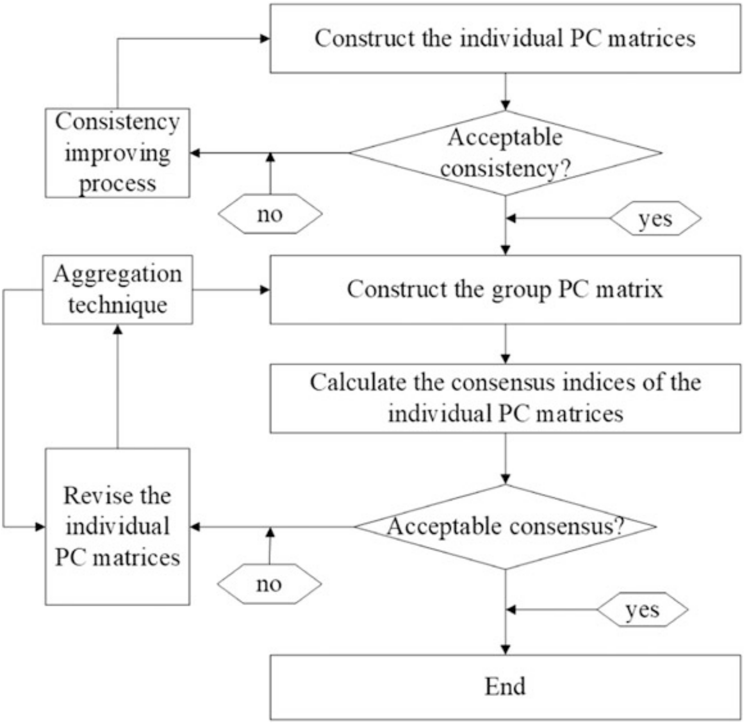

Fig. 9.1 The consensus-improving process

matrix are lower than a specified threshold, then the individuals are suggested to revise their preference until the consensus levels are satisfied. Most existing CRP models follow such a general framework (see Fig. 9.1), but there may be some differences in some specific details.

Brainstorming and the Delphi method are two famous methods to help DMs reach consensus. In brainstorming, DMs are freewheeling but are not allowed to express criticism. Therefore, the quantity of ideas is produced and will be evaluated later on, but not during the brainstorming phase (Osborn, 1942). The Delphi method is a framework based on the results of multiple rounds of questionnaires sent to DMs (Adler & Ziglio, 1996). The anonymous responses are aggregated and shared with the group after each round. The DMs can adjust their opinions in subsequent rounds. It is a repetitive communication process and can solve sophisticated matters through group communication and the exchange of opinions. Boynton (2006) used the Delphi method to identify key values which guide ethical decision-making in public relations. Lack of physical interactions, long response time, and the usefulness of received information are the main drawbacks of this method. Some researchers have tried to improve it, for example, Xie et al. (2012) developed an agile Delphi decision-making platform based on ASP.NET, making the decision more efficient.

For the GDM based on the AHP method (Saaty, 1980), Dong and Cooper (2016) proposed a consensus-reaching model in a dynamic decision environment. Their developed model provided feedback suggestions to adaptively adjust the credibility of individual DM. Considering the consistency and consensus in GDM based on preference relations, Chiclana et al. (2008) did consistency-reaching based on the additive consistency property and generated advice on how DMs should change their preferences in order to increase their consistency. Xia et al. (2013) developed an algorithm to improve the consistency level of an additive PC matrix, then proposed a consensus-improving algorithm, which can improve the consistency and consensus of additive PC matrices with fewer interactions with the DMs and can obtain the results quickly. Wu and Xu (2016) developed separate consistency and consensus-improving processes considering individual rationality and group rationality. Herrera-Viedma et al. (2007) presented a GDM model with incomplete reciprocal preference relations based on the additive consistency property.

To deal with the CRP for different preference structures, Herrera-Viedma et al. (2002) gave a consensus model for GDM problems considering preference orderings, utility values, additive PC matrices, and multiplicative PC matrices. Mata et al. (2009) proposed an adaptive consensus model to support consensus processes with multigranular linguistic information, which can improve the consensus level by searching for preferences in disagreement. Alonso et al. (2010) presented a web consensus support system to deal with different kinds of incomplete PC matrices. Their feedback system was based on the consensus degrees to reduce the proximity measure calculations. Since different consistency and consensus methods should be developed for different types of matrices. To provide a general framework, Xia and Chen (2015a) introduced two consensus-improving methods based on the alo-group. The proposed methods are convergent and can provide a general framework for some existing methods.

To help DMs to reach a consensus, other theories have been used in CRP. Altuzarra et al. (2010) proposed a consensus-building method based on the Bayesian approach, in which the consensus-building procedure is based on the identification of "agreement" and "disagreement" zones. Fu and Yang (2010) extended the evidential reasoning approach to group consensus situations for MCGDM under various kinds of uncertainties with pivotal group consensus requirements. Xu, Zhong, et al. (2015b) presented an exit-delegation mechanism to deal with clusters, when the proximity degree is not satisfied, the cluster is advised to exit the decision-making process and a delegation mechanism is then adopted to reserve the cluster's influence by setting trust weights for the other clusters. Liu et al. (2018) proposed an iteration-based consensus-building framework with self-confident multiplicative preference relations. They used a two-step feedback adjustment mechanism to assist the DMs to improve the consensus level. Liu, Du, and Wang (2019b) adopted Nash's bargaining idea to maximize group negotiation satisfaction and minimize system coordination deviation in the CRP. In the CRP, log files can describe how each individual DM has ranked the alternatives at each iteration of each session. By analyzing the log files, Triantaphyllou et al. (2020) gave a post-consensus analysis of GDM processes based on some graph theoretic and the mining of association rules.

With the rapid development of the economy and technology, the concept of large-scale group decision-making (LSGDM) (Liu et al., 2015) was introduced, in which the number of DMs varies from dozens to thousands. Wu and Xu (2018) proposed an LSGDM consensus model in which the clusters are allowed to change. A local feedback strategy with four identification rules and two direction rules is designed to guide the CRP. Based on the notion that cardinal consensus and ordinal consensus are of equal importance, Zhong et al. (2021) proposed a novel consensus-reaching model for LSGDM via the integration of cardinal consensus and ordinal consensus. The existing methods focus their analysis on the DMs and preferences but neglect the reasons why they provide such preferences. Morente-Molinera et al. (2021) introduced the argumentation measures, along with consensus measures indicating how DMs change their opinions in each round and what was the reason for it. This can help get a clear idea about how and why a specific resolution has been reached and determine which is the most influential DM.

Many researchers have reviewed the CRP methods. Perez et al. (2018) presented a systematic literature review on the evolution of consensus-reaching models under dynamic environments and critically analyzed their advantages and limitations. Zhang, Dong, et al. (2019b) gave some comparison criteria for measuring the efficiency of CPRs and designed a simulation experiment to analyze the efficiency of different CRPs.

9.3.2 Content-Oriented Consensus Improving

In a GDM process, most of the oriented-consensus improving methods require a moderator to spend time and resources to persuade DMs to change their original opinions. Therefore, cost should be considered in the improving process, such types of CRP methods may pay more attention to the content of decision-making but neglect the consensus level.

The concept of the minimum cost consensus model was first proposed by Ben-Arieh and Easton (2007). Let p_l represent the original opinion of the lth DM, $\overline{p_l}$ the adjusted individual opinion of e_l, $\overline{p}$ the adjusted group opinion, and $c_l \geq 0$ the unit consensus cost of DM e_l. The minimum cost consensus model is defined as (Ben-Arieh & Easton, 2007):

$$\min \sum_{l=1}^{m} c_l d(\overline{p_l}, p_l)$$
$$s.t. |\overline{p_l} - \overline{p}| \leq \varepsilon, l = 1, 2, \ldots, m$$

where ε denotes the established threshold. The model can obtain the optimal adjusted individual opinions $\overline{p}^*, l = 1, 2, \cdots, m$ and the optimal adjusted group opinion $\overline{p}^*$.

Dong et al. (2010) presented the optimization-based minimum adjustment consensus models based on OWA-based linguistic operators. Zhang et al. (2011) proposed a framework for consensus models under aggregation operators and investigated the relationship between the minimum cost consensus model and the minimum adjustment consensus model. To further explore the original minimum cost consensus model, Gong et al. (2015) adopted the linear prime-dual theory and presented their economic interpretations. Wu et al. (2018) discussed the scheme recommendation and users' trust measure using the feedback mechanism in the minimum cost consensus model with social network analysis. Considering that the cost coefficients are asymmetric due to the adjustment direction of DMs' opinions, Cheng et al. (2018) analyzed the impact of individual limited compromises and tolerance behaviors on the minimum cost consensus model. Zhang, Kou, and Peng (2019a) proposed consensus models under a certain degree of consensus, which considers both consensus degree and cost in GDM, in which the cost (compensation) is studied from both a moderator and individual DM.

While the above studies mostly focus on the preference for cardinality or interval value, minimum cost consensus models are also generalized to CRP based on PC matrices. Zhang and Pedrycz (2018) proposed two-stage optimization models to address individual consistency and group consensus. Wu, Huang, and Xu (2019c) developed multi-stage optimization models for CRP with fuzzy PC matrices to minimize the adjustment costs, the number of revised preference values, and DMs who need to make adjustments. Considering the belief degree given by DMs and uncertainty distribution to fit individual preferences, Gong et al. (2021) discussed five scenarios of uncertain chance-constrained minimum cost consensus models from different perspectives. Cheng et al. (2020) proposed a minimum adjustment consensus framework for the social network GDM with incomplete linguistic PC matrices. Labella et al. (2020) constructed a comprehensive minimum cost model with fuzzy PC matrices. The research paradigm for the mechanisms for the minimum cost consensus models and the minimum adjustment consensus models during the last decades was concluded by Zhang et al. (2020).

9.3.3 GDM Based on Social Network

With the development of social media and e-commerce, the social network relations of DMs may affect the process and result of GDM. Social network analysis (SNA) has become one of the most popular methodologies for investigating social ties among members. It provides a way to describe and analyze the interconnections among individuals. According to SNA, strong social ties between two DMs indicate that the DMs could be more willing to share opinions with each other openly; at the same time, a DM with more connections is more important and influential than another DM with fewer connections (Li & Lai, 2014). Alonso et al. (2013) demonstrated the characteristics of Web 2.0 communities in GDM contexts, such as their support for real-time communication and heterogeneous users. Li and Lai (2014) proposed a social appraisal mechanism to support decision-making through online social networks. Quijano-Sanchez et al. (2014) employed users' social interaction information derived from online social networks to develop a group recommendation application. Wu and Chiclana (2014) defined the trust degree of each DM using the in-degree centrality and proposed a trust-based consensus model with fuzzy preference relations.

Li et al. (2013) developed a group recommendation system for E-commerce platform users by analyzing their social networks of the trust relationship and showed that the system has a high prediction accuracy. Wu et al. (2017) put forward a CRP with the visualization that is more conducive for DMs to accept the recommendations. Kamis et al. (2019) proposed an influence-driven feedback system based on an influence measure. The individual behaviors of strategic manipulation (Dong et al., 2021) and bounded confidence (Zha et al., 2021) are also considered in social network GDM (SNGDM). Dong et al. (2018) reviewed the research paradigm and challenges of existing consensus problems in the social network context from the perspective of opinion evolution or dynamics. Ding et al. (2019a, b) investigated how the self-confidence level and the node degree influence the consensus opinion formation and the consensus convergence speed in the social network. Ureña et al. (2019) reviewed the existing pieces of literature about trust propagation and opinion dynamics in social networks and GDM frameworks. Ding et al. (2019a, b) presented an SNA-based conflict relationship investigation process to detect the conflict relationships among DMs for LSGDM. Wu, Zhang, et al. (2019b) proposed a two-stage trust network partition algorithm to reduce the complexity of LSGDM problems.

Dong et al. (2019) introduced a framework to achieve a potential consensus considering polarized opinions. Considering the dynamic relationships among DMs, they suggested using SNA to reach an agreement. Morente-Molinera et al. (2019) adopted sentiment analysis to analyze free texts and extract the preferences of DMs provided based on the social networks and provided two consensus measures. Based on the influence of network structure on the DMs' weights, Cheng et al. (2020) proposed a weight allocation method with the structural hole theory by analyzing the tie strength and topology structure of DMs social networks, and the consensus indexes at three levels are constructed to identify the DMs with lower consensus level. In order to explore the evolution of consensus, Wu, Liu, et al. (2019a) proposed a CRP based on consensus evolution networks constructed by the consensus degrees among DMs, in which the pairwise feedback adjustment method is proposed to improve consensus. Liu, Xu, et al. (2019a) took self-confidence into account in GDM based on the social networks. In their method, a consensus index considering self-confidence is defined to assess the consensus level among DMs, and a trust-based feedback mechanism is presented to improve the consensus efficiency. To analyze the influence of the relationship between DMs on the decision-making results, Li et al. (2021a, b) proposed an MCGDM with opinion dynamics based on a social trust network and used an opinion dynamics-based feedback mechanism to coordinate disagreeable opinions.

9.4 GDM Based on Behavior

Behaviors of DMs will affect the decision-making of DMs. Many behavior phenomena have been found from the real-life decision-making or by experiments and have been investigated and concluded as the famous behavior theories. Some of these theories have in turn been applied in decision-making.

9.4.1 GDM Considering Behavior

Regret theory states that DMs anticipate regret if they make the wrong choice, which may influence their decision when they make choice (Bell, 1982). According to regret theory, DMs may care more about the relative values than the absolute values of alternatives, especially, under the uncertain situations. By calculating the differences between each pair of alternatives under imprecise information, several types of optimal alternatives have been defined and identified by researchers (Wang, 2012; Wei et al., 2013). Xia et al. (2015) defined the relative measure of alternatives based on the alo-group and regret theory, which can measure the relative values of alternatives from different views. Several models have been proposed based on four principles to identify different types of optimal alternatives.

Prospect theory is a psychological theory that describes how people make decisions when alternatives involve risk, probability, and uncertainty (Kahneman & Tversky, 1979). Prospect theory assumes DMs value losses and gains differently and thus will make decisions based on perceived gains and perceived losses, but not on the real ones. Long et al. (2021) presented a consensus-reaching method for MCGDM problems with preference approval structures in prospect theory. Colman et al. (2008a) noted that traditional decision and game theories are based on the assumption that players seek to maximize their individual utilities. However, it is observed in some interactive decisions that maximizing the utility of the group of players as a whole seems intuitively reasonable, which is named as team reasoning (Colman, 2003). Colman et al. (2008b) reported that team reasoning predicts strategic choices more powerfully than orthodox game theory. Based on team reasoning, Xia et al. (2020a) considered all the DMUs in DEA as a team and introduced the team indexes, based on which several models are developed to estimate the values of the team indexes and identify the optimal DMUs under the condition that the team indexes are satisfied.

Baucells and Shapley (2000) employed bilateral agreements between pairs of DMs to derive the group decision. For a criterion or an alternative, a set of DMs $E = \{e_1, e_2, \cdots, e_m\}$ give their evaluation vector $u = (u_1, u_2, \ldots, u_m)$, where u_i is the evaluation of this criterion or alternative provided by DM e_i. Suppose any pair of DMs are willing to negotiate with each other about the evaluation of this criterion or alternative. If DMs e_i and e_j give their bilateral agreement as u_{ij}, then u_{ij} can be expressed as $u_{ij} = \frac{u_i + \delta_{ij} u_j}{1 + \delta_{ij}}$, where δ_{ij} is called the "comparison ratio" between e_i and e_j.

Suppose $m - 1$ pairs of DMs give their bilateral agreements, let $\lambda_1 = 1$, $\lambda_i = \delta_{1i}$, $i = 2, 3, \cdots, m$, then the group preference is represented by

$$u_N = u_{12\cdots n} = \sum_{i=1}^{n} \lambda_i u_i / \sum_{i=1}^{n} \lambda_i \tag{9.7}$$

To test DMs willingness to arrive at bilateral agreements, Heil and Kuntz (2005) studied a large capital investment decision by an executive team representing 35 German hospitals and found that it is sufficient to seek compromise among pairs in group decisions. Baucells and Sarin (2003) extended the method proposed by Baucells and Shapley (2000) to MCGDM. However, their methods are suitable only for the weighted arithmetic mean (Harsanyi, 1955) and may not ensure the consistency of the PC matrices (Saaty, 1980). Xia and Chen (2015b) extended Baucells and Sarin's method (Baucells & Sarin, 2003) and provided an MCGDM method based on bilateral agreements to aggregate PC matrices (Tanino, 1984). However, in the above GDM methods based on bilateral agreements, DMs are allowed to only express $m - 1$ pairs of bilateral agreements on alternatives to ensure that a consensus can be reached, which may neglect some decision information. Xia et al. (2020b) proposed a GDM based on a bilateral agreement matrix, in which all the bilateral agreements are considered.

Usually, non-cooperative behavior appears in GDM to protect personal or alliance interests. Palomares et al. (2014) presented a consensus model suitable to manage large scales of DMs that incorporates a fuzzy clustering-based scheme to detect and manage individual and subgroup non-cooperative behaviors. Quesada et al. (2015) introduced a methodology to deal with non-cooperative behaviors, in which a uniform-based weighting scheme was applied to assign importance weights to the DMs. Xu, Du, and Chen (2015a) further considered a consensus model that managed minority opinions and non-cooperative behavior. Li et al. (2021a, b) defined several cooperation degrees to detect the non-cooperative behaviors of DMs and employed a dynamic weight punishment mechanism for non-cooperative DMs. Liao et al. (2021) identified two kinds of conflicts among DMs and introduced a conflict resolution process with a feedback mechanism. Dong et al. (2016) introduced three kinds of non-cooperative behavior. When a non-cooperative behavior was detected, it was managed by penalizing the importance weights of the identified subgroup. To reduce the negative impact of non-cooperative behavior, Zhang et al. (2018) presented a consensus method to manage the non-cooperative behavior in MCGDM.

9.4.2 Behaviors in GDM

Discussion and communication are necessary for GDM. Bohlmann et al. (2006) used two empirical studies to demonstrate that individual-level post-discussion satisfaction judgments tend to become more extreme, named satisfaction escalation. Fisher (2017) showed that groups receiving in-process interventions pooled more critical information and made better decisions than groups receiving pre-task interventions. From a laboratory experiment, Ertac and Gurdal (2019) found women and individuals who are more trusting others are more likely to manipulate their own preferences when communicating with them and more likely to compromise in response to others' preferences as leaders. Keck and Tang (2021) explored that when the level of systematic error was high, group interactions will have a strong positive effect on the accuracy of quantitative judgments. Based on the assumption that GDM processes are often adopted to strengthen social bonds, Tan (2021) found that participation in a GDM process enhances kindness toward group members, irrespective of whether the decision leads to a success or a failure.

Social loafing and group polarization are common phenomenon in GDM. Chidambaram and Tung (2005) investigated social loafing in the context of GDM. The results indicate that small groups, which signify a small dilution effect, will increase individual contributions and better group outcomes compared to their larger counterparts. Zhu (2014) examined how CEO compensation decisions may be influenced by a major GDM tendency referred to as group polarization among outside directors and found that when outside directors on average tend to support even higher (lower) CEO compensation prior to board discussions, they will support even higher (lower) focal CEO compensation after the discussions. Bonnet et al. (2021) studied the operations and internal structure of business angel groups and found that business angels with a control-oriented decision-making style tend to be more actively involved in key angel group activities.

The sharing of information is a concerning problem in GDM. Galbreth et al. (2012) suggested that a firm can benefit from increased social sharing if the level of sharing is already high, enabling a pricing strategy targeted primarily at sharing groups rather than individuals. However, the point at which sharing becomes marginally beneficial for a firm depends on both the distribution of group sizes and the group decision mechanism. Gao et al. (2016) examined the impact of shared-display configurations on GDM. The results show that submission control has a positive impact on the level of participation, the satisfaction with the group process, and the commitment to the decisions made, but it negatively influences the decision quality. By exploring whether group members often overweigh shared information and undervalue unique information during discussions or not, Tsai and Bendersky (2016) demonstrated that expressing task conflicts as debates rather than as disagreements will make greater information sharing because receivers perceive senders to be more receptive to dissenting opinions.

In sequential decision-making experiments, participants often conform to the decisions of others rather than reveal private information, resulting in less information produced and potentially lower payoffs for the group. Parys and Ash (2018) found that alternating decision-making across members of different groups may improve welfare in sequential decision-making contexts since projects that appear in a sequence following a funded project are themselves less likely to receive funding. Criscuolo et al. (2021) examined how groups fall prey to the sequence effect when they make choices in evaluating research and development projects. They find robust support for the existence of a sequence effect in research and development projects as well as for the moderating effect.

Many researchers have compared the GDM with other decision-making. Barber et al. (2003) compared the investment decisions of individuals and clubs and found that both individuals and clubs are more likely to purchase stocks for good reasons. However, stock clubs favor such stocks more than individuals, despite the fact that such reasons do not improve performance. Arora et al. (2011) showed that among concordant dyads, the non-compensatory dyads make quicker decisions that result in higher dyadic welfare. Among discordant dyads, those that restrict their consideration set make quicker decisions that result in higher welfare than those that expand their consideration set. Drawing on fairness heuristic theory and literature on negative group schemas, Kouchaki et al. (2015) developed and empirically test the idea that, given the exact same decision outcome, people perceive groups to be less fair than individuals when they receive a decision outcome that is unfavorable, but not when they receive one that is favorable or neutral. Maciejovsky and Budescu (2020) compared groups and markets in their ability to pool and aggregate information in a hidden-profiles task. Their studies show that groups outperform markets when there were no conflicts of interest among participants, whereas markets outperform groups when conflicts of interest were present. Faralla et al. (2020) assessed in the laboratory the effect of promises on GDM and showed that promises and proposers elicit social conformity leading groups to exhibit more desirable social behavior.

9.5 Application of GDM

GDM has been widely applied in many areas, such as the supply chain management, circular economy, public transportation, safety control, artificial intelligence, and so on.

Supplier selection plays an important role in supply chain management due to its direct impact on the cash flow and profitability, and it can be considered as an MCGDM problem. Most of the existing MCGDM methods can be used in selecting the supplier. Chuu (2011) built an interactive GDM structure to evaluate the flexibility of supply chain management development comprising the evaluation hierarchy and the evaluation scheme. Mousakhani et al. (2017) proposed a method for green supplier selection under the GDM approach and Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method. Qin et al. (2017) extended the TOmada de Decisão Iterativa Multicritério (TODIM) method to MCGDM and presented its application to the green supplier selection problem. Banaeian et al. (2018) provided a GDM method combining fuzzy TOPSIS, fuzzy Vise Kriterijumska Optimizacijal Kompromisno Resenje (VIKOR), and fuzzy gray relational analysis (GRA) and used it in the selection of the supplier in the agri-food industry. Kamble et al. (2021) used an LSGDM technique to identify and rank the best circular economy practices in the auto-component industry. Liang et al. (2020) proposed an MCGDM based on the QUALItative FLEXible multiple criteria method (QUALIFLEX) method and Choquet integral to solve the green supplier selection problem. Yazdi et al. (2022) developed a comprehensive approach combining the Delphi method, the Stepwise Weight Assessment Ratio Analysis (SWARA) method, and the COmplex PRoportional ASsessment (COPRAS) method for selecting suppliers in the oil and gas industry.

For the application of GDM in other areas, a lot of work has also been done. Balezentis et al. (2021) proposed an MCGDM framework for the promotion of the heating systems based on the renewable energy sources integrating the Best-Worst method and modifying the Weighted Aggregated Sum Product Assessment (WASPAS) method. As an intensive travel mode, public transportation is an essential part of a circular economy construction. Based on the LSGDM of fuzzy preference relations, Zhang et al. (2021) examined the public transportation development decision-making under public participation, to promote the effective use of public transportation resources. Chen et al. (2021) proposed a combination of online review analysis and LSGDM to determine passengers' demands and to evaluate passengers' satisfaction. Skorupski and Uchronski (2020) proposed a multi-criteria assessment of variants of the modernization of the hold baggage screening system at an airport, considering various points of view of DMs and the context of decisions made. Cuoghi and Leoneti (2019) gave the application of an MCGDM method to aid the public sector to make decisions in choosing the construction alternatives for Belo Monte Dam.

Kao and Liu (2022) used the GDM based on DEA to select the robot. Guo et al. (2021) constructed an LSGDM framework for the site selection of the integrated floating photovoltaic-pumped storage power system based on an extended fuzzy Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) method. Chao et al. (2021) developed a consensus-reaching model to address heterogeneous LSGDM with non-cooperative behaviors and discuss its application in financial inclusion. In hazardous waste management, selecting the best Hazardous Waste Carrier is a standalone decision problem in hazardous waste generators, as hazardous waste may pose risks to human health and/or its environment if handled improperly. Büyüközkan et al. (2019) addressed the Hazardous Waste Carrier selection process by proposing a GDM based on AHP and VIKOR. Rahimi et al. (2020) introduced a framework comprising GIS techniques and fuzzy MCGDM for application in a landfill site selection problem. Wu et al. (2016) proposed a hybrid GDM approach to facilitate ship safety control by incorporating fuzzy logic, consistency-based linear programming, and the TOPSIS method.

9.6 Expected Future of GDM

In the last decades, a lot of GDM methods have been developed and have been used in many areas; however, there still exist new challenges. For example, in the application of GDM methods, the results may be contrary to the expectations, then the GDM methods should be improved, and for the new GDM problems, new GDM theories should be developed. In the following, we give some ideas about the expected future of GDM.

9.6.1 The GDM in Blockchain

A blockchain (Nakamoto, 2008) is a distributed ledger on a peer-to-peer network and has achieved great success in many applications. Each participant in the network has the potential right to record the transaction broadcast, and these participants do not trust each other. The key problem is how to maintain a consistent ledger collectively. Many consensus algorithms of blockchain have been developed. The proof of work is famous one, in which the node in the network that first solves a predefined difficult puzzle will record the transaction, but this process will waste a lot of energy. Other consensus algorithms have been developed to improve it, such as the proof of state, the proof of space, and others. Each consensus algorithm has its advantages and disadvantages. Making a consistent leger in a peer-to-peer network is actually a group decision-making. The nodes in the network can be considered as DMs and also as alternatives, the task is to evaluate the nodes in the network by using a criterion or more than one criterion to choose the one to record the ledger. Most of the existing consensus algorithm of blockchain uses only one criterion to choose the node that makes a record. Therefore, many GDM methods can be used to deal with such problems, but the difference is that in traditional GDM, the alternatives and DMs are not the same and the numbers of DMs are limited. New methodologies should be developed to deal with such problems.

9.6.2 The GDM Using Machine Learning

Many GDM methods have been developed and applied in many areas. For one specific problem, different GDM methods will produce different results, which is the best one? One GDM method can also be used in many problems, which is the suitable one? In addition, the existing GDM methods only use the explicit information for simply; however, there exists a lot of implicit information that will affect the decision. Many researchers have tried to use machine learning to simulate human decisions. For example, Peterson et al. (2021) used artificial neural networks to analyze the data obtained from the largest experiment on risky choices to predict and understand how people make decisions, they found that decision theories discovered through machine learning outperform the classic theories. They only focused on the MCDM; therefore, GDM based on machine learning is valuable to be studied in the future.

9.6.3 The Use and the Expression of GDM Behavior

A lot of experiments have been done to derive the behaviors of DMs in GDM, and some of them have in turn been used in GDM, but it is not enough. The human mind is the most complex and the most unpredictable thing in the universe. More behaviors need to be mined not only through experiments but also through real decision-making problems. How to express these behaviors is also a challenge. Many results obtained by using data mining seem to be reasonable, but why and how the results are obtained is usually a puzzle. The why and how can help DMs better make decisions in GDM. In addition, although many behaviors have been derived, but how to use them in GDM is another problem. Usually, the forming of a GDM theory based on behavior is a long and painful process but is significant.

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