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Implications of Including the Developer in the IS Delegation Framework

Akhona C. Khumalo
Karlstad University, akhona.khumalo@kau.se

Amirhossein Gharaie
Linköping University, amirhossein.gharaie@liu.se

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Research paper

Khumalo, Akhona C., Karlstad University, Karlstad, Sweden, akhona.khumalo@kau.se

Gharaie, Amirhossein, Linköping University, Linköping, Sweden, amirhossein.gharaie@liu.se

Abstract

The capabilities of artificial intelligence (AI) systems bring about new leaps in organizational change. While several work processes are now digital, and are increasingly getting automated, organizational processes thrive from augmenting AI-based tasks and human tasks. One framework depicting the augmentation between humans and AI is the delegation framework which theorizes on delegation of tasks between human agents and agentic IS artifacts. However, as the framework is limited to elaborating human agent-agentic IS agent roles, the role of the developer is missing. This study aims to shed light on the role of the developer within the delegation framework. We explore the implication of this involvement through the theoretical lens of adaptive structuration. We use cases drawn from 12 literature sources, qualified by assessing them used against the delegation framework guidelines, and analyzed them to identify developer roles. Our findings show that the developer influences the processes underlying the functioning of the agentic IS artifact, its attributes, its evolution, and mechanisms for delegation. The state of agency in an artifact is influenced and even largely defined by the developer. This implies that agency in an IS artifact can be viewed as encompassing more than their own abilities to act within their environments.

Keywords: Augmentation, Human-AI, Delegation, Agentic IS Artifact, Agency.

1 Introduction

The recognition of the importance for Human-AI hybrids in digital work expands our way of thinking about AI technologies in organizations. The need for human intelligence continues to have its place in organizational processes despite the proliferation of AI-enabled 'intelligent' artifacts that possess an agentic nature. While Artificial Intelligence (AI) has proven superior to humans in handling large amounts of data and in their computational and analytical capabilities, the ability to judge intuitively during decision-making remains a human superpower (Jarrahi, 2018). As Jarrahi (2018, p. 584) states, "Humans will likely outperform AI in evaluating subjective, qualitative matters (e.g., norms, intangible political interests, and other complicated social, contextual factors)". To leverage capabilities from both AI and humans in an organization, a symbiotic relationship is necessary. Augmentation is an implementation approach where a close interaction between humans and machines is assumed (Benbya et al., 2021).

Traditionally, Information Systems (IS) artifacts are viewed as serving the needs of humans in attaining their goals. However, AI systems are increasingly more independent and possess their own sense of agency. Agentic IS artifacts are not only able to learn, adapt, and act autonomously, but are also able to handle situations with a higher degree of uncertainty, as well as the transfer of rights and responsibilities to and from human agents, hence recognizing only human agency is insufficient (Baird & Maruping, 2021). A human-AI hybrid develops, and tasks are executed through a combined and complementary relationship where both humans and IS artifacts are agentic. In light of this, Baird and Maruping (2021), developed a theoretical framework that encapsulates the Human-AI artifact relationship and the transfer of rights and responsibilities between agents during execution of tasks. The relationship described by these authors is a dyadic relationship between an agentic IS artifact and a human agent (i.e., user).

Despite acknowledging the practical and theoretical contribution of the delegation framework in a dyadic way between the user and the IS artifact, we assume that the role of developer as another actor involved in the human-AI hybrid is missing. The developer plays an essential role in the creation and refining of the IS agent and influences its actions, however, the developer role has not been brought into focus when the delegation framework was proposed. It is important that we highlight the role the developer plays, and the developer's "impact on the foundational decision models and agency of the agentic IS artifact" (Baird & Maruping, 2021, p. 335).

The absence of a developer in the delegation mechanism is problematic. First, due to the impact of AI developers in decisions made by users (e.g., van den Broek et al., 2022; Xu et al., 2021), investigating the role of developers can create new responsibilities toward the result of delegation in the end (Matthias, 2009) which matters when considering ethical and regulatory issues. Second, due to the decision making capability of AI (Elliot et al., 2020), a fundamental inquiry is posited as whether users would exhibit sufficient trust in AI programs to relinquish decision-making authority to them (Baird & Maruping, 2021; Elliot et al., 2020). This question postulates that if the human agent perceives that the agentic IS artifact prioritizes the interests of the manufacturer over the interests of the human user, then trust in the program may falter. As a result, the human agent may become less willing to divulge all necessary information for the agentic IS artifact to make informed decisions and vice versa (Baird & Maruping, 2021). Finally, the initial goals of AI as part of their preferences are embedded in AI by design (Baird & Maruping, 2021). These preferences, whether revealed or clandestine, affect the relationship between user and AI. Consequently, any discrepancy between users and AI preferences in progressing the goal impacts the whole delegation between them. Scrutinizing the developer's role can assist in the development of delegation mechanisms in a better way that can attain their objectives.

Although the developer's contribution may not always be apparent (Kocaguneli et al., 2011; Tângari & Almeida Maia, 2015), their influence on the delegation mechanism can be significant. Comprehending the developer's role is crucial in comprehending the overall delegation process and the way agents interact with one another (Wooldridge & Jennings, 1995). The aim of his study, as per Baird and Maruping (2021) call, is to explore the delegation framework to assess how a triad between the human agent, the agentic IS artifact, and the agentic IS artifact developer would work. We utilize adaptive structuration theory (AST) (DeSanctis & Poole, 1994) as a theoretical lens to explain the triadic delegation process that ensues. We use cases of human-AI hybrid work found in literature to address the following questions: How does the role of the developer fit into the delegation framework? What are the implications of adding the developer role to the existing framework?

In the following sections we discuss supporting literature and describe the role of AST in developing an understanding of the delegation between human agents and agentic IS artifacts. We later detail the research method, and present findings and interpretations. We make eight propositions and discuss the study's implications on how the developer role affects the delegation framework.

2 Background

2.1 Human-AI hybrid

The development of AI has sought to find ways in which machines can accomplish more complex tasks and to endow machines with the ability to do human-like actions. Machines are designed and trained to be aware of and adapt to their environments, solve problems, interact intelligently with people and other machines, handle decision-making tasks that would have previously been reserved for humans, as well as to have learning capabilities (Berente et al., 2021; Kshetri, 2021; Raisch & Krakowski, 2021). The ability to collate large amount of heterogenous data from various sources, along with AI's computational and analytical capabilities give AI greater predictive power. AI systems are also designed to handle tedious tasks and provide decision support for humans (Dellermann et al., 2019). However, AI is proven in literature to suffer from limitations, such as the frame problem, biases in decision-making, the lack of context-specific judgements in decision-making, and inability to be handle various social issues within organizations and act intuitively (Jarrahi, 2018; Raisch & Krakowski, 2021; Salovaara et al., 2019).

The need for the human-in-the-loop has thus been highlighted by many (e.g., van den Broek et al., 2022; Wu et al., 2022; Zanzotto, 2019). The hybrid between humans and AI promises a powerful and profitable ensemble for many organizations. Domain experts' knowledge remains an important part of organizational processes as well as for training ML models. On the other hand, human monitoring and intervention is essential to ensuring well-functioning algorithms, that have not yet reached maturity. More importantly human intellect is key to the development of algorithms as well as integrating domain knowledge to their functioning (Dellermann et al., 2019). While AI algorithms are expected to learn from experience, over time, less dependence on human involvement can be expected. As AI is yet in its adoption years, hybrid work between machines and humans remains essential. This hybrid work entails delegation of tasks between agents to achieve some intended goal.

2.2 The notion of agency

A product of machine intelligence, albeit artificial, is the ability to individually decide and act, hence the agentic capabilities found in AI systems. According to Lewis (1998), the term agent means that some aspects of human-computer interaction (HCI) have been automated and can anticipate commands and act autonomously. Scholars such as Baird and Maruping (2021) and Raisch and Krakowski (2021) support that IS artifact have agency and no longer only act purely in response to human stimuli. Similarly, Chambon et al. (2014) defines agency as an individual's capacity to initiate and perform actions, and thus to bring about change, both in their own state, and in the state of the outside world. On the other hand, Popa (2021) argues that since artificial agency is linked to autonomy, human goals are inherent in AI agency, i.e., they are designed into the AI, and that goals that can be attributed directly to AI can be seen as sub-goals related to high-level human goals embedded in the design. We associate an agentic IS artifact to AI based on this notion of agency. Even so, we recognize that AI is a much broader field.

2.3 Delegation Framework

The new generation of agentic IS artifacts has arisen question about agentic primacy being associated with humans when theorizing about IS use and calls for us to consider that artifacts have agency. Considering human and the agentic IS artifacts characteristics and capabilities, and that rights and responsibilities for task execution and outcomes can be transferred to and from agentic IS artifacts, Baird and Maruping (2021) theorize on the concept of delegation – viewed as a transfer of rights and responsibilities between agents where delegator would be the agent transferring the task and the proxy is the agent to whom responsibility is transferred. In this conceptual model highlight the fluidity of the delegation by combining theorizing about the individual's use of the IS artifact to achieve a goal and the agentic IS artifact's use of the individual in goal attainment. Within the concept of delegation, it is assumed that the participating agents bring different strengths in the task execution process (Baird & Maruping, 2021).

For the purposes of this study and drawing from definitions in literature (Baird & Maruping, 2021; Jennings et al., 1998; Russell & Norvig, 2016), we consider the following as the characteristics to define an agentic IS artifact and keep in mind that agentic IS artifacts can be classed in different archetypes and thus a single IS artifact may not encompass all characteristics or may possess these capabilities in limited form: the ability to perceive and act in its environment, have a degree of intelligence, ability to carry out meaningful tasks autonomously, social, rational, flexible, proactive, situated, ability to learn, and handle some degree of uncertainty.

Based on the delegation framework, a bidirectional relationship exists between the human and an agentic IS artifact, transferring control between one another where the human requires the agentic IS artifact to perform certain tasks and the agentic IS artifact requests that the human take over certain tasks, thus a system of delegation happens between these two actors. At both ends of the spectrum are goals that the delegated tasks must fulfil. The delegation framework is comprised of constructs, such as the agents, the tasks that they execute, the delegation mechanisms that exist within the scope of executing tasks, and the outcomes of the executed tasks. Each of these tasks are associated with attributes relevant to the delegation process.

The three fundamental attributes of human agents and agentic IS artifacts are the resource-based assets and capabilities they possess (i.e., endowments), the motivation to engage in ana activity such decision models and goals (i.e., preferences), and the part they play in the delegation process based on rights and responsibilities (i.e., roles). The executed tasks are based on the type of action required (whether they are cognitive, digital, or physical), the level of complexity, and potential for subdivision (i.e., decomposability). Cognitive actions are actions involving thought, digital actions are actions that take place via electronic means, and physical actions are actions requiring physical execution such as a machine lifting parts of furniture during an assembly process. Situated action refers to the notion of being context aware and hence behaviour and actions affect and are affected by the conditions within that context (Gregor & Iivari, 2007). As Baird and Maruping propose, delegation is situated, and various situational incentives bear impact on the delegation process and outcomes. The outcomes in the framework denote the result of the situated delegation of tasks between the agentic IS artifact and the human agent.

The delegation mechanisms can be viewed as the causal instances that produce an effect (results in the reciprocal agent taking over rights and responsibilities from the delegator). Three delegation mechanisms are proposed, appraisal, distribution, and coordination. Appraisal refers to the process where one agent assesses the other's preferences in relation to their own to find compatibility and beneficial complementarities, and endowments to establish capability to execute a task. Distribution addresses the issue of how rights and responsibilities are transferred, negotiated, or regulated between agents, considering whether this is done partially or in full, is preferred or necessary, mutually agreed and provides incentive, and what boundary conditions are in place. Coordination highlights the need to ensure common understanding between agents and the need to manage dependencies between actions and tasks, aligning actions and goals, and maintaining accountability (Baird & Maruping, 2021).

2.4 Adaptive structuration theory

DeSanctis and Poole (1994) introduced adaptive structuration theory (AST), an extension of structuration theory that was originally formulated by the renowned sociologist, Anthony Giddens, during the late 1970s and early 1980s. Structuration theory integrates the two critical factors of structure and agency to proffer a comprehensive comprehension of social systems and conduct (Giddens, 1979, 1984)AST posits that the assimilation and use of advanced technologies, such as information systems, constitute a multifaceted process that requires the interaction of various factors, including technological, organizational, and individual factors.

DeSanctis and Poole (1994) discuss the role of adaptive structuration theory in understanding how advanced technologies are shaped by and shape social structures and practices. AST can be used to understand how advanced technologies are adapted and integrated into organizations and how they shape the ways in which individuals and organizations interact.

The dynamics of social structure and technology are instrumental in bringing about organizational change. In this regard, the theoretical framework of AST can shed light on the impact of technological structures on organizational change (Furumo & Melcher, 2006). The change process in AST rests on two key premises articulated by Orlikowski (1992): (1) the types of structures advanced technologies offer, and (2) the structures that emerge in human actions as they interact with these advanced technologies.

In the context of human-AI interaction, the technological structure of AI systems, as well as the societal norms surrounding their use, are important factors that shape the nature of these interactions (Bock et al., 2020). However, individual agency plays a significant role in how these interactions unfold. Specifically, the decisions and actions of individuals significantly influence how AI systems are used and how they evolve over time (Bock et al., 2020).

One way in which AST can be applied to human-AI interaction is by considering the feedback loop between structure and agency. As AI systems become more integrated into organization, they can create new structural elements that shape human behavior. For example, the use of AI in decision-making processes can lead to the creation of new norms and expectations around the use of AI. At the same time, human agency influences the development and use of AI. This reciprocal interaction between human agent and AI system (i.e., an agentic IS artifact) shows how delegation mechanism can be a potential way to create new structures on which human actions can be based and at the same time these actions trigger the creation of new structures (DeSanctis & Poole, 1994).

Given that, AST is an appropriate lens with which to explore the delegation framework as the architecture in the delegation framework constitutes advanced technologies and humans interacting with each other and handing over or taking over rights and responsibilities for task execution (Baird & Maruping, 2021).The delegation framework holds that both humans and IS artifacts have agency, and both have goals and responsibilities that they each want to fulfil or delegate. The nature of the processes and tasks carried out through delegation constitute a dynamic system. Different structures are created through interactions between human agents and agentic IS artifacts, while multi-agent systems will yield additional combinations of structures. Theoretically, how advanced information technology are allotted to task processes results in changes in social structures, and social structures evolve iteratively over time (Furumo & Melcher, 2006).

AST offers a valuable framework for analyzing the complex interplay between developers and the delegation mechanisms in the realm of information systems. As posited by Baird and Maruping (2021), delegation involves a bidirectional relationship between human and agentic IS artifacts, in

which control is transferred for the execution of tasks. In this context, AST provides a theoretical lens for comprehending how social structures and practices, including developer roles, influence and are influenced by the adoption and usage of advanced technologies such as agentic IS artifacts.

This theoretical lens emphasizes the importance of considering multiple factors – technological, organizational, and individual – to fully comprehend the adoption and use of advanced technologies. By incorporating the roles of developers in the delegation process, AST enhances an understanding of how their knowledge, skills, and preferences impact the delegation mechanisms and, conversely, how these mechanisms shape their roles.

AST also illuminates the feedback loops between the delegation process and social structures, including the potential for adoption of agentic IS artifacts to necessitate organizational changes, such as redefining job roles and responsibilities, which in turn may impact the delegation process. AST can help identify these feedback loops and explore how they can be managed to ensure effective delegation.

3 Method

Our research study is qualitative in nature and takes an interpretive approach. We used secondary data sources and base the method on the best fit framework synthesis method. The best fit framework synthesis method involves identifying primary research studies for inclusion following systematic review methods, as well as identifying the best fit model, framework, or theory as the a priori framework. The researcher then analyses the data from the included studies for quality and fit to the a priori framework and then develops new codes and themes on the evidence found in the data that is not captured in the a priori framework (Carroll et al., 2013). The best fit framework synthesis method has been used successfully in health-related studies (e.g., Carroll et al., 2013; Weber et al., 2022). This study, however, was modified in that it does not attempt to find frameworks from literature from which to form a priori framework, but utilizes an established theoretical framework, and instead of themes, guidelines from the selected theoretical framework are applied to the data to establish fit.

We reviewed a selection of cases discussing the human-AI hybrid in organizations. The cases were categorized and then analyzed by appraising the cases against the delegation mechanism theory baseline guidelines (Baird & Maruping, 2021). The delegation mechanism theory focusses on agentic IS artifacts and human agents (users) and their characteristics. Later, evidence from the data that highlights a developer role is identified, thematically analyzed and propositions are made that can contribute to a new conceptual framework.

3.1 Data collection

Using extant literature, we selected cases where organizations that have attempted Human-AI hybrid implementations. Scopus and Google Scholar were selected as the databases to find the relevant articles using the keywords "artificial intelligence", "machine learning", "case study", "Human AI hybrid" and "augmentation". The results on both databases were limited to peer-reviewed journal articles from 2018 to 2022. Our initial results equalled 40 articles, and these were imported into Rayyan after ensuring that there were no duplicates. Titles and abstracts of the 40 articles were screened individually by both authors and decided for inclusion in the study in a blinded fashion. Any conflicts were discussed and resolved for inclusion or exclusion by two researchers at a meeting. Following the screening of abstracts and selection process, 18 articles were agreed for inclusion.

The full text of the papers that were agreed for inclusion were scanned to make sure the cases are in line with human-AI hybrid that possesses the components that suggest the presence of a delegation mechanism. A total of 12 articles qualified for full reading and analysis. Each of these articles were classified and appraised whether they qualify as a unit of analysis based on the existing delegation framework and assess whether the roles of a human agent, and agentic IS artifact exist. Further, they were assessed for whether the role of a developer, as an agent, exists, and whether effective delegation takes place or if there is potential for effective delegation. Where a developer role is not clearly stated, the cases were analyzed and assessed to see if there is an opportunity for involvement of a developer as another agentic role involved in the delegation. This was done because the role of a developer is often not explicitly stated in studies even when it exists. Additionally, we note that, due to shortage of skills, the responsibilities of development, deployment, and evolving models is also often delegated to various job roles in different companies (John et al., 2023)

3.2 Analysis

For the analysis, as shown in table 1, we used the three-step guidelines provided by Baird and Maruping (2021) to ensure the cases were suitable according to the delegation framework. The first guideline is to investigate what the salient attributes of the task or outcome are. Afterward, the main delegation mechanism is specified, and the third step the agents' attributes are identified. This gridline helps to shape the delegation mechanism in each case and find the gaps that show developer roles as an agent affecting the delegation from the development perspective. Each case for which tasks, agent attributes, and delegation mechanisms were identified was considered fitting to the a priori framework. The degree of fit was also highlighted for each study and labelled on a scale weak, moderate, or high.

A table showing the studies used and their appraisal against the delegation framework guidelines can be found in supplementary resources[1].

We proceeded to inductively analyze the data for evidence of the developer role (see table 1).

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[1] https://docs.google.com/document/d/1XBb00i29IYs6qNm61GtLHDKJZ6XbXXas8Dkx_ldlB2s/edit?usp=sharing

Source of data	Role of developer in delegation
van den Broek et al. (2022)	Receiving feedback from the managers in different steps Alter algorithm rules Continuous update of algorithm functionality according to managers consultancy Coding knowledge Ability to merge human preferences and AI preferences
Grønsund & Aanestad (2020)	Update algorithm Altering the algorithm rules
Lebovitz et al. (2021)	Necessity of deploying know how knowledge by the help of human agents (users) when developing AI system
Mihai et al. (2022)	Providing the quality data for development of AI Pre-processing data to make it noise-free Detailed studying of contextual settings of the company to prospects for twin modelling and predicting the maintenance needs of the machines. Monitoring mechanism for continuous ingesting of data and checking for divergent behaviour within data.
Dimitropoulos et al. (2021)	Making the continuous co-learning ability of the AI possible based on the user feedback
El Koujok et al. (2020)	Interacting with the expert knowledge for identifying process variables (data preparation)
Xu et al. (2021)	Evaluation of the AI system using expert's knowledge Modifying the functionalities of AI based on expert interaction in evaluation phase Request of the expert to assign ML expert to assist the clinicians when working with AI system
Lepenioti et al. (2021)	Creating an adaptation mechanism where the users experience is integrated with the optimal policy generated by the model Developer designs the feedback loop
Quinn et al. (2018)	Train the model Receive data about discrepancies from analysts Update and alter rules and instructions Data preparation to increase the quality of sensory images Train segmentation models Adaptation Training
Salovaara et al. (2019)	Code rules for malware detection Test for reliability and adapt Code lessons learned Modify detection rules
Sturm et al. (2021)	Rapid Codification of beliefs Reconfiguration based on domain expert knowledge

Table 1. Inductively identified developers' role based on included source of data

The additional data depicted in table 1 is outside the a priori framework and thus can be considered new data. We listed the roles of the developer for each case based on the gaps they would fill as highlighted in each study. The list of roles was analyzed by identifying codes and producing salient themes. The codes and related themes were tabulated.

4 Findings

Our findings include 12 studies discussing cases that utilize a hybrid between human and AI. The cases explored implicitly or explicitly use the term human agent to refer to a number of specialties as long as they are human. Analysis shows that we can distinguish between some of the activities to highlight the developer role. We do not offer a full description of the developer role as the responsibilities and role labels differ between organizations. However, we believe that coding, modification of code, code error-fixing, and problem-solving related to functioning of the artifact, as well as controlling for appropriate input data, all fall within the work scope of a developer. Where AI is concerned, terminology such as rules definition, modification of rules, and provision of data labels, is also used.

4.1 Developer Role

Below we discuss the role and responsibilities of the developer based on the results and formulate relevant propositions. The main themes identified from the list of activities that would fall under developer responsibilities are initial coding of ML rules and ensuring quality data input, modification of rules, ensuring algorithm alignment with ground truth, aiding the ability to learn and adapt, and coding the ability to delegate responsibilities.

4.1.1 Initial coding of ML rules and ensuring quality data input

The first involvement of the developer is in the initial design and coding of the agentic IS artifact. Though we acknowledge that the role of the developer as discussed in this study is in many respects similar to that of the developer of any traditional IS system, here, we draw on the developer role in relation to the delegation framework. We maintain that agency of the IS artifact is initially by design. Firstly, we point out that the developer and the human agent (users or perhaps executive stakeholders) work conjointly in defining the requirements of the agentic IS artifact including aspects of the tasks or process that the human agent is willing to delegate. The required tasks and goals are thus predefined and the potential of having and giving preferences, rights and responsibilities, and delegation mechanisms is embedded in the artifact by the developer. The cases used in this study indicate that coding the quality of data input used to train the model also forms a big part of the developer's role. In Grønsund and Aanestad (2020) this is evident in that introduction of the algorithm necessitated changes in data acquisition process to circumvent issues pertaining to insufficiency and low data quality. In this early stage of human-AI hybrid adoption, literature places emphasis on this stage of rules definition and refining of data labels, albeit with the focus being on the artifact and not the developer behind it nor the delegation that happens between the involved agents. The following propositions are suggested. The first proposition emphasizes the involvement of developers in tasks and preferences of the IS artifact while the second proposition clarifies the incorporation of the developer in how the delegation mechanism is influenced by the developer. The last proposition highlights that delegation mechanism is designed based on known assets and capabilities of agents by the developer.

Proposition 1a: The developer and the user are involved in the delegation framework from the beginning; defining tasks and preferences of the agentic IS artifact.

Proposition 1b: The mechanisms for delegation between agents are incorporated into the design by the developer.

Proposition 1c: The developer influences the transfer of roles between agents based on known endowments and preferences of the human agent (user).

4.1.2 Ensuring algorithm alignment with ground truth

The accuracy of ML algorithms forms a significant aspect of AI and its ability to mimic human intelligence. Several of the included studies show that there is a need to monitor and evaluate the process and output of tasks executed by the ML algorithm and identify discrepancies and divergent behaviour (e.g., Lebovitz et al., 2021; Quinn et al., 2018; van den Broek et al., 2022). These evaluations assess whether the tasks are executed satisfactorily and that the set-out goals are attained. Where shortfalls are evident, it has become apparent that the agentic IS artifact had failed to discern as humans would, and take into consideration variations in context that would influence the outcome of the AI processing. In Lebovitz et al. (2021) it is highlighted that lack of appropriate use of ground truth results in unsatisfactory medical decisions. The HR case in van den Broek et al. (2022) highlights that the inclusion of domain experts versus their exclusion yielded fundamentally different results. In Quinn et al. (2018) the ML algorithm underperformed in identifying physical structures that were located too close to each other in a humanitarian project, requiring expert involvement. The need to incorporate domain expert knowledge in algorithms cannot be understated. Ground truth is introduced through the labels assigned to the dataset used to train ML models and are essential to measuring the performance against domain expert knowledge (Lebovitz et al., 2021). The responsibility of ensuring alignment of the algorithm with ground truth and thus increasing accuracy, falls in the hands of a developer. In these cases, delegation of this work to the developer is through a human agent (user). Indeed, the agentic IS artifact and the human agent are also designed and appropriately amended to handle and delegate these complex tasks according to their capabilities and preferences by the developer. Evaluations may also be used to reassign tasks and responsibilities when it becomes clear that one agent is incapable of fulfilling them.

The lack of alignment between outcomes and ground truth can be one way of assessing whether an agent is suitable for handling the task. Evaluations and audits are used to ensure that ML outcomes align with domain expert knowledge, i.e., the results are reliable and verifiable, and are similar or better than what a human expert would produce. Lack of alignment is often due to data sets used for training. Ensuring quality of data from which algorithms learn and the appropriate handling of that data is also managed by the developer.

According to Baird and Maruping (2021) when a task is delegated, one of three outcomes can be expected: goal attainment, progress, or failure. Based on the included cases, it is also evident that completed tasks can yield unsatisfactory results, and the need to delegate to the developer arises when task outcomes are unsatisfactory. The agentic IS artifact is often unaware. For this reason, delegation to the developer is often through the user who directly interacts with the agentic IS artifact. We purport that other types of failure to complete a task, lack of progress, or failure to execute a task by both the human agent and the agentic IS artifact (e.g., Pettersen, 2019) would also be a condition for delegation to a developer, and delegation to the developer may also originate from the artifact. We suggest the following propositions

Proposition 2a: Delegation to the developer originates mainly from (but not limited to) the human agent.

Proposition 2b: Failure to attain a goal or failure to progress by both agents may result in delegation to the developer.

4.1.3 Modification of rules

Modification of rules is linked closely to many of the listed roles of the developer, evaluation and monitoring, quality data input, continuous training, error-fixing, rectification of how processes are handled, and adaptation which all require that the ML algorithm be modified. Key reasons for modification are to improve performance and to introduce additional labels to aid processing and model training. Modification of rules, in addition to initial coding, is at the core of the developer role. In the delegation framework, the need for modification is usually delegated to the developer by the human agent who seeks better performance from its technological counterpart. In Grønsund and Aanestad (2020), the analyst audits and compares the algorithm's trade table with a human-generated version and notifies the data scientist who then alters or updates the algorithm. In Salovaara et al. (2019), the front-end teams escalate to one or more teams of experts in order to source problem causes and correct code against detected malware. In Lebovitz et al. (2021), the healthcare experts needed the involvement of a developer to re-establish how the (incorrect) decision was made. In cases not mentioned in this study's data, such as in the case of navigation systems, we also see a possibility of the agentic IS artifact delegating to the developer through information crowdsourced during the agentic IS artifact use. Modifications arising from this would be handled by the developer. As discussed in the cases mentioned in this subsection, algorithms evolved over time and improved to better handle tasks. The developer's ability and responsibility to enhance the interaction between human agents and agentic artifacts can assist in the evolution of the delegation process over time (e.g., Dimitropoulos et al., 2021). A proposition is made corresponding to the third theme as follows:

Proposition 3: The tasks, preferences, roles, and delegation mechanisms evolve over time based on the modifications applied by the developer.

4.1.4 Aiding the ability to learn and adapt

One of the key characteristics of AI and agentic IS artifacts, is the ability to learn from experiences and adapt its way of working to various situations, acquiring along the process the ability to handle higher levels of uncertainty. Though literature has focused on the learning ability of AI, it is becoming more evident that mutual learning is inherent in Human-AI hybrid systems. van den Broek et al. (2022) shows that the algorithm continuously acquired new knowledge on the HR staff and the HR managers continuously got aware of their mannerisms that were highlighted by the algorithm in action. In Sturm et al. (2021), the ML's and Human alignment with an organizational beliefs lead to the reconfiguration of the augmented system. Learning and adaptation is also aided by the developer through the changes in rules and data labels from which to learn. The developer is responsible for defining the conditions under which the artifact learns (Sturm et al., 2021). This enables the IS artifact to adapt to new situations and its environment. The adaptation can influence the preferences, and consequentially, the roles played by agents.

4.1.5 Aiding the ability to delegate and accept responsibilities

As highlighted under the initial coding section, the developer (aided by understanding the capabilities and preferences of the human agent) bears the responsibility to design the agentic artifact to take over certain tasks and responsibilities. The capabilities of the agentic artifact are understood and exploited by the developer. The agentic IS artifact then assumes agency and its ability to delegate and accept rights and responsibilities initially artificially through code, but it can gain independence as it learns, appraises other agents, and adapts to new situations. The capabilities of an ML agent such as its learning capability can change over time as the result of adjustments made by human agents to its initial setup. "Thus, the ML agents' initial setup determines a starting value for their learning capability, which is adjusted over time, as human agents' beliefs about the ML agents' specialized dimensions change" (Sturm et al., 2021, p. 1589). It seems this role of developer is a trigger for the artifact to show a dual behavior as elaborated in AST. In other words, the agentic artifact carries out responsibilities according to the structures embedded in it by the developer but when actions are repeating over time, there is a possibility for the structures to reproduce and evolve. This aspect which arguably refers to duality of structure will be discussed further in the next section.

How the artifact evolves affects and is affected by the tasks, preferences, and roles of an artifact. The changes to the artifact consequently cause changes in the way human agents handle tasks, their preferences, and the roles they assume. The above two themes highlight the evolution that transpires over time, underscored by the initial involvement of the developer. Based on both themes, two propositions are suggested as follows

Proposition 4a: The tasks, preferences, and roles of a human agent are indirectly influenced by the developer through the resultant design of the agentic IS artifact. (Dynamics of preferences and goals)

Proposition 4b: The developer initially influences the structure (the sociotechnical structure entailed in the delegation process/framework) and the human-artifact interaction over time makes the evolution of the structure possible.

To sum up, based on the five themes relating to the developer role, augmentation is achieved through collaborative processes between human agents and agentic IS artifacts, each contributing in some way by executing one or more tasks towards achieving a goal. Underlying the interaction between the human agent and the agentic IS artifact in an augmented process is the ability to delegate rights and responsibilities between each other. The ability of the agentic IS artifact to act autonomously has its basis on the development work put in it at its inception and through its evolution process. Its agency is not static but dynamic and evolving over time also due to the feedback loops between artifact, human agent, and developer following incorporated activities such as auditing, monitoring, and evaluation. The developer assumes responsibility for the alteration and updates to the artifact as illustrated in the cases used in this study. Additionally, the preferences of human agents to delegate certain tasks may lead to the modification of agentic IS preferences through code changes and model updates.

Feedback loops are essential to product evolution. Feedback loops are often defined by developers (Lepenioti et al., 2021). Though not explored in detail in this work, we wish to highlight that feedback loops in delegation may be incorporated into the design by the developer. Feedback loops from the outcome of the delegation process can be informative and lead to further changes in the way agents interact and delegate tasks (Baird & Maruping, 2021).

5 Discussion

In this section we explain how the developer role fits into the delegation framework. Further we discuss the implications of the involvement of the developer.

The first theme, initial coding of ML rules and ensuring quality of data input, shows how the developer is involved from the beginning, influencing both agent attributes and the mechanisms involved in a delegation process, which can be explained in three propositions. Proposition 1a shows that developers play a role in the formation of tasks, preferences, and roles in a human-AI hybrid even before the delegation between human agent and agentic IS artifact. Since the goals of the delegation are part of preference attributes, when developers define goals for the agentic IS artifact, they influence how agentic IS artifact should recognize the delegation preferences. Defining the preferences is impactful on the human-AI hybrid since both the human agent and agentic IS artifact assess compatibility and complementarities of each other for delegation. Developers through interacting with human agents from the beginning, contribute to determining which tasks and in which circumstances are suitable for delegation to the agentic IS artifact and vice versa.

According to proposition 1b, within the delegation framework, developers are responsible for designing and delegation mechanisms. They determine how tasks are assessed, how rights and responsibilities are distributed, and how coordination between agents is managed. The research by Lebovitz et al. (2021) showed how the lack of clarity about the way developers materialized the diagnosis process using AI, would influence the doctors trust of agentic IS artifacts and their willingness to delegate certain tasks. By incorporating delegation mechanisms into the design of the agentic IS artifacts, developers ensure that the delegation process delivers what it is promising from the beginning. Proposition 1c emphasizes the importance of developers for considering the known endowments and preferences of human agents (users) particularly in appraisal mechanism where agents assess each other's endowments and preferences prior to delegation of tasks.

Our findings include situations where agentic IS artifacts failed to complete a task satisfactorily, highlighting the need to delegate to a developer for employing means to ensure alignment between ground truth and the outcomes produced by an agentic IS artifact. It is worth noting that such failures impact on agents trust and willingness to delegate. Two propositions were put forth. Proposition 2a highlights that because the human agent (user) interacts with the artifact first-hand, they are often mediating between the artifact and the developer when delegation is necessary. It is often through information filtered from the human agent that requirements for modification, rectification, and updates to the algorithms reach the developer. Examples in the findings show that when the agentic artifact fails to complete a task, it is often the human user that will raise a query. However, it is foreseeable that delegation from artifact to developer can be handled directly. Proposition 2b addresses the possibility of a circumstance where one agent upon appraisal, prefers to delegate a critical task to the other agent, but the proxy fails to complete the task. The proxy can delegate the task back to the delegator or the tasks fails to progress. This would be the case where the initial delegator had based its delegation on its own inability to complete the task and its appraisal of the reciprocal agent showing that it is best to delegate. In some cases, several tries may suffice, albeit not efficiently, while others may call for abandonment of the task. An additional complication would result from failure to intervene by the delegator. Failure would often result in an ability to efficiently attain a goal. It then proceeds that delegating to a developer would be necessary; originating from either the human agent or the agentic IS artifact.

Another key responsibility of the developer is that of modification. Though modification is often linked to the evaluation stage of an agentic artifact, it is not uncommon when the artifact is operational, leading to updates. Modification of an algorithm is often linked to the way tasks are handled by the artifact, rules relating to the introduction of additional tasks, the failure to complete tasks, incorrect execution of tasks, and changes in preferences. Based on how tasks are handled, and how this affects preferences, the transfer of rights and responsibilities, and roles fulfilled by agents are also influenced. The modifications, actioned by the developer, contribute to how the agentic IS artifact evolves. This is the essence of our third theme and associated proposition.

Despite agentic artifacts being designed to learn from their environments, they are rarely built without a purpose. In proposition 4a, we highlight that the human agent is also influenced by the developer. Since the developer designs an agentic IS artifact, defining the tasks it is intended to perform and how it performs them, and the human agent is made aware of the artifact's abilities, the human agent delegates tasks based on the information acquired from the developer. Meaning, at the initial stages, the tasks the human agent will delegate or retain are governed by their understanding of what the artifact can do. Over time, how well or how badly the artifact performs can affect the human preferences over what will be delegated, thus impacting roles and the handling of tasks. The role of the developer influences human agent attributes (preferences and roles) and the delegation mechanisms.

Given the discussions in the above propositions, it is evident that the developer influences the entire structure entailed in the delegation framework (proposition 4b). The basis of the initial interaction between agents is the design of the resultant artifact by the developer. The social structure will evolve over time; as the agentic IS artifact learns, its preferences and hence willingness to delegate will change. Agentic artifacts may gain autonomy over previously shared tasks for instance, causing human agents' roles to evolve. Human responsibilities and preferences also change over time owing to the changing nature of the artifact and their level of confidence of the artifact's abilities and efficiency. Some evolutions are initiated by modifications and refinements by the developer. The structure is continuously reproduced over time; the effects of which can be expected to extend also to how organizational processes evolve.

The developer role is an indispensable part of the delegation that happens in a human-AI hybrid, despite that it might not always be visible. Though the role of the developer of agentic IS artifacts has not shifted too far from the role the developer plays for traditional IS artifacts, two distinctions can be made. First, the state of agency in an IS artifact, i.e., its ability to perceive and act in its environment, based on attributes, task definition, decision models, and how delegation mechanisms materialize, is achieved through the involvement of a developer. Secondly, the developer underscores the relationship in the human agent-agentic IS artifact dyad and the delegation mechanisms they employ. However, the role of the developer is often not an explicit one.

One implication of involving developers in the delegation framework reflects on the agency as a fundamental concept in the delegation framework. Involving developers in delegation potentially paves the way for understanding where the agency for each side of delegation originates. In line with AST, which avoids the technocentric view of technology (Gopal et al., 1992) our assumption is that IS artifact is not a neutral tool to be used to solely accomplish a predefined goal devoid of social and organizational context (Salmana & Nagy, 2019). When it comes to the agency of human agent and agentic IS artifact, Baird and Maruping (2021) introduced agency as a relational and relative concept. This means that agency exists within a set of actors through which humans and IS artifacts interact (Descombes, 2001; Kawatoko, 2017; Suchman, 1998). However, simultaneously, agency was considered as a characteristic in the nature of the human and IS artifact by acknowledging it several times. For instance: We now consider (1) agency, (2) the increasingly agentic nature of IS artifacts (Baird & Maruping, 2021, p. 317). Since the assumption of relative agency and natural agency might seem controversial, we found it interesting that involvement of developer into the delegation framework not only could shed light on agentic role as a relational and relative concept, but it inspired us to comprehend that the agency is shaped through a process where the interactions between different sides of delegation including human agent, agentic IS artifact and developer makes the agentic role meaningful.

This assumption shows its importance particularly when our result showed a nexus between agentic characteristics and the quality of delegation mechanism. After the occurrence of the delegation, performance of agentic IS artifact affects the decision of user for delegation. The endowment of the IS artifact affects the acceptance quality of the agentic artifact. The developer's responsibility to improve this interaction in different ways as elaborated in the previous section (e.g., ensuring algorithm alignment with ground truth, aiding the ability to learn and adapt, etc.) make the delegation between user and agentic artifact evolve overtime.

We showed how the developer plays a role in delegation framework from the beginning where the IS artifact is being developed (proposition 1a) even before any delegation between IS artifact and user occurs. It implies that involvement of developer is prior to imagining any proxy and delegator for user and IS artifact. Additionally, the developer influences the attributes of the agentic IS artifact that consequently shape the understanding of users about AI endowments (proposition 4a). Agency is not independent of the delegation outcome, meaning that the quality of delegation influences the judgment about the agentic role of the human agent, agentic IS artifact, and even developer. In this regard, Sovacool et al. (2020) argued how the agency of an artifact, which imbues it with a sense of free will, affects the structures of interactions among human actors, acting as constraints. This is similar to AST that rejects the idea that individuals including IS artifacts and users have free will to accomplish a task. In each delegation process, new structures are produced that define what, when and how to delegate (Baird & Maruping, 2021). At the same time, AST rejects the idea that the agent's actions are determined by structures (Gopal et al., 1992). In our context, it means both agency and structures are essential for the comprehension of the interaction between human and agentic IS artifact because a user has the agency or the ability to make decision and act accordingly, but these actions are shaped by the structures provided by agentic IS artifact. Therefore, none of these actors in the delegation framework have the agency in the nature as the agency is constrained by the structures that each actors' action via delegation of different tasks creates and IS artifact, user and developer gain their agentic role through the recursive delegations.

This study attempted to show the role of the developer in the delegation process as a type of human-AI hybrid, depicting the influence and involvement of the developer in this process. By doing so we argue that first, the developer is one role in the delegation mechanism that should be considered when human-hybrid occurs. Although the presence of a developer is not always evident, the influence of a developer in different stages of development and even implementation of agentic IS artifact (e.g., AI) turns our attention to the assumption of the developer's role as an agent in a human-AI hybrid. Second, by such a notion, despite room for further research, it can be claimed that the presence of a developer contributes to forming a different comprehension of agency.

6 Conclusion

In this study, we have explored the developer's role in the delegation framework that supports the interactions and division of work between humans and agentic IS artifacts in an augmented system of work. First, we highlight the developer role in the delegation framework. Findings show that the developer is involved in the initial coding of ML rules and ensuring quality data input, modification of rules, ensuring algorithm alignment with ground truth, aiding the ability to learn and adapt, and coding the ability to delegate responsibilities. Secondly, we highlight the implication of considering the developer's involvement on the overall structure and how the notion of agency of an IS artifact cannot be viewed simply as an inherent characteristic of the artifact. The developer influences several aspects of the delegation framework and impacts the agentic nature of the IS artifact. This is worth keeping in mind amidst the discourse of the accountability of agentic IS artifacts. However, the evolution of the artifact agency and delegation mechanisms involved as it matures is dependent on the artifact's capabilities and the continuous interplay between the human agent, the agentic artifact, and the developer. The roles and tasks of the human agent, on the other hand, through interdependence with the agentic artifact, can also be indirectly influenced by the developer. The augmented system of working discussed highlights the structures formed, and the iterative learning and dynamism of agency results in the reproduction and evolution of this structure. By conceptually drawing on the developer role we highlight the additional complexity underpinning the delegation relationship. This addition can help both organizations and developers to visualize and take into consideration the developer role and its impact to the delegation framework prior to development.

Agentic IS artifacts lend themselves to a mutual learning process where algorithms are continuously being trained and the human agent reflects and readjusts (Grønsund & Aanestad, 2020; van den Broek et al., 2022). By bringing the developer into the picture, we highlight the significance of the involvement of developers in the continuous learning and evolution of agentic artifact.

In continuation of developer role in delegation mechanism and potential influence of developer in human-AI hybrid interaction, future studies can explore the impact of personal and psychological traits of developer on the agentic IS artifact. Moreover, it seems imperative to include more empirical research regarding the role of developers in human-AI hybrid for further investigation.

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