Artificial Intelligence and Knowledge Sharing: Contributing Factors to Organizational Performance

Abstract

The evolution of organizational processes and performance over the past decade has been largely enabled by cutting-edge technologies such as data analytics, artificial intelligence (AI), and business intelligence applications. The increasing use of cutting-edge technologies has boosted effectiveness, efficiency and productivity, as existing and new knowledge within an organization continues to improve AI abilities. Consequently, AI can identify redundancies within business processes and offer optimal resource utilization for improved performance. However, the lack of integration of existing and new knowledge makes it problematic to ascertain the required nature of knowledge needed for AI's ability to optimally improve organizational performance. Hence, organizations continue to face reoccurring challenges in their business processes, competition, technological advancement and finding new solutions in a fast-changing society. To address this knowledge gap, this study applies a fuzzy set-theoretic approach underpinned by the conceptualization of AI, knowledge sharing (KS) and organizational performance (OP). Our result suggests that the implementation of AI technologies alone is not sufficient in improving organizational performance. Rather, a complementary system that combines AI and KS provides a more sustainable organizational performance strategy for business operations in a constantly changing digitized society.

Keywords: Artificial Intelligence, Business Processes, Knowledge Sharing, Organizational Performance, Performance Management.

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1. Introduction

Artificial intelligence (AI) is a collection of information communication technologies (ICTs) that imitate human intelligence for the primary purpose of improving jobs, creating greater efficiencies, and driving economic growth (Arakpogun et al., 2021). Knowledge, on the other hand, is the key component that enables AI innovations adding value to intelligent agents and systems (Robbins, 2019). The *intelligent agents* (IA) that results from AI activities hold numerous know-hows that are required to improve productivity and create new knowledge for business processes. AI-driven approach for instance is a strategy whereby IA enable the accessibility of valuable information via technology-driven platforms for employees. Furthermore, IA has a wide range of capacities in contributing to organization's approaches for innovation through strategic knowledge activities. This renaissance is driven by evidence that competitive advantages in the industries are more limited and significant for growth (Liebowitz, 2006).

However, IA needs an enabling *intelligent systems* (IS) environment to grow and engage with the reality of existing challenges in a given organization (Huang & Rust, 2018). Therefore, where there is a lack of an enabling environment, organization struggles with the development and implementation of intelligent systems, the process of distribution, retention, and knowledge re-use. Under such circumstances, methods for knowledge retrieval, sharing and re-use are limited and challenging to implement. Thus, a complementary approach that combines AI and knowledge sharing (KS) tool with other organizational factors need to be considered. The focus of such a complementary relationship is on improving productivity by constructing a knowledge-based system around the workforce in the organization (Malik et al., 2020).

How an organization create, share and re-use available knowledge determines the level of sustainable competitive edge and growth in the digital economy, which is, in turn, driven by intelligent use of knowledge (Yilmaz, 2016). According to Argote and Fahrenkopf (2016), knowledge is the primary source of improving organizational performance and if all conditions meet organization's demand, it is a vital source of competitive edge for the organization. Hence, strategy of business entities is to consistently develop new concepts that will encourage innovation at all levels of operation and impact employees' interactions to further enhance performance. Furthermore, AI provides a platform for the decision-makers in the organization to promote KS activities that will benefit both employees and the organization (Argote, 2013, 2015). Faced with a new challenge, the nature of knowledge that is required by IA can be problematic to ascertain, the need to develop fundamental knowledge maps is, therefore, important to the success of the AI-KS implementation.

To address this gap, our study aims to explore the impact of AI-KS implementation on organizational performance by considering key organizational performance (OP) factors. Organizations can effectively manage tangible resources using strategy tools to analyze complex tangible components such as tacit knowledge. However, there are challenges in allocating resources to knowledge activities given the difficulty in quantifying how tangible the outcomes of knowledge interactions are to the measurement units for tangible resources (Wang et al., 2016). Furthermore, the understanding that the economy is shifting from the traditional market to an innovative knowledge-based market is galvanizing evidence to embrace knowledge as a sustainable approach to retaining market presence and edge (Eilert et al., 2017).

Recent research has shown that AI is an important tool for improving services and the wider economy in an era of digitization era (Huang & Rust, 2018; Olan et al., 2021; Olan et al., 2021). Performance growth now depends more on innovative product and service, not only as a collaboration between departments, units, and teams but as progression to sustaining who-knows-what and sharing the know-how to foster growth. Moreover, research has also shown that organizations are shifting towards AI by changing their business process competitiveness and innovative strategies (Parkes & Wellman, 2015).

In this paper, the complementary relationship between AI and KS provides the answer to the research gap on the lack of integration of existing knowledge such as lessons learnt from completed projects in an organization to the business processes, the introduction of AI technologies enables an organization to improve employee's efficiency with access to a knowledge database. In addition, by exploring existing knowledge, an organization continues to generate new knowledge from business processes and employees' interactions. Therefore, this paper search for answers to the following research questions (RQs):

RQ1. Why is AI important for organizational know-how activities?

RQ2. How does AI-KS integration contribute to organizational performance (OP)?

This study develops a meta-framework based on extant literature in AI technologies, knowledge management and performance management using a *set-theoretic comparative approach* to simultaneously test three complementary relationship factors underpinned by the conceptualization of AI, KS, and OP. This paper is organized as follows: the literature review explains the theoretical basis for the concept of AI, KS, and OP. This is followed by a methodology section that describes the data, analysis and presents the results of the study. Further, there is a discussion section on the results, limitations of the study and future research.

2. Literature Review

The implementation of AI over the last decade has led to organizational successes. As such, organizations are gradually embracing the benefits of AI (Arakpogun et al., 2021). Previous studies have discussed the challenges and benefits of AI (Arakpogun et al, 2021, Huang &

Rust, 2018, Olan et al., 2021; Olan et al., 2021) while others looked into the analyzes of the future of AI to individuals and communities (Zahraee et al., 2016). Broadly, research on AI has been divided into two - the economic and technology literature (Huang & Rust, 2018). This paper will be exploring the theoretical literature around AI.

One of the important developments in organizations is the advancement of knowledge activities that enable managers to utilize available knowledge and expertise effectively and readily when required (Zhao et al., 2016). Knowledge is a key element for innovation and growth in organization, especially for employees to efficiently discharge their assigned duties and roles. The challenges that are associated with the implementation of a KS culture or systems are complex and difficult (Lombardi, 2019; Olan et al., 2022). However, certain literature has tackled some of the challenges of implementing KS systems, knowledge networks, culture, and organizational learning (Wu, 2016; Olan et al., 2022).

OP is a set of organization's goals and objectives, which are aligned with the key performance indicators (KPIs) with KPIs often used for measuring the targets required to achieve the vision of the organization (Obeidat et al., 2016). The relationship between AI and KS as a system for promoting knowledge activities will directly improve the organizational performance, provided all other organizational factors are constant (Huang et al., 2016). The remaining part of this section will be exploring AI, KS, and OP theories.

2.1 Understanding Artificial Intelligence, Intelligent Agents and Systems

AI comprises intelligent agents (IA) and intelligent systems (IS), which enable organizations to carry out intelligent and cognitive activities that integrate the business process with tasks, enabling organizations to be innovative (Arakpogun et al., 2021; Miller, 2019). IA consists of human intelligence that the intuitive abilities produce creative and novelty ideas that drive innovations in organization, this is classified as a competitive edge due to higher experience-based thinking (Liebowitz, 2006). IA is characterized by creative thinking, problem-solving skills, and intuitive abilities, also IA possesses analytical and explorative qualities (Amershi, 2019; Robbins, 2019; Wright & Schultz, 2018; Zahraee et al., 2016). IA is considered as the foundation for building a strong AI, as such, IA is built on human cognition and learning attributes (Chen et al., 2012; Martínez-López & Casillas, 2013). IA can thus be compared to a 'human child' with the ability to learn and absorb new ideas faster, including consciousness, self-learning, and other features of human intelligence (Chen, et al., 2012).

According to Wooldridge and Jennings (1995), IA is not a new development in the technology industry as its application can be seen in autonomous computer systems. Rather, IA is a major component of a computer system that is set in a given environment with the characteristics of autonomous actions designed to achieve preconceived objectives. There are difficulties in underpinning the concept of autonomous properties of IA, however, studies suggest that IA autonomy simply demonstrates that such a system be able to function independent of human interventions and manage its own actions and internal state (Padgham & Winikoff, 2002; Zhao et al., 2020). According to Asgari and Rahimian (2017), it is important that IA develop an analogy distinguishing the notion of autonomy with respect to data and understanding of the encapsulation of object-oriented systems. IA objects capture data state and manage the contents in the state in that it can control access or retrieval of data using methods that the data objects allow. Similarly, IA functions as a tool for encapsulating behavior with the idea that an object on its own does not possess the characteristic to encapsulate behavior.

AI technologies depend on IS, which automatically carry out routines, repeat tasks and share intelligence (Miller, 2019). In addition to these properties, IS can process complex information, problem-solving and alternative solutions. IS are designed to support human limitations such as learning and adaptive abilities (Pavlou, 2018). Thus, humans can carry out more intelligent and cognitive processes now than ever with the assistance of IS that provide support and efficiency. IS has been implemented as a mining technique that facilitates intelligent communications and better analysis for teams and individuals (Liu et al., 2020). According to Gretzel (2011), IS has evolved from understanding and mirroring nature to applicable innovations and discoveries. The transition of computer systems fosters successes in implementations of IS that are incorporated with AI technologies to ensure continuous performance actions leading to a knowledge-based system.

One of the functions of IS is to apply the autonomous learning operators (IA) to predict the impacts of actions in the environment and analyzing the significance of these actions (De-Graaf & Malle, 2017). The unified theories of cognition show that adapting IS in the class of niches describes the intermediate between the nature of IA technologies and the effectiveness of adopting human knowledge (Hopgood, 2012). Therefore, IS presents dynamic variability in characterizing required tasks, resource allocation, contextual requirements, and performance indicators. In addition, IS niches and IA possess common pervasive quality as that of human behavior to function effectively (Bryson, 2018). IS hierarchically composes AI technology components for perception, knowledge acquisition and cognition processes (Pearl, 2014). IS perception processes consist of acquisition, abstractions, and filtering of data before transporting it for the next action (Gregor & Benbasat, 1999). On the other hand, knowledge acquisition manages the execution of the processed data via external actions while cognition processes influence knowledge acquisition directly through actions of reflex arcs and coordination processes (Gregor & Benbasat, 1999).

Organizations are implementing AI as a different way of responding to the challenges and problems with the aim of deriving a solution with the most informed decision in real-time completed on behalf of decision-makers (Chen et al., 2012; Chen & Chen, 2013; Husain et al., 2013; Martínez-López & Casillas, 2013; Pavlou, 2018; Soriano & Huarng, 2013). AI thus brings many benefits to the organization, however, the struggles with the right implementation of business knowledge and available resources are challenges bedeviling organizations (Patnaik, 2015).

2.2 Knowledge Sharing: Understanding Organizational Knowledge

The exchange of know-how between organizational employees is an important element of organizational knowledge process (Cabrera & Cabrera, 2002). According to Cummings (2004), the resource-based view of the organization is a strategic tool for competitive advantage, which is unique by characteristics of physical, human resources, and organizational assets. Organization aims to sustain a competitive advantage by relying on assets that are valuable, rare unique and making it difficult for competition to imitate or substitute. A few researchers have argued that organizational knowledge is the required resource to attain this strategy, therefore, should be considered as a strategic asset in the organization (Cabrera & Cabrera, 2005; Gruber, 1995; Lin, 2008; Yang & Wu, 2008). In addition, organizational knowledge can be a track from specific historical events such as internal and external interactions, past projects with lessons learned and adaptation policies by the organization.

Oyemomi et al. (2019) identified that path dependency characteristic is responsible for the rareness and uniqueness of organizational knowledge as the history of learning experiences differs from one organization to another. Supra-individual characters and co-specialized capabilities make it difficult to appropriate collective knowledge by other organizations and harder to simulate or imitate due to causal ambiguous features (Van den Hooff & Huysman, 2009). Consequently, collective knowledge is embedded in the complex organizational business processes that include formal and informal inter-employees' associations and is a common and undocumented network of norms and practices. Most studies argued organizational theory of knowledge discovered a taxonomic distinction of organizational knowledge by establishing two unique knowledge classifications known as explicit and tacit knowledge (Nonaka & Von Krogh, 2009)

Knowledge or expertise that exists with the organization is communicated, shared, transferred, or coordinated through a channel that can be described as KS (Ertek et al., 2017). The aim here is to foster organizational productivity, continuous innovation and sustain a competitive edge. Tacit and explicit knowledge is the foundation for organizational knowledge where the interaction of these types of knowledge produces new knowledge that the organization can use for innovation and strategy purposes (Ikujiro, 1994; Nonaka & Von Krogh, 2009; Von Krogh et al., 2001). Tacit knowledge here refers to knowledge that is owned by individuals, acquired over time, and unconsciously becomes part of the individual (Goksel & Aydintan, 2017). The sharing of tacit knowledge is strongly encouraged in organizations as this produces new knowledge that helps in refining business processes and strategies in the organization. On the other hand, explicit knowledge is seen as codified knowledge and is available in the form of documents, processes, reports and can be stored and shared in an IS within an organization (Ikujiro, 1994).

Organizations implement KS as a system to promote organizational resources/capabilities that are driven based on knowledge. Thereby promoting interactions in different forms such as socialization, which will lead to the generation of new knowledge that improves employees' performance (Argote et al., 2003; Von Krogh et al., 2001). According to Von Krogh et al. (2001), organizations can leverage on socialization as a strategic environment to promote the sharing of tacit knowledge as employees can interact during social engagements and create new knowledge. This new knowledge becomes the foundation for innovation, efficiency, and competitive advance for the organization. For explicit knowledge, externalization as a social construct and environment enables employees to interact with the systems and share tacit knowledge (Erden et al, 2012).

However, there are potential barriers to the implementation of KS in the organization, including the implementation of a KS system, employees' attitudes to the new system, lack of will to participate and cost associated with implementation (de Vasconcelos et al., 2017). Therefore, these challenges necessitate further research on the implementation of KS systems.

2.3 The Intersectionality of Artificial Intelligence and Knowledge Sharing

The intersectionality between technologies and KS sharing has been highlighted in extant research. For example, Dong and Yang (2015) establish that organizations rely on the interaction between technologies and KS to create innovative solutions. Accordingly, the social exchange theory predicate that the intersection between AI and KS provides an organization with a sequence of activities that propel a chain of reciprocity between entities involved in the exchange relationship (Russell & Norvig, 2002; Turner & Kuczynski, 2019). Such intersecting exchanges form new important relationships that promote understanding of employees' know-how. Further building on the fundamentals of the social exchange theory, De Boeck et al (2018) and Duggan et al (2020) introduced AI-enabled consumer social exchange as a bridge of interdependent entities with AI at the center for introducing the consumer-to-consumer relationship, which is also known as the taxonomy of mediation mechanisms.

AI-KS intersection nurtures the understanding of the many analytic mediation mechanisms that fit both the organization and employees in a real-world system influencing digitalized competitiveness (Eslami et al., 2019; Ma & Brown, 2020; Russell & Norvig, 2002; Turner & Kuczynski, 2019). Hence, AI broadly refers to intelligent support systems built on algorithms, natural language processing, machine learning methods, and human intelligence to provide support for human activities and decision-making (Akkiraju et al., 2006; De Boeck et al., 2018). Thereby providing precepts knowledge from the organization and its underlying environment. As such, the relationship between employee-to-employee, employees-to-employee, organization-to-employee, and organization-to-employees knowledge sharing engagements through an enabled AI social exchange environment and the impact on employees' productivity and performance requires an underpinning theoretical understanding.

While there are different standpoints on how employees and organizations' systems interactions are planned (Russell & Norvig, 2002), there is a need to further our understanding of the AI-KS intersectional perspective. Insights from such understanding are critical to envisioning employee interactions with AI-enabled organizational processes and enhancing the learning curves from activities driven by KS social exchange. Organizations invest in AI-enabled innovations that can store, share, and create new knowledge on different cloud databases and other platforms. However, critical review shows that the social exchange between employees and the AI-enabled cloud platforms does not progress knowledge engagements or performance (Russell & Norvig, 2002). In examining the context of intersecting mechanisms, the role of organized social interaction underlines AI-KS mechanisms (Olan et al., 2022). Whilst AI-based communication is centered on augmentation mechanisms such as smart/auto-replies and auto-corrections in emails as well as other social media applications (Akkiraju et al., 2006; Liebowitz, 2001); it is also essential to note that the nature of social exchange can broadly take two forms: direct and generalized/indirect social exchanges.

2.4 Organizational Performance

Researchers in the field of performance management in the past have discussed performance solely as operational and financial perspectives that impact directly on organizational competitiveness and strategies (Grinyer et al., 1988; Neider & Schriesheim, 1988; Scholz, 1988). The operational perspective focuses more on the organizational success factors ranging from cost management, processes management and overall quality control that led to the long-term competitive edge (Davis & Schul, 1993; Priem, 1994). Conversely, financial perspective generally refers to an assessment of the organization's assets and liabilities, and how revenues are generated to reflect the organization's financial statements (Lin & Carley, 1997; Roland et al., 1997). The role of technology in improving OP is important to achieving organizational goals such as operational excellence, financial targets, and customer satisfaction. According to Alessandri and Khan (2006); Darlington (1996); Drew (1997), an organization's continuous investment in AI and other information technology (IT) has a huge contribution to the improvement of business processes, equipping employees with know-how and continuous training. Thus, in turn, has a direct impact on the improvement of OP.

Scholars have commonly agreed that OP can continue to grow when the organization successfully implement an alignment of performance measurement and the organization's business strategies (Alessandri & Khan, 2006; Darlington, 1996; Drew, 1997; Ghosh et al., 2017; Lin & Carley, 1997; March & Sutton, 1997). In addition, strategic performance measurement combines both organizational goals and operational activities, leading to acceptable business processes that improve employee performance. Zhu, Wang, and Bart (2016) discuss the relevance of implementing IT solutions that have the potential of impacting positively on employees' attitudes. It is thus crucial that the organization manages and identifies factors that can influence employees' attitudes towards discharging their duties and roles and by extension, help in achieving higher performance. Organizations are also encouraged to find a balance between the implementation of performance measurement units and the attitudes of employees to improving performance (Gorane & Kant, 2017; Jourdan & Kivleniece, 2017; Kundu & Mor, 2017).

While IT innovations continue to evolve over the past decades, organizations' strategies are also changing and paving the way to new methods that influence business strategies. These new business strategies help to achieve and improve OP (Tzabbar et al., 2017). It is also suggested that organizations should implement business processes with strategies that continuously monitor employees' activities with the aim of providing support through informal systems that are embedded in the performance measurement systems (Azar & Ciabuschi, 2017). Furthermore, scholars have discussed the potential linkages between measurement systems and business processes, arguing that this intersection is imperative as the new system provides information on achieving organizational goals (Zidane et al., 2016).

2.5 Conceptual Model

Argote and Fahrenkopf (2016); Lombardi (2019); Miller (2019) discussed the importance of knowledge management, performance, and AI respectively. However, there is a limited direct relationship between these individual research areas. Based on previous studies, this paper is able to derive a logical relationship between AI and KS as existing parallel studies show that the role of AI-KS relationship is important for improving OP nomological structure and measurement (Ikujiro, 1994; Liebowitz, 2006; Lombardi, 2019).

Previous research in the field of knowledge management have suggested that KS leads to the increase of competitive advantage, and that organization can invest in this area to enhance innovation among employees (Argote & Miron-Spektor, 2011). KS roles in an organization can change employees' behavior and indirectly facilitate the transformation of tacit knowledge to explicit knowledge with the resulting new knowledge stored in the organization in the form of reports and documents (Argote et al., 2003; Ikujiro, 1994). This will then lead to innovativeness and efficiency, which combine to drive employees' performance. According to Culver, Green, and Redden (2019), AI implementations lead to advancement in organizational innovativeness. Specifically, AI components (IA and IS) are influencing factors in advancing an organization's competitiveness. In addition, organizational competitive advantage is highly dependent on the ability of the organization to create innovations from employees' knowledge interactions (Soriano & Huarng, 2013). Table 1 shows a summary of the literature review based on the contribution of citations to the research areas.

Table 1 Summary literature review on background studies

According to the literature from many streams, AI-KS partnership can directly contribute to the advancement of KS practices and processes to promote innovative ideas and facilitate strategic business processes that lead to improving performance (Argote & Fahrenkopf, 2016; Argote et al., 2003; Argote & Miron-Spektor, 2011; Levin & Cross, 2004; Miller, 2019; Nonaka & Von Krogh, 2009; Von Krogh et al., 2001). AI has the potential to facilitate and develop enabling environments for the implementation of a KS system that promotes employee interactions (Culver et al., 2019). According to Martínez-López and Casillas (2013); Miller (2019); Pavlou (2018), the introduction of AI-KS system as a process for innovation improves interactions among employees and creates new knowledge, skills and contribute to OP. Furthermore, to strengthen employee relationships, the organization is required to improve the organizational structure and environment.

Extant studies have shown AI as the antecedent for promoting KS activities and ensuring organizational competitiveness (Chen et al., 2012; Huang & Rust, 2018; Zahraee et al., 2016). As shown in Figure 1, KS activities are divided into two parts: tacit and tacit to explicit KS, where the social environment for employees' interactions are socialization and externalization respectively. Also, AI has two components that are reflected in the conceptual framework - IA and IS. The implementation of AI-KS system has the foundation built on these concepts from literature from technological and knowledge management theories.

Figure 1: The Conceptual Framework – An integrated AI-KS system for organizational performance

Figure 1 proposes an integration of AI components with concepts in KS at the intermediate level in the organizational network. This is designed to capture new knowledge via adopted strategies in the organization's business processes. Rather than implementing a new system entirely, organization is positing a logical method to existing business processes by merging AI and KS. This concept assumes that the proposed framework considers most of the organizational factors that can positively or negatively impact the introduction of the AI-KS system. AI-KS system thus focuses on improving performance at all levels in the organization by consolidating organizational business processes to enhance process efficiencies and capture knowledge for innovation (Chesbrough, 2010; Abdallah, 2017).

3. Methodology

3.1 Data Sample and Collection

This paper adopts a systemic data sampling method that surveys organizations' workforce that ranges from strategic, mid-managerial and operational level with every organization provided with the same questionnaire to maintain uniformity of data. The organizations that are represented in the construct are independent, have the right to intellectual property, talented employees, and invest in innovation through research and development (Banker & Morey, 1986). Organizations are striving to remain competitive in a challenging digital economy. As such, the need to explore and provide a better understanding of the available resources are indisputable factors for organizational success. Furthermore, organizations mirror real-case scenarios to analyze the predictive and conditions set for the framework. There is a validity response rate of 52% - an indication that there is a low non-response rate and there is no bias in this survey (Balezentis et al., 2016).

The construct reliability and validity in this study use existing measurement scale to define and categorizing items into groups and sub-groups of an expert panel consisting of academics, members of organization’s strategic, mid-managerial and operational levels. These groups were engaged for validation of the questionnaire. Thereafter, data collection started with the approved questionnaire after detailed scrutiny by the expert panel with all questionnaire items aligned to the three components discussed in the conceptual framework in Section 2.4 (Bogetoft et al., 2016). At the data collection stage, this study utilized predictor and criterion variables developed from the same organizational respondent to mitigate bias.

3.2 Research Design

This study applied a fuzzy set-theoretic approach underlying two main arguments - complementarity and equifinality with the patterns of attributes defining the different features leading to varying results on the arrangement of the relationships (Fiss, 2007). Contextually, complementarity and equifinality in set-theoretic approach demonstrate attributes within a set of either present or absent conditions rather than showing the net effect of the isolated conditions to determine the result. In addition, complementarity is described as the existence of matching casual factors leading to a higher level of result while equifinality is said to have occurred when the combination of causal factors demonstrates at least two different pathways that lead to the same level of result (Frambach et al., 2016).

According to Greckhamer et al. (2013), assumption mismatch consequential from methodological gratuity demonstrates impeccable results capturing, not to mention the analyses, complementarity and equifinality hypothetically propelling to equivocal outcomes. Therefore, by focusing the research on the net effect of a variable omitting the significant absence or presence of alternative variables, data analysis continues to find it hard to identify the situations for a particular variable (e.g., if there is less or more influence on the result). Thus, complementarity and equifinality of the set-theoretic approach address this common error in using correlation-based analysis. Conventional approaches use a given population sample and consider the set-theoretic technique by distributing constructs of each perspective with another, which helps develop both positive and negative relationships. For example, relationships that are not supported by the results are classified as negative relationships based on testing with the available data. On the other hand, they can generate results that are supported by another set of data.

3.3 Analytical Techniques

Fuzzy set logic is more associated with the pure sciences and engineering, where in the past, social sciences, economics, and management generally implemented very little or no ‘fuzzy’ (Ragin, 2009). Researchers encounter challenges that involve approximate reasoning and the fact that it can affect decision-making. Therefore, the level of fuzziness is considered a major problem in management and social sciences compared to the applied and pure sciences that include engineering (Guo, 2009). Recent research shows the development of two hybrid methodologies of the fuzzy logic system that support fuzzy analysis in social sciences and management as well as decision-making in international marketing (Cardenas et al., 2016; Lousteau-Cazalet et al., 2016). As such, there is a systemic application of fuzzy logic in management analysis.

Fuzzy set theory, causal symmetry as discussed by Woodside (2013), looks into the relationship of predictors by the means of values and latent variables characterized by high and low values for sufficiency and predicting variables as they occur. Causal symmetry consists of more than one complex combination of antecedents and requires not just variables but also causal recipes to complete an analysis (Keshtkar & Arzanpour, 2017). Fuzzy set results can be classed as incomplete or incorrect causal if the casual symmetry is not applied during analysis. This leads to a misunderstanding of the fuzzy set phenomena. This study aims to implement a casual explanatory method that focuses on analyzing the parameters of predictions as discussed in the fuzzy set theory (Casillas & Martínez-López, 2009). The significant implication of applying casual symmetry is that there is uniform heteroscedasticity in the testing and analysis of data (Schmitt et al., 2017). This suggests that the results in this paper follow rigorous step-by-step processes.

Fuzzy-set analysis is used to prepare data for calibration on a Boolean algebra concept (Ragin, 2009). This study carried out the following configurational analysis on the following steps, using 5-point Likert scale values and categorical data based on fuzzy-set membership scores (Schmitt et al., 2017). Likert scale values are linked to the four associated variables: intelligence agents and intelligent systems of artificial intelligence, socialization and externalization of knowledge sharing, and organizational performance. The associated variables are coded as the average scores of the corresponding measured variables. Three anchors are defined as full non-membership score (=0.05), full-membership score (=0.95), and the crossover point of maximum ambiguity (=0.50). The membership scores over 0.5 indicate a case of more in than out; those lower than 0.5 indicate a case of more out than in. This study follows Ragin's (2009) principle that calibration of membership scores in the fuzzy set must be grounded in theory and the external knowledge of causal conditions. Analysis of causal necessity is a separate process from the analysis of causal sufficiency. Necessary conditions refer to those conditions that have to be present for the outcome of interest to exist (Fiss, 2007). A condition or combination of conditions with the consistency level exceeding the threshold of 0.8 is considered a necessary condition (Ragin, 2009).

4. Data Results

This paper carried out several tests for consistency, coverage, and unique path for reflective constructs (Sengupta, 1992). The initial pathway in Table 2 identifies the consistency and coverage, either close to or exceeding the average critical threshold value of 0.70. in addition, the raw coverage and consistency average are close to or exceed 0.50 to 0.70 respectively for all the constructs in the tests, confirming the support or ignoring the solution or combined path in the test.

Tables 2 and 3 present the results of the consistency and coverage testing by using casual conditions which shows whether the association is supported or ignored (Qin et al., 2009). These tables show an association of unions that are supported to exist and satisfy the casual condition for symmetry while the ignored associations are discarded as the associations are not satisfying the casual condition for symmetry. Furthermore, the casual condition for association meets the cut-off value of 0.80 – thereby providing evidence of symmetry validity of each construct.

Table 2: Result of KS, AI, and OP components comparativity

This paper explores the relationship among three components in Tables 2 and 3 with emerging results classified by recommendations to either support or ignore an association based on the casual condition configured during testing. Therefore, fuzzy set-theoretic logic allows the investigation of associations by several probabilities for traditional analysis and small for some statistical analyses.

Table 3: Result of KS and AI components comparativity

The results in Tables 2 and 3 indicate that complex antecedent and casual conditions are required pre-requisite for associating items in the criteria of KS combining AI variables with KS items characterized by the equivalent negated variables of AI. Complex antecedent condition demonstrates an association of KS variables to AI variables that highly influence the condition of OP. Furthermore, while KS has a defining role on both AI and OP items, KS and AI have a significant and positive impact on OP. However, some associations in the results in Tables 2 and 3 are not supported. While this result might be unique to organizations that participated in the survey, the focus on the associations is the critical factor for an organization to implement functioning KS activities in the business processes – further underlining AI as an influencing factor in this study.

5. Discussion

This paper compares three associations that can contribute towards organizational innovativeness and OP by using data collected from selected organizations to test the nomological relationships. The associations testing uses the casual conditions in fuzzy set qualitative comparative analysis (fsQCA) to explain the complex causal antecedent conditions identified in the relationships. The results provide a consistent pathway in the common associations, which generated more interpretable associations (Woodside, 2013). The outcome of robust associations demonstrates accurate interpretations of the relations among KS, AI and OP with the comparisons in Tables 2 and 3 supporting the majority of the associations. Therefore, the association of KS and AI in an organizational structure can promote innovation and productivity. Table 3 not only supports KS activities but shows a very high proportion of variance and best prediction for OP – a clear indication that organization can implement a KS system parallel to existing business processes, remain competitive and achieve set goals.

Another implication arising from this study is that the gap between KS activities, which are difficult to integrate with organizational business processes, is bridged with the help of AI via the development of an AI-KS framework linking KS activities with AI components (IA and IS) and OP. Tables 2 and 3 indicate that most associations tested underline that KS and AI play important roles in organizational competitiveness (Lombardi, 2019). This result can help decision-makers in the organization to leverage on the potential opportunities that can drive productivity and innovation by implementing AI-enabled KS activities in the business processes.

Our result also highlights how employees' attitudes play important role in integrating an AI-KS system with the existing organizational context. Hence, organizations need to focus on ensuring that there is a commitment to analyze employee's responses to the introduced KS system. Corroborating this, Argote (2015) argue that while knowledge is significant for competitive advancement, organization should also nurture knowledge assets that exist in the workforce. Organizations can gradually transit from a more traditional mindset and evolve through knowledge activities to remain operational and productive. While the future of an organization may be uncertain, emerging innovations through knowledge engagements secure continuous contribution to performance and completive advantages.

5.1 Why is AI Important for Organizational Know-how Activities?

This study emphasized the social construct, contextual and dynamic character in the resource-based view of knowledge. The implementation of collective knowledge has received a consensus on employees' interactions in the organization. However, the degree of technological growth in organization is constantly changing because of advancements in design and implementation. Furthermore, the continuous evolution of technologies (including AI) is remarkable and transverses how organizations re-think their priorities. Thus, organizational knowledge activities are dependent on advanced technologies such as AI to foster the application of knowledge outcomes with business processes (Tsui, Garner, & Staab, 2000).

The result shown in Table 2 suggests a support consistency association for AI and KS activities – a signal that the implementation of AI technologies acts as an enabler for processing complex knowledge interactions such as tacit-to-tacit knowledge activities. According to Olaisen and Revang (2018), AI technologies support organizational knowledge activities by managing complex collective knowledge that is difficult for employees to apply and integrate into business processes. The important role of AI technologies in promoting organizational knowledge activities is towards improving organization performance and competitive advantages.

5.2 How Does AI-KS Integration Contribute to Organizational Performance?

Organizations rely on outcomes from financial, product market and shareholders return to make strategic decisions (Ho, 2008). The identification of knowledge as a resource-based entity in the organization has propelled a shift in defining organizational assets. The need to invest in systems that promote intellectual capital or organizational knowledge activities demonstrates the important role of employees in improving organizational performance. The implementation of AI-KS system is to catalog knowledge priority with business processes, and by extension, a robust efficiency and productivity. Table 3 emphasized that although AI-KS integration is important to promoting existing knowledge, it is also essential for the creation of new knowledge. Furthermore, AI-KS system impacts positively on the three performance perspectives (financial, product market, and shareholders return) by enhancing employees' efficiency, know-how and know-when.

The results in Table 3 further underpin the organizational strategic value of AI-KS system to support knowledge activities. In practice, employees' acceptance of engagement using AI-KS system suggests that other benefits such as building organizational knowledge networks become add-ons to the organizational business processes. Thus, AI-KS system strengthens the partnership between employees and the organization through common ownership of knowledge resources in a manner that brings untapped resources together with the aim of improving performance.

6. Implications and Conclusion

6.1 Theoretical Implications

This study carried out a fuzzy set-theoretic analysis by mapping complementary and equifinality causality associations on constructs of the identified three perspectives: organizational knowledge activities, AI technologies and organizational performance. This gave rise to the exploration of the inter-connectivity among three theoretical fields underpinned by extant research and enabled this paper to develop a holistic conceptual framework based on resource-based theory. Hence, this study is embedded in the specific context of the application of knowledge, understanding the vital role of AI technologies, and the emergence of the contribution of this phenomenon to existing literature. This study provides important specific insights into how AI-KS system contributes to organizational performance, particularly the various steps followed in analyzing the data as a valuable contribution to the alignment of AI-KS conceptual framework.

6.2 Industry Implications

Business processes are important segmentation that forms the core peripheral of an organization with employees carrying out daily activities using processes that analyze their functions and tasks. Organizations depend on employees' knowledge and expertise to formulate strategies that sustain competitive advantage. The literature discussed in this study further supports the implementation of AI-KS system in practice. As such. there are three stages in this study that further contribute to practice. Firstly, there are three underpinning theoretical backgrounds: organizational knowledge sharing, AI technologies and organizational performance. The resulting developed constructs based on our conceptual framework demonstrate that organizations benefit from the implementation of AI-KS system.

Secondly, when AI technologies are deployed to ensure knowledge engagements in the organization, it is clear that employees develop more trust in interacting and exchanging tacit knowledge. Lastly, organizational strategies require new knowledge to improve organizational performance by adapting an AI-KS system. Complex processes are then identified and the introduction of solutions by the new system makes the organizational business processes more efficient. The approach in this study suggests that, by using a resource-based approach, employees' interactions further the extraction of knowledge by implementing AI technologies to manage organizational knowledge activities.

6.3 Conclusions

While the advancement of AI-enabled cutting-edge technologies has helped to improve business operations and performance, many organizations continue to face reoccurring challenges in their business processes. The main reason for these challenges hinges on the point that organizations often find it difficult to integrate existing and new knowledge into the learning process of AI. This creates a lack of an enabling environment and causes organizations to struggle with the development and implementation of intelligent systems, the process of distribution, retention, and knowledge re-use. As such, the benefits of AI to organizational performance become limited.

To address this knowledge gap, this study applies a fuzzy set-theoretic approach underpinned by the conceptualization of AI, KS, and OP. We then conduct data collection using an online survey. The data analysis suggests that the implementation of AI technologies alone is not sufficient to improve organizational performance. Rather, the association of knowledge activities such as lessons learned from completed projects with AI technologies contributes to performance and efficiency. This study further discovered that knowledge activities are not considered as a key factor for improving performance, making organizations make limited investments in implementing robust knowledge systems. We draw on our findings to recommend to organizations the significant contribution of an AI-KS system towards a more sustainable organizational performance strategy for business operations in a constantly changing digitized society. By so doing, the paper contributes to the existing literature in knowledge management by identifying AI technologies as a significant tool that promotes knowledge activities in an organization.

The limitation in this paper is that the conceptual framework and analysis considered a suitable organization' conditions where other factors such as leadership system, culture and technology are supportive. However, organizations without such conditions were not considered in this study. Future research can compare the results from organizations with suitable conditions to those without suitable conditions. The outcome could complement our paper and provide a solution to the limitations identified here. Finally, the associations that support the framework in this research could be introduced to organizations intending to engage their workforce in more knowledge interactions in a manner that promote innovation.

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Figures and Tables

Figure 1 The Conceptual Framework – An integrated AI-KS system for organizational performance

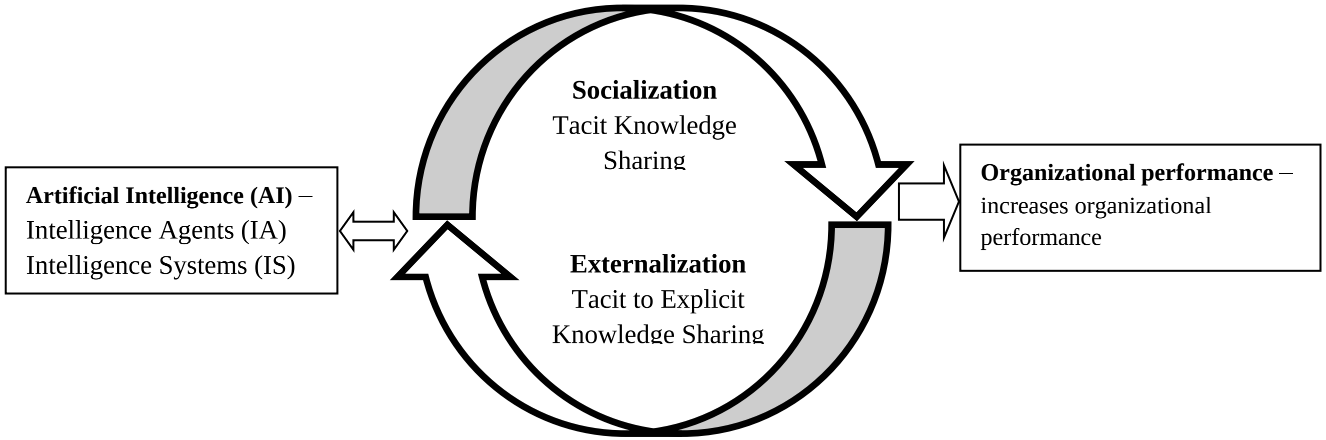

Table 1 Summary literature review on background studies

Citations (category order)	Context AI, KS, & OP	Research aims	Summary/main outcome	Relationship between AI, KS, & OP	Benefit of AI, KS, & OP
(Chen & Chen, 2013)	Innovation/technology	Technology supporting service industry through the implementation of AI systems	Service industry remains competitive and implement new innovations and learning system	A proposed decision support system that integrates concepts that promote innovation	An innovation model designed from the service industry which is applicable to other sectors
(Huwe & Kimball, 2000)	Performance	A performance management system that takes into to account employees' contribution to the organization, taking measurements that contribute to productivities	The application of key performance indicators KPIs in counting employees' contributions to the organization	The advantage of the proposing KPIs in the conceptual stage of associations	A performance management system that considers all existing KPIs
(Lombardi, 2019)	Knowledge Management	Strategy models incorporating business strategic, business processes with knowledge framework	The holistic approach presented here, has compared the traditional business process with a knowledge driven business process	A synthetic strategy design with the aim of creating new innovations, reducing business processes, and leading to increased organizational performance	A holistic approach targeting new knowledge in the organizational business processes
(Liebowitz, 2006)	Strategic Intelligence	Development and experimental intelligence doe organizational strategies	The organizational system efficiency and productive is on the decrease. with strategic intelligence, competitiveness and enhanced perform can start again	The intelligent system supports organizational strategies by reviewing sectors where intelligent strategy can be implemented	Organization intelligent systems are important for enhanced organizational performance
(Pavlou, 2018)	Internet of Things	Development of a hybrid intelligent system which supports the organization strategy process. The purposes for this system are to enhance strategic intelligent information on setting planning.	The system was empirically assessed with organization decision-makers. Results showed that the hybrid system was useful and helpful in supporting the key aspects of organization strategy development	An artificial intelligence network is developed to analyze and predict the organization growth while emerging organization strategy. Problem-solving is evaluated through interactions.	Artificial intelligent composed of system thinking, expert systems and fuzzy logic

Table 2: Result of KS, AI, and OP components comparativity

	KS-IA-OP				KS-IS-OP					
Consistency	0.648344	0.663247	**0.782438**	**0.772698**	**0.707672**	**0.724664**	**0.794016**	0.697460	**0.773250**	**0.778194**
Raw coverage	0.196212	0.374276	0.115329	0.172121	0.102809	0.159101	0.110858	0.250632	0.153986	0.033637
Unique coverage	0.054184	0.241412	0.037515	0.032313	0.032455	0.058696	0.016003	0.120965	0.028882	0.010464
Solution consistency	0.635798				**0.714627**					
Solution coverage	0.538797				0.454133					
A1: KS•IA⊂OP-Consistency	**0.791743**	**0.954857**	**0.796242**	**0.875266**	**0.748266**	**0.776939**	**0.833337**	0.672732	0.688173	**0.865103**
A1: KS•IA⊂OP -Raw coverage	0.054777	0.042356	0.059158	0.046974	0.054794	0.041098	0.039283	0.016219	0.018201	0.005915
A2: ~KS•IA⊂OP -Consistency	0.645642	0.663392	***0.774616***	***0.771952***	***0.721813***	***0.723961***	***0.793858***	0.697353	***0.772928***	***0.780676***
A2: ~KS•IA⊂OP -Raw coverage	0.192817	0.375529	0.111991	0.171354	0.102856	0.158391	0.109838	0.250811	0.154502	0.033991
A3: KS•~IS⊂~OP - Consistency	0.615825	0.600694	0.643375	0.600694	0.596100	0.600781	0.600781	0.600781	0.600781	0.600781
A3: KS•~IS⊂~OP -Raw coverage	0.046819	0.046819	0.046819	0.046819	0.044053	0.047553	0.047553	0.047553	0.047553	0.047553
A4: ~KS•~IS⊂OP -Consistency	0.544902	0.542449	0.517564	0.524309	0.525862	0.532296	0.532542	0.526383	0.539682	0.528046
A4: ~KS•~IS⊂OP -Raw coverage	0.897811	0.736226	0.933547	0.896900	0.934876	0.897471	0.937648	0.798192	0.905846	0.958520
Solution path hypothesis result	Ignore	Ignore	Support	Support	Support	Support	Support	Ignore	Reject	Support
Combined solution path unique coverage of same hypothesis result			0.069828		0.117618				0.028882	
Overall hypothesis result	**Support**				**Support**					

Table 3: Result of KS and AI components comparativity

	KS-AI							KS-IA-IS				
Consistency	**0.758981**	0.672589	**0.746798**	**0.788748**	**0.872892**	**0.753113**	**0.745734**	0.697646	**0.802344**	**0.893413**	**0.714466**	**0.768479**
Raw coverage	0.153345	0.118903	0.145043	0.139896	0.094074	0.136517	0.121743	0.131969	0.145075	0.155288	0.104384	0.074119
Unique coverage	0.077501	0.012854	0.020641	0.048869	0.027373	0.048765	0.021669	0.040570	0.068934	0.063018	0.020535	0.014923
Solution consistency	0.688993							0.699581				
Solution coverage	0.410388							0.322408				
A1: KS•AI⊂OP -Consistency	**0.794100**	**0.871676**	**0.833135**	**0.786903**	**0.870305**	**0.752888**	**0.746007**	**0.853988**	**0.883733**	**0.862407**	**0.712902**	**0.764976**
A1: KS•AI⊂OP -Raw coverage	0.092813	0.099467	0.116176	0.139381	0.092826	0.134638	0.120067	0.087861	0.092437	0.107623	0.102684	0.073019
A2: ~KS•AI⊂OP -Consistency	***0.779091***	0.673811	***0.747583***	***0.849189***	***0.835916***	***0.888739***	***0.855904***	0.698485	***0.809106***	***0.895238***	***0.864201***	***0.910380***
A2: ~KS•AI⊂OP -Raw coverage	0.146954	0.118632	0.144035	0.075568	0.070472	0.074925	0.089832	0.132414	0.136581	0.154362	0.081173	0.068686
A3: KS•~IA⊂~IS - Consistency	0.557086	0.556765	0.556765	0.578579	0.567134	0.572559	0.561409	0.575412	0.578739	0.575412	0.575637	0.571539
A3: KS•~IA⊂~IS -Raw coverage	0.527130	0.532670	0.532670	0.513636	0.532670	0.505430	0.512516	0.606197	0.603014	0.606197	0.578663	0.591108
A4: ~KS•~IA⊂IS -Consistency	0.447217	0.447961	0.435137	0.434078	0.434078	0.434078	0.434078	0.585850	0.570792	0.550756	0.566924	0.566924
A4: ~KS•~IA⊂IS -Raw coverage	0.433866	0.444984	0.436043	0.458084	0.458084	0.458084	0.458084	0.502510	0.495574	0.493919	0.535422	0.535422
Solution path hypothesis result	Support	Ignore	Support	Support	Support	Support	Support	Ignore	Support	Support	Support	Support
Combined solution path unique coverage of same hypothesis result			0.244818						0.16741			
Overall hypothesis result	**Support**							**Support**				