Architecting Intelligent Service Ecosystems: Perspectives, Frameworks, and Practices

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Abstract. The current advancement of Artificial Intelligence (AI) combined with other digitalization efforts significantly impacts service ecosystems. Artificial intelligence has a substantial impact on new opportunities for the co-creation of value and the development of intelligent service ecosystems. Motivated by experiences and observations from digitalization projects, this paper presents new methodological perspectives and experiences from academia and practice on architecting intelligent service ecosystems and explores the impact of artificial intelligence through real cases supporting an ongoing validation. Digital enterprise architecture models serve as an integral representation of business, information, and technological perspectives of intelligent service-based enterprise systems to support management and development. This paper focuses on architectural models for intelligent service ecosystems, showing the fundamental business mechanism of AI-based value co-creation, the corresponding digital architecture, and management models. The focus of this paper presents the key architectural model perspectives for the development of intelligent service ecosystems.

Keywords: Service ecosystems · Value co-creation · Intelligent digital architecture · Architecture engineering · Management

1 Introduction

Intelligent service ecosystems together with their digital platforms [1] are now considered one of the most important foundations for new business models that contribute to developing and implementing corporate strategies. In 2019, seven of the ten most valuable companies in the world provided digital platforms for service ecosystems (e.g.,

R. A. Buchmann et al. (Eds.): BIR 2021, LNBIP 430, pp. 150–164, 2021.
https://doi.org/10.1007/978-3-030-87205-2_10

Microsoft, Facebook, Alibaba, Amazon) [1]. Together with their service ecosystems, platforms generate value by inducing collaboration and co-creation between actors and facilitating actions between external consumers and producers of products and services [2]. Artificial intelligence plays a crucial role in the design of such intelligent service ecosystems [1].

Crucial to the design of intelligent service ecosystems are creative ideas, competencies, and capabilities for intelligent digitization, with timely adaptation to ever shorter innovation cycles with appropriate implementation and execution concepts within suitable business models. However, there is a lack of substantial methodological experience from academia and practice, especially case studies that take a holistic perspective on designing intelligent service ecosystems.

The essential ultimate success of a platform does not result primarily from the platform itself or the technology's use. Instead, successful platforms result from the so-called ecosystem of the platform. The ecosystem of the platform is based on the totality of users who collaborate via the platform. These users can be distinguished into several groups. To establish a platform, it is necessary to achieve sufficient growth in several groups. Network effects play a central role in this process. They can occur within but also between user groups. Fostering these network effects is a critical task in the development of a platform. An ecosystem is characterized by a set of interacting resources, such as organizations, individuals, and autonomous actors and systems, that jointly develop their capabilities and roles according to the Service-Dominant Logic (S-D logic) [3]. From a technical perspective, digital services are slices of code that perform a specific functionality to enable business offerings [4] of digital products and services composed of business services, data services, and infrastructure services.

Based on the S-D logic [5], a service ecosystem is a self-contained and self-adaptive system of loosely coupled resource-integrating actors connected by shared institutional logic and mutual value creation through service exchange. S-D logic was initially developed in 2004 by Stephen Vargo and Robert Lusch [6]. S-D logic represents a new type of service logic that focuses on intangible resources, the co-creation of value, and close business relationships. S-D logic focuses on an emerging understanding of economic exchange that favors services based on specialized skills over traditional manufactured goods.

The following *research questions* can substantiate our approach:

RQ1: How does artificial intelligence impact value co-creation in service ecosystems using a Service-Dominant Logic theoretical lens?
RQ2: What are integral perspectives for architecting and managing intelligent service ecosystems?

We will present new perspectives and frameworks from academia and practice for architecting AI-based service ecosystems. First, we introduce the research background and methodology base. The paper's core addresses our research questions: (1) we present AI-powered co-creation mechanisms, (2) we provide new perspectives motivated by AI and associated digital technologies in our comprehensive and holistic approach to architecting and managing intelligent service ecosystems. Finally, we summarize our discussion from science and conclude our findings and future research.

2 Research Background

We are at a turning point in the development and application of intelligent digital systems. We see excellent prospects for digital systems with artificial intelligence (AI) [7, 8] to contribute to improvements in many areas of work and society with the potential of digital technologies. We understand digitalization based on new methods and technologies of AI as a complex integration of digital services, products, and associated systems, with a high degree of automation, autonomy, and self-adaptation. Artificial intelligence is receiving a high level of attention due to recent advances in various areas such as image recognition, translation, and decision support [9]. Advances in AI are driving the changing role of technology for service ecosystems. The contribution of artificial intelligence can be categorized in terms of the four roles of technology [10]: assistive (human-in-the-loop, hard-wired system), augmentative (human-in-the-loop, adaptive system), automating (no-human-in-the-loop, hard-wired system), and autonomous (no-human-in-the-loop, adaptive system). The assistive type of AI technology [2] fits into the traditional domain of service ecosystems and service science [11] of using technology as a strategic driver and improving service functionality. However, the remaining three categories, augmenting, automating, and autonomous AI technologies, imply an increasing degree of agency and direct interactions with humans and the environment. The changing role of technology, from a tool to an "actor" in value co-creation [12], requires a new conceptualization of technology in service science [13]. Service system [14] entities are responsible actors, as in [11], and clarifies under what conditions a technology such as a cognitive assistant (CA) becomes a responsible actor.

Data, computation currently drive artificial intelligence progress and advances in machine learning, perception and cognition, planning, and natural language algorithms. AI enables exciting new business applications such as predictive maintenance, logistics optimization, and customer service management improvement. Artificial intelligence supports decision-making in many business domains. Therefore, most companies expect AI to provide a competitive advantage. Today's advances in AI [15, 16] have led to a rapidly growing number of intelligent services and applications. The collaborative development of capabilities through intelligent digital systems promises significant benefits for science, business, and society.

In contrast to symbolic AI [7], machine learning [17] uses an inductive approach based on a large amount of analyzed data. We distinguish three basic machine learning approaches [15, 16]: supervised, unsupervised, and reinforcement learning. In supervised machine learning approaches, the target value is part of the training data and is based on sample inputs. Typically, unsupervised learning is used to discover new hidden patterns within the analyzed data. Reinforcement learning (RL) is an area of machine learning with software agents [8] that maximizes cumulative rewards. The exploration environment is specified in terms of a Markov process, as many reinforcement learning algorithms use dynamic programming techniques. Reinforcement learning does not require labeled input/output pairs, and suboptimal actions do not need to be explicitly corrected.

Artificial intelligence is often characterized as impersonal: From this perspective, intelligent systems operate automatically and independently of human intervention. The public discourse on autonomous algorithms working on passively collected data contributes to this view. However, this prospect of huge automation obscures the extent to which human work necessarily forms the basis for modern AI systems and makes them possible in the first place. The human element of intelligent systems includes optimizing knowledge representations, developing algorithms, collecting and tagging data, and deciding what to model and interpret the results. The study of artificial intelligence [18] from a human-centric perspective requires a deep understanding of the role of human ethics, human values and customs, and the practices and preferences for development and interaction with intelligent systems. With the success of AI, new concerns and challenges regarding the impact and risks of these technologies on human life are emerging. These include issues of the limited feasibility of AI-based systems, the security and trustworthiness of AI technologies in digital systems, the fairness and transparency of systems, the still limited explainability of derived solutions and decisions, and the intended and unintended impacts of AI on people and society.

Enterprise Architecture (EA) [19, 20] has evolved for more than a decade as a discipline with a scientific background and functional decision-support capabilities and models for forward-looking AI technology-based businesses and digital organizations [21]. Enterprise architecture aims to model, align, and understand essential interactions between business and IT to set the stage for a well-aligned and strategically oriented decision framework for both digital business and digital technologies [22].

3 Value Co-creation in Platforms and Ecosystems

Platform strategies are becoming a critical component for many business models [23]. Platforms enable direct interactions between multiple otherwise unconnected groups of actors [24]. Platforms enable interactions between two or more groups of actors. A shift in strategic focus to building communities and engaging resources of platform members is identified as a new perspective in [25].

During the evolution of platforms, different ways of value creation were used [26]. Product platforms such as Windows or IBM 360 used complementary products to create value. On social platforms the creation of network effects and ecosystems through platforms provides a new source of competitive advantage [27].

So far, a strict separation between value producer and value consumer was the basis of value creation models. In recent years, however, there has been a significant change. The focus of research is now on value co-creation models [28], in which value is created through the interaction of several partners [6]. Typically, the former consumer takes an increasingly active role, which leads to his role being referred to as prosumer [29].

Lusch and Nambisan [12] developed a model for value co-creation from a service innovation perspective using an SD-Logic [3] theoretic lens. The basis for service provisioning is resource liquefaction, in which the resources are made accessible and manageable regardless of their physical presence (4). The aim of the whole is to increase resource density, i.e., the accuracy of fit of the services offered and requested (5). Platforms foster resource liquefaction and resource density. In [2], the model has been used to develop a model for value co-creation on platforms, Fig. 1. The platform in the middle of the value co-creation model links different groups of actors. The following phases are differentiated: In the first phase, there is an exchange of information about the value proposition (1). The platforms enhance the exchange of information on service propositions and thus increases resource liquefaction. In the second phase, the suggestions are filtered so that the suggestions of interest to the respective actuators are selected (2). The filtering improves the fit of service propositions and thus the resource density. Finally, in the third phase, the exchange of services takes place. For this purpose, the operational execution of the service exchange is to be ensured (3).

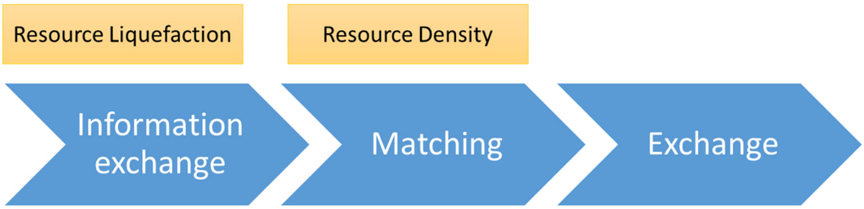

Fig. 1. SD-logic-based value co-creation model for platform ecosystems [2].

Artificial intelligence can be used in all three phases of the above model. Artificial intelligence-based interfaces can facilitate the exchange of information to actors, such as is done on assistant-based platforms [2]. The filtering of offers and requests based on the similarity function is a classic application of artificial intelligence. The automation capabilities of artificial intelligence come into play in the third phase of the model, the exchange of services. Artificial intelligence coordinates the actions of the actors. For example, when renting an apartment on Airbnb [30], granting access to the apartment and releasing the apartment are physical operations that need to be coordinated.

Artificial intelligence improves resource liquefaction, e.g., by improving access to information on hitherto unstructured data sources that describe the resource. For example, artificial intelligence can extract the powerful feature from a service description and tag it appropriately. In this way, artificial intelligence decouples information from its physical form or device [12]. Resource density is the principle of mobilizing contextual information on platforms as effectively and efficiently as possible [12]. Artificial intelligence increases it by improving the coordination of service offers and inquiries.

4 Intelligent Service Architecture

According to [31], a service ecosystem is a self-contained, self-adjusting system of loosely coupled recourse integrating actors connected by value co-creation through service exchange. In our understanding, a successful digital service platform [32] should support a network of actors and host a set of loosely coupled open services and software products as part of a rapidly growing digital ecosystem [12]. The DEA Cube (Digital Enterprise Architecture Reference Cube) in Fig. 2 extends our holistic architecture reference and classification framework from [21] to drive bottom-up integration of dynamically composed micro-granular architecture services and their models. Furthermore, the DEA Cube abstracts from a particular business scenario or technology

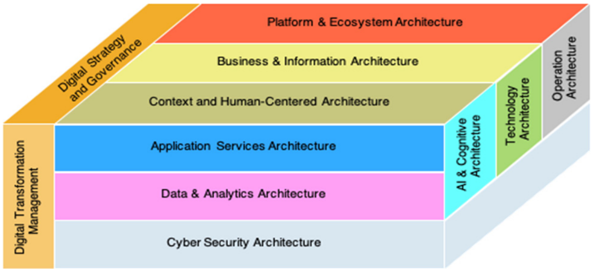

Fig. 2. Digital enterprise architecture reference cube (DEA Cube).

because it can be applied to different architectural instantiations to support intelligent ecosystems independently of different domains.

Metamodels and their architectural data [33] are the core part of a digitalization architecture. Architecture metamodels should support analytics-based architectural decision management and the strategic as well as IT/business alignment. Three quality perspectives are essential for an adequate IT/business alignment and are differentiated as (I) IT system qualities: performance, interoperability, availability, usability, accuracy, maintainability, and suitability; (II) business qualities: flexibility, efficiency, effectiveness, integration and coordination, decision support, control and follow up, and organizational culture; and finally (III) governance qualities: plan and organize, acquire and implement deliver and support, monitor and evaluate.

DEA addresses first the top of the Platform and Ecosystem Architecture [12, 32]. A digital platform is a repository of business, data, and infrastructure services used to configure digital offerings from digital services rapidly. Digital services and components are slices of code that perform a specific task. We position reusable digital services as parts of an ecosystem of services. Further, a digital platform linearizes the complexity of cooperating services. The value of a platform to users [32] results from the number of platform and service users. Platforms do not own or control their resources and are therefore well suited for scalability within the ecosystem. DEA extends the platform and ecosystem architecture by a set of close related architectural viewpoints.

A digital strategy [34] is a combination of initiatives where a company will select online activities to help realize its digital business objectives/vision. Digital governance [35] should additionally set the frame for digital strategies and digital innovation management. The second aim of governance is to define and assess rules for value-oriented digital compliance.

Five strategic domains define the focus of Digital Transformation Management, as in [36]: customers, competition, data, innovation, and value. Customers' most important strategical changes in a digital business are: customers as a dynamic network, two-way communication for co-creation, key influencers, marketing to inspire purchase and loyalty, common value flows, and economies of value. Strategic changes also affect competitors, as competition across fluid industries, blurred differentiation between partners and competitors, competitors cooperate in critical areas (coopetition). Key assets reside in external networks, platforms, and ecosystems with partners that exchange value and all gain due to network effects.

The Business & Information Architecture [37] connects the business strategy with model structures for business products, business services, business control information, business domains, business process models, and business rules to provide a specification framework for associated service-oriented information systems.

According to the basic definition of Dey [38], a context includes any information that characterizes the situation of an entity and relates to an interaction between users, applications, and the environment. Bazire [39] summarizes other context definitions as "context acts like a set of constraints that influence the behavior of a system (a user or a computer) embedded in a given task". Sandkuhl [40] addresses an original context modeling approach for enterprise IT applications to support human actors. An information demand context model is an extract from an enterprise model for a specific role, taking into account all the roles' tasks and linked to the specific resources.

The AI and Cognitive Architecture outlines fundamental components, services, mechanisms, and methods to support the intelligent behavior of evolved digital systems and services. Artificial intelligence and cognitive computing simulate and extend human thinking and intend to mimic the working model of the brain [41] without knowing exactly how the biology of the brain works. Cognitive computation [42] is inspired by neurobiology, cognitive psychology, AI, and connectionism. Connectionism represents a cognitive theory executed by adaptive and learning neural networks. IBM's cognitive computing program [43] focuses on next-generation information systems that leverage AI technologies and data analytics to enable understanding, reasoning, learning, and interaction. Cognitive systems continuously build knowledge through learning, understand natural language, support problem solving, and interact with humans more naturally than traditional programmed systems. A significant aspect of AI technology is robust or trustworthy AI. Transparency includes ways to explain AI results (e.g., why a system recommends a particular course of action), metrics to measure the effectiveness of an AI algorithm, verification and validation of intelligent systems, computer security, and the regulatory aspects that govern the safe, responsible, and ethical use of AI technology.

The Data Architecture [44] describes and classifies the data structures used by an enterprise and its computer application software. A data architecture consists of models, policies, rules, or standards that govern what data is collected and how it is stored, arranged, integrated, and used in data systems and organizations. Data architectures deal with data in storage, data in use, and data in motion; descriptions of data stores, data groups, and data elements; and mappings of these data artifacts to data qualities, applications, locations, etc.

The Application Services Architecture [4, 45] is the software reference architecture of application services that compiles the main application-specific service types and defines their relationship through a layered model by services that build on each other. The core functionality of domain services is linked with application interaction services and with business processes services of the customer organization. The core functionality of domain services is linked with application interaction capabilities and with the business processes of the customer's organization.

The Cybersecurity Architecture [46] specifies the organizational structure, standards, policies, and functional behavior of a computer network, including security and network functions. Cybersecurity architecture is also how the various components of a cyber or computer system are organized, synchronized, and integrated. A cybersecurity architecture framework is a component of the overall architecture of a system and guides the design of an entire product/system.

The Technology Architecture [47] models domain-agnostic software and hardware platforms to support the deployment of business, data, and application services. Technology includes IT infrastructures, platforms, middleware, networks, communications, processing, and related standards.

The Operations Architecture [48] relies on service management processes to enable the ongoing support and management of AI-based infrastructures of a digital enterprise. A company's IT infrastructure typically consists of many different systems and platforms, often located in different geographic locations. Kubernetes is an open-source container orchestration system initially developed by Google to automate the deployment, scaling, and management of service-based applications. Kubernetes [49] provides a platform for automating the deployment, scaling, and operation of application containers for images created with Docker [50] across clusters of hosts.

5 AIDAF Framework for Digital Platforms and Service Ecosystems

We have shown in [51] that companies that have previously applied TOGAF [19] or FEAF can successfully use the AIDAF integrated EA framework to support cloud computing when strategically promoting cloud/mobile IT. The model proposed by AIDAF [52] with the Architecture Board (AB) is shown in Fig. 3, as below. The AIDAF is an EA framework integrating an adaptive EA cycle for different business units. It involves the Architecture Board performing architecture reviews and enabling the alignment between IT architecture strategy and solution architecture in information system projects, including digital IT solutions [51, 52]. Therefore, the AIDAF framework is essential and necessary for developing a digital IT strategy and supporting digital transformation.

In the adaptive EA cycle, IS/IT project plan documents with the architecture of new digital IT projects can be developed on a short-term basis initially. Context phase refers to defining phase materials, where architectural guidelines for Cloud services, security, and digital IT can be defined as common ones in the enterprise, per business needs and demands. During the Assessment/Architecture Review phase, the AB should direct and review the architecture in the IS/IT project [53].

In the Rationalization phase, the stakeholders and AB decide upon replaced or decommissioned systems by the proposed new information systems. The equivalent project team can begin implementing the new digital IT project after deliberating issues and action items [51–53]. In the adaptive EA cycle, corporations can adopt an EA framework like TOGAF and simple EA framework that is a simple mid- to long-term perspective EA structure composed of Deliverables (target architecture, roadmaps), EA processes (financial/budgeting approval process by deliverables) and Principles (architecture directions, policy), based on an operational division unit in the upper part of the above Fig. 3, equivalent to Figure 1 of [51–53] in alignment between EA guiding principles and each division's principles, corresponding to differing strategies in business divisions in the mid-long-term. TOGAF Architecture Development Method (ADM)

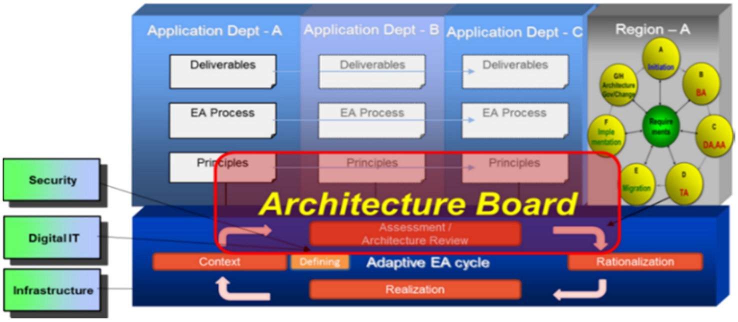

Fig. 3. AIDAF model with architecture board and governance.

describes a step-by-step approach to developing enterprise architecture as a core element [53].

We refer to cases of applying the AIDAF framework to Industry 4.0 Architecture – RAMI 4.0 [54]. At the enterprise level, we show a digital platform usage scenario for a drug platform board (DPB) in Fig. 4.

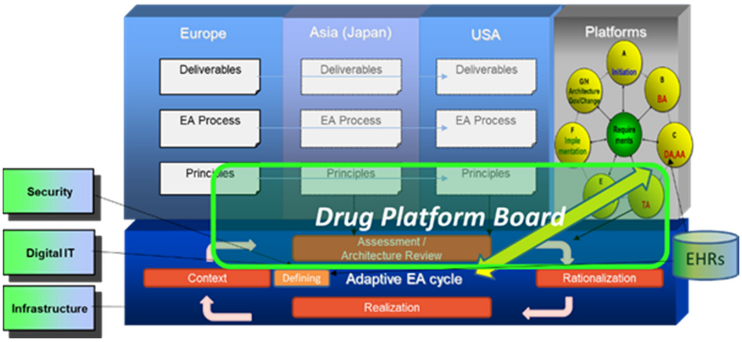

Fig. 4. AIDAF model for DPB.

In particular, the Architecture Board, the example of the EA framework structure in a specific global healthcare company examined in previous papers [51, 54]. In a global EA rollout, we are handling cloud, mobile IT, and big data strategic projects and systems that took priority in Europe and US Group companies well by structuring and implementing EA with the above AIDAF to be consistent with global IT strategy focusing on cloud, mobile IT, big data and digital IT [51, 53].

The AIDAF model with DPB covers the core drug digital platforms, such as drug development and clinical decision support (CDS) platforms, that are used by new drug development planners, managers, digital IT practitioners in each region and are reviewed by the DPB. We describe the CDS digital platform [55] in Fig. 5 at an ecosystem level.

The CDS platform provides recommendations based on the available patient-specific data (EHR) and medical facts (knowledge base) among the healthcare ecosystem partners [55].

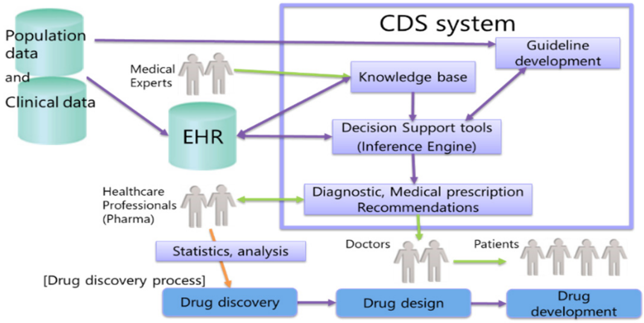

Fig. 5. Reference architecture for CDS system in the ecosystem [55].

6 Discussion

We are summarizing our results and synthesizing our core findings and experiences. A digital platform and an ecosystem should enable shared value creation for all stakeholders and facilitate the exchange of goods, services, and social currency. DEA - The Digital Enterprise Architecture Reference Cube provides our new architectural reference model for the bottom-up integration of dynamically composed micro-granular architecture services and their models. A DEA-aligned platform integrates core technology services as a base that provide standardized access points and repositories for intelligent service ecosystems composed of business services, data services, and infrastructure services. Artificial intelligence is a powerful and useful technology to support essential functionalities of intelligent service ecosystems and the Service-Dominant Logic-grounded value co-creation process.

The newly introduced architecture domain in DEA of the Context- and Human-Centered Architecture, together with the realigned AI & Cognition Architecture, supports the growing set of automated functionalities that do not follow an explicit preformulated model. The DEA Cube provides a comprehensive architectural reference model to compose micro-granular architecture service models, like the Internet of Things and Microservices, to support intelligent digital services and products.

The DEA perspective of digital strategy [34, 56, 57] and governance [35] defines the base for well-aligned management practices through specifying essential architectural management activities: plan, define, enable, measure, and control. The business & information architecture establishes the link between the enterprise business strategy and the results of supporting strategic initiatives through information systems.

The context and human-centric architecture ensure the treatment of system-wide contexts and user-specific models to enable dynamic adaptability and customizability of system behavior. AI models various mental processes using computers, while cognitive computing simulates human brain functions as a computational model. The canonical architecture of an AI system [58] outlines key components to support the development of an effective AI solution. The canonical AI architecture includes sensors and other data sources and components for data conditioning, AI algorithms, human-machine teaming, user capabilities, processing technologies, and robust AI. The data analytics architecture refers to systems, protocols, and technologies used to collect, store, and analyze data based on machine learning and statistical analytics.

The cybersecurity architecture helps position security controls and breach countermeasures and shows how they relate to the organization's overall system framework. The technology architecture describes fundamental software and hardware capabilities required to support the deployment of business, data, and application services. Finally, the operations architecture ensures that these systems function correctly by automating operational tasks and control of the systems. Implementing an operations architecture consists of a dedicated set of tools and processes that automate IT operations in a coordinated manner.

The AIDAF (Adaptive Integrated Digital Architecture Framework) is a new digital architecture framework that can address the digital agility elements for digital IT strategy and digital transformation lack in existing traditional EA frameworks [53].

7 Conclusions and Future Research

We identified the needs and solution mechanisms for architecting intelligent service ecosystems by presenting our new AI-induced, augmented, and integral methodological perspectives and frameworks. We first outlined the research background and presented our applied methodology to create and evaluate a new type of enterprise architecture by applying architectural methods from science and practice. Next, we set this transparent methodological background in the context of AI-based digitalization, in which we map the core results to fit our research questions. We have established an integral view by introducing new perspectives arising from the fusion of AI with service ecosystems and digital architectures by adequately aligning comprehensive frameworks and methodologies for architecting intelligent service ecosystems. First, in our architectural approach, we introduced AI-enhanced co-creation mechanisms in line with the Service-Dominant Logic (SD-L) as a prerequisite for intelligent service ecosystems on digital platforms. Second, we presented an advanced service reference architecture for intelligent service ecosystems and an integrated approach to adaptive architecture engineering and management. For this purpose, we aligned the DEA - Digital Enterprise Architecture Reference Cube with AIDAF - the Adaptive Integrated Digital Architecture Framework. Last, we have summarized our findings and recommendations from methodological experiences from science and practice for a new and innovative style of architecture of intelligent service ecosystems.

The strengths of our research result from our novel approach to support intelligent digitalization for architecting intelligent service ecosystems. We have integrated an AI-powered co-creation model with an integral and scalable digital architecture reference model in conjunction with the framework for adaptive architecture development and management. Limitations of our work arise from an ongoing validation of our research and open questions of comprehensive AI approaches and related inconsistencies and semantic dependencies. In particular, we cannot quantify the impact of artificial intelligence or specific technologies on mechanisms and elements in intelligent service ecosystems. Furthermore, we still need to prioritize artificial intelligence technologies for supporting specific tasks in intelligent service ecosystems.

Our future research will investigate in more detail how artificial intelligence affects value creation in service ecosystems, particularly resource liquefaction and resource density. Artificial intelligence is a very diverse technology with different types of model building and problem-solving capabilities. Therefore, an important research task will be to identify those artificial intelligence technologies that are particularly suited to support the creation of intelligent service ecosystems. Future research will also address mechanisms, reference architectures, methodologies, and guidelines for the flexible and adaptive integration of intelligent digital architectures for AI-based service ecosystems based on study results from use cases of digital transformation and our educational experiences from academia and practice.

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