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Characterizing the Roles of AI-Enabled Non-Human Agents in Service Systems

Research Paper

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Abstract. Machines are becoming more versed at adapting to environmental impulses and their operational contexts, changing their roles in service systems. These machines can autonomously fulfill goals within defined boundaries set by legal actors and thereby exhibit agency. As interactions are at the core of services, the integration of such non-human agents into value co-creation has the potential to heavily impact the innovation of services. Following a four-step type construction approach based on empirical open-source data on 130 services, we develop a multi-dimensional characterization of six roles that non-human agents fulfill in service systems. Taking a systemic perspective, we identify service system interactions involving non-human agents and how their contributions impact value propositions. Our findings forward the understanding of service processes involving non-human agents and their impact on value co-creation, benefiting both theory and practice through knowledge on the engineering of service systems and value-driven, user-centered human-machine interactions.

Keywords: *artificial intelligence, non-human agents, robots, service systems*

1 Introduction

Service systems, characterized as dynamic configurations of actors, technologies, and other resources interacting to realize value (Maglio et al., 2009), undergo an evolution through the advent of AI-enabled machines as novel entities. AI-enabled technologies encompass both existing systems improved through the introduction of AI, commonly termed AI-enhanced, and entirely new systems developed with AI from the outset, commonly termed AI-based (Rzepka & Berger, 2018). The integration of AI creates a pivotal change, as it endows machines with the capability to interact with their environment and autonomously adjust their actions based on external stimuli (Beck et al., 2022; Pakkala & Spohrer, 2019; Seeber et al., 2020a,b). Growth in these AI interaction capabilities stems from progress in machine learning, which empowers machines to discern intricate patterns within data on social interactions (Andersen et al., 2016)

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and facilitates the capturing of tacit knowledge, which is fundamental to human interactions but challenging to code explicitly (Brynjolfsson et al., 2023). Moreover, the integration of conversational interfaces based on Natural Language Processing and Generative AI has further transformed interactions with machines (Schmidt et al., 2023). These collective advancements in the field of AI distinguish novel, AI-enabled interactive technologies from ordinary data-driven ones and catalyze the genesis of a new entity in service systems, referred to in this paper as AI-enabled non-human agents.

The capability to adaptively interact with their surroundings allows non-human agents to assume new roles in the co-creation of value and facilitates novel configurations of service systems (Maglio, 2017). When positioned within a system of actors, these capabilities enable technologies to exhibit agency, i.e. autonomous action in the pursuit of goals within a solution space defined by rules, norms and institutions through the concurrent interaction with and influencing of other actors in socio-technical systems (Beck et al., 2022; Pakkala & Spohrer, 2019). The advent of interactive AI-enabled technologies consequently demands novel abstractions and conceptual frameworks to characterize the contribution of non-human agents within the dynamics of value co-creation interactions in service contexts (Ågerfalk, 2020; Pakkala & Spohrer, 2019; Kaartemo & Helkkula, 2018; Maglio, 2017; Medina-Borja, 2015).

The orchestration of the complex interplay between non-human agents and human actors is forwarded as the "key managerial issue of our time" (Berente et al., 2021, p. 1440), holding potential for profound impact on value co-creation (Kaartemo & Helkkula, 2018) but also carrying the risk of harmful unintended consequences (Bock et al., 2020; Enholm, 2022). Beck et al. (2022) therefore encourage studies to gain a better understanding of the various forms of non-human agents and potential consequences of their introduction for individuals and firms. Seeber et al. (2020a) explicitly call for a typification of non-human agents to enhance the structured description of their facets, which can benefit their effective implementation in organizations. Although research has examined the roles of physical robots or digital assistants (e.g. Čaić et al., 2018; Knote et al., 2021), a comprehensive characterization of roles fulfilled by non-human agents in service system interactions and how they are integrated into such interactions is yet to be established. To address these research gaps, we pose the research question *"What roles do AI-enabled non-human agents fulfill in service systems?"*. We approach this research question by systematically analyzing empirical data on 130 services involving AI-enabled non-human agents obtained from the database Crunchbase.

2 Theoretical Background

2.1 Service Systems

The effective utilization of AI-enabled solutions goes beyond a fine-tuned algorithm or flooding data pipeline and has to consider the embedment and interplay of a solution with its social context (Berente et al., 2021). A narrow focus on technical aspects critically underestimates the complexity and interdependencies involved in AI-enabled value co-creation, as value is increasingly co-created in dynamically changing actor configurations, commonly described with the terms service systems or service ecosystems (Barile et al., 2016). A systemic perspective, like the one of service systems (Maglio et al., 2009; Spohrer & Maglio, 2010), is therefore necessary to examine the role of adaptive, interactive technologies, i.e. non-human agents, in value co-creation. Service systems are socio-technical systems with a complex, dynamic interplay of human actors, technologies, and their environment to achieve specific outcomes (Böhmann et al., 2014). These systems are conceptualized as sequenced ensembles of nine generic relations formed between humans, non-human agents and organizations in expectation of functional contributions (Pakkala & Spohrer, 2019). To enhance comprehension, such systems can be further broken down into modular components (Parnas, 1972). In this realm, services can be decomposed into modularized service processes (Peters, 2016), with each module being specified by a clear functionality (Peters, 2014). Traditionally, technologies have been rather seen as passive resources being used by actors to facilitate the co-creation of value (Vargo & Lusch, 2016). Given recent technological advances, a wider array of service processes can be performed by AI-enabled non-human agents, giving rise to the concept of AI service modules (Peters & Zaki, 2018). Consequently, as the nature of activities non-human agents perform in AI service modules and how they are integrated into service system interactions remain open questions, in this study, we concentrate on elucidating the reciprocal relation between human actors and non-human agents. The delineation of non-human agent roles, which capture expected contributed activities (Biddle, 1979), creates a framework for understanding complementary interactions between people, technologies and their environment and offers knowledge for the engineering, management, and innovation of service systems.

2.2 Non-Human Agents

Research on AI solutions as non-human agents in socio-technical systems is nascent and a common term for the phenomenon has yet to be established (Alter, 2023). Research often refers to the underlying technological object, with labels such as *intelligent agents* (e.g. Kühl et al., 2020, Larivière et al., 2017), *AI agents* (Rai et al., 2019), *technological agents* (Yu et al., 2021), or simply *algorithms* (Tarafdar et al., 2022). Other researchers delineate the overall phenomenon, *technological agency* (Pakkala & Spohrer, 2019) or *service AI* (Bock et al., 2020), or the researched activity, as with *algorithmic management* (e.g. Benlian et al., 2022; Möhlmann et al., 2021). We use the term non-human agents, as it is technology-agnostic, omits misleading terms like autonomy and, through reference to agency, reflects a link to a responsible legal actor.

A clear delineation of attributes characterizing non-human agents is crucial to determine services in scope for analysis in this study. Although no consensus on the definition of non-human agents exists, an examination of recurring themes in literature on this topic can yield defining attributes. We will discuss commonalities along four fundamental characteristics of non-human agents forwarded by Dhiman et al. (2022) and Russel and Norvig (2020), which should not be considered as finite: Non-human agents (i) act upon their environment in an (ii) autonomous fashion (iii) without outside intervention for a certain time to (iv) pursue a goal. A prime unifying aspect is the described ability of non-human agents to adapt activities based on impulses from the environment

(Ågerfalk, 2020; Andersen et al., 2016; Bock et al., 2020; Dhiman et al., 2022; Knote et al., 2019; Kühl et al., 2022; Maedche et al., 2016; Murray et al., 2021; Russel & Norvig, 2020). A condition specifying this attribute is that the adaption of actions shall happen over a longer time or many interactions without the direct intervention of a designer or legal entity responsible for the non-human agent (Ågerfalk, 2020; Beck et al., 2022; Dhiman et al., 2022; Russel & Norvig, 2020). We follow Kühl et al. (2022) that non-human agents can draw the inferences guiding their adaptive activities either from a static knowledge base or, as forwarded in stricter characterizations (e.g. Andersen et al., 2016; Dhiman et al., 2022), from an evolving knowledge base, modified by a backend learning from previous interactions. Other technologies have actuation capabilities as well, but rule-based, non-adaptive ones. Hence, the key distinction of non-human agents, and basis for discussions about their perceived autonomy, is that their activities are tailored to interactions with changing actors or changing contexts (Beck et al., 2022; Murray et al., 2021; Seeber et al., 2020b). However, autonomy is a misleading term, as non-human agents only act autonomously within rules and contexts predefined by a legal actor responsible for it (Beck et al., 2022). The condition that non-human agents require a liable legal actor, setting goals and boundaries for possible activities, is forwarded by a range of authors (Ågerfalk, 2020; Dhiman et al., 2022; Pakkala & Spohrer, 2019), hence can be interpreted as another defining aspect.

Taking into account the presented arguments, we establish a working definition for non-human agents by slightly adapting the attributes of Dhiman et al. (2022) and Russel and Norvig (2020): Non-human agents interact with other service system entities and adapt their actions based on stimuli from humans, machines or the environment. Over longer periods of time or several interactions, they decide on activities to pursue a goal without the direct intervention of a responsible legal actor. Non-human agents perform actuations within a realm of boundaries preset by a designer or legal actor responsible for it, which represents an indirect intervention limiting the array of possible activities.

2.3 Roles of Non-Human Agents

Roles capture anticipated activities or contributions that an entity is expected to provide a system (Biddle, 1979). Research on non-human agent roles has been conducted in adjacent fields with different objectives. One academic discourse describes roles to aid the design and management of organizational settings involving non-human agents. Alter (2023) offers frameworks to describe and evaluate functional non-human agent roles with regards to their suitability to perform various facets of work. Bittner et al. (2019) and Siemon (2022) outline roles for the subset of conversational agents to illustrate design options for non-human agents and modes of integration into the specific setting of collaborative teams. Another academic discourse probes how interactions with non-human agents and their functional contributions impact value co-creation. Knote et al. (2021) do not provide roles, but identify five clusters of intelligent personal assistants, a subset of non-human agents, and link them to affordances they provide for value co-creation. However, the authors point out a limited data set and encourage research with a wider array of observations. For the context of elderly care, Čaić et al. (2018) use roles to categorize various forms of non-human agents based on their value co-creation and co-destruction potential. Concludingly, current research is conceptual (Alter, 2023) or literature-based and augmented with a sample of practical cases (Knote et al., 2021) or validated with experts (Bittner et al., 2019). Čaić et al. (2018) base their findings on empirical data gathered in an artificial setting for hypothetical scenarios, which is common for studies on value co-creation involving non-human agents (Lu et al., 2020). We aim to extend this research, which concentrates on specific settings and hardly covers real-world interactions with non-human agents, by providing a comprehensive analysis of non-human agent roles, grounded in empirical data, to reflect the status quo of commercially-available non-human agents and illustrate their integration into service system interactions as well as proposed value for interaction partners.

3 Research Approach

This study aims to uncover roles of non-human agents in interactions with other service system entities and how these interactions contribute to underlying value propositions. Typologies commonly serve to categorize individual observations by identifying shared characteristics (Ragin, 1987) and roles represent a specific kind of types, which involve categorizing entities based on the expected activities or contributions they bring to a system (Biddle, 1979). Types provide valuable analytical advantages in service research, aiding the organization, comparison, and communication of research findings (Vargo & Lusch, 2004). The roles in this study have been constructed in a desk-research approach, following four steps for the empirically grounded construction of types in qualitative research (Kluge, 2000): (1) developing relevant dimensions for analysis, (2) grouping cases, (3) constructing types, and (4) characterizing the constructed types.

In step (1), relevant dimensions for the analysis of empirical cases are established before data collection (Kluge, 2000). This study draws on the service systems perspective (Maglio et al., 2009; Spohrer & Maglio, 2010), hence the initial analytical dimensions mainly revolve around the nature of different interactions non-human agents are involved in, coded based on the interaction dimensions for human-AI interaction (Hinsen et al., 2022), and their expected contribution to the co-creation of value.

In Step (2), cases are assigned to these dimensions and grouped along similar combinations of attributes (Kluge, 2000). The sample comprises services with non-human agents, i.e. AI-enabled technologies with the capability to adjust their conduct depending on the context of their interactions with humans, machines, or the environment. The sample is limited to digital non-human agents, falling into the category of virtual service robots (Wirtz et al., 2018), and focus on services for English-speaking users. While AI has historically been explored predominantly in academia, industry now plays a pivotal role in advancing and applying AI (Ågerfalk, 2020). Consequently, this study uses data on commercially-available services instead of relying on literature sources. An initial sample was retrieved from Crunchbase, which constitutes a recognized practice in research on management and information systems (e.g. Engelbrecht et al., 2016; Hilbig et al., 2018; Riasanow et al., 2017), as it provides a comprehensive database on firms and their offerings. The search string combines common attributes describing non-human agents or its base technology (intelligent, autonomous, artificial intelligence and AI) with instantiations of digital technologies (agent, application and service), leading to twelve initial word pairs. Discussions of the search string at an international research seminar prompted advice to add the terms autonomous system and autonomous software as well as combinations of bot/bots and AI or machine learning, leading to the formation of a second search string. The first search string has contained these phrases: *“autonomous system“; “autonomous agent“; “autonomous software“; “autonomous application“; “autonomous service”; “intelligent agent”; “intelligent application”; “intelligent service”; “artificial intelligence agent”; “artificial intelligence application”; “artificial intelligence service“; “AI agent”; “AI application”; “AI service“.* The second search string was run with this syntax: *“bot” OR “bots” AND “artificial intelligence” or “machine learning”*. The search in August 2023 yielded 1004 unique companies. Crunchbase data was augmented with data from ancillary sources, including firm websites, journalistic reports, developer documentation, customer stories, social media posts and press releases. Data analysis was conducted in a rigorous multi-phase coding process to ensure accuracy, depth in the qualitative analysis and inter-coder reliability. In the first phase, three researchers scrutinized these data sources to determine whether sampled companies offer a service involving an AI-enabled adaptive non-human agent fitting our working definition, which left 237 companies in scope. Common reasons for exclusion included firms not offering a solution involving an AI-enabled digital non-human agent, insufficient public information on coding dimensions defined in step (1), firms or websites no longer being operational, or information not being available in English. In another round of scrutiny, in-depth information on each service was collected until saturation was achieved (Creswell, 2007) and three researchers examined in more detail whether the remaining services fit the sample criteria, reducing the final sample to 130 services from 99 companies. 48 % of non-human agents are customer-facing, 42 % for employees and 10 % marketed as adaptable for both internal and external use. Most non-human agents are integrated into customer service and sales operations. However, analyzed non-human agents also contribute to IT development or human resource, legal, educational, and marketing activities. In the second coding process phase, data was coded in MAXQDA in two coding cycles. Initially, descriptive coding (Saldaña, 2013) was used to summarize the essence of passages with information on the coding dimensions defined in step (1): functional contributions, interaction partner value, integration type and links to other service system entities. An illustrative anchor example offers the passage "We empower your team to provide personalized and efficient support with generative AI, raising the bar for excellence in customer service [19AA5, Parloa]", which was described with 1st order code Interaction partner value and 2nd order code Efficiency (cf. coding scheme in table 1).

Step (3) involves constructing types from groups with similar combinations of attributes. This step marks the final phase of the coding process and was performed using pattern coding, a method commonly applied after descriptive coding to identify commonalities and variations in data (Saldaña, 2013). As roles capture expected contributions of an entity to a system (Biddle, 1979), the construction of roles primarily focused on identifying patterns of services where non-human agents provide similar functional contributions. Initially, eight patterns of functional contributions to service system interactions were identified. Four functional contribution patterns were realized through distinctive interaction processes, hence were translated into the roles Information Provider, Generator, Coach and Algorithmic Manager. The functional contribution pattern pairs “Recommendation” and “Behavior change advice” as well as “Self-service enablement” and “Task fulfillment” were realized through similar interaction processes, hence the primary ones were integrated into the latter, more frequently observed ones, and eventually translated into the respective roles Advisor and Concierge. This condensed the sample to six roles, each characterized by a distinct combination of functional contribution and interaction process. The construction of roles was performed in discussions of three researchers, to ensure investigator triangulation (Yin, 2018) and internal homogeneity (Kluge, 2000) of non-human agents grouped into respective roles.

Step (4) entails the communication of constructed types based on the identified combinations of attributes (Kluge, 2000). We present these findings in a multi-dimensional characterization of non-human agent roles in service interactions in the next section.

Table 1. Coding scheme with 1st and 2nd order codes and frequencies of roles in the sample

1st Order Code	2nd Order Code	IP	Con	Gen	Coa	Adv	AM
Functional Contribution	Individual information	x					
	Task fulfillment		x				x
	Resource generation			x			
	Capability development				x		
	Behavior change advice					x	
Interaction Partner Value	Availability	x	x		x		
	Efficiency	x	x	x		x	x
	Effectiveness			x	x	x	
	Well-being				x		
Type of Integration	Assistance	x	x	x			
	Augmentation				x	x	
	Automation						x
Interaction Impulse	Human	x	x	x	x		x
	Non-human agent					x	
Action Direction	Human	x	x	x	x	x	x
	Machine (Database/ Automation)	x	x				
Percentage of roles in the sample		40	24	10	6	5	15

4 Results

We identified six roles non-human agents fulfill in service systems and characterize them by outlining their mode of integration into service systems, typical interactions with other service system entities and how these interactions are expected to contribute to the realization of proposed value. Three roles are expected to provide assistance to human actors: (A) Information Provider, (B) Concierge and (C) Generator. Two roles are expected to perform augmentation to human capabilities: (D) Coach and (E) Advisor. The sixth and final role is expected to automate processes in interactions between human actors: (F) Algorithmic Manager. Figure 1 and the ensuing paragraphs illustrate the integration of non-human agents in these six roles into service system interactions.

(A) Information Providers offer relevant or personalized information in an answer to a human query. In essence, non-human agents in this role assist human actors in accessing relevant information stored in external databases. Common use cases in our sample are, in the context of customer-facing interactions, the resolution of customer service inquiries or provision of personalized offerings, or, in internal organizational settings, responses to inquiries from employees regarding, for example, employment terms and conditions. The typical service system interaction described in connection to this role is (A1) a human actor giving the interaction impulse by inquiring for information with a textual or verbal directive and (A2) the non-human agent perceiving the intent of an inquiry and drawing on its knowledge-base or connected databases to (A3) provide relevant or personalized information adapted to the human inquiry. The objective of human actors to engage in this service system interaction is the reception of information. The primary proposed added value of the integration of a non-human agent in the Information Provider role for the human interaction partner is constant availability and efficiency, i.e. reduced contribution of own effort to receive desired information.

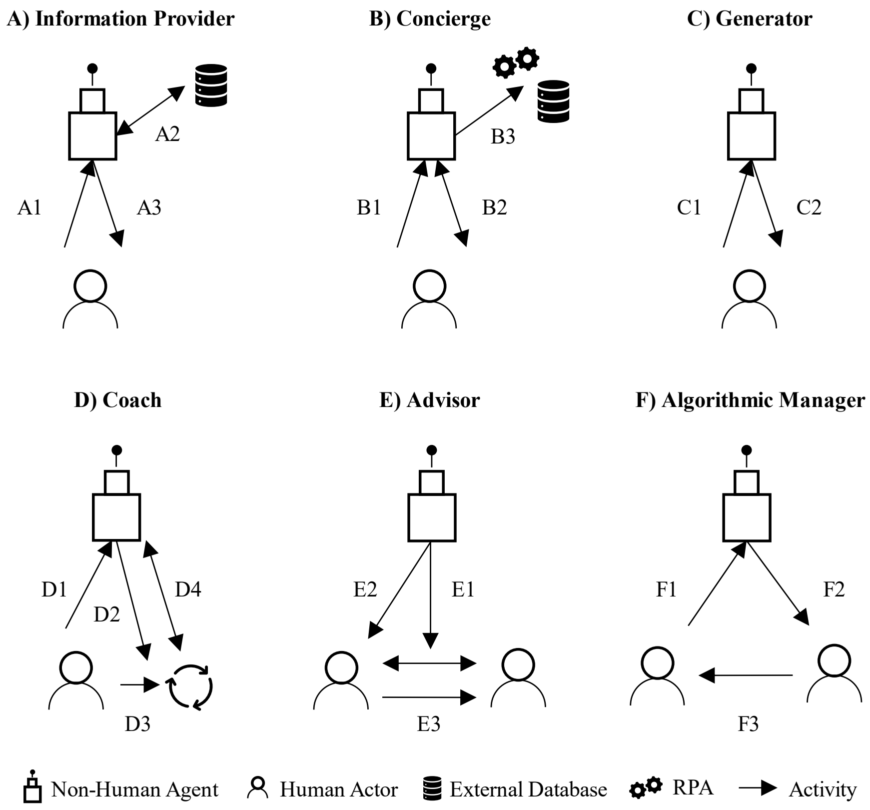

Figure 1. Identified service system interactions of non-human agents

(B) The Concierge triggers automations to satisfy a perceived need of a human actor. In essence, non-human agents in this role assist human actors in triggering other machines for the fulfillment of tasks. Common use cases in our sample are the scheduling of appointments or processing of account operations, such as bank transactions. The typical service system interaction described in connection to this role is (B1) a human actor textually or verbally giving the interaction impulse by directing the non-human agent to solve a task, (B2) the non-human agent obtaining the necessary information for the fulfillment of this task and (B3) subsequently performing a manipulation to a database or triggering a robotic process automation (RPA) to finalize the underlying task. The objective of human actors to engage in this service system interaction is to have a specific task fulfilled. The primary proposed added value of the integration of a non-human agent in the Concierge role for the human interaction partner is constant availability and efficiency, i.e. less own effort required to obtain a desired result.

(C) Generators produce content following a human directive. In essence, non-human agents in this role assist human actors in generating or adapting resources. Common use cases in our sample are the generation of text, visual media items and designs, or computer code. The typical service system interaction described in connection to this role is (C1) a human actor giving the interaction impulse by textually directing the non-human agent to generate content with specific attributes, in so called prompts, and (C2) the non-human agent generating the digital resource. The human actor can adapt the generated content or use it as it is for further actions. The objective of human actors to engage in this service system interaction is to receive a desired digital resource. The primary proposed added value of the integration of a non-human agent in the Generator role for the human interaction partner is efficiency, i.e. the creation of a digital resource with less contribution of own efforts, or effectiveness, i.e. at a higher quality than the human can produce with its own capabilities.

(D) Coaches suggest behavioral change and exercises or personalize learning units for personal development. In essence, non-human agents in this role augment human actors in the fulfillment of a desired activity. Common use cases in our sample are the support through adapted cognitive exercises or psychological approaches. The typical service system interaction described in connection to this role is (D1) a human actor giving the interaction impulse by textually or verbally setting a goal or articulating an issue to be solved, for example reaching a language proficiency level or well-being through stress relief. (D2) The non-human agent subsequently creates exercises or approaches adapted to this set directive, with (D3) the human counterpart executing the suggested exercise or approach while (D4) being accompanied by the non-human agent, which provides corrective guidance or solutions as needed. The objective of human actors to engage in this service system interaction is to improve their proficiency in performing specific actions and develop certain capabilities. The primary proposed added value of the integration of a non-human agent in the Coach role for the human interaction partner is constant availability, increased well-being and effectiveness, i.e. superior performance in certain actions compared to what the human actor can achieve solely with their existing skills or knowledge.

(E) Advisors suggest behavioral change to human actors in interactions with other human actors in the professional context. In essence, non-human agents in this role augment humans and their capabilities through advice for better task performance. Common use cases in our sample are the provision of responses or next best actions. The typical service system interaction described in connection to this role is (E1) the non-human agent following a social interaction between two human actors in the background and (E2) giving the interaction impulse by proactively suggesting one human actor responses or next best actions for an ongoing interaction, based on best practices learned from previous observed interactions or background information on the product or customer from internal systems. (E3) The human actor can take the content of the suggestion or follow the advice for behavioral change, adapt the generated advice or ignore it. The primary proposed added value of the integration of a non-human agent in the Advisor role for the human interaction partner is effectiveness, i.e. resolution of challenges at a higher quality than the human can produce with own capabilities, or efficiency, i.e. less contribution of own efforts to solve a problem.

(F) Algorithmic Managers assign tasks or hand over an interaction to a human actor. In essence, non-human agents in this role automate the matching between human actors. Common use cases in our sample are the adaptive routing of human actors to suitable human interaction partners for the resolution of customer inquiries or for the provision of personalized offerings, or, in internal organizational settings, connecting employees to human resource clerks. The typical service system interaction described in connection to this role is (F1) a human actor giving the interaction impulse by articulating a problem or need to a non-human agent, which perceives the intent of the inquiry and (F2) matches the human actor with a human counterpart at the service provider, who has sufficient skills and knowledge to (F3) solve the inquiry. The objective of human actors to engage in this service system interaction is to find the right human counterpart to solve a task. The primary proposed added value of the integration of a non-human agent in the Algorithmic Manager role for the human interaction partner is efficiency, i.e. less own effort required to find a suitable human counterpart for value co-creation.

A noteworthy observation in our data is the occurrence of certain roles being grouped within the same solution. For instance, the Information Provider is described to transition into an Algorithmic Manager and/or Concierge under specific circumstances. If the Information Provider cannot supply the requested information, fails to discern the customer intent or the customer explicitly prefers human interaction, solutions fulfilling this role often shift into the role of Algorithmic Managers, directing texts or calls to a human actor. Additionally, information inquiries may lead to the identification of an intent, which the AI-enabled solution can offer to fulfill by triggering automations, transforming into a Concierge. In turn, solutions assuming the roles of Coaches, Generators, or Advisors are commonly specialized and mostly only fulfill this specific role.

5 Discussion and Contributions

This empirical research illustrates six non-human agent roles in service system interactions and outlines the expected value of their contributions. We provide a first delineation of common service system interactions between non-human agents and humans and describe the sequence and direction of contributions and activities these technologies are involved in. The findings inform the scientific discourse about the changing role and nature of technology in value co-creation (Maglio, 2017; Medina-Borja, 2015). This study addresses a gap on empirical research into the impact of non-human agents on value co-creation (Lu et al., 2020) and considers interactions with both service providers and beneficiaries, an aspect that has received limited attention in prior research (Kaartemo & Helkkula, 2018; Lu et al., 2020). This paper augments existing research on types of AI-enabled solutions in adjacent fields (e.g. Alter, 2023; Bittner et al., 2019; Čaić et al., 2018; Knote et al., 2021; Siemon, 2022) by drawing on findings from an approach using empirical open-source data on commercially-available services. Our study thereby provides a multi-dimensional conceptualization and abstraction of agentic AI-enabled information systems (Baird & Maruping, 2021), which answers a call for structured descriptions of various facets of this phenomenon (Seeber et al., 2020a).

Our research contributes to the nascent literature on the engineering of service systems involving AI-enabled non-human agents. Each of the identified six roles is characterized by performing a specific function, thereby can be regarded as a service module (Peters, 2014). More specifically, non-human agents fulfilling one of the six outlined roles constitute different AI service modules, which can be integrated into modular service structures (Peters & Zaki, 2018). By illustrating the systemic integration of non-human agents in different roles into service processes, we also uncover interfaces between service modules. The Concierge constitutes an AI service module, which commonly has an interface with another digital service module, as it is characterized by triggering automations. In turn, Algorithmic Managers constitute an AI service module, which hands over the interaction with a human actor to another human actor, thereby commonly has an interface with a traditional service module. Finally, in our sample, the Information Provider often transitions into the role of an Algorithmic Manager and/or Concierge, hence we infer it constitutes an AI service module, which commonly has an interface with another AI service module. Building on discussions on modular compositions of multiple machines involved in value creation on platforms (Schmidt et al., 2023), we explore connections between non-human agents and other machines within the roles of Information Provider and Concierge and thereby delineate existing compositions through which systems of multiple machines interact in service systems. Humans interact with service modules at different touchpoints during a customer journey (Peters & Zaki, 2018) and we specify these interactions between a human actor and the AI service module, by describing whether a non-human agent in a specific role assists or augments the human actor. We furthermore contribute an empirical validation and extension for three of nine interaction dimensions for human-AI interaction (Hinsen et al., 2022) observable in our data. Human actors set the interaction impulse for interactions with Information Providers, Concierges, Generators, Coaches and Algorithmic Managers, while interactions with Advisors are triggered by non-human agents. Moreover, for each role, we describe the interaction result and depict action directions in Figure 1. Finally, we draw on the actor relations conceptualized by Pakkala and Spohrer (2019) and illustrate empirically observable constellations of these different actor relations in practical settings. For instance, service system interactions involving Concierges encompass a constellation of human-to-machine, machine-to-human and machine-to-machine relations, while Advisors are embedded into interactions involving human-to-human and machine-to-human relations. The abstraction of ensembles of such relations from empirical data provides a basis for more in-depth examinations of the interplay and interdependencies in value co-creation with non-human agents.

AI-enabled non-human agents are projected to offer significant productivity gains in the service sector (Wirtz et al., 2018), but expectations need to be carefully managed for a successful introduction thereof (Berente et al., 2021). The six roles with related integration types provide managers with an overview of embedding options, which demonstrably leads to a broader consideration of use cases and more innovative ideas for interactions between human and non-human agents (Ringfort-Felner et al., 2022). Moreover, the roles can help to systematically uncover social attributes, which humans unconsciously ascribe to machines during interactions (Nass & Moon, 2000), and thereby enable managers to support employees in interactions with non-human agents.

6 Limitations and Future Research

The study is subject to limitations, which offer avenues for future research. Firstly, generalizability of results should be taken with a caveat. The sample is intentionally limited, given its exploratory nature. Future research can bolster robustness of findings with a representative sample from a specific industry and systematically explore roles applicable to that particular sector. Moreover, our open-source data does not cover service failure and value co-destruction, as it primarily stems from service provider sources. Hence, approaches observing interactions with deployed non-human agents can further increase the validity and breadth of findings. While we characterize roles based on value propositions by non-human agent providers, empirical studies show spikes in productivity triggered by AI-enabled solutions in the Advisor role (Brynjolfsson et al., 2023; Dell'Acqua et al., 2023) and offer blueprints for research designs involving such real-world observations. Secondly, social and cultural aspects shape the roles non-human agents can assume in specific contexts (Berente et al., 2021). Cultures differ across dimensions, such as uncertainty avoidance (Hofstede, 2001). These cultural differences might lead to divergent attitudes towards contexts, in which AI is acceptable, across different regions. This study samples services targeted at English-speakers, hence replicating it with a focus on a particular societal context or cultural sphere, or conducting a comparative analysis among different types thereof, promises more nuanced insights into non-human agent roles. Thirdly, this study deliberately focuses on interactions with digital non-human agents, however, research indicates that anthropomorphism influences user well-being (Holthöwer & van Doorn, 2023; Pitardi et al., 2022) and sharing intensions (Kim et al., 2022). Future research including physical robots might thus yield additional attributes to characterize non-human agent roles.

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References

Ågerfalk, P. J. (2020), ‘Artificial intelligence as digital agency’. *European Journal of Information Systems*, **29**(1), 1–8.

Alter, S. (2023), “How Can You Verify that I Am Using AI? Complementary Frame-works for Describing and Evaluating AI-Based Digital Agents in their Usage Contexts”, *in* ‘Proceedings of the 57th Hawaii International Conference on System Sciences’, pp. 5856–5865.

Andersen, J. V., Lindberg, A., Lindgren, R. & Selander, L. (2016), “Algorithmic Agency in Information Systems: Research Opportunities for Data Analytics of Digital Traces” *in* ‘Proceedings of the 49th Hawaii International Conference on System Sciences’, pp. 4597–4605.

Baird, A. & Maruping, L. M. (2021), ‘The Next Generation of Research on Is Use: A Theoretical Framework of Delegation to and from Agentic Is Artifacts’, *MIS Quarterly*, **45**(1), 315–341.

Barile, S., Lusch, R., Reynoso, J., Saviano, M. & Spohrer, J. (2016), ‘Systems, networks, and ecosystems in service research’, *Journal of Service Management*, **27**(4), 652–674.

Beck, R., Dibbern, J. & Wiener, M. (2022), ‘A Multi-Perspective Framework for Research on (Sustainable) Autonomous Systems’, *Business & Information Systems Engineering*, **64**(3), 265–273.

Benlian, A., Wiener, M., Cram, W. A., Krasnova, H., Maedche, A., Möhlmann, M., Recker, J. & Remus, U. (2022), ’Algorithmic Management’, *Business & Information Systems Engineering*, **64**(6), 825–839.

Berente, N., Gu, B., Recker, J. & Santhanam, R. (2021), ’Managing artificial intelligence’, *MIS Quarterly*, **45**(3), 1433–1450.

Biddle, B. J. (1979), *Role theory: Expectations, identities, and behaviors*. Academic Press.

Bittner, E. A. C., Oeste-Reiß, S. & Leimeister, J. M. (2019), “Where is the Bot in our Team? Toward a Taxonomy of Design Option Combinations for Conversational Agents in Collaborative Work” *in* ‘Proceedings of the 52nd Hawaii International Conference on System Sciences’, pp. 284–293.

Bock, D. E., Wolter, J. S. & Ferrell, O. C. (2020), ‘Artificial intelligence: Disrupting what we know about services’, *Journal of Services Marketing*, **34**(3), 317–334.

Böhmann, T., Leimeister, J. M. & Möslein, K. (2014), ‘Service Systems Engineering’, *Business & Information Systems Engineering*, **6**(2), 73–79.

Brynjolfsson, E., Li, D. & Raymond, L. R. (2023), Generative AI at Work, NBER Working Paper 31161.

Čaić, M., Odekerken-Schröder, G. & Mahr, D. (2018), ‘Service robots: value co-creation and co-destruction in elderly care networks’, *Journal of Service Management*, **29**(2), 178–205.

Creswell, J. W. (2007), *Qualitative inquiry and research design: Choosing among five approaches*. Sage Publications.

Dell'Acqua, F., McFowland, E., Mollick, E. R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Krayer, L., Candelon, F. & Lakhani, K. R. (2023), Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality, Harvard Business School Working Paper No. 24-013.

Dhiman, H., Wächter, C., Fellmann, M., Trenz, M. & Fleisch, E. (2022), ‘Intelligent Assistants’, *Business & Information Systems Engineering*, **64**(5), 645–665.

Engelbrecht, A., Gerlach, J. & Widjaja, T. (2016), “Understanding the Anatomy of Data-Driven Business Models - towards an Empirical Taxonomy”, *in* ‘Proceedings of the 24th European Conference on Information Systems’.

Enholm, I. M., Papagiannidis, E., Mikalef, P. & Krogstie, J. (2022), ‘Artificial Intelligence and Business Value: a Literature Review’, *Information Systems Frontiers*, **24**, 1709–1734.

Hofstede, G. (2001), *Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations Across Nations.* Sage Publications.
Hilbig, R., Hecht, S., Etsiwah, B., Mention, A.-L. & Torkkeli, M. (2020), "The Rise of Data-Driven Business Models in the Berlin Start-up Scene" *in* 'Managing Digital Open Innovation', pp. 353–377.
Hinsen, S., Hofmann, P., Jöhnk, J. & Urbach, N. (2022), "How Can Organizations Design Purposeful Human-AI Interactions: A Practical Perspective From Existing Use Cases and Interviews", *in* 'Proceedings of the 55th Hawaii International Conference on System Sciences', pp. 196–205.
Holthöwer, J. & van Doorn, J. (2023), 'Robots do not judge: service robots can alleviate embarrassment in service encounters', *Journal of the Academy of Marketing Science*, **51**(6), 767–784.
Kaartemo, V. & Helkkula, A. (2018), 'A Systematic Review of Artificial Intelligence and Robots in Value Co-creation: Current Status and Future Research Avenues', *Journal of Creating Value*, **4**(2), 211–228.
Kim, T. W., Jiang, L., Duhachek, A., Lee, H. & Garvey, A. (2022), 'Do You Mind if I Ask You a Personal Question? How AI Service Agents Alter Consumer Self-Disclosure', *Journal of Service Research*, **25**(4), 649–666.
Kluge, S. (2000), 'Empirically Grounded Construction of Types and Typologies in Qualitative Social Research', *Forum Qualitative Sozialforschung Forum: Qualitative Social Research*, **1**(1).
Knote, R., Janson, A., Söllner, M. & Leimeister, J. M. (2021), 'Value Co-Creation in Smart Services: A Functional Affordances Perspective on Smart Personal Assistants', *Journal of the Association for Information Systems*, **22**(2), 418–458.
Kühl, N., Schemmer, M., Goutier, M. & Satzger, G. (2022), 'Artificial intelligence and machine learning', *Electronic Markets*, **32**(4), 2235–2244.
Larivière, B., Bowen, D. E., Andreassen, T. W., Kunz, W. H., Sirianni, N. J., Voss, C. A., Wünderlich, N. V. & Keyser, A. D. (2017). '"Service Encounter 2.0": an investigation into the roles of technology, employees and customers', *Journal of Business Research*, **79**, 238–246.
Lu, V. N., Wirtz, J., Kunz, W. H., Paluch, S., Gruber, T., Martins, A. & Patterson, P. G. (2020), 'Service robots, customers and service employees: what can we learn from the academic literature and where are the gaps?', *Journal of Service Theory and Practice*, **30**(3), 361–391.
Maedche, A., Morana, S., Schacht, S., Werth, D. & Krumeich, J. (2016), 'Advanced user assistance systems', *Business & Information Systems Engineering*, **58**(5), 367–370.
Maglio, P. P. (2017), 'Editorial Column—New Directions in Service Science: Value Cocreation in the Age of Autonomous Service Systems', *Service Science*, **9**(1), 1–2.
Maglio, P. P. & Spohrer, J. (2013), 'A service science perspective on business model innovation', *Industrial Marketing Management*, **42**(5), 665–670.
Maglio, P. P., Vargo, S. L., Caswell, N. & Spohrer, J. (2009), 'The service system is the basic abstraction of service science', *Information Science and e-Business Management*, **7**, 395–406.
Medina-Borja, A. (2015), 'Editorial column—Smart things as service providers: A call for convergence of disciplines to build a research agenda for the service systems of the future', *Service Science*, **7**(1), ii–v.
Möhlmann, M., Zalmanson, L., Henfridsson, O. & Gregory, R.W. (2021), 'Algorithmic management of work on online labor platforms: when matching meets control', *MIS Quarterly*, **45**(4), 1999–2022.
Murray, A., Rhymer, J. & Sirmon, D.G. (2021), 'Humans and Technology: Forms of Conjoined Agency in Organizations', *Academy of Management Review*, **46**(3), 552–571.

Nass, C. & Moon, Y. (2000), ‘Machines and Mindlessness: Social Responses to Computers’, *Journal of Social Issues*, **56**(1), 81–103.

Pakkala, D. & Spohrer, J.C. (2019), “Digital Service: Technological Agency in Service Systems”, *in* ‘Proceedings of the 52nd Hawaii International Conference on System Sciences’, pp. 1886–1895.

Parnas, D. L. (1972). ‘On the criteria to be used in decomposing systems into modules’, *Communications of the ACM*, **15**(12), 1053–1058.

Peters, C. (2014), “Together They are Strong - The Quest for Service Modularization Parameters”, *in* ‘Proceedings of the 22nd European Conference on Information Systems’.

Peters, C. (2016), *Modularization of Services - A Modularization Method for the Field of Telemedicine. Research on IT / Service / Innovation / Collaboration*. Kassel University Press.

Peters, C. & Zaki, M. (2018), Modular Service Structures for the Successful Design of Flexible Customer Journeys for AI Services and Business Models – Orchestration and Interplay of Services, Working Paper Series of the Cambridge Service Alliance.

Pitardi, V., Wirtz, J., Paluch, S. & Kunz, W. H. (2022), ‘Service robots, agency and embarrassing service encounters’, *Journal of Service Management*, **33**(2), 389–414.

Rai, A., Constantinides, P. & Sarker, S. (2018), ‘Editor’s Comments: Next-Generation Digital Platforms: Toward Human–AI Hybrids’, *MIS Quarterly*, **43**(1), iii–ix.

Ragin, C. C. (1987), *The comparative method: Moving beyond qualitative and quantitative strategies*. University of California Press.

Riasanow, T., Galic, G. & Böhm, M. (2017), “Digital transformation in the automotive industry: Towards a generic value network”, *in* ‘Proceedings of the 25th European Conference on Information Systems’, pp. 3191–3201.

Ringfort-Felner, R., Laschke, M., Neuhaus, R., Theofanou-Fülbier, D. & Hassenzahl, M. (2022), „It Can Be More Than Just a Subservient Assistant. Distinct Roles for the Design of Intelligent Personal Assistants”, *in* “Proceedings of the Nordic Human-Computer Interaction Conference”, pp. 1–17.

Russell, S.J. & Norvig, P. (2020), *Artificial Intelligence: A Modern Approach*. Pearson Education.

Rzepka, C. & Berger, B. (2018), “User interaction with AI-enabled systems: A systematic review of IS research”, *in* ‘Proceedings of the 39th International Conference on Information Systems’, pp. 1-21.

Saldaña, J. (2013), *The Coding Manual for Qualitative Researchers.* Sage Publications.

Schmidt, R., Alt, R. & Zimmermann, A. (2023), ‘Assistant platforms‘, *Electronic Markets*, **33**(1), 1–14.

Seeber, I., Bittner, E., Briggs, R., de Vreede, T., de Vreede, G.-J., Elkins, A., Maier, R., Merz, A., Oeste-Reiß, S., Randrup, N., Schwabe, G. & Söllner, M. (2020a), ‘Machines as teammates: A research agenda on AI in team collaboration‘, *Information & Management*, **57**, 103174.

Seeber, I., Waizenegger, L., Seidel, S., Morana, S., Benbasat, I. & Lowry, P.B. (2020b), ‘Collaborating with technology-based autonomous agents: Issues and research opportunities’, *Internet Research*, **30**(1), 1–18.

Siemon, D. (2022), ‘Elaborating Team Roles for Artificial Intelligence-based Teammates in Human-AI Collaboration’, *Group Decision and Negotiation*, **31**(5), 871–912.

Spohrer, J.C. & Maglio, P.P. (2010), “Toward a science of service systems” *in* ‘Handbook of service science’, pp. 157–194.

Tarafdar, M., Page, X. & Marabelli, M. (2022), ‘Algorithms as co-workers: Human algorithm role interactions in algorithmic work’, *Information Systems Journal*, **33**(2), 232–267.

Vargo, S. L. & Lusch, R. F. (2004). 'Evolving service dominant logic: Perspectives on value creation and service ecosystems', *Marketing Theory*, **4**(3), 381–400.

Vargo, S. L. & Lusch, R. F. (2016), *Service-Dominant Logic: Premises, Perspectives, Possibilities*. Cambridge University Press.

Wirtz, J., Patterson, P.G., Kunz, W.H., Gruber, T., Lu, V.N., Paluch, S. & Martins, A. (2018), 'Brave new world: Service robots in the frontline', *Journal of Service Management*, **29**(5), 907–931.

Yin, R. K. (2018), *Case Study Research and Applications: Design and Methods*. Sage Publications.

Yu, B., Vahidov, R. & Kersten, G. E. (2021), 'Acceptance of technological agency: Beyond the perception of utilitarian value', *Information and Management*, **58**(7), 103503.