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RESEARCH PAPER

Insight monetization intermediary platform using recommender systems

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Abstract

Fundamental changes have prepared the grounds for a rapid movement towards becoming data and insight-driven. Businesses are continually seeking approaches to create more value from data. The main purpose of this article is to propose a model by which experts as Human Intelligence, can participate to share their expectations to orient the data processing towards the generation of insights needed to target industries and consequently, the realization of indirect data monetization. A set of recommendation systems as Artificial Intelligence, facilitate the submission and validation of expectations, access to data, and selling insights. The model also encompasses a direct data monetization strategy, wherein participants access or request their requirements in an Online Insight Marketplace. We have used the design science methodology to develop and validate our proposed model. The model is validated by comparison with competitive models from the literature, and also by bringing evidence from real-world applications which relate to the components of our model.

Keywords Recommender system · Data monetization · Expert expectation · Collaboration · Insight

JEL classifications M1 · M2 · M31 · M41 · M5

Introduction

For many years, the assumption has been that online platforms have been gaining monetary value solely by offering products and services to users. But a study (Li et al. 2018), on the Facebook-Cambridge Analytica data scandal, showed that consumers have been exchanging their valuable data for access to products or services provided by these social or e-commerce platforms. Scholars have identified the problems regarding this approach, such as the fact that users are either not compensated for sharing their data, or receive non-monetary rewards, and that educating consumers about the value of their shared data, may prevent them from voluntarily agreeing to businesses collecting their data (Choi et al. 2019).

An essential aspect of proposing an innovative model is motivating people to participate. Firms tend to source innovation or find solutions to problems from external actors as well as their internal R&D departments (Lucena 2011; Lassen and Laugen 2017). In our proposed model, experts and professionals are motivated to participate in socially collaborative interactions to share their knowledge and experience by providing expectations that form insights. The result of a lifetime of expertise in a particular industry can be suggested as "expectations". In this research, "expectation" refers to a demand or need of a business segment/industry that can be instrumental in carrying out business activities, planning, budgeting, decision making, resource allocating and other strategic and tactical decisions of firms acting in that segment or industry.

In the case of this paper, experts could willingly participate, collaborate, and provide their expectations and preferences

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from a product or service that in form of an insight could be valuable for trade on an intermediary platform.

Collaboration among data scientists for serving insights to buyers, and data-driven analysis are proliferating (Anadiotis 2017). The analysis of data, and the actions taken out as an outcome of the analysis, generate insights that create value. A study by IBM Business Tech Trends, results in the fact that only one in five companies have the required skills to gather and utilize insights (Monnappa 2017). Mastering such skills can help businesses gain insights into consumers (Ernst and Young 2011). Companies, such as Dell and Starbucks, have moved towards customers creating online platforms where users can engage in ideation (in some cases include expectations) (Chua and Banerjee 2013; Gallaugher and Ransbotham 2010). It has been suggested which using strategies that target insights from customer usage data, enables product improvements (Erfan 2018). But, usage data are not the only source that helps businesses harness insights from customers. As proposed in the current paper, expectations are an invaluable human source of knowledge. But unlike eliciting insight from data that can be automated, human knowledge doesn't apply to automation and based on this paper can lead to the generation of useful insights.

Before the advent of Web 2, gathering big data about customers was a dream. After the spread of social media, mobile-to-mobile (m-to-m) interactions, and the sharing of all kinds of content and artifacts on social media and digital platforms, many businesses and organizations became owners of big data. Managers are expected to use a variety of Artificial Intelligence (AI) tools to extract patterns embedded in this data, to have a picture of the future of customer behavior and needs, and to be able to respond to their information needs about organizational decisions. Because AI tools were limited to using explicit human knowledge, they were limited to extracting the right insights from this vast amount of data. Many organizations did not know what to look for in this massive data. In this article, we try to get help from Human Intelligence (HI) to eliminate this shortcoming. HI includes tacit knowledge that scientists have not yet been able to turn into explicit knowledge (Hanafizadeh and Ghamkhari 2019). HI can make inferences about data and events that AI lacks. This study uses a combination of HI (experts and professionals) and AI (recommender systems) to create insights that can be an essential need for different business segments. Recommender systems can be beneficial for both users and service providers (Pu et al. 2011; Pathak et al. 2010). Some recommender systems collect and use buying behaviors to understand their preferences from using products and services (Pu et al. 2012; Köhler et al. 2016) which can lead to enhancements or innovations. As these businesses participate in the co-creation of these insights, they realize its essential importance and are much eager to pay the right price to own and have access to it. The world is moving towards a highly-knowledge intensive era, where insights derived from data will significantly create value (Gandhi et al. 2018).

The authors intended to answer the following questions in this paper:

(1) Is it possible to propose a hybrid approach to recommendation systems which uses AI and HI to produce valuable insights?

(2) Is it possible to provide a model that helps experts monetize their contributions?

The innovation of this research is in providing a platform that combines HI (participation of experts and professionals), which includes tacit knowledge, with AI (recommender system) to create insight. This platform enables the participation of experts (represented by HI in the current paper) to structure the expectations of the industry side and leading it to insight. The proposed model simply applies existing knowledge to propose an innovative platform by which experts are compensated for their participation. This participation takes place in forms of sharing invaluable comments that can be used to provide useful insights to different businesses or industries using data provided by third-parties. The merits of the proposed model have been presented as in the forms of a table and also a figure depicting various components of the model and its counterparts to evaluate and validate the proposed and developed model.

This paper focuses on experts to help them monetize their expectations and tacit knowledge based on a set of recommender systems. To the best of our knowledge, academic research on the monetization of expert expectations and derived insights is not present, and this work is the first that addresses this concept.

Our research process included realizing a problem situation, analyzing published literature for ideas, providing a solution for the improvement of the problem, and eventually evaluating the solution by providing a comprehensive comparison of the components of the solution with existing literature and real-world applications.

The remainder of this paper addresses the following. Section 2 presents the literature review. This section reviews the building blocks of the model and essential theories for the formation and development of the model. Section 3 includes the method applied for achieving the objective of this paper based on a Design Science Research (DSR) approach. For this, a five-stage review process was used which includes the definition of review scope, the conceptualization of the topic, literature research, literature analysis and synthesis, and research agenda. Section 4 describes the artifact including the orchestration of various components of the proposed model, components of the model along with their actions, and also illustrates the collaboration of different parties in various procedures/processes using a method named Business Process Model Notation (BPMN) which helps illustrate the business processes and model interactions. Section 5 presents the evaluation of the proposed model based on theory, and also the comparison with existing applications and instances from the real-world. The discussion section focuses on the elaboration of the model in different context-industries, namely bank, e-commence, and e-tourism. The final section presents the conclusion, limitations, and future directions for research.

Literature review

Recommender systems

Recommender systems have been in the literature since the mid-90s, from the papers on collaborative filtering (Ekstrand et al. 2011; Zhang et al. 2014).

Recommender systems provide users with recommendations of products and services that are of interest to users. Such systems aim to match user requirements with the most suitable offerings. As a result of the advent of technology, and its combination with technology, various scientific areas such as social computing, social networks, big data, or cloud computing have enabled industries to build entirely new products, services, processes, and business models. Researchers refer to prior studies on recommender systems that mostly concern collaborative filtering and content-based filtering (Eirinaki et al. 2018). Some studies propose knowledge-based techniques (Burke 2000).

The primary purpose of a recommender system is to decrease the overload of information for users based on a filtering mechanism that provides relevant recommendations (Resnick and Varian 1997). Recommender systems apply to different areas of e-commerce and e-business, such as recommending movies, music, and other applications (Lu et al. 2015). Recommender systems result in the reduction of consumer search costs in products available on e-commerce websites and online platforms (Resnick and Varian 1997) and helping potential buyers to find their preferred products or services, or find solution to their problems.

Collaborative filtering is a common approach implemented in recommender systems (Langseth and Nielsen 2012). This approach utilizes the product or service ratings, comments, or opinions of consumers, to recommend products or services to other consumers. Content-based filtering is also another technique widely used by recommender systems that represent user interests (Lin et al. 2017; Sánchez and Bellogín 2019). Reviews and comments are in fact, some sort of insight by consumers which can provide opinions to the vendors for improving their products (Lin et al. 2017).

User engagement

Despite all advances in recommender systems, there is a broader range of real-life applications that requires attention. In the case of collaborative filtering approach in recommender systems, when the number of products and services without any collaborations from the users, increases, these types of systems can't generate appropriate recommendations. Unfortunately, this problem is common since most users won't participate often (Luo et al. 2014), potentially due to a lack of incentives or motivations for collaboration.

The project conducted by the World Economic Forum, "Rethinking Personal Data" (Kearney 2014), highlighted that providing free access to services in return for exposing data from users will no longer be sustainable in the coming years, and can't keep motivating and engaging them for continuing their participation. Customer engagement in social interactions is considered as a competitive advantage for business growth (Shen et al. 2019). Engaging customers in the process of improving products and services can, in effect, prevent expensive costs of attracting and retaining customers due to the continued competition and switching costs (Campbell et al. 2013). Therefore, the success of an electronic commerce platform (or in our case an intermediary platform for data monetization) through social interactions (user participation) is highly dependent on customer engagement (Zhang et al. 2014).

Motivation and satisfaction

Previous studies conclude that consumers have actively occupied in social commerce behaviors and users presumably participate and submit posts that display their sentiment, expectations, or opinions (Banerjee et al. 2009; Neri et al. 2012; Hajli (2015); Hsu et al. 2019).

It is essential to understand whether individual users are motivated enough to engage and participate and whether they are receiving the appropriate compensation (Bergemann and Bonatti 2019).

Motivation is an essential factor in the engagement of users (Wang and Clay 2012). Different types of extrinsic motivation by which individuals are motivated to obtain the desired outcome have been identified (Wang et al. 2019b), and external motivation is one of the extrinsic motivation types. Wang and colleagues use reviewer rankings to determine external motivation due to the reason that Amazon doesn't provide monetary rewards for reviews (Wang et al. 2019a, b).

As a customer engages with a product or service, experiential satisfaction plays an important role, that translates as the satisfaction experienced through interacting with a product or service. Customers compare their experiences with their expectations. This comparison forms the basis for customer satisfaction (Bigné et al. 2005). The more the experience is aligned with the requirements and expectations of a customer, the more the satisfaction is resulted from experience (Wu and Li 2017; Wu 2017). Elevating customer satisfaction, thus requires awareness of individual customer expectations (Pine and Gilmore 2000). According to a report by Harvard Business

School back in Pine and Gilmore 1998, experiences are a distinct economic offering required for upgrading and progressing the offerings made to customers to the next stage of economic value based on their expectations (Pine and Gilmore 1998).

To understand the experiences that a customer expects, discussing the essence and factors affecting expectations seems essential. Expectations are a form of empirically derived knowledge which expresses the belief that an event will or should happen (Grecu and Brown 2000).

The generic model proposed by Zeithaml et al. (1993) consists of four main sections; the expected service, the desired service, the adequate service, and a combination of both predicted and desired service (Zeithaml et al. 1993). Experts in our model help narrow down the gap between expected and desired or adequate service for potential customers who are eagerly seeking insights that fit their business or industry requirements. In our case, we focus on a specific segment of customers, namely "Experts" who are willing to provide their professional experiences and expertise. These experiences and expertise will be utilized as a valuable source in the form of insight on this intermediary platform, in return for monetary or non-monetary compensation. An intermediary is an "organization or a body that acts as an agent or broker between two or more parties" (Howells 2006). Companies don't have all the resources for a constant move towards innovation or problem-solving. If a company intends to solve its problems or innovate, experts (HI) outside the company can be suitable candidates.

Synthesize of HI and AI

A vast amount of data has been generated since the rise of the internet, particularly the emergence of web 2.0, yet applying the gathered data is the concern of data owners, although the potential advantages are clear on paper. Despite the many achievements and promising results of capturing the value of these enormous volumes of data, the initial desires of pioneers have not been fully met. Apart from complexities in implementation, the challenges of generating useful insights from the underlying data and information have paved a way for a rather novel solution. This solution attends the fact that the excessive focus on AI has reaped the potential for developing completely new solutions by the combination of HI and AI (Agrawal et al. 2017).

The synthesize of HI and AI, rather than the previous competition among them is considered to be the key answer for overcoming the underlying complexities of generating insights. Based on this, AIs will perform the routine tasks of providing data to facilitate and assist the process of decision making for experts (Lichtenthaler 2018). Recommender system bots help this process by making quick and to the point recommendations tailored for a specific requirement using AI.

Expectations of experts as a form of knowledge or expectations crafted into useful insights can be shared, integrated, and sold.

Data monetization

Monetization is defined as utilizing something of value as a source of monetary or non-monetary achievement in this paper. The concept of data monetization is recognized and studied in a few scientific pieces of research. The monetization of data occurs when a transaction eventually takes place in which a valuable service or product is exchanged. This transaction would require two parties who can agree on the valuation of the traded service or product (Fred 2017).

Data monetization is an act of converting data into a valuable product or service or information which will result in a monetary or non-monetary benefit (Najjar and Kettinger 2013). ***Resources and supplies*** are necessary components for the success of data monetization and there are three pathways to data monetization through insights exist, moving from low capabilities to higher capabilities (Najjar and Kettinger 2013). The direct path to higher capabilities can pose certain risks for businesses since it requires enhancing technical and analytical capabilities at the same time. This direct pathway requires massive investment in human resources, training, and infrastructure. Resources and supplies include key requirements, actors, hardware, software, innovative technologies, required business, and mathematics analytical capabilities, and networking capabilities (Najjar and Kettinger 2013).

Hanafizadeh and Harati Nik (2020) identify a variety of data sources that they consider as ***Assets***. In our proposed model, these assets are translated into third-party data which are accumulated data over the years, that industries have not significantly identified its true potential. Hanafizadeh and Harati Nik (2020) use the term Data-driven operations for these activities which, for instance, include the storage of insights in Insight Repository (IR), extracting and analyzing semantics, processing expert profiles, and especially recommendation. In our proposed model, ***monetization*** happens in the result of creating ***value*** for ***end consumers*** from expectations obtained from experts, which are then transformed into valuable insights.

For generating monetary value, data can be utilized ***directly*** or ***indirectly*** (Moore 2015). In the direct approach, data is traded for monetary value in the form of a transaction. The indirect method uses data, refines data, and produces information, services, or products that are purchased. Considering the latter approach, data is improved to create something more valuable such as an insight which is the value provided as an outcome of the processes explained in this paper. Something worth noting is that the definition provided by Wixom (2014) doesn't explicitly suggest that data monetization requires a transaction of money. Therefore, data monetization could also translate to the exchange of data for a non-monetary benefit such as a point or a token.

Companies that use ***data analytics***, and the ***derived insights*** for enriching their products and services, are wrapping their offerings with data via an indirect approach, which is called "Data Wrapping." Data wrapping is a creative ***trading model*** approach that helps companies identify problems and find ways to solve them (Woerner and Wixom 2015; Wixom and Ross 2017). Most companies don't have the required information capabilities and require a platform by which they could get their hands on valuable insights from their gathered data and resolve this without the need to acquire the technical (hardware, software, network) and analytical (knowledge and skills in mathematical, business, and data fields) capabilities for monetizing their data. Industry-specific business capabilities are often low regarding both factors.

The new data economy is about insights and insight providers are willing to help resolve problems or answer questions of decision-makers (Belissent 2017). The platform modeled in this paper will help such companies gain invaluable insights from their data by using the knowledge of experts in a specific field who are willing to participate. Digital giants such as Amazon, Google, Netflix, Disney, and Airbnb monetize data by gaining an intimate understanding of their customers, but what if businesses would want to hear expert ideas on their products and services and source innovation from outside of their boundaries. This is where the term data monetization emerges, which is a rather new concept that has not been diversely researched. This term has been significantly used by consulting firms and magazines, such as Accenture, Deloitte, KPMG, Ernst and Young, and Gartner (Deloitte 2015; KPMG 2015; Mulhall et al. 2017; Gartner 2019; Ernst and Young 2019). Monetization is still a hot trend in theory and practice, that is noticed by well-known players in the IT industry.

Method

The objective of this paper was to propose a novel platform for helping experts monetize their knowledge and experience in form of an insight. A DSR approach, which is a knowledge contribution framework that helps extend the existing knowledge base in a new problem area was adopted to achieve this objective.

The concept of monetizing expert knowledge is complex and requires the synthesize of multiple fields of study based on various theories. The DSR approach was selected to design, build, and evaluate a framework capable of evaluating the applicability and completeness of the proposed model. The contributions have been demonstrated by reasoning and comparison with applications in the real-world and also competing models in the literature. This paper and the evaluation provided, make contributions to real-world applications and point out their strength spots or weaknesses compared to the proposed model (Hevner et al. 2004). This study is not a systematic review in nature; however, for the sake of replicability and fulfilling a rigor research design, a five-stage review process is used as illustrated in Table 1 (Brocke et al. 2009). Appendix provides a glossary for acronyms used in this paper.

Definition of review scope

This study is descriptive and interpretive syntheses in nature (Evans 2002). The concept of monetizing expert knowledge is complex and requires the synthesize of multiple fields of study based on various theories. For the sake of better illustrating the processes between various components proposed by the paper, process models were used. The paper also follows a path based on Covin and Slevin (1991) towards presenting a concept of a platform based on a general idea that depicts direct or significant effects between various components and actors. A set of recommendation systems facilitate access to required data for experts, the generation, submission, and validation of their expectations, also sales of the insights in this model.

The conceptualization of the topic

The authors started by studying titles, abstracts of the articles, relevant topics among the central issues, and themes of monetization and recommender systems that were selected. The initial phase was similar to the process introduced by Bano and Zowghi (2015) and Brocke et al. (2009).

The primary search process included the following keywords in the third step of the literature search process proposed by Brocke et al. (2009):

(1) Data monetization, (2) Recommender systems, and (3) Expectation.

Literature search

Online search engines such as Web of Science, Scopus, and Google Scholar helped the authors in the initial phase of the literature search. Then we selected the following databases for extending the research process; ACM Digital Library, IEEE explore, Science Direct, and Springerlink. Conference proceedings were also searched but only to articulate ideas on the topic. Some deemed relevant were later added to references. For constructing appropriate search strings, the authors used Boolean operators.

Consequently, related references of the retrieved resources were searched to complete the search process. Fig. 1 provides an illustration of the process of selecting the *key identified publications* for shaping the main idea around the articulation of this paper.

Table 1 Generalstages description method/technique/tool/approach outputs

General stages	Description	Method/technique/tool/approach	Outputs
1. Definition of review scope	The purpose of the literature review conducted for this paper was extracting relevant theories and existing research to help synthesize outcomes to gain new ones in Literature analysis and synthesis step This paper is meant for specialized scholars in the field of data monetization and recommender systems and focuses on research outcomes and applications of the reviewed literature with the goal of integrating their findings. The organization of the paper is considered to be conceptual with a strong support for the applicability of recommender systems and previous studies in facilitating the main objective of the paper. The primary coverage of the literature was exhaustive and selective, but due to the vast number of literature in the field of recommender systems, the literature pivotal to the topic of data monetization was covered	–	The scope of research and areas which are related to the realized problem that was the excessive focus on AI, and the incapability of such an approach in resolving all problems. In fact, a combination of both AI and HI is thought to be the solution of scenarios which go beyond the capabilities of AIs, or are complex to implement
2. Conceptualization of topic	Useful topics and potential areas where the required knowledge related to our paper was primarily listed based on the output of the review scope and key terms were extracted	–	Key terms: Data monetization, Recommender systems, expectation
3. Literature search	Finding relevant papers, identifying underlying theories was the next required phase Extracting secondary data from paper findings and conclusions was followed	A process model of interactions using Business Process Model Notation (BPMN)	23 key identified publications on recommender systems and approaches, and 5 key identified publications on “Data Monetization” excluding Big Data related procedures illustrated in Fig. 1
	Studying titles, abstracts of the articles, relevant topics among the central issues, and themes of monetization and recommender systems		16 pertinent *key identified publications* related to expert motivation for participating in the proposed model, plus 6 other articles retrieved from references from the citations of the primary articles illustrated in Fig. 2
4. Literature analysis and synthesis	Proposing the model based on a series of interactions between participants, utilizing recommender systems for enhancing the necessary components of the model. Synthesize of theories and using secondary data to shape the initial conceptual model, selecting appropriate modeling approach to represent the conceptual model and its detail operations schematically	A modified version of a value creation process framework in the field of data monetization Proposed by Fred (2017)	The basis of the model for the articulation of the recommender systems required for shaping the model based on Hsu et al. (2019) and the creation of the main components needed for the elicitation and approval of insights
4. Research agenda	The research agenda provides the vital characteristics of the design of process models required for depicting the new model proposed in the paper around state of the art. This section describes the	Conceptual modeling based on schematic legends described by Weill and Vitale (2001)	Basis model for the articulation of the recommender systems required for shaping the model based on Hsu et al. (2019) and the creation of the main components needed for the elicitation and approval of insights
			The core concept of the recommender system with a data monetization approach illustrated in Fig. 4
			Meso-level model of interactions and information exchanges

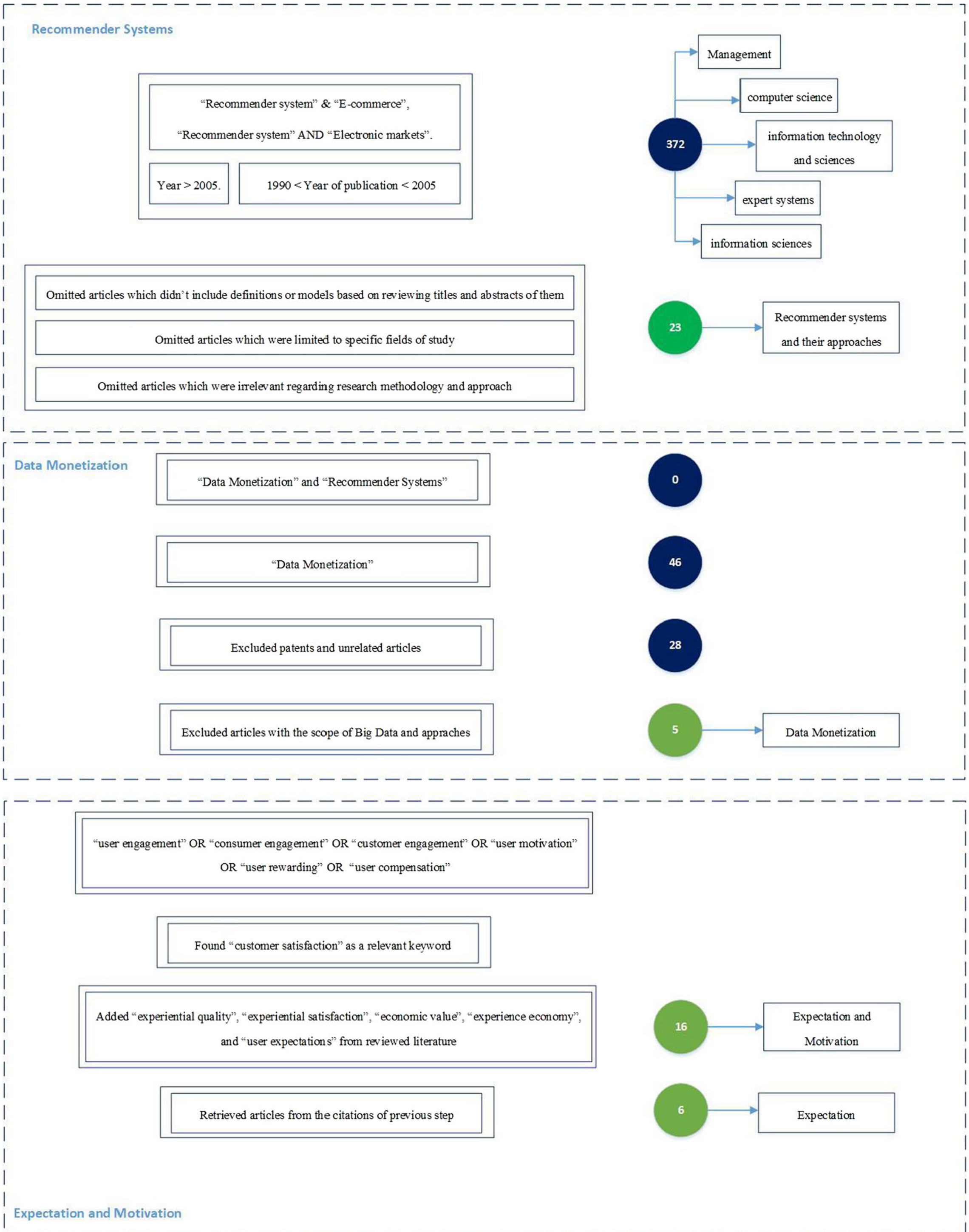

Fig. 1 The process of eliciting and selecting 50 key publications in shaping the main idea of the paper

Literature analysis and synthesis

In this section, all explored background research and the resulting theories and models that form our conceptual model have been provided. A value creation process framework in the field of data monetization proposed by Fred (2017) was used. The conceptual model proposed in this paper and the ensuing process models which depict the interactions among its components were formed based on the following theories and models. The proposed model of this paper includes significant modifications to the basic model adopted by Fred (2017). Understanding needs, data gathering, data cleaning, data integration, and data analysis have been separated to create the Data Vendor Community (DVC) component of our model. In this community, the platform enables actors to benchmark their data offerings easily, or request their data requirements, review data provider proposals, sign contracts, and trade data with Data Providers (Data Vendors).

The core concept of the proposed model accepts an expectation as an input and attends to *elicit informational needs of expert*, processes the input by *using data gathered by Data Vendors,* and *creates value in forms of an insight* that is utilized for improving current products or services or develop innovative products and services. The middle component of Fig. 2 labeled *Improve/Innovate* that is based on Fred (2017), demonstrates the cyclic and continuous process of value creation using data and information. The process starts from the step of understanding needs which are a prerequisite for the search and gathering of relevant data from various suppliers and assets depicted as the Asset Management component in Fig. 2.

When the required data is gathered, it will be stored in data storage, is cleaned, integrated, and processed as well as analyzed further. The result of this component is an expectation that should be processes, transformed into an insight, distributed and shared after an evaluation, confirmation, and token allocation process (reward/compensation) by a group of professionals. At this state, insight can be considered as the product of this data-driven operation which is sold to a buyer.

Using data, converting needs into invaluable insights, and indirect sales of the output to an end consumer is one of the leading monetization objectives of this platform. Fred (2017) states that the ***indirect data monetization*** is a comprehensive approach since it may be associated with several offerings including information-based products (product development and innovations) and information-based services (consulting and advisory, R&D, and designing services). Since in the indirect data monetization, the organization's offerings consist of refined information-based products and services, the value is created and delivered to the customers based on the utilization of data and information, and organizational actions. The organizational action block can also be considered as a phase that creates and adds value perceived by end consumers. Indeed, an organization may adopt new methods to satisfy them, especially in the case of information-based services.

Before an expectation is processed and an insight is derived from it, the evaluation and confirmation process should be conducted by professionals who have vast sufficient knowledge about the proposed expectation and its surroundings. These professionals would also require external data and information regarding the specific topic in review from data providers. This approach is considered as a ***direct data monetization*** approach where professionals directly buy required data and information from third-parties to better evaluate and select the best expectations. This will help the professionals receive better compensations in this process. Timely, useful data recommendations can facilitate this process for them.

Recommendation occurs in all components of the proposed model, which has been illustrated as a horizontal block at the bottom of Fig. 2. The approach taken by Hsu et al. (2019) introduces a basis for our recommendations throughout the process of monetizing expectations. To motivate users, inevitably, a mechanism should be established which would reward professionals based on their actions which has been briefly mentioned as future research fields in the discussion section.

Research agenda: Choosing an appropriate modeling approach

This approach was selected to design, build, and utilize a framework capable of evaluating the applicability and

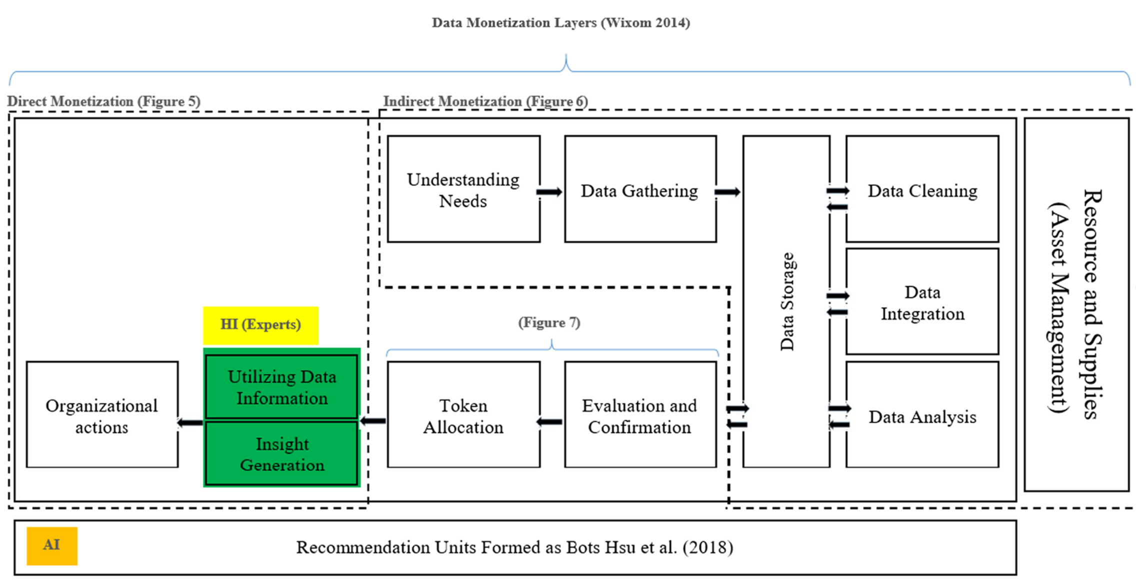

Fig. 2 Synthesize of models and theories

completeness of the proposed model. In their article, Wynn and Clarkson (2018), provide vital characteristics of design and development process models, that are used by researchers in defining the positioning of their proposed new models around state of the art.

Inspired by the illustration of human/robot interactions proposed in the article on recommendations in social networks by Hsu et al. (2019), the basis for the articulation of the recommender systems required for facilitating the creation of the proposed model was formed. The authors developed a model for monetizing expert expectations and corresponding insights. Based on this model, the authors intended to illustrate the procedure of human/robot interaction required for eliciting insights.

Based on the map of literature from Wynn and Clarkson (2018), we chose the Meso-level analytical model for modeling purposes. This kind of modeling helps portray design and development tasks as a discrete task where the interactions and information exchanges are used to form an end-to-end flow. Since the Meso-level analytical modeling method/ approach is used to depict processes as flowchart diagrams, it is specifically useful for understanding and communicating the proposed design. The Business Process Model Notation (BPMN) (White 2004), which is an effective method for illustrating business processes, is considered as one of the task precedence models proposed by Wynn and Clarkson (2018). This diagram is formed using a set of notations or graphical elements that were chosen to be distinguishable (White 2004), which have been utilized for depicting the model's details.

Artifact description

Data, information, and knowledge are the main components of transmitted content. Content is an outcome of the intellectual and cognitive process (Hanafizadeh and Yarmohammadi 2016). Participants in the content creation process impact the nature of content by using context-specific expectations (Hanafizadeh and Yarmohammadi 2016).

Expectations are particularly appealing in two aspects. First, from a content perspective, they tend to combine knowledge and information from related or unrelated sources. Second, since experiences naturally form to respond to a specific need, it is valid to use the word experience in terms of usability and application. Experiences form the basis desires and expectations of a user. We used expectations of experts for generating valuable insights for resolving critical problems in a business segment/industry. External sources can help improve the process in which companies resolve their problems if different motivational factors are considered and provided for them (Hossain 2018).

The target audience of the model proposed in this study are experts in a segment of an industry. Thompson et al. (2003) refer to community members as the source of expert knowledge about their community's expectations, thus having a unique role in sharing their experiential expertise. Thompson et al. (2003) also state that collaborations in the scientific community offer excellent chances to engage in research, which is certifying. Expectations have been realized with strong ties to collaboration and working in teams (Grecu and Brown 2000). Social collaborations' convergence with electronic markets has paved the way for a new era where people including scholars, can engage in social interactions (Shen et al. 2019) that could lead to monetary value for participants. Wang et al. (2019a, b) state that this convergence provides a channel for promoting sales through participant engagement.

Doha et al. (2019) investigated factors that influenced individuals toward social commerce, reviewing literature focused on economic factors as key drivers of users' participation.

By expanding this statement further based on the target audience of the present study, it's possible to conclude that participants can gain monetary value by selling their expert knowledge (expectations). Creating the model, required the synthesize of previously mentioned theories.

The basis of our proposed model is a platform that uses a set of recommender systems as its core. The purpose of this platform is to monetize a participant's expectations used to form insights. The model has been developed to find a solution for monetization through the combination of HI (expert expectations and generated insights), by the utilization of AI (analytical and intelligent algorithms provided by recommender systems).

It should be noted that our main focus in this paper relies on industry-specific insights (Fig. 3). Expectations of actors that we called *Expert Participants* are transformed into insights that result in creating value. The platform recommends these insights to actors who are actively looking forward to good insights that help them solve their problems called *Insight Hunters*. Once the commercialization process of selling an insight to an *Insight Hunter* is finalized, all parties who have participated in this process will gain a monetary or non-monetary value.

Monetizing expert expectations and insights

The most important idea around the proposed model is the process of monetizing expert expectations and inferred insights, therefore the authors named this model, Monetizing Expert Expectation Model (MEEM). Before getting started at explaining the proposed model and its processes, Table 2 provides the components of this model along with their actions.

Figure 4 utilizes the schematic legends described by Weill and Vitale (2001) for depicting the roles and relationships between actors and model components, the flow of information, money, and service, who owns data, transactions, relationships,

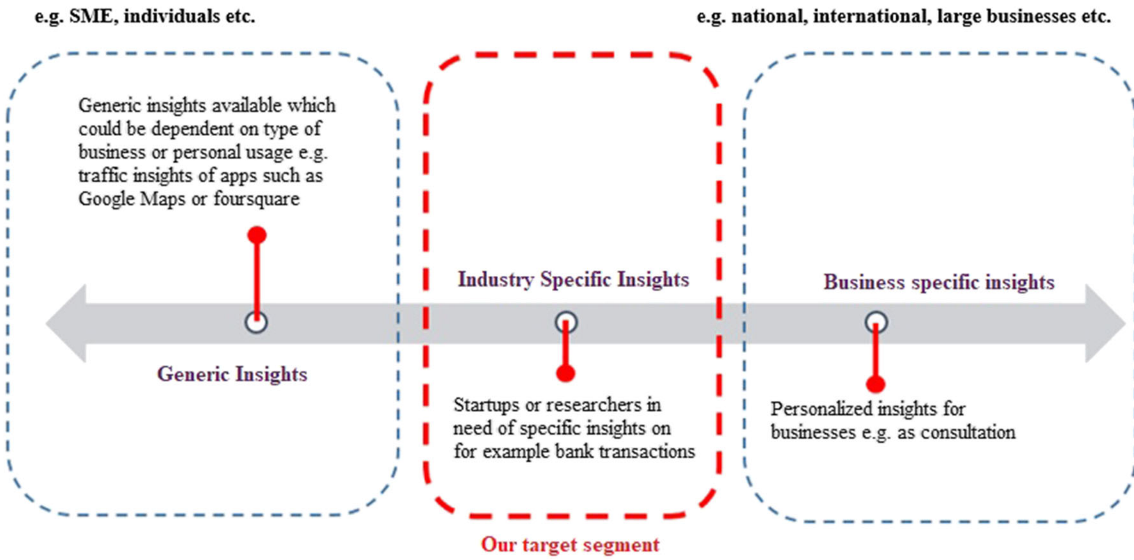

Fig. 3 Generic to business-specific insights

and intellectual property. Thus, this illustration represents the orchestration of various components and actors of MEEM.

To illustrate the collaboration of different parties in various procedures/processes, the model in Figs. 5, 6, and 7 were depicted using BPMN. Fig. 5 shows the process model of the procedures of human/platform interactions following the registration processes.

The main step of the process illustrated in Fig. 5 starts with a Match-making bot proposing related topics provided by *Insight Hunters* to *Expert Participants*. For the sake of recommending topics that best fit the experts field of expertise, the Collective Intelligence Social Tagging (CIST) has been embedded in the Match-making bot (Wang and Sharma 2018). In this process, *Insight Hunters* who provide topics of their interest, generate tags to help enhance the recommendation process. Only tags provided by high-quality Insight Hunters that are relevant, searchable, reusable, valid, meaningful, extensible, and stable are considered as high quality tags. Finally, an examining mechanism combined of knowledgeable examiners and AI technology will help accepting the tags systematically (Wang and Sharma 2018).

1) The steps taken in Fig. 5 are as followed:

1.1. A recommendation bot called Bot uses both collaborative and content-based filtering for extracting and analyzing the primary profile created by *Expert Participants. The* profile includes preferences, articles, scientific works, textual documents, and other data uploaded by the Expert Participant. This data might also be gathered and crawled through various databases available online.
1.2. The Match-making Bot retrieves the top 10 categorized list of problem topics submitted by *Insight Hunters* and shows them to *Expert Participant*s. The platform makes sure the topics are closely related to the fields of expertise of experts using CIST.
1.3. *Expert Participants* select a topic among the list from step 1.2 based on their knowledge and expertise to provide expectations.
1.4. *Expert Participant* starts contributing by offering expectations that are in fact, requirements based on prior experiences and expertise (These requirements may generally be valuable for other players in the same industry as well -refer to Fig. 3). For this, the *Expert Participants* might require additional data for better articulation of knowledge and eventually, generating valuable insights. *Data Vendors* can provide data requirements for the experts.
1.5. The process of accessing *Data Vendor* datasets for providing better expectations has been illustrated in Fig. 6.
1.6. After the formation of expectation offerings by *Expert Participant*s, accepting the terms and conditions is mandatory before finalizing the submission process. *Expert Participant*s should review and approve or deny terms and conditions, which include the minimum required score from peers.
1.7. If the *Expert Participant* agrees with step 1.6, a Publisher bot will post the *Expert Participant*'s expectation offerings to relevant forums in the *Professional Community* based on its category.
1.8. To encourage different actors to participate, a specific approach based on *karma* has been designed. We call this karma, MEET (Monetizing Expert Expectation Token). MEET will help the platform determine the level of participation. Professionals

Table 2 Main components with actions (actors) in the proposed model

Actor	Abbr.	Description	Actions
Insight Hunter	IH	Based on the registration process, these actors require a solution to their problem that might be an enhancement or improvement to their products and services	• Submit topics of their problems along with sufficient description to the platform.
Expert Participants	XP	Expert is indeed a professional of its field, however, with higher knowledge and experience and particularly a reputation among his or her peers' community. Experts register on the platform and fill out primary information. These actors provide their expectations from a product or a service which is then validated by a community in the platform, and then turned into valuable insights for IHs.	• Select topics of interest provided by IHs • Provide expectations based on selected topics • Submit data request to Data Vendors • Evaluate data proposals submitted by Data Vendors • Access/Reject smart contract with Data Vendors • Participate in a community formed between Data Vendors and XPs • Fill out mandatory information including fields of interests, their reputations, duration of their work experience • Requests access to Expectation Repository • Inserts expectation into Expectation Repository • Contribute to the social media platform for answering PCs Comments and provide further explanation if required
Professional Community	PC	Professionals of various fields also register on the platform.	• Interacts with posted expectations by the platform pot in the social media platform by providing comments, rejecting, requiring explanation or accepting expectations • Rate expectations based on a 5-point Likert scale • Interact with the eventual insights provided by Insight Providers and inserted by the bot into the Insight Repository
Recommender Bot	Bots	Before participating in the platform, XPs and professionals allow the recommender robot (bot) to interact with them. This bot is responsible for providing recommendations in the evaluation and confirmation of expectations by professionals, match-making of experts and IHs, and various other recommendations in the platform. Bots include *Match-maker, publisher, friend, data hunter, contractor, referee, crawler, Tokenizer*	• Recommends appropriate topics of interest to XPs based on their profile • Posts expectations of XPs in the PC social media platform • Analyzes interactions of professionals on the insights to retrieve content and sentiment-related information. • A bot proposes a smart contract for the agreement of terms, services, transactions, etc. • Calculates overall point of the insight based on results of the previous step • Automatically interact with professionals and their peers
Insight Provider	IP	A person who is valid to turn expectation to insight, which can make a need for data. Insight providers might require raw or processed data such as visualizations for generating insights	• Access Data Vendor repositories • Develop insights based on the approved expectations accepted by the PC
Data Vendor	DV	Data providers who have gathered data in various categories and provide access to these data based on free or premium plans	• Participate in DVC for becoming popular as a valid data provider • Submit data proposals to XPs • Provide data repository access to XPs

with higher MEET, correspond to more active participation.

1.9. The process of approving an expectation offering has been illustrated in Fig. 7.

1.10. A **Content-based recommendation bot** called Contractor Bot prepares and recommends a Smart Contract to *Expert Participant*.

11.1 *Expert Participants* can start finalizing their contribution to the platform if they accept the Smart Contract. After this, they can insert verified expectation offerings to the *Expectation Repository*.

1.12. An Informer Bot sends notifications to *Insight Providers* to inform them of a new expectation in the *Expectation Repository*.

1.13. *Insight Provider*s develop insights corresponding to the offered expectation. Similar to the *Expert Participants* explained in step 1.4, *Insight Providers* can also access *Data Vendor* datasets as required. Data offerings accessed by *Expert Participants* that have proved to be useful will be stored in the Data Offering Repository (DOR). Also in this case, CIST is used for tagging datasets for helping *Insight Providers* to better search and access required data.

1.14. After an insight is developed, the insight should be submitted to the *Insight Repository*.

1.15. The Informer Bot sends notifications to a bot that is dedicated to sales of insights (Agent Bot) in the ***Online Insight Marketplace***.

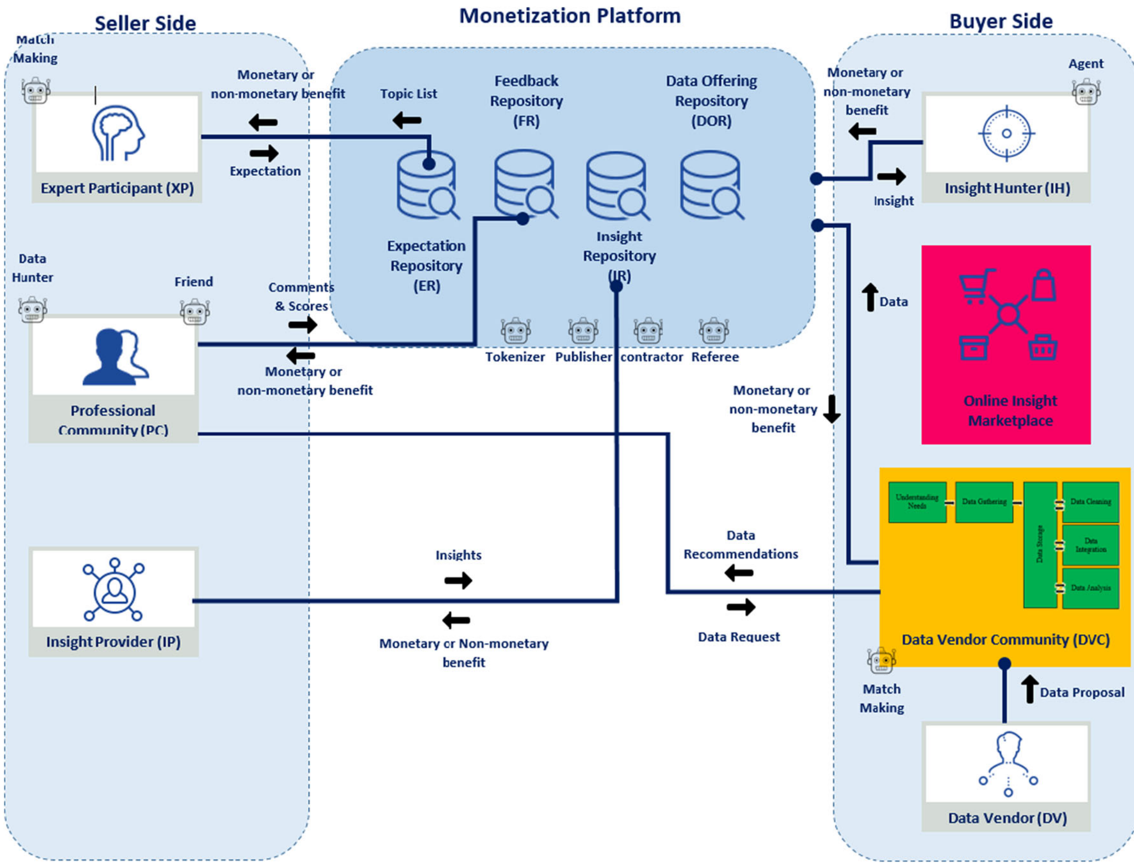

Fig. 4 The orchestration of various components of MEEM- Bot icons facilitate the processes of components located near them

a. In this marketplace, *Insight Hunters* can participate in various purchasing mechanisms which some have been proposed in the limitations and future studies section. One mechanism which could be an exciting topic is an Online Auction where *Insight Hunters* can bid for an insight.

1.16. After the sales of an insight, a Tokenizer Bot can follow-up the commercialization of the provided insight via mechanisms for instance based on blockchain technology which can be an interesting topic for further research. In case the insight is commercialized, the participants of the platform will receive MEET based on their participation.

2) Data Vendors have a two-way connection with the platform. This has been illustrated in Fig. 6.

2.1. *Data Vendors* profile their data on the platform and showcase their offerings.
2.2. A Crawler Bot has the task of indexing and categorizing data offerings provided by *Data Vendors*.
2.3. *Expert Participants*/*Insight Providers* create search strings based on requirements.
2.4. A recommendation bot called Data Hunter Bot, automatically crawls repositories and its databases to identifies, match, and recommend. *Data Vendors* that fit the defined data requirements defined by *Expert Participants*.
2.5. *Expert Participants/Insight Providers* request access to datasets if they are interested and accept the terms and conditions, which will result in a **Direct Monetization** process in the platform for gaining access to required data. Other than using available datasets, *Expert Participants* can also submit data requests to *DVC* for gaining access to premium *Data Vendor* datasets.
2.6. A request must be submitted to *DVC* via provided forms.
2.7. A **Content-based recommendation bot** called Requirement Bot will recommend data requests to *Data Vendors* based on rankings.
2.8. *Data Vendors* review data requests and accept if they can fulfill requirements. The incapability of fulfilling requests based on contract terms will result in a penalty for the *Data Vendors*.
2.9. **A Content-based recommendation bot** called the Contractor Bot will provide the *Data Vendor* with a personalized smart contract that needs to be signed.

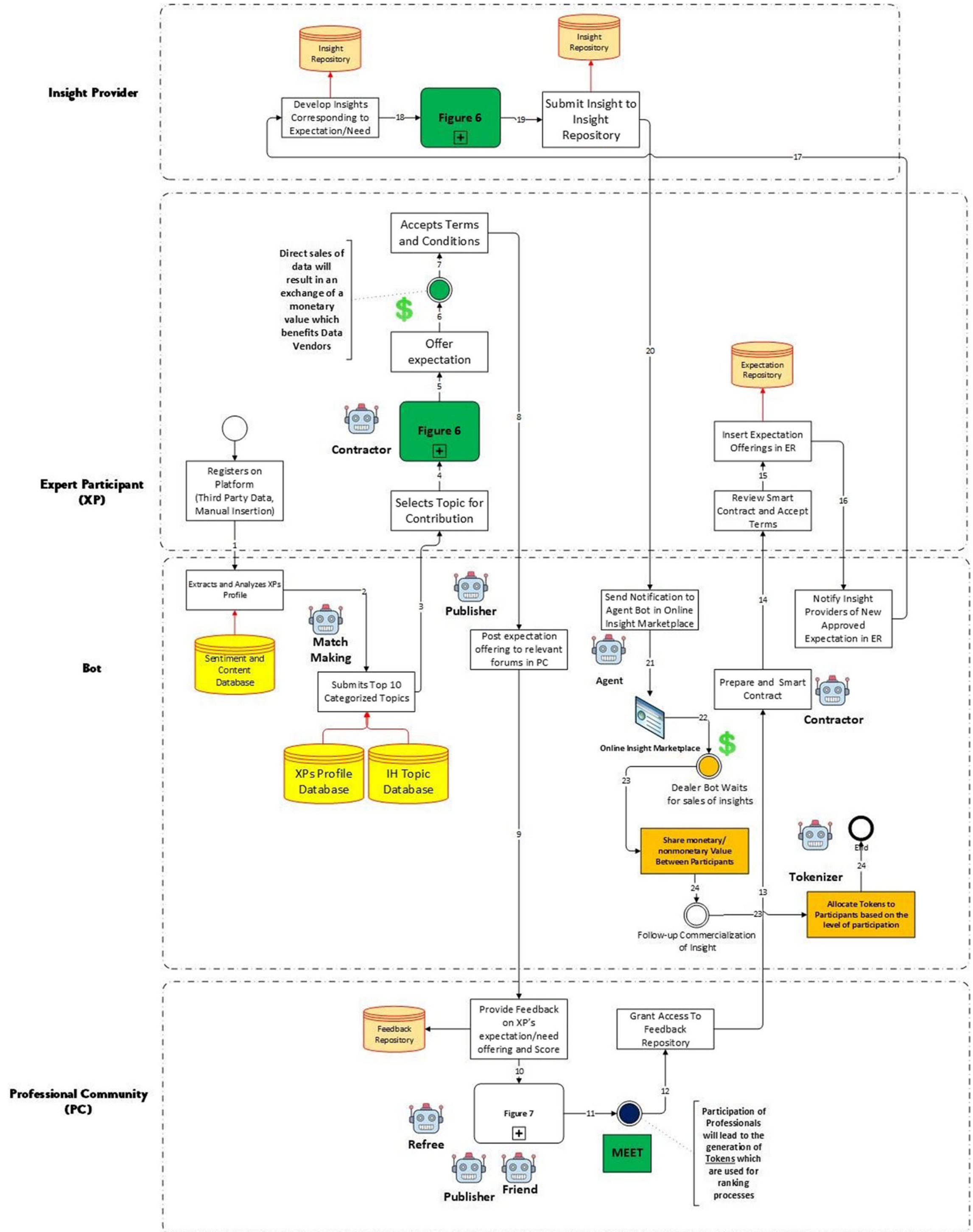

Fig. 5 Procedure of Human/Participant/Component/Robot Interactions in MEEM

2.10. *Data Vendors* should submit their proposals via tools provided by the DVC. This data proposal will include smart contractual terms such as time limits, commercial interests. Commercial interests can be in forms of monetary value or solely the requirement to receive the eventual insight provided as a result of gaining access to *Data Vendor*s' data.

2.10.1. *Data Vendor* proposals should be evaluated by *Expert Participant*s.

2.10.2. If the proposal is accepted, the Contractor Bot proposes a smart contract that can be signed.

2.10.3. If the proposal is rejected, the smart contract with *Data Vendor* will be terminated.

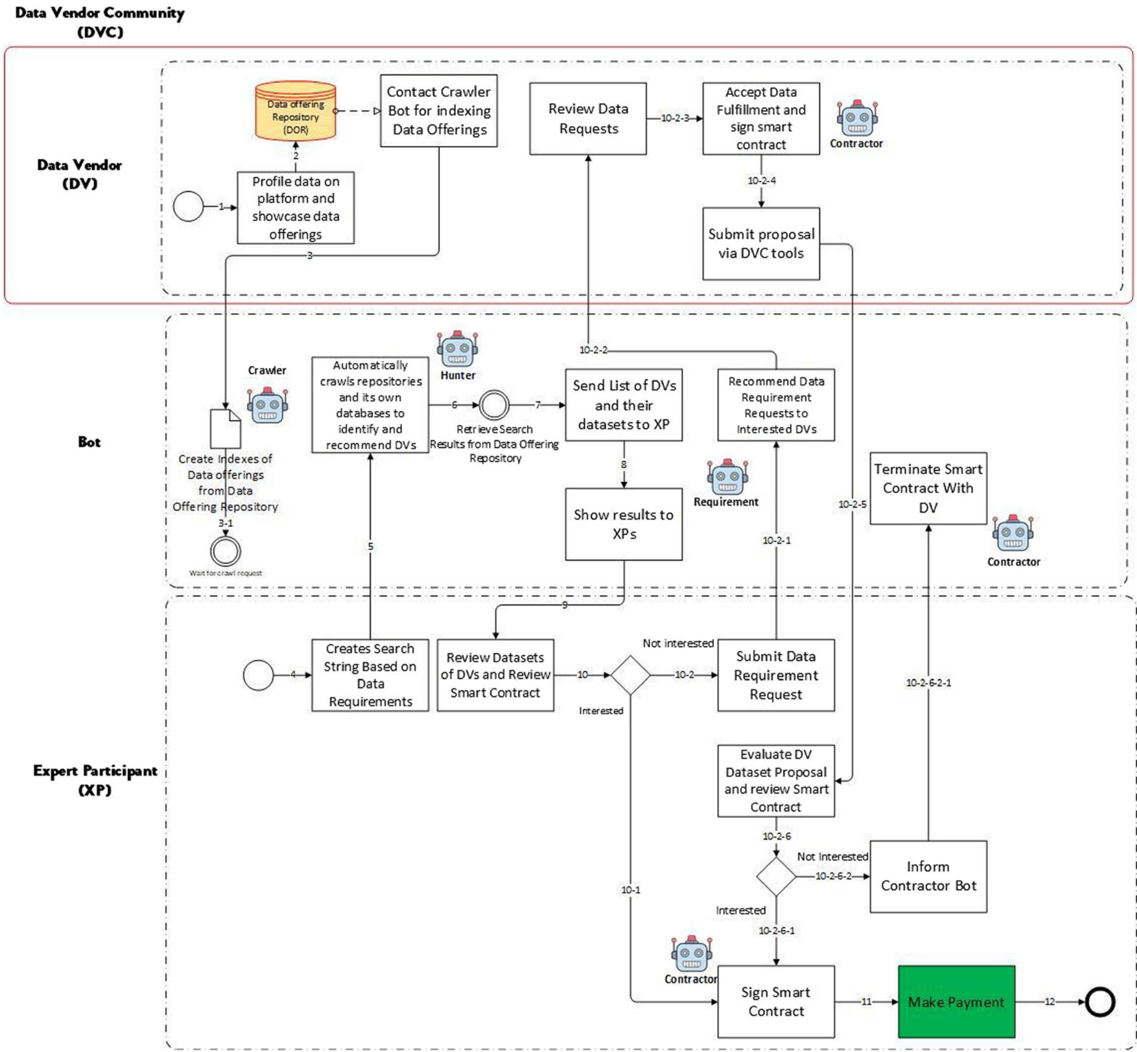

Fig. 6 Data Vendor connection with platform and interactions of Expert Participants with Data Vendors for accessing required data

2.11. Agreed datasets should be provided in the time limit set by the smart contract.

2.12. The payment is made following the instructions of the smart contract.

In addition to interacting with the *Expert Participants* and collecting insights, as mentioned in the above steps, several bots keep track of *Professional Community* interactions with each expectation offering, which has been depicted as in Fig. 7. This figure explains the process of expectation approval by professionals. The information flow and the analysis procedure provided by Hsu et al. (2019), shaped the initial idea of the recommendation approach taken in this part. To increase MEET, professionals will allow certain bots to interact based on their category, which will eventually lead to observing more expectation posted by these bots on their registered forums. As stated by Hsu et al. (2019), since users who befriend the bot understand that it is a software component, the element of trust is also excluded.

3) After an expectation offering is posted on a forum, professionals start their interactions by leaving comments, reviews, and submitting posts in related forums.

3.1. A **Content-based recommendation bot** called the Referee Bot extracts and analyzes sentiment words from professionals' interactions using the sentiment word database. The procedure is designed in a way to preserve sentiments as the primary factor affecting the evaluation outcome.

3.2. Sentiments are not the only factor affecting the outcome. The Friend Bot which the professionals have allowed it to interact with them, follows and responds to comments, reviews, and posts provided by the professionals immediately.

A recommendation bot Publisher Bot posts recommendations to the professionals. The number of clicks on these resources can be utilized as a measure for the effectiveness of recommendations by the bots.

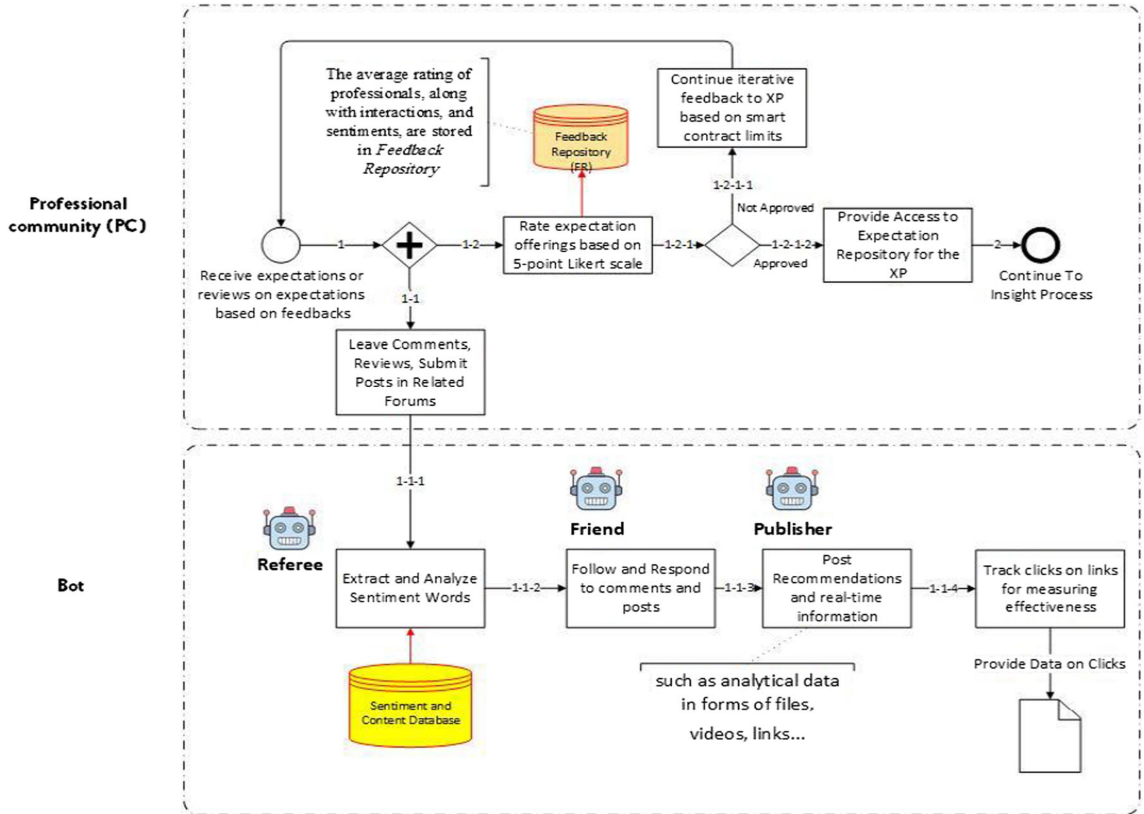

Fig. 7 Process of expectation approval by professional, and insight recommendation to IHs

3.3. These bots can recommend real-time information such as analytical data regarding that specific topic which includes data and information in forms of files, videos, or links which the bots provide to the professionals via their discussion threads. These resources can help professionals better determine their scores for expectations.
3.4. Professionals also have to rate the offering based on a 5-point Likert scale.
3.5. The average rating of professionals, along with interactions, and sentiments, are stored in *Feedback Repository*.
3.6. This process is iterative until expectation offering passes minimum scores.
3.7. Every expert receives limited chances for passing minimum scores. The limitation on this is determined based on the smart contract accepted by the expert.
3.8. *Expert Participant* addresses feedbacks from peers and revises expectations until it gets approved.
3.9. If an expectation offering is approved, the *Professional Community* can provide access to the Expectation Repository for the *Expert Participant*.

Evaluation

Users around the globe are connecting through social media sites, some of which are designed for experts. According to Gallant (2019), LinkedIn is where most Fortune 500 decision-makers and top executives spend their time. This social media which targets professionals, has over 500 million members (Elder and Gallagher 2017; Lunden 2017; Darrow 2017) and their content feeds on LinkedIn is viewed over 9 billion times per week (Gallant 2019). Some of this content includes experts in specific fields of interest, providing free consultancies to businesses by commenting and reacting to material posted on LinkedIn. Experts engage in activities such as giving feedback on expert comments and reviews on services and products, for instance, redesigned websites. By utilizing our proposed model, feedbacks translate into expectations that have been processed by the Professional Community (PC) and then stored in the Feedback Repository (FR).

Businesses are continually seeking for approaches to create more value from data. Some are offering what they call "Insight-as-a-Service" (IaaS), where professional services are part of the offering (Morgan 2016). Based on (Monnappa 2017), IaaS provides insights, and practical action plans to implement them, which is its difference from Software-as-a-Service (SaaS). It is essential to understand that the central concept surrounding the contribution of this paper is monetizing insights, not available data. Data acts as a supporting tool for providing better expectation offerings. Nonetheless, the evidence provided in the theoretical implication section presents a somewhat clear understanding of the significance of insights that most companies are leveraging their capabilities for tapping into this enormous potential.

Evaluation based on theory

Monetary value is not a far-fetched concept in a model which proposes a mechanism for communicating expert knowledge. In the upcoming years, systems will emerge, which will enable monetizing knowledge at large scales (Choi 2019). *Data Vendors*, in our model, are interested parties in gaining monetary value from their stored data.

In this section, the components of MEEM are compared with three competing models in Table 3. (1) Hanafizadeh and Harati Nik (2020), provide a model called "Data Monetization Configuration" which along with the model provided by Buff et al. (2015) and Wixom (2014) help us compare our model with them and show that we not only share similar components, but our model also introduces a recommendation component. As mentioned before, the framework presented by Fred (2017) formed the basis of our model; therefore, it was also used to provide a better picture of the merits of what this paper has endeavored to create. Through this comparison, we emphasize the similarities between the models which confirms the fact that our model is as *complete* as the previous models in the field of monetization that have been theoretically validated. Also, there have been some additions that were not present in the earlier models, or at least not all models included those components. Therefore, we show the advantage of our models in comparison with the competing models.

It should be noted that components of MEEM, might not exactly be the same as the components described by competing models. For example, Buff et al. (2015) identify a role described as follows: "*Data professionals who ensure that appropriate data management activities are employed, and that data quality is appropriate for the context of intended use. These professionals are keenly aware of data's end-to-end lifecycle requirements, and they work to manage the requirements effectively.*".

Part of the actions committed by the professionals engaged in the *Professional community* includes the descriptions defined by Buff et al. (2015) for *Data management/Quality professionals*. Therefore, our logic for denying the existence of a component in competing models was not solely based on the fact that the component has not been precisely addressed in them. In many cases, if the component was even merely mentioned in the descriptions of the model or in the process of explaining the model, we regarded the component as available. Also, there might be components used by the competing models which MEEM doesn't currently address, but some have been proposed in the limitations and summary of the future research section of this paper.

Examples of such components include the role of *Developers/Designers* proposed by Buff et al. (2015) or the *Accessing and Processing restrictions layer* mentioned by Hanafizadeh and Harati Nik (2020).

For the sake of explaining the merits of the proposed model in this paper with competing models, rows with bold and dashed borders have been highlighted (✗).

Table 3 Comparison of the components of MEEM with Hanafizadeh and Harati Nik (2020), Buff et al. (2015), Wixom (2014), and Fred (2017).

		The components of MEEM	Hanafizadeh & Harati Nik (2019)	Buff et al. (2015)	Wixom (2014)	Fred (2017)
Monetization Layer	-	Expectation (Goods)	✗	✗	✗	✗
	-	Trading Model	✓	✗	✓	✓
	-	Insight Hunter	✗	✗	✗	✗
	-	End consumer	✓	✓	✗	✗
	Benefit	Monetary value	✗	✗	✗	✓
		Non-monetary value (e.g. Token)	✗	✗	✗	✓
	Data-driven and financial operations	Pricing	✗	✗	✗	✓
		Valuation	✗	✗	✗	✓
Improve and Innovate		Data gathering	✓	✓	✗	✓
		Data cleaning	✓	✓	✗	✓
		Data integration	✓	✓	✗	✓
		Data analysis	✓	✓	✗	✓
	Output	Insight	✗	✓	✗	✗
		Value	✓	✓	✓	✓
	Data marketplace	Data Vendor Community (DVC)	✗	✗	✗	✗
Resources and Supplies	**IT and analytics**	Capabilities (or Assets)	✓	✓	✓	✓
	People	Experts (or similar actors)	✓	✓	✗	✗
		Insight Provider	✗	✓	✗	✗
		Professional Community (Professionals)	✗	✓	✗	✗
		Data Vendor	✗	✗	✗	✗
	Data storage	Feedback Repository	○	○	○	○
		Insight Repository	○	○	○	○
		Expectation Repository	○	○	○	○
	-	Other resources and supplies	✓	✓	✗	✗
Recommendation	**Bots**	Data and information	✗	✗	✗	✗
		Match-making of experts with end-consumer requirements	✗	✗	✗	✗

The following components have not been identified in any of the competing models: ***Expectations, Insight Hunter (IH), Data Vendor (DV), Data Vendor Community (DVC), Recommendation Bots***.

Fig. 8 Comparison of MEEM with existing real-world applications

Components of competing models, outputs, and added-values of outputs		Our Model: Monetizing Expert Expectations Model (MEEM)	Amazon Mechanical Turk	Kambria	Datarade
Actors or Participants	Expert expectations	✓	●	●	●
	Requesters	✓	✓	✓	✓
	Students	●	✓	✓	✓
	Entrepreneurs	✓	✓	✓	✓
	Independent Workers	●	✓	●	✓
	Micro/Small Enterprises	✓	✓	✓	✓
	Insight Providers	✓	●	●	●
	Freelancers	●	✓	✓	●
	Buyers	✓	●	●	✓
Data Storage	Expectation Repository	✓	✓	●	●
	Feedback Repository	✓	✓	●	●
	Insight Repository	✓	●	●	●
	Database/Silo	✓	✓	✓	✓
Other Monetization, Improve ,Innovate & Recommendation	Social Platform Community	✓	●	●	●
	Quality Validation	✓	✓	●	✓
	Task Management	●	✓	✓	●
	Rewarding (Token based)	✓	✓	✓	●
	Dispute Resolution	✓	✓	●	●
	User Profiling	✓	✓	●	✓
	Recommendation	✓	✓	●	✓

Proposed by competing models
Common in one/two/all of competing models
● Not Available
✓ Available

These components have been separated with dotted border lines. Regarding some of the components under Data Storage, it should be pointed out that expectation repository, insight repository, and feedback repository can be present if the underlying model identifies expectations, insights, or feedbacks somewhere in their processes. But since the competing models are different from ours, therefore these components were omitted in the comparison process ().

Evaluation based on comparison with existing applications

In Fig. 8, we endeavor to evaluate our model by comparing its components with existing applications that help users monetize their knowledge or expertise. This Figure presents a comparison of our proposed model (MEEM) with real-world applications.

Our competing models in practice are (1) **Amazon Mechanical Turk (MTurk)** is a crowdsourcing marketplace that allows individuals and businesses to outsource their tasks to a distributed workforce, e.g., completing a survey, and conducting simple data validations, (2) **Kambria** is an open innovation decentralized platform where professors, students, or researchers can collaborate in researching, developing, and commercializing innovative ideas. The platform rewards participants with its cryptocurrency, and (3) **Datarade** is a platform for connecting data vendors and data buyers. This platform identifies and indexes all existing and emerging data vendors across countries and data types, and provides them based on free or premium plans to interested buyers.

The following components introduced in competing models and MEEM were used for the sake of comparison which includes ***People*** (Experts, requesters, entrepreneurs, independent workers, buyers, insight providers, micro/small enterprises, and freelancers), ***Data Storage*** (Expectation repository, feedback repository, insight repository), ***Social community or forums***, ***Quality assurance or verification***, ***Task management***, ***Rewarding mechanism***, ***Dispute resolution mechanism***, ***User profiling***, and ***Recommendation***. The outputs of each model have also been mentioned, along with a description of whether any added value could be generated using the output of each model. The logic behind determining the availability or unavailability of a component in a competing model, in this case, is based on available content and description provided by the real-world model on their websites or other commercial resources that the authors visited for the sake of this research.

In cases where no relevant components were found, either academic resources were not available for the models mentioned in this section, or the authors found the resources irrelevant to the topic covered in this section.

It should be noted that the implications brought in this section help us validate the ***applicability*** of the proposed model in this paper. To better understand the process by which the authors concluded that a component exists in a specific model or not, it should be stated that in case a component was not directly relevant to the objectives and aims of the model presented on the website, the authors noted the unavailability of that component. Otherwise, the component was concluded to be available on that specific model. For example, we found that Amazon Mechanical Turk could include the *Expectation repository* component since a requestors place a diverse set of work requirements which are in fact, expectations which workers should take out and complete. But in the case of *Buyers*, we concluded that the process of registering a task and doing a HIT (Human Intelligence Tasks) by a worker in Amazon Mechanical Turk doesn't directly or necessarily mean that a Buyer is involved.

Four main components that were unique in our proposed model: ***Expert expectations***, ***Insights***, ***Insight Providers***, and ***Social platform/community***.

Discussion

To further clarify our model, and to elaborate on our approach, the remaining of this study examines examples from the financial sector, e-commerce, and e-tourism contexts.

Our main contribution is presenting a model by which experts can monetize their expectations and following insights after a professional community approves the insights. Making an effort towards monetizing insights requires a dynamic, data-driven approach that resolves obstacles regarding the procedures needed to implement this model. The monetization process enables the participants to access the necessary data from third parties to gain a better understanding of the scope of the problem in hand to provide better expectations. Peers evaluate these expectations to guarantee their applicability and usefulness. Upon approval, insight providers will elaborate and generate insights interesting for a potential buyer to utilize. In the case of commercialization, participants receive a monetary/non-monetary value.

An important aspect of such platforms is the time frame in which the processes of the model take place. When crowdfunding platforms began, there was an implicit understanding that each round of funding would have a limited time to raise money (Burns 2014; Quilageo 2015). But there are times which a campaign doesn't require an actual time frame. Thus fund-raising can continue for an indefinite period or according to a term by TechCrunch, a "Forever Funding" campaign (Constine 2014). Similarly, in our proposed model, time can be limited to a deadline or might be open.

In the following, discussions on how the given idea overcomes and addresses some of the initially stated problems are briefly described.

Gain insights into current product and service flaws and problems

Apart from the financial sector, when we take a look at a competitive market, we understand that it is essential for e-commerce businesses to enhance their products and services continuously. For this, once the product enters the market, it is necessary to get feedback, which is crucial to stay competitive, particularly in the case of electronics goods (Dasgupta and Sengupta 2016). Most online shops utilize recommender systems for eliciting preferences and interests of their users to provide product recommendations (Heimbach et al. 2015). Our proposed model is an effective method for receiving feedback from experts and professionals who provide invaluable insights, which previously required enormous investments in market analysis and R&D. Recently it was stated that the majority of papers in the field of recommender systems, attend the application of user insights in real-world scenarios, including electronic markets such as Amazon (Linden et al. 2003; Ziegler et al. 2005), Netflix (Bobadilla et al. 2013), MovieLens (Miller et al. 2003; Park et al. 2012; Bobadilla et al. 2013), and Youtube (Davidson et al. 2010), Airbnb (Zervas et al. 2015; Lin et al. 2017). After comparing data sharing platforms, Richter and Slowinski (2019), express that data is a driver for innovation utilized for the enhancement of products and services. Thus, companies are eager to seek value from external participants and find appropriate candidates for knowledge transactions (Yusuf 2008). Proposing an intermediary platform which helps identify qualified experts to generate insights as some form of knowledge, is appealing for businesses. By this, e-commerce platforms can use insights generated from expert expectations to understand the flaws of their products, determine enhancements, and ways to improve their product features and ensure customer satisfaction.

Facilitate product/service enhancement and reduce market analysis and R&D costs

As another instance for the applicability of our model, it has been studied that changing the focus from service to experience, will result in higher experiential value for tourists, and lead to shaping an invaluable knowledge around tourism services (Sørensen and Jensen 2015). Tourists are precious origins for expectation and insight creation, considering the focus on experts in the presented model (Poon 1993). Expanding knowledge on tourists and enhancing products and services which generate value requires experience encounters (Sørensen and Jensen 2015).

Wang et al. (2019a), analyzed tourism experiences in rural Taiwan's coffee states and understood that coffee producers encountered challenges in creating economic value by coffee tourism. This use case is an apparent application of our model, where experts in marketing strategies and tourism can help businesses better understand customer expectations. Valid insights are critical for decision-making in today's businesses. Tourisms' experience has a central role in the tourism industry (Sugathan and Ranjan 2019). There are various indications of tourisms' tendency towards helping businesses create their desired experiences (Prahalad and Ramaswamy 2004). Yachin (2018) claims that tourism services' customers are an invaluable source of knowledge that is not effectively employed. One of the main focusses of our model regarded experts sharing their experiences and desired outcomes (expectations), which applies to the tourism industry. Thus, this model can lead to facilitating the enhancement and development of a product or a service and also help reduce the time, effort, and money required for conducting market analysis and research and development costs.

Accelerate decision-making processes

Digitization has had a significant impact on the financial services sector, which is probably since a substantial amount of its products rely on the information (Puschmann 2017). The convergence of finance and technology has resulted in shaping a term called "Fintech" which holds within innovative financial solutions enabled by Information Technology (Puschmann 2017). Also, Puschmann (2017) claims that the word "Fintech" is also closely related to "financial innovation" in most recent literature. According to Frame and White (2014), financial innovation is an approach that better satisfies financial system participants' expectations.

For the past 30 years, the activities of banks have changed moving towards commercial businesses due to advances in IT and financial services, which have transformed them into data-intensive firms (Frame and White 2014). These developments have led to financial innovations that force banks to enhance their products and services. In their case study on Omani banks on Big Data and Internet of Things (IoT), Saxena and Al-Tamimi (2017) discuss how customer relationships are forged via banks by providing real-time customer-centric solutions.

Srivastava and Gopalkrishnan (2015), state that banking firms have been gathering valuable data from customers and transactions. But the truth is most of these data had no strategical value in the first place and thus were collected without any plan. By utilizing our model, data owners can effectively understand applications for the vast amounts of data through expectation sharing which results in monetary value.

Bohlin et al. (2018) introduce Social Network Banking by studying 100 practices of banks on Social Networking Sites (SNSs), concluding that these networks provide tremendous business potentials. They find that SNSs can provide non-financial services to SNS users while receiving a new type of information, defined as *feelings or perceived experience*.

Relying on insights provided by our model, businesses can take adequate measures to address their requirements. Experts in the field of financial technologies have a crucial role as an Insight Provider that can help banks create value from gathered data (Li et al. 2018). Thus, banks can expect to receive several offerings from different professionals. By employing their databases, they may be able to prepare invaluable insights into the market, and sell those insights as a way of making money out of their data or help them accelerate their decision-making processes.

Conclusions

Becoming data and insight-driven has become an essential requirement for the continuing and flourishing of the future of businesses. Businesses are continually seeking approaches to create more value from data and data is considered as a monetization asset. The present paper provides a synthesis of the existing literature on monetization, recommender systems, and expectations to answering this question; Whether we can provide a model by which experts can monetize their knowledge and expertise. Combining literature on data monetization, recommender systems, and value creation based on data, a conceptual model, was formed which the authors called Monetizing Expert Expectations Model (MEEM).

In the synthesize of theories process, extensive background research led to the selection of three theories and models that formed the basis of our conceptual model. These included a value creation process framework in the field of data monetization (Fred 2017), a three-layered model for data monetization (Wixom 2014), and recommendations (Hsu et al. 2019). The core concept of the proposed model accepts an expectation as an input which attends to elicit informational needs of expert, validates the expectation by the participation of professionals who contribute to the platform by using real-time recommendations of assisting data and information, processes the validated input using data gathered by data providers, and creates value in forms of an insight which is sold to a potential buyer. Along this process, two different approaches towards monetization occur, direct and indirect data monetization. In the former, data provided to Insight Providers and Expert Participants by Data Vendors are considered as a direct sales of data in forms of raw or processed data. In the latter refined data and information, services or products are purchased by a potential buyer. Thus, considering the latter approach, data is improved to create something more valuable such as an insight in this paper.

MEEM is based on a set of recommender systems that utilize recommender bots to collect expert expectations, which leads to the recommendation of validated expectations and subsequent the sales of insights to *Insight Hunters*. *Professional community* involvement in the procedure of measuring the effectiveness of expectations ensures *Insight Hunters* that the insights generated based on these expectations are applicable and practical. Therefore, the main concern which the paper endeavored to resolve was helping experts to monetize their knowledge and expertise (referred to as HI in this paper). Since AI tools are limited to using explicit human knowledge, they can hardly handle the complexity of eliciting and extracting useful insights from high volume of data. In a worse case, knowing what to look for in data requires an extensive knowledge in specific fields which most organizations don't possess. In this article, we proposed a model in which HI helps overcome this shortcoming. HI can make inferences about data and events that AI lacks. This study uses a combination of both these kinds to create invaluable insights. Finalized insights are submitted to an *Online Insight Marketplace*, where a sales bot called Agent Bot will follow mechanisms such as auction for selling the insight to the highest bidder. After the sales of insight to a buyer, a bot tracks the application and commercialization of the insight. In the case of commercialization, participants in the platform will receive a specific token coined by the platform based on a Smart Contract and the level of their participation.

The components of MEEM were compared with three competing models in the implications for the theory section. Through this comparison, we emphasized the commonalities between the models that confirmed the fact that our model is **as *complete*** as the previous models in the field of monetization that have been theoretically validated. Also, through the presentation of components that competing models lacked, we presented the merits of the proposed model in this paper. The components of MEEM were also compared with existing real-world applications in the implications for practice section of the paper. By this, we showed that not only MEEM shares significant components with the existing models, but also introduces components that provide an advantage for this model over competing models. The unique components offered by MEEM include insights, expectations, and a social community where professionals participate in, to enhance and validate the expectations provided on the platform.

Limitations and summary of future research

The model illustrated in this paper has some limitations. It should be noted that the model may require customization in specific industries. Thus, the setups of its elements may require modifications according to the nature of that industry.

First, assumptions should be established and the effectiveness of recommendations by the bots proposed in this paper requires investigation. The bots need implementation in a simplified environment, which simulates the platform where they can communicate with the users and conduct the processes explained in the model development section. The recommended expectation should be collected and analyzed, which will probably require defining several measurement items.

Second, while we have attempted to highlight some examples of implications, there are ripe areas for research that requires developing questions related to this area. The main focus of this study was to propose the processes of the model, which eventually lead to the monetization of expert expectations and subsequent insights. Recommender systems are utilized as a basis for social networks based on user contextual information, enhance Collaborative Filtering (CF), and solve the issues of cold start and sparsity (Yu and Li 2018). But what if, users themselves would participate in sharing their information in return of monetary value from exposing their data. Revenue from information sharing is another potential motivation for experts to participate in this platform, which requires further research. Business models have enormous research potential, where users can access data gathered by third-parties and monetize them by participating in a platform created for such practices. Thus, the whole ecosystem encapsulating our model can be an exciting topic for further research. Regarding the monetization of insights, the present study doesn't address the insight valuation mechanisms, and eventually, pricing. An auction mechanism could be a potential candidate for this which could be an exciting topic for future research.

Third, Vaidya and Khachane (2017) describe recommender systems as tools for solving data and information overload. Based on these capabilities, the platform can help users identify data and information categories and determine fair prices for limited or full access to their data. According to Moore (2015), quantifying information's value and managing data as an enterprise asset is essential, which Gartner chose to introduce the term "Infonomics" for emerging theories and practices. Determining the value of expectations and insights in this platform could be based on a bidding mechanism (Lotame 2019).

Fourth, there are issues related to regulation, data ownership, and privacy. Regulations often tend to shape after technological innovations, and are inconsistent and dispersed across industries and geographic regions (Moore 2015). Even though consumers value their privacy, but they tend to provide their information in return for a monetary value or a service (Moore 2015), which is interesting for future research in the scope of our proposed model.

Fifth, regarding the infrastructure required for this model, some aspects of blockchain which could help enhance the performance of this platform or remove complications include identity authentication, privacy protection, transaction monitoring, ownership rights, and decentralized security. One important concern regarding the monetization process is validating the legitimacy of the rightful owner of an insight. Using blockchain's potentials, the legitimate owner of offerings proposed by *Expert Participant*s can be accurately determined. Therefore, the platform can define the extent by which the expectations of experts and their subsequent insights are commercially applied. Thus, blockchain technology can ensure the follow up of insights until they get commercialized in parts or whole. Since this platform utilizes a monopolistic model for selling expert expectations, novel data-sharing approaches that protect user privacy such as blockchain are applicable for securing user data and ensuring trust (Frey et al. 2017). Also, blockchain provides invaluable means for protecting Intellectual Property (Clark and McKenzie 2018). Similar to patents or any other intellectual properties, innovations are hard to value before a tangible result (Chesbrough 2003). Thus, in this model, participants gain monetary value whenever the actual value of their engagement is commercialized. In this case, the model requires a mechanism for protecting intellectual assets by a licensing strategy. Blockchain seems to be a reliable candidate, also providing means to digitally facilitate verification or enforcement of negotiations based on smart contracts.

Finally, an essential aspect of proposing an innovative model is to motivate people to participate. A quantitative study that investigates various elements that affect expert non-monetary motivation towards participation could be of interest to researchers. But several aspects regarding the motivation of participants have been identified that are crucial for the success of these platforms (Pinto and dos Santos 2018). Apart from motivating users to participate in making contributions on this social platform similar to other social platforms that they choose to engage in, some tools help to capture responses and opinions of users. Based on a study by Symonds (2011), Survey Monkey, for instance, can be employed to obtain the expectations and preferences of users in the context of the present study. A study on tools that can help enhance our proposed model's processes will be interesting.

Appendix

Glossary of Acronyms

AI: Artificial Intelligence
BPMN: Business Process Model Notation.
CIST: Collective Intelligence Social Tagging.
DOR: Data Offering Repository.
DSR: Design Science Research.
DVC: Data Vendor Community.
FR: Feedback Repository.
HI: Human Intelligence.
HIT: Human Intelligence Tasks.
IaaS: Insight-as-a-Service.
IH: Insight Hunter.
IP: Insight Provider.
IR: Insight Repository.
IT: Information Technology.
MEEM: Monetizing Expert Expectation Model.

MEET: Monetizing Expert Expectation Token.
PC: Professional Community.
SaaS: Software-as-a-Service.

References

Agrawal, A., Gans, J., & Goldfarb, A. (2017). What to expect from artificial intelligence? MIT Sloan Management Review. Retrieved from https://sloanreview.mit.edu/article/what-to-expect-from-artificial-intelligence. Accessed 3 June 2019.

Anadiotis, G. (2017). Insights platforms as a service: What they are and why they matter. ZDnet. Retrieved from website https://www.zdnet.com/article/insight-platforms-as-a-service-what-they-are-and-why-they-matter. Accessed 5 Sep 2019.

Banerjee, N., Chakraborty, D., Dasgupta, K., Mittal, S., Joshi, A., Nagar, S., & Madan, S. (2009). User interests in social media sites: An exploration with micro-blogs. *In Proceedings of the 18th ACM conference on Information and knowledge management*, (pp. 1823-1826). ACM. https://doi.org/10.1145/1645953.1646240.

Bano, M., & Zowghi, D. (2015). A systematic review on the relationship between user involvement and system success. *Information and Software Technology, 58*, 148–169. https://doi.org/10.1016/j.infsof.2014.06.011.

Belissent, J. (2017). Insights services drive data commercialization. Forrester. Retrieved from website https://go.forrester.com/blogs/17-03-08-insights_services_drive_data_commercialization. Accessed on 28 Aug 2019.

Bergemann, D. & Bonatti, A. (2019). The Economics of Social Data. Cowles Foundation Discussion Papers 2171, *Cowles Foundation for Research in Economics*, Yale University. https://doi.org/10.2139/ssrn.3459796.

Bigné, J. E., Andreu, L., & Gnoth, J. (2005). The theme park experience: An analysis of pleasure, arousal, and satisfaction. *Tourism Management, 26*(6), 833–844. https://doi.org/10.1016/j.tourman.2004.05.006.

Bobadilla, J., Ortega, F., Hernando, A., & Gutiérrez, A. (2013). Recommender systems survey. *Knowledge-Based Systems, 46*, 109–132. https://doi.org/10.1016/j.knosys.2013.03.012.

Bohlin, E., Shaikh, A. A., & Hanafizadeh, P. (2018). Social network banking: A case study of 100 leading global banks. *International Journal of E-Business Research (IJEBR), 14*(2), 1–13. https://doi.org/10.4018/IJEBR.2018040101.

Brocke, J, V., Simons, A., Niehaves, B., Riemer, K., Plattfaut, R. & Cleven, A. (2009). Reconstructing the giant: On the importance of rigor in documenting the literature search process. *ECIS 2009 Proceedings*, 9, (pp. 2206-2217). https://aisel.aisnet.org/ecis2009/161/.

Buff, A., Wixom, B, H., & Tallon, P. (2015). Foundation for data monetization. MIT Center for Information Systems Research. Retrieved from website https://cisr.mit.edu/publication/MIT_CISRwp402_FoundationsForDataMonetization_BuffWixomTallon. Accessed 26 Mar 2019.

Burke, R. (2000). Knowledge-based recommender systems. *Encyclopedia of library and information systems, 69*(32), 175–186 http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.21.6029.

Burns, C. (2014). Indiegogo tests crowdfunding campaigns with no time limit. Resource document. Slashgear. https://www.slashgear.com/indiegogo-tests-crowdfunding-campaigns-with-no-time-limit-17346816. Accessed on 27 Aug 2019.

Campbell, D. E., Wells, J. D., & Valacich, J. S. (2013). Breaking the ice in B2C relationships: Understanding pre-adoption e-commerce attraction. *Information Systems Research, 24*(2), 219–238. https://doi.org/10.1287/isre.1120.0429.

Chesbrough, H, W. (2003). Open innovation: The new imperative for creating and profiting from technology. Resource document. Harvard Business School Press. https://www.nmit.edu.my/wp-content/uploads/2017/10/Open-Innovation-the-New-Imperative-for-Creating-and-Profiting-from-Technology.pdf. Accessed 13 Apr 2019.

Choi, P. (2019). The next gig economy will be on-demand knowledge. Retrieved from Quartz website https://qz.com/work/1527544/the-next-gig-economy-will-be-on-demand-knowledge. Accessed 17 May 2019.

Choi, J. P., Jeon, D. S., & Kim, B. C. (2019). Privacy and personal data collection with information externalities. *Journal of Public Economics, 173*, 113–124. https://doi.org/10.1016/j.jpubeco.2019.02.001.

Chua, A. Y., & Banerjee, S. (2013). Customer knowledge management via social media: The case of Starbucks. *Journal of Knowledge Management, 17*(2), 237–249. https://doi.org/10.1108/13673271311315196.

Clark, B., McKenzie, B (2018). Blockchain and IP law: A match made in crypto heaven. World Intellectual Property Organization Magazine, Retrieved from website https://www.wipo.int/wipo_magazine/en/2018/01/article_0005.html. Accessed 16 May 2019.

Constine, J. (2014). Indiegogo tries “forever funding” campaigns without end dates. TechCrunch. https://techcrunch.com/2014/09/17/indiegogo-forever-funding. Accessed 1 Sept 2019.

Covin, J. G., & Slevin, D. P. (1991). A conceptual model of entrepreneurship as firm behavior. *Entrepreneurship theory and practice, 16*(1), 7–26. https://doi.org/10.1177/104225879101600102.

Darrow, B. (2017). LinkedIn claims half a billion users. Fortune. Retrieved from https://fortune.com/2017/04/24/linkedin-users. Accessed 3 July 2019.

Dasgupta, S., & Sengupta, K. (2016). Analyzing consumer reviews with text mining approach: A case study on Samsung galaxy S3. *Paradigm, 20*(1), 56–68. https://doi.org/10.1177/0971890716637700.

Davidson, J., Liebald, B., Liu, J., Nandy, P., Van Vleet, T., Gargi, U. & Sampath, D. (2010). The YouTube video recommendation system. *In Proceedings of the fourth ACM conference on Recommender systems*, (pp. 293–296). ACM. https://doi.org/10.1145/1864708.1864770.

Deloitte. (2015). Analytics trends 2015: A below-the-surface look. Retrieved from website https://www2.deloitte.com/content/dam/Deloitte/tr/Documents/deloitte-analytics/tr-analytics-trends-2015.pdf. Accessed 23 Jan 2019.

Doha, A., Elnahla, N., & McShane, L. (2019). Social commerce as social networking. *Journal of Retailing and Consumer Services, 47*, 307–321. https://doi.org/10.1016/j.jretconser.2018.11.008.

Eirinaki, M., Gao, J., Varlamis, I., & Tserpes, K. (2018). Recommender systems for large-scale social networks: A review of challenges and solutions. *Future Generation Computer Systems, 78*(part 1), 413–418. https://doi.org/10.1016/j.future.2017.09.015.

Ekstrand, M. D., Riedl, J. T., & Konstan, J. A. (2011). Collaborative filtering recommender systems. *Foundations and Trends in Human-Computer Interaction, 4*(2), 81–173. https://doi.org/10.1561/1100000009.

Elder, R., Gallagher, K. (2017). LinkedIn reaches a half-billion users. Business Insider, Insider Inc. Retrieved from website https://www.businessinsider.com/linkedin-reaches-a-half-billion-users-2017-4. Accessed 13 Apr 2019.

Erfan, F. (2018). It's All in the Preparation: Four Strategies to Monetize Your Data. Dataversity. Retrieved from website https://www.dataversity.net/preparation-four-strategies-monetize-data. Accessed 2 Sept 2019.

Ernst and Young. (2011). Digital data opportunities: Using insight to drive relevance in the digital world. Retrieved from website https://www.ey.com/Publication/vwLUAssets/Digital_data_opportunities/$FILE/EY_Digital_data_opportunities.pdf. Accessed 13 Mar 2019.

Ernst and Young. (2019). How the IoT and data monetization are changing business models. Retrieved from website https://www.ey.com/

en_us/advisory/how-the-iot-and-data-monetization-are-changing-business-models. Accessed 22 Apr 2019.

Evans, D. (2002). Systematic reviews of interpretive research: Interpretive data synthesis of processed data. *Australian Journal of Advanced Nursing, 20*(2), 22–26 https://www.ajan.com.au/archive/Vol20/Vol20.2-4.pdf.

Frame, W, S. & White, L, J. (2014). Technological change, financial innovation, and diffusion in banking. Oxford, United Kingdom, *Oxford University Press*. https://doi.org/10.1093/oxfordhb/9780199640935.013.0019.

Fred, J. (2017). *Data monetization-how an organization can generate revenue with data? (Master of Science thesis)*. Tampere: The Tampere University of technology http://urn.fi/URN:NBN:fi:tty-201703281232. Accessed 5 May 2019.

Frey, R, M., Bühler, P., Gerdes, A., Hardjono, T., Fuchs, K, L., & Ilic, A. (2017). The effect of a blockchain-supported, privacy-preserving system ondisclosure of personal data. *IEEE 16th International Symposium on NetworkComputing and Applications (NCA),* (pp. 1–5). IEEE. https://doi.org/10.1109/NCA.2017.8171385.

Gallant, J. (2019). 48 eye-opening LinkedIn statistics for B2B marketers in 2019. Foundation. Retrieved from website. https://foundationinc.co/lab/b2b-marketing-linkedin-stats. Accessed 2 May 2019.

Gallaugher, J., & Ransbotham, S. (2010). Social media and customer dialog management at Starbucks. *MIS Quarterly Executive, 9*(4) https://aisel.aisnet.org/misqe/vol9/iss4/3.

Gandhi, S., Thota, B., Kuchembuck, R., Swartz, J. (2018). Demystifying data monetization. MIT Sloan management review. Retrieved from website https://sloanreview.mit.edu/article/demystifying-data-monetization. Accessed 29 May 2019.

Gartner. (2019). Five strategies for the CIO building a business case for data monetization in asset management. Retrieved from website https://www.gartner.com/en/documents/3903263/five-strategies-for-the-cio-building-a-business-case-for. Accessed 13 Mar 2019.

Grecu, D. L., & Brown, D. C. (2000). Expectation formation in multi-agent design systems. In J. S. Gero (Ed.), *Artificial Intelligence in Design'00, (pp. 651–671)*. Dordrecht: Springer. https://doi.org/10.1007/978-94-011-4154-3_32.

Hajli, N. (2015). Social commerce constructs and consumer's intention to buy. *International Journal of Information Management, 35*(2), 183–191. https://doi.org/10.1016/j.ijinfomgt.2014.12.005.

Hanafizadeh, P., & Ghamkhari, F. (2019). Elicitation of tacit knowledge using soft systems methodology. *Systemic Practice and Action Research, 32*(5), 521–555. https://doi.org/10.1007/s11213-018-9472-9.

Hanafizadeh, P., & Harati Nik, M. R. H. (2020). Configuration of data monetization: A review of literature with thematic analysis. *Global Journal of Flexible Systems Management, 21*(1), 17–34. https://doi.org/10.1007/s40171-019-00228-3.

Hanafizadeh, P., & Yarmohammadi, M. (2016). An integrated conceptualization of content in an information society. *Information Development, 32*(4), 880–889. https://doi.org/10.1177/2F0266666915572926.

Heimbach, I., Gottschlich, J., & Hinz, O. (2015). The value of user's Facebook profile data for product recommendation generation. *Electronic Markets, 25*(2), 125–138. https://doi.org/10.1007/s12525-015-0187-9.

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MISQ, 28*(1), 75–105. https://doi.org/10.2307/25148625.

Hossain, M. (2018). Motivations, challenges, and opportunities of successful solvers on an innovation intermediary platform. *Technological Forecasting and Social Change, 128*, 67–73. https://doi.org/10.1016/j.techfore.2017.10.018.

Howells, J. (2006). Intermediation and the role of intermediaries in innovation. *Research Policy, 35*(5), 715–728. https://doi.org/10.1016/j.respol.2006.03.005.

Hsu, P. Y., Lei, H. T., Huang, S. H., Liao, T. H., Lo, Y. C., & Lo, C. C. (2019). Effects of sentiment on recommendations in social network. *Electronic Markets, 29*(2), 253–262. https://doi.org/10.1007/s12525-018-0314-5.

Kearney, A, T. (2014). Rethinking personal data: A new lens for strengthening trust. World Economic Forum. Retrieved from website: http://www3.weforum.org/docs/WEF_RethinkingPersonalData_ANewLens_Report_2014.pdf. Accessed 9 July 2019.

Köhler, S., Wöhner, T., & Peters, R. (2016). The impact of consumer preferences on the accuracy of collaborative filtering recommender systems. *Electronic Markets, 26*(4), 369–379. https://doi.org/10.1007/s12525-016-0232-3.

KPMG. (2015). Framing a winning data monetization strategy. Retrieved from website https://assets.kpmg/content/dam/kpmg/pdf/2015/10/framing-a-winning-data.pdf. Accessed 12 August 2019.

Langseth, H., & Nielsen, T. D. (2012). A latent model for collaborative filtering. *International Journal of Approximate Reasoning, 53*(4), 447–466. https://doi.org/10.1016/j.ijar.2011.11.002.

Lassen, A. H., & Laugen, B. T. (2017). Open innovation: On the influence of internal and external collaboration on the degree of newness. *Business Process Management Journal, 23*(6), 1129–1143. https://doi.org/10.1108/BPMJ-10-2016-0212.

Li, W, C., Nirei, M. & Yamana, K. (2018). Value of data: There's no such thing as a free lunch in the digital economy. *US Bureau of* Economic Analysis Working Papers. Retrieved from website https://www.bea.gov/system/files/papers/20190220ValueofDataLiNireiYamanaforBEAworkingpaper.pdf.

Lichtenthaler, U. (2018). Substitute or synthesis: The interplay between human and artificial intelligence. *Research-Technology Management, 61*(5), 12–14. https://doi.org/10.1080/08956308.2018.1495962.

Lin, K, P., Shen, C, Y., Chang, T, L. & Chang, T, M. (2017). A consumer review-driven recommender Service for web E-commerce. *In 2017 IEEE 10th Conference on Service-Oriented Computing and Applications (SOCA)* (pp. 206-210). IEEE. https://doi.org/10.1109/SOCA.2017.35.

Linden, G., Smith, B., & York, J. (2003). Amazon.com recommendations: Item-to-item collaborative filtering. *IEEE Internet Computing, 7*(1), 76–80. https://doi.org/10.1109/MIC.2003.1167344.

Lotame. (2019). How to monetize your data? Lotame. Retrieved from website https://www.lotame.com/how-to-monetize-your-data. Accessed 6 September 2019.

Lu, J., Wu, D., Mao, M., Wang, W., & Zhang, G. (2015). Recommender system application developments: A survey. *Decision Support Systems, 74*, 12–32. https://doi.org/10.1016/j.dss.2015.03.008.

Lucena, A. (2011). The organizational designs of R&D activities and their performance implications: Empirical evidence for Spain. *Industry and Innovation, 18*(02), 151–176. https://doi.org/10.1080/13662716.2011.541103.

Lunden, I. (2017). LinkedIn hits 500M member milestone for its social network for the working world. TechCrunch. Retrieved from website https://techcrunch.com/2017/04/24/linkedin-hits-500m-member-milestone-for-its-social-network-for-the-working-world/ [accessed 3 March 2019.

Luo, X., Zhou, M., Xia, Y., & Zhu, Q. (2014). An efficient non-negative matrix-factorization-based approach to collaborative filtering for recommender systems. *IEEE Transactions on Industrial Informatics, 10*(2), 1273–1284. https://doi.org/10.1109/TII.2014.2308433.

Miller, B, N., Albert, I., Lam, S, K., Konstan, J, A. & Riedl, J. (2003). MovieLens unplugged: Experiences with an occasionally connected recommender system. *In Proceedings of the 8th international conference on Intelligent user interfaces,* (pp. 263-266). ACM. https://doi.org/10.1007/978-1-4471-3754-2_16.

Monnappa, A. (2017). Insights-as-a-service: The next big thing in analytics. *Simplelearn*. Retrieved from website https://www.

simplilearn.com/insights-as-a-service-iaas-next-big-thing-in-analytics-article. Accessed 7 Sept 2019.

Moore, S. (2015). How to Monetize Your Customer Data? Gartner. Retrieved from website. http://www.gartner.com/smarterwithgartner/how-to-monetize-your-customer-data. Accessed on 24 Aug 2019.

Morgan, L. (2016). 8 reasons to consider insights-as-A-service. Information Week. Retrieved from website https://www.informationweek.com/big-data/big-data-analytics/8-reasons-to-consider-insights-as-a-service/d/d-id/1324801. Accessed 15 June 2019.

Mulhall, J., de Jong, B., Weterings, I. (2017). Data rich, profit poor. Accenture. Retrieved from website https://financialservices.accenture.com/rs/368-RMC-681/images/accenture-data-rich-profit-poor-pov.pdf. Accessed 18 June 2019.

Najjar, M. S., & Kettinger, W. J. (2013). Data monetization: Lessons from a Retailer's journey. *MIS Quarterly Executive, 12*(4), 213–225 https://aisel.aisnet.org/misqe/vol12/iss4/4.

Neri, F., Aliprandi, C., Capeci, F., Cuadros, M. & By, T. (2012). Sentiment analysis on social media. *2012 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining,* (pp. 919-926). IEEE. https://doi.org/10.1109/ASONAM.2012.164.

Park, D. H., Kim, H. K., Choi, I. Y., & Kim, J. K. (2012). A literature review and classification of recommender systems research. *Expert Systems with Applications, 39*(11), 10059–10072. https://doi.org/10.1016/j.eswa.2012.02.038.

Pathak, B., Garfinkel, R., Gopal, R. D., Venkatesan, R., & Yin, F. (2010). Empirical analysis of the impact of recommender systems on sales. *Journal of Management Information Systems, 27*(2), 159–188. https://doi.org/10.2753/MIS0742-1222270205.

Pine, B. J., & Gilmore, J. H. (1998). Welcome to the experience economy. *Harvard Business Review, 76*, 97–105.

Pine, B. J., & Gilmore, J. H. (2000). Satisfaction, sacrifice, surprise: Three small steps create one giant leap into the experience economy. *Strategy & Leadership, 28*(1), 18–23. https://doi.org/10.1108/10878570010335958.

Pinto, L. F. S., & dos Santos, C. D. (2018). Motivations of crowdsourcing contributors. *Innovation & Management Review, 15*(1), 58–72. https://doi.org/10.1108/INMR-02-2018-004.

Poon, A. (1993). Tourism, technology, and competitive strategies. *Journal of Travel Research, 32*(3), 78–78. https://doi.org/10.1177/2F004728759403200372.

Prahalad, C. K., & Ramaswamy, V. (2004). Co-creation experiences: The next practice in value creation. *Journal of Interactive Marketing, 18*(3), 5–14. https://doi.org/10.1002/dir.20015.

Pu, P., Chen, L. & Hu, R. (2011). A user-centric evaluation framework for recommender systems. *In Proceedings of the fifth ACM conference on Recommender systems,* (pp. 157-164). ACM. https://doi.org/10.1145/2043932.2043962.

Pu, P., Chen, L., & Hu, R. (2012). Evaluating recommender systems from the user's perspective: Survey of the state of the art. *User Modeling and User-Adapted Interaction, 22*(4–5), 317–355. https://doi.org/10.1007/s11257-011-9115-7.

Puschmann, T. (2017). Fintech. *Business and Information Systems Engineering, 59*(1), 69–76. https://doi.org/10.1007/s12599-017-0464-6.

Quilageo, (2015). DIY Crowdfunding. How it Can Solve the Six. Big Crowdfunding Problems. 6. Quilageo Inc Marketing, Inc. Retrieved from website https://europa.eu/capacity4dev/file/23002/download?token=bBYbB1r9. Accessed 3 September 2019.

Resnick, P., & Varian, H. R. (1997). Recommender systems. *Communications of the ACM, 40*(3), 56–59. https://doi.org/10.1145/245108.245121.

Richter, H., & Slowinski, P. R. (2019). The data sharing economy: On the emergence of new intermediaries. *IIC-International Review of Intellectual Property and Competition Law, 50*(1), 4–29. https://doi.org/10.1007/s40319-018-00777-7.

Sánchez, P., & Bellogín, A. (2019). Building user profiles based on sequences for content and collaborative filtering. *Information Processing and Management, 56*(1), 192–211. https://doi.org/10.1016/j.ipm.2018.10.003.

Saxena, S., & Al-Tamimi, T. A. S. M. (2017). Big data and internet of things (IoT) technologies in Omani banks: A case study. *Foresight, 19*(4), 409–420. https://doi.org/10.1108/FS-03-2017-0010.

Shen, X. L., Li, Y. J., Sun, Y., Chen, Z., & Wang, F. (2019). Understanding the role of technology attractiveness in promoting social commerce engagement: Moderating effect of personal interest. *Information and Management, 56*(2), 294–305. https://doi.org/10.1016/j.im.2018.09.006.

Sørensen, F., & Jensen, J. F. (2015). Value creation and knowledge development in tourism experience encounters. *Tourism Management, 46*, 336–346. https://doi.org/10.1016/j.tourman.2014.07.009.

Srivastava, U., & Gopalkrishnan, S. (2015). Impact of big data analytics on banking sector: Learning for Indian banks. *Procedia Computer Science, 50*, 643–652. https://doi.org/10.1016/j.procs.2015.04.098.

Sugathan, P., & Ranjan, K. R. (2019). Co-creating the tourism experience. *Journal of Business Research, 100*, 207–217. https://doi.org/10.1016/j.jbusres.2019.03.032.

Symonds, E. (2011). A practical application of survey monkey as a remote usability testing tool. *Library Hi Tech, 29*(3), 436–445. https://doi.org/10.1108/07378831111174404.

Thompson, L. S., Story, M., & Butler, G. (2003). Use of a university-community collaboration model to frame issues and set an agenda for strengthening a community. *Health Promotion Practice, 4*(4), 385–392. https://doi.org/10.1177/2F1524839903255467.

Vaidya, N. & Khachane, A, R. (2017). Recommender systems-the need of the eCommerce ERA. *2017 International Conference on Computing Methodologies and Communication (ICCMC),* (pp. 100-104). IEEE. https://doi.org/10.1109/ICCMC.2017.8282616.

Wang, X., & Clay, P. F. (2012). Beyond adoption intention: Online communities and member motivation to contribute longitudinally. *Journal of Organizational Computing and Electronic Commerce, 22*(3), 215–236. https://doi.org/10.1080/10919392.2012.696928.

Wang, Y., & Sharma, R, S. (2018). Design of front-end for recommendation systems: Towards a hybrid architecture. *International Conference on Electronic Business 2018 Proceedings*, (pp. 220-230). ICEB. https://aisel.aisnet.org/iceb2018/80.

Wang, M. J., Chen, L. H., Su, P. A., & Morrison, A. M. (2019a). The right brew? An analysis of the tourism experiences in rural Taiwan's coffee estates. *Tourism Management Perspectives, 30*, 147–158. https://doi.org/10.1016/j.tmp.2019.02.009.

Wang, X., Lin, X., & Spencer, M. K. (2019b). Exploring the effects of extrinsic motivation on consumer behaviors in social commerce: Revealing consumers' perceptions of social commerce benefits. *International Journal of Information Management, 45*, 163–175. https://doi.org/10.1016/j.ijinfomgt.2018.11.010.

Weill, P., & Vitale, M. (2001). *Place to space: Migrating to eBusiness models*. Boston: Harvard Business Review Press.

White, S, A. (2004). Introduction to BPMN. IBM cooperation, 2(0), 0, retrieved from website: http://www.bpmn.org/. Accessed 2 Apr 2019.

Wixom, B, H. (2014). Cashing in on your data. CISR Research Briefing. MIT Center for Information Systems Research. Retrieved from website https://cisr.mit.edu/publication/2014_0801_DataMonetization_Wixom. Accessed 21 Apr 2019.

Wixom, B, H. & Ross, J, W. (2017). How to monetize your data? MITSloan: Research Highlight. Retrieved from website https://sloanreview.mit.edu/article/how-to-monetize-your-data. Accessed 17 Aug 2019.

Woerner, S. L., & Wixom, B. H. (2015). Big data: Extending the business strategy toolbox. *Journal of information technology, 30*(1), 60–62. https://doi.org/10.1057/2Fjit.2014.31.

Wu, H. C. (2017). What drives experiential loyalty? A case study of Starbucks coffee chain in Taiwan. *British Food Journal, 119*(3), 468–496. https://doi.org/10.1108/BFJ-08-2016-0349.

Wu, H. C., & Li, T. (2017). A study of experiential quality, perceived value, heritage image, experiential satisfaction, and behavioral intentions for heritage tourists. *Journal of hospitality and tourism research, 41*(8), 904–944. https://doi.org/10.1177/2F1096348014525638.

Wynn, D. C., & Clarkson, P. J. (2018). Process models in design and development. *Research in Engineering Design, 29*(2), 161–202. https://doi.org/10.1007/s00163-017-0262-7.

Yachin, J. M. (2018). The 'customer journey': Learning from customers in tourism experience encounters. *Tourism Management Perspectives, 28*, 201–210. https://doi.org/10.1016/j.tmp.2018.09.002.

Yu, W., & Li, S. (2018). Recommender systems based on multiple social networks correlation. *Future Generation Computer Systems, 87*, 312–327. https://doi.org/10.1016/j.future.2018.04.079.

Yusuf, S. (2008). Intermediating knowledge exchange between universities and businesses. *Research Policy, 37*(8), 1167–1174. https://doi.org/10.1016/j.respol.2008.04.011.

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1993). The nature and determinants of customer expectations of service. *Journal of the Academy of Marketing Science, 21*(1), 1–12. https://doi.org/10.1177/0092070393211001.

Zervas, G., Proserpio, D. & Byers, J. (2015). A first look at online reputation on Airbnb, where every stay is above average. Where Every Stay is Above Average. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2554500.

Zhang, H., Lu, Y., Gupta, S., & Zhao, L. (2014). What motivates customers to participate in social commerce? The impact of technological environments and virtual customer experiences. *Information and Management, 51*(8), 1017–1030. https://doi.org/10.1016/j.im.2014.07.005.

Ziegler, C, N., McNee, S, M., Konstan, J, A. & Lausen, G. (2005). Improving recommendation lists through topic diversification. *In Proceedings of the 14th international conference on World Wide Web,* (pp. 22-32). ACM. https://doi.org/10.1145/1060745.1060754.

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