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Artificial Intelligence, Decision Making, and the Knowledge Creation Process

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ABSTRACT

The continued evolution of artificial intelligence (AI) presents new opportunities for businesses to improve performance through better decision making. Prior literature has emphasized the relationship between AI and decision making as structures contributing to improved decision quality. This paper proposes that knowledge is a critical construct in the decision-making process and that it is the combined interactions of AI, decision making, and knowledge management within decision support systems and processes that contribute to improved decision quality. This paper outlines research trends that have occurred over the years and where the conversations regarding AI, decision making, and knowledge converge. Proposed in this paper is a research framework to classify AI capabilities in the knowledge creation process to further our understanding of these critical linkages.

KEYWORDS

Artificial intelligence, decision making, knowledge creation, knowledge management, explicit knowledge, tacit knowledge

INTRODUCTION

The continued evolution of artificial intelligence (AI) presents new opportunities for businesses to improve performance through better decision making (Loucks, Davenport, & Schatsky, 2018). The AI market is estimated to be $19.1 billion globally in 2018, with better decision making ranked as the third top priority for companies among 1,100 IT and line-of-business executives noted in a survey conducted by Deloitte (Loucks et al., 2018). Gartner reported in their 2018 technology trend survey that AI was the number one strategic technology (Panetta, 2017). Furthermore, Gartner indicated that "the ability to use AI to enhance decision making, reinvent business models and ecosystems, and remake the customer experience will drive the payoff for digital initiatives through 2025" (Panetta, 2017, p.1).

Businesses today continue to increase their investments in AI with the expectation of improving outcomes such as making better decisions (Shrestha, Ben-Menahem, & von Krogh, 2019; Duan, Edwards, & Dwivedi, 2019). Recent articles have highlighted improved decision-making capabilities among groups with the use of AI technologies (Duan et al., 2019; Metcalf, Askay, & Rosenberg, 2019;). Researchers have noted the increasing reliance on AI for decision making within organizations and the linkage between data synthesis, information creation, and predictions (Shrestha et al., 2019). The information interaction patterns in decision making are necessary constructs that link knowledge creation and decision making (DeSanctis & Gallupe, 1987). Nonaka and Toyama (2003) propose that knowledge creation and utilization are the most important competitive advantage of a firm.

Researchers have categorized decisions as structured, semi-structured, and unstructured according to the degree of certainty or specificity of the problem (Phillips-Wren, 2012; Shrestha et al., 2019). Structured decisions are quantitative and may have a known solution, whereas unstructured decisions are qualitative and interpretive (Phillips-Wren, 2012; Simon, 1987). Semi-structured decisions lie between structured and unstructured. Of note, structured decisions are procedural, rules-based, repeatable, and do not require human judgment (Phillips-Wren, 2012). AI technologies perform well in structured decision-making processes (Shrestha et al., 2019). However, unstructured decisions are primarily unsupported by AI due to the need for human judgment, experience, and intuition (Simon, 1987). Humans perform well in unstructured situations (Shrestha et al., 2019; Simon, 1987). Over the years, AI within decision support systems continues to be limited to structured decision making (Shrestha et al., 2019). AI technologies support semi-structured decision making in a limited manner where human capabilities are augmented, such as providing data or analytical support (Phillips-Wren, 2012). However, as AI advancements continue, such as machine learning, opportunities for AI to expand support for semi-structured, and unstructured decision making will increase (Duan et al., 2019).

AI has the potential to both replace and augment humans in the workplace (Metcalf et al., 2019). Metcalf et al. (2019) state, "when machines and people are connected in the right ways, they can achieve greater intelligence and make better decisions" (p. 85). Business and academic arenas have used the term artificial intelligence (AI) for decades. Duan et al. (2019) state that "there is no commonly accepted definition of AI" (p. 63). Literature has referred to AI as "the capability of a machine or computer to imitate intelligent human behavior or thought" (Seeber et al., 2019, p. 3). Duan et al. (2019) define AI as "the ability of a machine to learn from experience, adjust to new inputs, and perform human-like tasks" (p. 63). Alternatively, Tambe, Cappelli, and Yakubovich (2019) provide a broader definition of AI as "a broad class of technologies that allow a computer to perform tasks that normally require human cognition" (p. 16).

The purpose of this paper is to understand the relationship between AI, decision making, and knowledge management as essential structures contributing to improved decision quality. This paper outlines research trends that have occurred over the years and where the conversations regarding AI, decision making, and knowledge management converge. Furthermore, this paper proposes a research framework to classify AI capabilities in the knowledge creation process to understand the phenomenon of AI-supported decision making systems as they move towards semi-structured and unstructured decision making.

LITERATURE REVIEW

The foundation of this literature review is a structured approach to identify articles relevant to the topics of interest. Specific search phrases included artificial intelligence, decision making, decision support systems, expert systems, knowledge creation, knowledge management, and combinations of these phrases. Article abstracts were reviewed for relevancy and selected based on context and content. Backward and forward reviews of citations yielded additional relevant articles. This literature review includes only peer-reviewed articles pertinent to decision making, artificial intelligence in decision making, and knowledge management.

Artificial intelligence and decision making

Several terms should be clarified to understand the progression of literature related to AI technologies used for decision making. Historically, some researchers use the term expert systems as an alternative term for AI decision systems (Edwards et al., 2000). However, using the term expert systems is incorrect because expert systems do not learn (Kaplan & Haenlein, 2019). Linking AI and decision making in research has revealed differing classifications of a task and AI technology characteristics. For example, Kaplan and Haenlein (2019) classify three types of AI as analytical, human-inspired, and humanized based upon three managerial competencies: cognitive intelligence, emotional intelligence, and social intelligence.

Recent research in the context of artificial intelligence technologies used for decision making has illustrated both the potential for improving decision making with AI-based decision support systems and the need for continued research (Duan et al., 2019; Shrestha et al., 2019; Taylor, 2019). For example, Metcalf et al. (2019) conduct two experiments using artificial swarm intelligence (ASI) to support decision making, and results suggest that individuals within a group using ASI make higher quality decisions. ASI, defined as a type of AI technology, based on "distributed, self-organized decision making" (Metcalf et al., 2019, p. 86). Furthermore, Metcalf et al. (2019) advocate human-AI augmentation in decision making where humans are better with tacit knowledge and AI with explicit knowledge. "Tacit knowledge includes personal experience, skills, perceptions, intuition, mental models, beliefs, and feelings" (Metcalf et al., 2019, p. 85). Explicit knowledge is data and facts. AI can analyze large volumes of data to understand what is "known" (Metcalf et al., 2019, p. 85). When decisions require a combination of explicit and tacit knowledge, researchers suggest human-AI augmentation to produce better decisions (Metcalf et al., 2019).

Decision support systems

With the emergence of technologies supporting decision making, such as Group Support Systems (GSS) and Decision Support Systems (DSS) in the 1990s, literature studying the relationship between group performance and GSS/GDSS emerged; most notably with works by DeSanctis and Gallupe (1987) and DeSanctis and Poole (1994). The need for classifications of GSS/DSS systems in research was identified by DeSanctis and Gallupe (1987), resulting in a three-level classification system; still used today. GSS/DSS features and capabilities form the basis for the three-levels. This system classification will be discussed further in model development.

AI-enhanced DSS have emerged and shown the potential to improve human decision-making as exemplified with the experiment using ASI by Metcalf et al. (2019). Literature has focused on either human replacement or augmentation for decision making (Edwards et al., 2000). Through the lens of the decision-making process, effective decision making consists of intelligence activities for information acquisition, synthesis, and sensemaking (Duan et al., 2019). Current research in digital decisioning identifies structured decisions among the best candidates for DSS automation (Taylor, 2019). However, Taylor (2019) notes that candidates for automation change over time. As technology improves and machines develop domain knowledge and expertise, DSS broadens the inclusion of different types of decisions (Taylor, 2019).

The classification of DSS used in research remains as defined by DeSanctis and Gallupe (1987), as previously discussed in this paper. The addition of AI-enabled capabilities engenders the question: How do we classify new and AI-enabled DSS capabilities that were not envisioned by developers of previous classification systems? To answer this question, we need to understand more about the current state of AI capabilities and linkages with decision making and knowledge creation.

Knowledge management and decision making

Researchers have proposed the need to expand the purpose of decision support systems to include knowledge management (Nemati, Steiger, Iyer, Herschel, 2002). The use of AI technologies proposed to enhance knowledge management begins with knowledge creation and continues through knowledge storage and dissemination. Knowledge management is "the practice of adding actionable value to information by capturing tacit knowledge and converting it to explicit knowledge" (Nemati et al., 2002, p. 145). Decision-makers interact to create ideas and knowledge through Nonaka's (1994) four processes for knowledge creation. The continual interaction and exchange of tacit and explicit knowledge among individuals create ideas which, in turn, create organizational knowledge (Nonaka, 1994). Nonaka (1994) refers to this exchange as "communities of interaction" (p. 15). The two dimensions of knowledge creation, tacit and explicit, form the knowledge creation process. Tacit knowledge is both cognitive and technical (Nonaka, 1994). Nonaka (1994) refers to mental models as analogies that elicit our understanding of the world around us. Explicit knowledge is facts, or discrete knowledge that can be codified and examined (Metcalf et al., 2019). Nonaka (1994) refers to explicit knowledge as digital, and that which resides in digital repositories.

The knowledge creation process comprises four patterns of interaction between tacit and explicit knowledge or conversations (Nonaka, 1994). The four patterns are: tacit to tacit; tacit to explicit; explicit to tacit; and explicit to explicit. These form an iterative cycle of creating knowledge that Nonaka (1994) terms the "spiral of organizational knowledge creation" (p. 20).

Individuals acquire tacit knowledge through shared experiences, or socialization of tacit knowledge (Nonaka, 1994). The internalization of explicit knowledge creates tacit knowledge, such as learning new concepts or skills (Nonaka, 1994). As existing mental models are re-examined and interpreted, tacit knowledge converts to explicit knowledge in the process of externalization (Nonaka, 1994). Furthermore, new combinations of information contribute to explicit knowledge creation (Nonaka, 1994). Each of these four interaction patterns forms an iterative loop, or spiral, process to create knowledge.

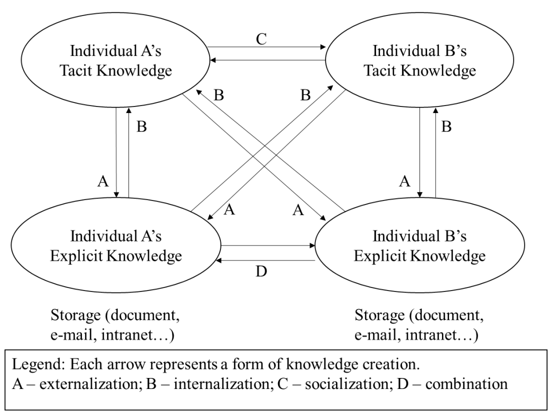

Figure 1. Alavi and Leidner's (2001) interpretation of Nonaka's (1994) knowledge creation modes

The work by Alavi and Leidner (2001) builds upon Nonaka's (1994) modes of knowledge creation to provide a more practical illustration of the social interactions for knowledge exchange, illustrated in Figure 1. Furthermore, Alavi and Leidner (2001) extend Nonaka's (1994) research to propose the role of IT in four knowledge management processes. The four processes and associated IT are knowledge creation (data mining, learning tools), knowledge storage and retrieval (electronic bulletin boards, knowledge repositories, and databases), knowledge transfer (electronic bulletin boards, discussion forums, and knowledge directory), and knowledge application (expert and workflow systems) (Alavi & Leidner, 2001).

Tacit knowledge is the domain of humans, whereas explicit knowledge is the domain of GSS/DSS (DeSanctis & Gallupe, 1987; Zigurs & Buckland, 1998). Two recent articles have focused on the creation of explicit knowledge through GSS/DSS and AI-enabled technologies (Metcalf et al., 2019; Seeber et al., 2019). However, the creation of both tacit and explicit knowledge through AI decision support systems that participate in the knowledge creation process remains an under-researched area.

CLASSIFICATION MODEL DEVELOPMENT

Drawing from previous classifications of AI and GDSS capabilities, patterns emerge for a proposed research framework. The three-level GDSS classification previously mentioned by DeSanctis and Gallup (1987), is based on system capabilities and summarized as: Level 1 GDSS capabilities for information access and exchange; Level 2 GDSS for modeling, analysis and structure; and Level 3 GDSS for group interaction styles as structured by Parliamentary Procedure or Robert's Rules of Order. This classification model was structured based on then-current (at the time) capabilities of GDSS solutions.

Literature containing classifications of AI capabilities include a diverse set of classifications based on feature/function, cognition, and learning. Davenport and Ronanki (2018) classified AI using business capabilities, including process automation (digital and physical tasks; robotics), cognitive insight (analysis and prediction), and cognitive engagement (natural language processing, intelligent agents, recommendations, interactions). Shrestha et al. (2019) developed a three-level AI classification of AI-based decision making structures.

The increasing integration of AI capabilities in DSS necessitates a new classification framework to study the interactions between AI and humans in decision making and knowledge creation processes. This paper proposes a classification framework based on relevant AI capabilities adapted from previous classifications identified in prior literature (Alavi & Leidner, 2001; DeSanctis & Gallupe, 1987; Gupta & Bostrom, 2005; Sambamurthy, Bharadwaj, & Grover, 2003; Sanzogni, Guzman, & Busch, 2019). DeSanctis and Gallupe (1987) developed a three-level classification for GDSS based on support capabilities. This classification system exemplifies aligning system capabilities with decision-making processes and is used to further our understanding of the relationship between technology features as structural components and group performance. The classifications are generalizable and straightforward.

Gupta and Bostrom (2005) developed a three-level classification of knowledge portal systems based on common attributes of knowledge integration, collaboration, and personalization. The framework allows for the integration of attributes across the classification levels consistent with the nature of knowledge portals to integrate knowledge across the organization (Gupta & Bostrom, 2005). Additionally, the framework is flexible enough to be generalizable and specific (Gupta & Bostrom, 2005).

A classification of digital options for knowledge systems was developed by Sambamurthy et al. (2003) within the context of increasing agility allowing organizations to identify and seize opportunities for competitive advantage. Digital options are the IT-enabled capabilities that support work processes and knowledge management across the organization (Sambamurthy et al., 2003). Two dimensions for digitized knowledge are defined; reach and richness. Digitized knowledge reach is the accessibility and comprehensiveness of knowledge, and richness is patterns of interaction among organizational participants (Sambamurthy et al., 2003).

Recently, Sanzogni et al. (2019) developed a framework of artificial intelligence capabilities relative to the knowledge domain based on three dimensions of tacit knowledge and one dimension of explicit knowledge. It is the proposition of Sanzogni et al. (2019) that AI is not capable of processing tacit knowledge based on current capabilities and a close examination of the three dimensions of tacit knowledge. AI capabilities are not explicitly linked with knowledge dimensions in the framework proposed by Sanzogni et al. (2019). The work by Sanzogni et al. (2019) focuses primarily on the impact of power relations in knowledge management processes. Power relations are the negotiations among individuals for identity, control, and rules in the social work environment (Sanzogni et al., 2019).

The AI classifications proposed in this paper are relative to the four knowledge creation processes developed by Nonaka (1994). The knowledge creation process is an iterative cycle of knowledge creation that depends upon the continual exchange of tacit and explicit knowledge to create shared understandings and new knowledge (Nonaka, 1994). This classification framework is applicable across all forms of AI capabilities used in knowledge creation. Within the decision making context, this classification framework proposes a linkage between AI capabilities and the knowledge creation process. Note that socialization is not yet a part of the traditional decision-making process and DSS.

Table 1 represents the research framework for the classification of artificial intelligence capabilities for AI in the knowledge creation process. The table identifies the AI classifications associated with each knowledge creation process, and examples of AI capabilities are listed. Classifications are an adaptation of literature sources including Alavi and Leidner (2001), DeSanctis and Gallupe (1987), Gupta and Bostrom (2005), Sambamurthy et al. (2003), and Sanzogni et al. (2017).

Knowledge Creation Process[a]	AI Classifications	Examples of AI Capabilities[b]
Socialization (tacit to tacit)	Shared experience[a]	• Conversational interfaces (i.e.: natural language processing) • Virtual assistants • Communities of practice (social networks) • Knowledge portals
Externalization (tacit to explicit)	Information creation[c]	• Advanced analytics • Business intelligence • Dashboards/visualization • Recommender systems • Decision support systems
Combination (explicit to explicit)	Information processing[c]	• Data mining • Big data
Internalization (explicit to tacit)	Knowledge integration/assimilation[c]	• Knowledge management repository/organizational memory system • Electronic bulletin boards and discussion forums • Machine learning

Table 1. AI Classifications in Relation to the Knowledge Creation Processes

Note: [a]Nonaka (1994). [b]List derived from AI technologies identified in Alavi and Leidner (2001), Davenport and Ronanki (2018), Goasduff (2019), Mittal, Kuder and Hans (2019), Sambamurthy et al. (2003), and Sanzogni et al. (2017). [c]Terminology derived from process descriptions in Nonaka (1994) and Sambamurthy et al. (2003).

CONTRIBUTION

Researchers have proposed the need to expand the purpose of decision support systems to include knowledge management (Nemati et al., 2002). The use of AI technologies proposed to enhance knowledge management begins with knowledge creation and continues through knowledge storage and dissemination. The goal of both the AI classification structure and a research framework is to understand the social interactions between humans and technology, which are critical within the knowledge creation process. From a practical standpoint, linking AI, decision making, and knowledge management within decision support systems and processes have the potential to improve the quality of decisions. The movement of AI technologies into unstructured decisioning is possible through the combination of AI, decision support systems, and knowledge management. As a theoretical contribution, the classification system proposed in this paper exemplifies aligning system capabilities with decision-making processes and is used to further our understanding of the relationship between technology features as structural components. The classifications are generalizable and straightforward. The creation of tacit and explicit knowledge through AI decision support systems that participate in the knowledge creation process remains an under-researched area.

FUTURE DIRECTION

These ideas can be utilized in future research to enhance the knowledge creation, assimilation, and dissemination processes that support the conversion of explicit to tacit knowledge. The literature review revealed the current decision support domain for AI technologies within structured decisions and highlighted the difficulties associated with AI movement into unstructured decisions. In the pursuit of improved decision quality, determining how we use AI capabilities to augment decision-making and knowledge creation processes is a subject for future research.

CONCLUSION

The increasing integration of AI capabilities in DSS necessitates a new classification framework to study the interactions between AI and humans in decision making and knowledge creation processes. This paper proposes a classification framework based on relevant AI capabilities adapted from previous classifications identified in prior literature. Linking AI, decision making, and knowledge management within decision support systems and processes have the potential to improve the quality of decisions. The movement of AI technologies into unstructured decisioning is possible through the combination of AI, decision support systems, and knowledge management.

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