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AI: A knowledge sharing tool for improving employees' performance

Femi Olan[a], Richard B. Nyuur[b], Emmanuel Ogiemwonyi Arakpogun[c] and Ziad Elsahn[d]

[a]Essex Business School, University of Essex, Southend-on-Sea, UK; [b]International Business, Marketing and Strategy Department, Professor of International Business, Faculty of Management, Law & Social Sciences, University of Bradford, Bradford, West Yorkshire, UK; [c]Stirling Management School, University of Stirling, Stirling, UK; [d]Edinburgh Business School, Heriot-Watt University, Edinburgh, UK

ABSTRACT

The utilisation of artificial intelligence (AI) is progressively emerging as a significant mechanism for innovation in human resource management (HRM). The capacity to facilitate the transformation of employee performance across numerous responsibilities. AI development, there remains a dearth of comprehensive exploration into the potential opportunities it presents for enhancing workplace performance among employees. To bridge this gap in knowledge, the present work carried out a survey with 300 participants, utilises a fuzzy set-theoretic method that is grounded on the conceptualisation of AI, KS, and HRM. The findings of our study indicate that the exclusive adoption of AI technologies does not adequately enhance HRM engagements. In contrast, the integration of AI and KS offers a more viable HRM approach for achieving optimal performance in a dynamic digital society. This approach has the potential to enhance employees' proficiency in executing their responsibilities and cultivate a culture of creativity inside the firm.

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Artificial intelligence; Human Resource Management; knowledge sharing

1. Introduction

The emergence of artificial intelligence (AI) and it's potential of affecting HRM practices and jobs at different levels have been acknowledged and led to calls for research on how AI will alter HRM practices, the trajectory of occupational change and employment growth (Troth & Guest, 2020). Accordingly, there is a substantial research gap on the reality of AI in human resource management practices in organisations (Tambe et al., 2019). There is therefore limited research on how the emergence of AI technologies could impact HRM practices and workplace performance (Tambe et al., 2019; Troth & Guest, 2020). This paper seeks to cover this research gap by examining the role of AI in employees' workplace performance. AI

CONTACT Femi Olan femiolan@outlook.com; femi.olan@essex.ac.uk Essex Business School, University of Essex, Southend-on-Sea SS1 1LW, UK

can be described as a set of algorithm-based computer instruction, which has been programmed to learn and self-adapt to a given environment (Huang & Rust, 2018; Robbins, 2020). The adaptation of AI, however, can only be driven with data that show forecasts and intelligent performances through understanding of human activities such as learning human interactions (Wright & Schultz, 2018). AI is also a knowledge sharing (KS) tool that evolves from, for example, automated machine learning, robotic business process automation and data mining (Mattsson et al., 2019; Olan et al., 2022, 2022, 2022). AI thus have the ability of tackling real-world situations, identifying real-time errors on behalf of decision makers, and facilitating real-time decision making (Pavlou, 2018). AI is therefore considered as part of the next digital frontier with the potential of far-reaching opportunities in various parts of the society including human resource management (HRM) and other organisational activities both 'now' and in the near 'future' (Bughin et al., 2018; Manyika et al., 2017).The future of organisational performance thus lie on its ability to efficiently and effectively deploy the potentials of AI by generating relevant data from digital collaborations (Zahraee et al., 2016). As such, it is becoming common practice for existing and potential employees to have at least 'basic' information technology (IT) skills, which was hitherto classified as expert skills for IT professionals. HRM is now striving to increase employee's familiarity with AI tools, productivity, and overall organisational performance (Pak et al., 2019). That said, to mitigate challenges and increase employees' performance using AI, the interests of employees must be recognised while recognising concerns relating to appreciating individual expertise, workers trust, data protection, information sharing policies and business ethnics (Jayawickrama et al., 2016, 2017).

Similarly, research on workers performance theory (Malik et al., 2017) supports the proposition that mutual benefits for both the employees and HRM can be the outcome of a positive interaction and economic relations (Klein & Potosky, 2019). More organisations are now providing HRM emerging AI tools that reflect different forms of skills sharing for their workforce to manage performance related to various roles and duties (Jiang et al., 2012). In doing so, organisations focus on facilitating the design of employees- specific competencies that lead towards developing interactive social environment to maintain competitive advantage. Specifically, organisations provide HRM with AI enabling tools that allows workforce interactive activities associated with the performance management of employees (García-Sánchez et al., 2017; Malik et al., 2020; Shirouyehzad et al., 2017).

This could be in the form of HRM costs reduction, regular team building training, development curricula and contribution in decision-making that are centred on encouraging KS (Bughin et al., 2018; Manyika et al., 2017). Jiang et al. (2012) thus argues that an organisation's HRM that deploys AI tools in such collaborative manner would signal commitment and trust, which would, in turn, facilitate and increase employees' performance.

This paper aims to fill the gap where little or no research on the integration of AI-KS system to examine how key KS activities lead to enhancing EP through innovation. Hence, with the following research questions developed from theoretical gaps, this study focus on delivering possible AI-KS framework that considers HRM practices that are operational in the organisation.

RQ1: Are there existing employees' behaviour that support technology adoption?

RQ2: How does effective knowledge sharing activities advance implementation of AI technologies.

This research paper presents a meta-framework that is constructed by drawing upon existing literature in the fields of (AI) technologies, (KS), and (HRM). The study carried out a survey with 300 participants by employs a deductive approach and utilises a fuzzy set-theoretic comparison technique to examine three interrelated elements. These factors are investigated within the context of the conceptualisation of AI, KS, and HRM, and are found to be mutually supportive. Furthermore, this study outcomes from the framework analysis on organisations that are gradually embracing technology and KS activities, where employees' engagement is the key to generating innovative ideas and enhancing performance, leading to further organisational competitive advantage.

The rest of the paper is organised as follows: the literature review explains the theoretical basis for the concept of AI, HRM, KS and employee's performance. This is followed by an in-depth methodology, which describes the data, analysis and present the results of the study. In addition, there is a discussion section on the results, limitations of the study and further research.

2. Literature review

The last decade has witnessed a surge in research on AI and its innovative applications on issues related to the management of organisations (Chen et al., 2012). This body of research highlights the challenges and opportunities of AI for organisations, people, and economy. It also underscores the effective link that exists between how people are gradually embracing AI tools within the organisation and the impact on organisational performance (Ahmed et al., 2023; Alkraiji et al., 2023; Aram et al., 1971; Bandara et al., 2023; Cheung et al., 2023; LIKENS, 1978; Long, 1978; Onjewu et al., 2023; Riemann, 1978). With respect to this paper, three aspects stand out: understanding of the opportunities of AI, how the implementation drives the business and corporate strategy, KS as a tool for employee's interactions and the concept of employee's performance in HRM. AI as a KS tool is a new concept and somewhat unfamiliar with the traditional knowledge sharing processes (KSP), as such, the replacement of KSP analytic will emerge through the opportunities available (Aram et al., 1971; Bitencourt Machado et al., 2015; Kroll, 2015).

2.1 Understanding of the opportunities of AI

AI has emerged with many potential benefits to society. For example, AI could further harness the identification and creative skills of employees while taking advantage of the emotional intelligence of employees as data point (Huang & Rust, 2018; Soriano & Huarng, 2013; Zahraee et al., 2016). Organisations are beginning to leverage on these opportunities to mitigate uncertainties, reduce the time spent on supervision and improve the effectiveness of decision-making processes. In reality, the application of AI varies as this intelligence are designed to perform specific task(s) by utilising specific data, which were gathered from 'leaning' to achieve a certain goal (Landay & Harms, 2019; Robbins, 2019). With such data, HRM can provide additional benefits to employees in a more efficient manner. This partly explains why the pace of using business target data in the field of HRM field is gradually surpassing organisations analytics in recent years (Bagdadli & Gianecchini, 2019; Wales et al., 2011).

One of the limitations that could occur in this process is the issue of unexpected technical issues, which may arise with initial programs and affect organisational goals. Furthermore, the insufficient level of transparency on algorithms, which has attracted public attention, could also raise further questions, particularly around the diversity of programmers and ethical concerns on the implementation of AI (Amershi, 2019; Patnaik, 2015). However, there has been some achievement regarding ethnical issues raised around the use of AI, one of which is the regulations associated with the development of machine learning (ML) (Dao et al., 2011; Martínez-López & Casillas, 2013; Williams, 2009). ML allows AI system to gain access to useful learning information from many datasets and define its own rules, which, in turn, boost the performances and cognitive skill development of AI (Chen & Chen, 2008; Prasad & Prasad, 2008).

Studies on opportunities of AI, both from the data and the information system application perspectives, have been carried out recently, leading the justification of encouraging innovations around ML. ML is developed to address ethical concerns in the process of decision-making around AI (Chen et al., 2012). ML has the capability to learn from issues encountered while using data, either from humans or from environments where the system is operating, to avoid similar repetitive complications (Cheung et al., 2023b; Cunningham et al., 2023; Spanaki et al., 2023, 2023; Zhao et al., 2022).

In addition, developing uniform principles to guide the design of AI system, ML programs and algorithms are believed to be effective in ensuring ethics compliance. Nevertheless, as AI and ML systems are designed to work on specifics, this is a very difficult topic for researchers and experts of AI. Patnaik (2015) argues that little or lack of sufficient assistance from organisation ethical norms or policy guidelines highlights the need to regulate the development of AI to achieve a fair balance between the effective application of AI and ethics. Patnaik (2015) further points out that the construction of ethical principles will depend on each applicability of the technology in question whilst also recognising that cultural framework and the sensitivity of data sharing.

2.2 Knowledge sharing as a tool for employee's interactions

Effective KS for interactions in organisations is achievable through people and technology – employees have the emotional connections and know-how, while technology drives effective communications and determines how the identification, transfer, and circulation of useful knowledge are disseminated around the organisation. Olan et al. (2019) argues that knowledge management (KM) practice is KS illustrates the opportunities related to working with intangible assets such as know- what, know-how, know-when and know-why. While technology can help to advance the transfer and circulation of knowledge, emphasis should be placed on the organisation. Amershi (2019); Olan et al. (2016) argue that for an organisation to implement successful KS activities, there is need for the workplace to create an environment that supports sharing. Jung and Takeuchi (2010) specifically recommend that organisations need to enable and promote shared knowledge to improve performance.

According to Ikujiro (1994); Nonaka and Von Krogh (2009); Sharma and Harsh (2017); Von Krogh et al. (2001), SECI model in much research, demonstrates how knowledge is transform from one form to another, the environment where the knowledge is transform is important to how it is stored in employees or systems. Despite the different views on the SECI model, it has sturdy theoretical foundation to be implemented in organisational, professional, and personal cultural levels (Rai, 2011). Also, AI and its impact on knowledge transformation and the application of the SECI model will enhance the insights of an organisation into the knowledge transformation and processes involved in it (Malik et al., 2020). The use of the SECI model for identification of knowledge transformation and sharing in different knowledge intensive organisations in the USA and Spain is widely acknowledged (Choudri et al., 2016). Therefore, SECI model is a multi-organisational development that helps in promoting knowledge transformation while investing in the employees (Cheung et al., 2023a; DiVaio et al., 2021; Dwivedi et al., 2020; Narayanamurthy & Tortorella, 2021; Wamba-Taguimdje et al., 2020).

2.3 Employee's performance

Given that employees are vital assets in any organisation, researchers have continuously tried to understand the mechanisms which HRM could utilise to impact organisational performance (Jordan et al., 2019; Klein & Potosky, 2019). Scholars have partly tried to understand the HRM performance link from two standpoints – the systems perception or the strategic perception (Jiang et al., 2012). The systems perception views HRM performance link with respect to HRM-practices and performance as a unified management approach of how the whole of HRM-practices and policies can contribute to the competitive edge of the organisation and enhance performance (Buenechea-Elberdin et al., 2017; Busco et al., 2012). Such view reflects a transition of how significant HRM is gaining competitive edge and moving towards organisational performance in present-day enterprises (Collins et al., 2021; Prentice et al., 2020; Verma et al., 2021).

According to Wales et al. (2011), strategic perception in the HRM performance has taken on different meanings in the literature. Jiang et al. (2012) have discussed the external factors between various HRM-practices and the competitive strategy of the organisation, the approach that organisations can support various HRM-practices and strategic goal. These practices and policies can develop employees' skills, knowledge, and motivation such that employees focus on ways that are supportive of organisation's strategy (Malik et al., 2020; Pak et al., 2019). The issue of strategic HRM participation has been explored in a few publications.

For instance, Torresen (2018) suggests that the combination of HRM-practices with organisational strategies results can improved competences and make organisations more effective and efficient. Amershi (2019) stresses that the alignment of HRM- practices and organisational strategy can yield many benefits such as higher employee's performance, cost effectiveness, increased employee's commitment, and innovation.

Furthermore, Malik et al. (2020) found that HRM-practices help organisations develop problems solving methods at the lower level, thus leading to better organisation management, which subsequently helps to build responsible systems. Furthermore, there has been discussions that a respectable relationship between employees and management can foster a better comprehension of the issues relating to employees' duties and roles (Buenechea-Elberdin et al., 2017).

2.4 Conceptual framework

In the AI, KS, and HRM, employees' performance (EP) is a pre-requisite for the competitiveness of an organisation. While it is commonly discussed that performance is a function of organisational competitiveness. To support this assertion that performance can be a primary antecedent of organisational goal, this paper requires both performance and organisational processes, and how it supports employees' efficiencies. Notwithstanding the acknowledgement of AI in effective organisation's implementation, AI tools, HRM practices, KS, and employees, therefore, the relationship between AI, KS and specific HRM processes is not investigated (Amershi, 2019).

Historically, Hu et al. (2017) recommend that performance is higher when both measurable organisation's processes and objectives are complementing each other through standards of measurement. It is recommended that cognitive process in measurement is a set of activities explicitly dependent on objectives, which supports business processes. Olan et al. (2022); Olan et al. (2019) described three fundamentals, which are intention, autonomy' and fluctuation of the performance improvement process most likely to persuade employees' commitment to the organisational agenda. Table 1 shows the contributions of research outputs from various scholars and how the conceptualisation in this paper came into existence. The principal factors in the AI and KS studies can increase employee's commitments to a significant level.

The business processes include employees, groups, and organisational level upgrading. Thus, cognitive process of knowing and understanding is the purpose to facilitate the decision to share valuable information. In the business processes, organisations are mandated to be innovative in obtaining, connecting, and disseminating information. Nevertheless, employee's independence is a multifaceted factor that provides employees the autonomy to engage in knowledge interactions.

Moreover, HRM practice offers a mutual system of learning in which employees can share and exchange know-how or work experiences through social interaction. Busco et al. (2012) found employee's cognitive capacities could be changed if employees are exposed to a new AI architecture. In other words, AI either pacifies the environment in which knowledge sharing takes place or it tends to regulate employee's behaviour, which is important for knowledge sharing and transfer. Thus, organisations should provide an environment in which employees utilise these cognitive capacities during workplace socialisation for knowledge sharing and transfer.

The concept of KS was also discussed in terms of employee's behaviour. For example, Olan et al. (2016) argued that KS is a performance enhancing phenomenon as organisations facilitate strategies in the KS process. AI helps employee's commitment to interactive engagements because of different sociological factors capable of influencing people (see Figure 1).

Table 1. Summary literature review on background studies.

Citations (category order)	Main context within A HRM/KS	Research aims	Summary/main outcome	Relationship between AI, KS, and HRM	Benefit of AI, KS, and HRM to the organisation
(Schmidpeter & Osburg, 2013)	Innovation/ technology	An innovation support system that supports employees' interactive activities, designed to promotes sharing, transfer and circulation of know-how, know- what, know-why and know- when.	This system can benefit the organisation by building a re-usable knowledge depository for decision-makers in order to: 1) Associate other possibilities and select most competitive products or services to launch on the market where there are continuous competitions; 2) improve the understanding of employees' understanding.	The proposed system enables more effective innovative decision support by providing substantial and inclusive solutions that could help organisations develop more competitive products and services from employees' interactive strategies.Therefore, no comparisons in other strategies that are introduced. Therefore, no comparisons in other strategies that are introduced.	An innovation support system that consists of model (for employees interactive behaviour and employees sharing value) is proposed. this model is based on system dynamics, an analytical method for studying KS systems.
(Pak et al., 2019)	Employee's behaviour	Decision-making system in ERP processes do not usually take employee's dynamic nature in organisation; this is mostly due to the inherent limitations of the ERP system, for example, the weaknesses of fixed and static parameter settings. To tackle these weaknesses, the authors propose two decision concepts that optimally solve the problem, by considering the dynamic aspects of employee's skill sets as well as the limitations.	Behaviour towards employee or team, enabling the design of effective interaction $_{\text{strategies}}$ will increase employee's willingness to share and have a positive impact on generating higher innovative products and servicesin the long term, and enhance confidence in team development in terms of idea generation and partnership improvement.	The advantage of the proposing experimental studies with an ideal cultural belonging.	A decision support systembased on an AI, KS, and HRM model optimised by iterative search.

(*Continued*)

Table 1. (Continued).

Citations (category order)	Main context within A HRM/KS	Research aims	Summary/main outcome	Relationship between AI, KS, and HRM	Benefit of AI, KS, and HRM to the organisation
(A. Malik et al., 2020)	Management	Strategy models incorporating business strategic decisions must cover both HRM and KS,so business activities must be coordinated with employees' functional areas. This paper aims to build on the body of HRM practice models by expressing a conceptual model, based onmixed numbers nonlinear programming, which encompasses the main relevant business activities.	The holistic approach presented here, has compared with the traditional serial decision strategy is shown to be more beneficial. The potential of applying data mining methods in this research is highlighted, as this approach use enables statistical data-driven models to reach for the organisation's activities, which can be later be applied in an optimisation scheme.	A synthetic strategy design d planning problem is resolved by both the proposal and traditional serial decision strategy. Empirical outcomes support the benefits of the former approach.	A holistic approach targeting strategy design planning.
(Williams, 2009)	e-Business	Development and experimental assessment of an e-enabled organisation's proposed system, organisation's activities for developing business strategies, competitive planning and associated e-business platforms.	The organisation system is efficient and effective in terms of improving decision making strategy, improving confidence in strategy development, connecting strategic analysis with employees' judgement and inventiveness, helping strategic thinking, and improving the quality of organisation's strategic decision making.	The intelligent system supports reducing the cognitive loads to develop organisation strategies. The system is also evaluating the terms of efficiency and effectiveness compared to traditional models through a questionnaire.	Organisation intelligent system.

(*Continued*)

Table 1. (Continued).

Citations (category order)	Main context within A HRM/KS	Research aims	Summary/main outcome	Relationship between AI, KS, and HRM	Benefit of AI, KS, and HRM to the organisation
(Huang & Rust, 2018)	Technology	Development of a hybrid intelligent system which supports the organisation strategy process. The purposes for this system are: 1) provide a competitive process for strategic analysis; 2) support team assessment of strategic organisational factors; 3) help a simultaneous consideration of help a simultaneous consideration of organisational strategic analysis with managerial perception and decision; 4) facilitates decision-makers to deal with uncertainty and fuzziness; and 5) produce strategic intelligent information on setting planning.	The system was empirically assessed with organisation decision-makers. Results showed that the hybrid system was useful and helpful in supporting the key aspects of organisation strategy development. The results generated by this system reported to be very sound, astonishingly precise, and clearly dazzling leadership judgement.	An artificial intelligence network is developed to analyse and predict the organisation growth while the fuzzy rule-based system deals with the uncertainty of strategic principles and implements cognitive for emerging organisation strategy. Problem-solving is evaluated through interactions.	Artificial intelligent composed of artificial neural systems, decision support systems, system thinking, expert systems and fuzzy logic.

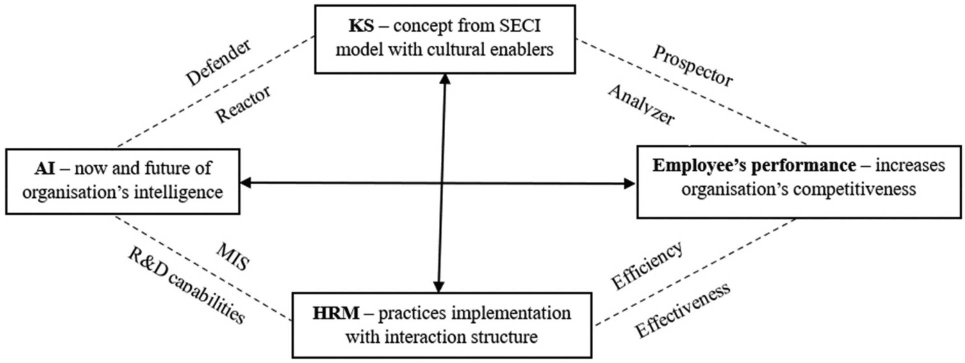

Figure 1. The conceptual framework – an integrated AI enabled KS for employees' performance.

Values are deep-rooted and may not be easily articulated, but it would influence on KS capability because it manipulates individual behaviour that could be a source of useful KS. Therefore, it is suggested that the relationship between norms and values backs the desired behaviour, which is necessary to create and sustain knowledge sharing capability. It further indicated that, AI demonstrates a specific set of practices that are required in daily routines. Thus, practice symbolically provide a direct lever for change that may be needed to support KS and employee's performance.

3. Methodology

3.1 Data sample and collection

This paper chose a deductive approach to find the associations of the components of the three aspects of the conceptuality in the literature review (De Santis et al., 2017; Olan et al., 2019, 2022). The approach is considered suitable given the scarcity of empirical work exploring the Association of AI as a KS tool for performance from a dynamic perspective. According to Shipley et al. (2013), deductive studies have become one of the most common ways of conducting quantitative inquiry. This paper opted for an in-depth deductive study approach (Arshad et al., 2014) to enhance knowledge of the role of AI entities during the implementation of KS stages of the employees' interactions. According to Karatop et al. (2015), it is imperative that associations of the entities be studied over time. Similarly, Moraga et al. (2003) argue that KS studies should be quantifiable and show how association content, governance and structure emerge over time.

This design allows this paper to deeply comprehend the dynamics of the socio-technical association. Through purposeful sampling (Klashanov, 2018), this paper identified three perspectives to examine, these perspectives showed diverse characteristics in terms of the AI entities, the types of knowledge and the employees' performance.

The Qualtrics platform was utilised to extend invitations to potential participants from Europe for their involvement in the study. A total of 426 participants completed the questionnaire. We specifically targeted individuals in the field of HR, including professionals, experts, and researchers. Additionally, we wanted professionals and researchers in the field of AI who possess a minimum of one year of practical experience in any of the following areas: HRM, technology management, management, and innovation. The study participants were provided with information regarding the objectives of the research, while the survey underwent rigorous evaluation by a team of expert reviewers. Upon the conclusion of the online survey process, a total of 300 respondents successfully fulfilled the survey requirements. Before doing the comprehensive data collection, preliminary testing was conducted using a sample size of seven.

3.2 Analytical techniques

Scholars for example, Arshad et al. (2014); De Santis et al. (2017); Karatop et al. (2015); Moraga et al. (2003) have proposed fuzzy theory in an attempt to validate and systematise two human capabilities within an organisation: the capability to converse, reason and make decisions in an environment of imperfect data, and the ability to perform a wide variety of physical and mental tasks without using quantities or measurements. The organisation is permeated with fuzziness (De Santis et al., 2017; Keshtkar & Arzanpour, 2017), fuzzy logic is desirable to deal effectively with fuzzy issues. Fuzzy logic has demonstrated its ability to analyse problems in areas of an organisation, especially in engineering sciences. Unfortunately, according to Woodside (2013), social scientists generally tend to avoid fuzzy logic in their research. In economics and management, decision-makers face difficulties involving much flawed knowledge and imprecise factors in circumstances where estimated reasoning is in fact the leading way to making decisions. The level of fuzziness is higher for management situations than it is for most engineering situations. Unfortunately, management science has not consequently given attention to fuzzy logic.

The fsQCA is a set-theoretical analysing technique that was developed for investigation of phenomena not only in engineering and natural sciences but also in social sciences, representing complex causality for instance the features of configurational equifinality and casual asymmetry in limited number of analysis (Cardenas et al., 2016; Hajek & Prochazka, 2016; Zhang et al., 2017). The fsQCA consists of associations of variables among independent and dependent conditions, which are absent using statistical denotations in analysis techniques. Furthermore, fsQCA offers a structural method for data calibration of collected questionnaires into fuzzy set and for creating fuzzy set membership assignment.

fsQCA validate a complete and wide-ranging interpretation of the antecedents and complex results of AI and KS association. In addition, Complementarity and equifinality are two main discussions of this paper. The underlying statement as the set theoretic method provides a direction for characteristics determinate and the distinctive structures with produce different outcomes depending on the variables.

4. Data results

The set-theoretic approach is uniquely suitable for analysing the impact of complementarity between a business unit's KS and AI depending on the performance variables which it is built on, the set associations of how variables combine to form the outcomes, which can show substantial higher support for causal complexity (Klashanov, 2018). In distinction from regression analysis, nonparametric set methods support model representativeness in a reduced amount of a concern because investigators do not conclude that data derived from a specified probability dispersal.

Part of QCA procedure, the calibration of sets analyses investigation constructs by reduced sample dependence. As set membership is well-defined relatively to practical knowledge rather to the assumption by sample means, by this means acknowledging the significant of sample representativeness.

The initial pathway shows the important influence of KS variables, with AI variables and inclusion of organisation's variables, outcomes are high performance of organisation's activities for knowledgeable organisational interactive employees (consistency = 0.88; coverage = 0.75). Secondly, the pathway shows that combination model after complex solution, as indicated in Table 2 below, there are results supporting the associations (frequency cut-off = 1.00; consistency cut-off = 0.90). Limited corresponding annulled value of HRM-practices in combining other antecedent conditions.

In Table 2, the results recommend a set-theoretic approach allow for the investigation of situations, in which the number of associations is probably large for traditional analysis, and small for some statistical analyses. Although fsQCA firstly measured a small-N approach, recent research uses extended QCA to analysis large-N settings without any problem.

Table 2. Descriptive statistics of membership scores of survey data after calibration.

Survey data	Mean	Std. Dev.	Min.	Max.	N Cases	Missing
Knowledge sharing: KS						
Prospector (p)	0.07675969	0.1860109	0.00012339	0.95257	107	0
Analyser (a)	0.5891829	0.3795915	0.00012339	0.99959	107	0
Defender (d)	0.1822357	0.3078002	0.00012339	0.9955	107	0
Reactor (r)	0.01510802	0.06770562	0.00012339	0.64566	107	0
Differentiation (dif)	0.4970566	0.413801	0.000049522	0.99945	107	0
Low-Cost leadership (lc)	0.4859037	0.3995412	0.00074603	0.99966	107	0
Artificial intelligence: AI						
Operation capabilities (op)	0.5204947	0.404373	0.00027961	0.99978	107	0
R&D capabilities (rd)	0.5359848	0.4050848	0.00055278	0.99753	107	0
MIS capabilities(mis)	0.5054322	0.4291049	0.0000061442	0.99995	107	0
Sale & distribution capabilities (sd)	0.5148085	0.4215927	0.000037169	0.99331	107	0
Marketing capabilities (mkt)	0.5303368	0.4190876	0.000013007	0.99925	107	0
Performance dimensions: PD						
Input efficiency: Expense ratio (ie)	0.4532633	0.3889686	0.00091105	0.99753	107	0
Output efficiency 1: Loss ratio (oe1)	0.5119707	0.3844112	0.00055278	0.99753	107	0
Output efficiency 2: Investment Yield (oe2)	0.4389924	0.3259911	0.047426	0.99945	107	0
Effectiveness 1: Net written premium growth (ef1)	0.4658962	0.3812927	0.017986	0.99945	107	0
Effectiveness 2: Market shares (ef2)	0.5024591	0.417362	0.0066929	0.98201	107	0
Adaptability 1: Number of new products offered (ad1)	0.5139921	0.4050486	0.047426	0.99978	107	0
Adaptability 2: Percentage of net written premium accounted for by new product within the past year (ad2)	0.4468843	0.4096512	0.047426	0.99999	107	0
Overall performance 1: Combined ratio (oa1)	0.5215535	0.398142	0.00055278	0.99753	107	0
Overall performance 2: ROE (oa2)	0.555875	0.4073075	0.0000061442	0.99945	107	0

4.1 Complex causal statements AI, KS, and EP outcome

The outcome shows the complex antecedent conditions with associating member scores in the result criteria of EP combining to AI variables, KS and the equivalent negated variables of EP. Hereafter, this paper procedures with consistency scores which shows complex causal combinations for variables conditions and cut-off consistency score of 0.80. This outcome demonstrations that the combinations of consistency scores are some worth higher than the threshold. Table 3 also demonstrates how all solutions are supportive. In conclusion, consistency values are higher than 0.74, which indicates that all coverage values with range between 0.25 and 0.90 are considered as previous studies (Woodside, 2013) suggests that this range has priority in associations.

Complex antecedent condition demonstrations association of KS variables to AI variables which highly influence the condition of OP. In the same way, KS also combinates antecedent conditions of supportive complex causal combination. In addition, when high impact of AI is associated with one of the derived pathways, this suggest that there is a significant association for high.

Table 3. Result of KS and AI components comparativity.

	KS-IE			KS-IEF
Condition	S1	S2	S3	S1
Prospector (P)	θ*	θ*	θ*	θ*
Analyser (A)	θ	●	●	θ
Defender (D)	θ	θ	θ	θ
Reactor (R)	θ*	θ*	θ*	●
Differentiation (Dif)	θ	θ	●	●
Low cost (Lc)	θ	●	θ	
Observed cases	7	5	4	1
Consistency	**0.724529**	**0.713514**	**0.704821**	**0.900405**
Raw coverage	0.229618	0.209680	0.183706	0.022014
Unique coverage	0.137127	0.107350	0.069850	0.022014
Solution consistency		**0.718015**		**0.900405**
Solution coverage		0.437901		0.022014
T1: H•S⊂Y -Consistency	0.539667	0.545450	0.622072	**0.808104**
T1: H•S⊂Y -Raw coverage	0.043730	0.043524	0.036555	0.003689
T2: ~H•S⊂Y -Consistency	***0.722497***	***0.713185***	***0.703511***	***0.890097***
T2: ~H•S⊂Y -Raw coverage	0.227479	0.210136	0.183932	0.022590
T3: H•~S⊂~Y – Consistency	***0.814957***	***0.814957***	***0.814957***	0.651971
T3: H•~S⊂~Y -Raw coverage	0.112421	0.112421	0.112421	0.100733
T4: ~H•~S⊂Y -Consistency	0.463812	0.478831	0.485383	0.523584
T4: ~H•~S⊂Y -Raw coverage	0.837649	0.873858	0.891719	0.934861
Solution path hypothesis result	Reject	Reject	Reject	Support
Combined solution path unique coverage of same hypothesis result		0.314327		0.022014
Overall hypothesis result		**Reject**		**Support**

5. Discussion

In the contributions, HRM defines the right AI tools that develop, enable, motivate, and retain KS culture that an organisation's human capital contributes to reaching the organisational goals. However, due to a changing labour market, it is questionable whether these HRM should focus target at all categories of employees, in addition to the relationships between HRM introducing AI tools and employee performance, the impact of employee adaptation to the new system or alternatively retaining relationship already existing.

AI and KS are shown to have significant implications in contemporary HRM, as indicated by the findings presented in Table 3. These technologies provide a wide range of advantages:

The utilisation of AI facilitates the streamlining of human resources (HR) processes, namely in the automation of repetitive tasks such as candidate screening and administrative responsibilities. This automation allows HR professionals to allocate their time and efforts towards strategic initiatives and fostering employee engagement. The utilisation of AI-driven analytics in the field of human resources enables the collection of data-driven insights, hence enhancing the decision-making process in various domains like talent acquisition, retention, and performance management. AI-powered KS platforms play a crucial role in facilitating the flow of information and expertise among employees, hence cultivating a culture of continual learning and collaboration inside the organisation. Enhanced recruitment: The utilisation of AI in the recruitment process facilitates the identification of highly qualified candidates through the analysis of resumes and their alignment with job descriptions. This approach mitigates bias and enhances the likelihood of securing the most suitable individuals for a given position. The utilisation of AI holds promises in the realm of employee well-being, as it has the potential to accurately forecast instances of employee burnout and provide appropriate interventions. This application of AI has the capacity to enhance overall well-being and job satisfaction among employees.

The integration of AI has the potential to foster creativity and innovation within organisational settings. This is achieved by the automation of mundane and repetitive work, which liberates employees to concentrate on more inventive and imaginative parts of their professional responsibilities. Additionally, AI systems can offer valuable insights and analysis, further augmenting the creative capabilities of individuals within the organisation. Therefore, the integration of AI and KS is crucial in the field of HRM. This integration serves to optimise various HR processes, enhance decision-making capabilities, cultivate a culture of continuous learning, and promote employee well-being. Ultimately, these advancements contribute to the overall effectiveness and competitiveness of the company.

KS practices in workplaces are becoming most popular benefits for employee's performance, as KS can help to advance employees' skills set and, consequently, result in greater employee satisfaction, accomplishment and self-belonging (Malik et al., 2020). However, scholars have highlighted the fact that the implementations of KS practices do not guarantee employees interactions. The importance of KS culture is particularly significant in day-to-day responsibilities of the employees, in this case, KS practices are not formalised but each organisation develop and implement the most suitable for the employees. The key benefits of proposing an AI enable KS tool for employees in an organisation to identify an enabling environment for the retention of skilled employees, provide a platform to improve organisational productive and reduce costs through better efficiency (improving products and services to customers), and increasing profitability (Chen & Chen, 2013; Pak et al., 2019).

This paper scrutinises the AI influence the implementation of KS tool for improving employee's performance. The association (LCD-IE) is derived from the three possible components, external validity which requested respondents to associate these AI variables with other competitors, KS typology cataloguing method support the research results (Huang & Rust, 2018; Klein & Potosky, 2019; Soriano & Huarng, 2013) and enable me to consider both best cost and stuck in the middle, data unintentionally fall into narrow sense accepts that AI positions are largely attractive or profitable, even if there are examples of unsuccessful implementations of AI systems. Chen et al. (2012) recommends that erroneously classified AI variables for LC and DIF units are under median as fixed in the middle of the table, which in turn results in the finding that stuck in the middle also performs well.

HRM-practices drive employees' motivation to share knowledge with each other and collaborate during team activities, thus improving the value of organisation's workforce. Consequently, improving organisational performance with employees' innovative discovery during KS activities (DiVaio et al., 2020; Vrontis et al., 2022). These performance criteria consist of values, infrastructures, technological innovations, and employees' satisfactions, which in turn promote the organisation's agenda through the benefits of AI.

6. Conclusions, limitation, and future research

The substantial application of AI in any organisation can lead to the improvement of employees' performance if there is an enabling KS environment. fsQCA helps with the data analytic technique to develop associations for the positive influence of HRM on the implementation of a new practice for AI enabled KS tool. The use of fsQCA in this paper discusses new aspects for AI contribution to employees' performance.

This paper is not without its limitation. The developed conceptual model took into consideration three factors, other factors such as leadership, technology, and cost, which may or may not support the antecedent conditions of the associations in the complex solutions were omitted. Future research could consider other factors mentioned above by categorising precise associations based on country where organisations are planning AI implementation. Finally, this paper emphases solely on variables in association and complex solution, in view of other factors which are indirect variable for AI and EP. There are many indirect variables that provide analytical outcomes to advance the validity of the results.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributors

Femi Olan PhD, is a Senior lecturer ® (Associate Professor) at the Strategy, Operations, and Entrepreneurship (SOE) of the Essex Business School (EBS). My research interests are in the following areas: digital entrepreneurship, knowledge management, performance management, and information technology with key focus in (1) the societal implications of technology, (2) the contribution of artificial intelligence to entrepreneurial resilience, and (3) emerging issues in digital entrepreneurship. My research has been published in world-leading and internationally excellent journals in the information systems and management disciplines. These include Information Systems Frontiers (AJG3, IF 6.191), Journal of Business Research (AJG3, IF 7.550), International Journal of Production Research (AJG3, IF 8.568) and Technological Forecasting & Social Change (AJG3, IF 8.593) among others. I am currently an Editor for Cogent Business & Management Journal (AJG 1*, IF 2.000) and Guest Editor for the (1) Annals of Operations Research (AJG 3*, IF 4.854) special Issue on Fake News, Misinformation and Supply Chain

Disruptions, (2) Sustainability (IF 3.251) Special Issue on Sustainable Agriculture-Food Supply Chains: Innovation, Technologies, and (3) Decisions and Information Systems Frontiers (AJG 3*, IF 6.191) Special Issue on Information Management in Times of Crisis. I am a coordinating board member of the Euro Working Group – Decision Support Systems (EWG-DSS), member of the organising committee for annual conference of EWG-DSS International Conference on Decision Support System Technology (ICDSST), and I have presented my research work at several international and UK conferences. I have undertaken high value projects funded by UK Higher Education Academy (HEA) and the European Commission. I supervise PhD students in the area of relevant to the Department of Entrepreneurship, Innovation and Strategy and also acted as an examiner for PhD students internally, externally and internationally.

Richard B. Nyuur PhD, is Head of International Business, Marketing and Strategy Department and Professor of International Business at the University of Bradford School of Management. Prior to joining the University of Bradford, he was an Associate Professor of International Business and Strategy at Newcastle Business School (Northumbria University, UK), and held a number of leadership roles including the Head and Deputy Head of the Entrepreneurship, Strategy and Innovation Department, and the Faculty Director of Study Abroad and International Student Wellbeing, among others, all within the Faculty of Business and Law. His research broadly engages with international business and strategy focusing specifically on foreign direct investment (FDI); SME internationalisation, international innovation and strategic adaptiveness; international human resource management, and corporate social responsibility. His publications have appeared in top-tier journals such as, British Journal of Management, Journal of International Management, International Marketing Review, Journal of Business Research, Journal of Small Business Management, International Journal of HRM, Technological Forecasting & Social Change, Multinational Business Review, Critical Perspectives on International Business, Thunderbird International Business Review, Human Resource Development International, and International Journal of Business Governance and Ethics. He has successfully co-guest edited special issues for Critical Perspectives of International Business journal, and IEEE Transactions on Engineering Management Journal. Richard currently serves on the editorial boards of Critical Perspectives of international Business, Journal of African Business, and European Journal of Economics and Management. He is also a Fellow of the Institute for Trade and Innovation (Offenburg University, Germany).

Emmanuel Ogiemwonyi Arakpogun PhD, is an academic in Digital Economy and International Business Strategy with research interests that interlink the liberalisation of the telecoms market and the application of universal access policies as a combined strategy for creating innovative solutions to closing the digital divides in the global south, particularly African countries. His publications and 'pipeline' research span various aspects of strategy and ICT4D using a case study approach. He reviews journals listed on the Chartered ABS, including Government Information Quarterly, Information Technology & People, International Journal of Entrepreneurship and Innovation, and Journal of Management Information Systems. He also reviews for the Academy of Management (AOM) and the Academy of International Business (AIB). Prior to joining the University of Stirling, Emmanuel worked with Newcastle Business School, Northumbria University, as Senior Lecturer in Digital Economy and International Business Strategy. Before academia, Emmanuel worked in the banking and FinTech sectors in Nigeria and the UK. He also worked briefly with Robert Bosch GmbH, the German multinational engineering and technology company, as a Sales Analyst covering European Sales and Project Management.

Ziad Elsahn PhD, is an Associate Professor in strategy and enterprise. Ziad's research interests lie at the intersection of International Business, Strategy and Organisation theory. Specifically, his research focuses on internationalisation, knowledge coordination within and between organisations, strategising and organising for institutional change and sustainable development, and strategy making processes and practices. He explores these issues in the context of cooperatives and multinational enterprises.

ORCID

Femi Olan http://orcid.org/0000-0002-7377-9882

References

Ahmed, W., Önkal, D., Das, R., Krishnan, S., Olan, F., Hardey, M., & Fenton, A. (2023). Developing techniques to support Technological solutions to disinformation by analyzing four conspiracy networks during COVID-19. *Ieee Transactions on Engineering Management*, 1–18. https://doi.org/10.1109/TEM.2023.3273191

Alkraiji, A.I., Jayawickrama, U., & Olan, F. (2023). Taxonomy of critical success factors based on players and activities across ERP projects: The perspective of ERP vendors. *International Journal of Business Information Systems*, *43*(2), 186–215. https://doi.org/10.1504/ijbis.2023.131351

Amershi, B. (2019). Culture, the process of knowledge, perception of the world and emergence of AI. *AI & SOCIETY*. https://doi.org/10.1007/s00146-019-00885-z

Aram, J.D., Morgan, C.P., & Esbeck, E.S. (1971). Relation of collaborative interpersonal relationships to individual satisfaction and organizational performance. *Administrative Science Quarterly*, *16*(3), 289–297. https://doi.org/10.2307/2391901

Arshad, M., Islam, S., & Khaliq, A. (2014). Fuzzy logic approach in power transformers management and decision making. *IEEE Transactions on Dielectrics and Electrical Insulation*, *21*(5), 2343–2354. https://doi.org/10.1109/TDEI.2014.003859

Bagdadli, S., & Gianecchini, M. (2019). Organizational career management practices and objective career success: A systematic review and framework. *Human Resource Management Review*, *29*(3), 353–370. https://doi.org/10.1016/j.hrmr.2018.08.001

Bandara, F., Jayawickrama, U., Subasinghage, M., Olan, F., Alamoudi, H., & Alharthi, M. (2023). Enhancing ERP responsiveness through big data technologies: An empirical investigation. *Information Systems Frontiers*, 1–25. https://doi.org/10.1007/s10796-023-10374-w

Bitencourt Machado, T.R., Sornberger, G.P., & Josende Coan, F.M. (2015). Evaluation of organizational performance in small and medium enterprises: Multicase study in dealers agricultural machinery and implements. *Revista Contabilidade E Controladoria-Rc C*, *7*(3), 21–37. https://doi.org/10.5380/rcc.v7i3.36772

Buenechea-Elberdin, M., Sáenz, J., & Kianto, A. (2017). Exploring the role of human capital, renewal capital and entrepreneurial capital in innovation performance in high-tech and low-tech firms. *Knowledge Management Research & Practice*, *15*(3), 369–379. https://doi.org/10.1057/s41275-017-0069-3

Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2018). Notes from the AI frontier: Modeling the impact of AI on the world economy. *McKinsey Global Institute*, *4*.

Busco, C., Frigo, M.L., Giovannoni, E., & Maraghini, M.P. (2012). Control vs. creativity: Strive toward a twofold purposeful imbalance to keep management control from killing creativity and innovation.(COVER STORY). *Strategic Finance*, *94*(2), 29.

Cardenas, J.R.G., Nebot, A., Mugica, F., & Vellido, A. (2016). A decision making support tool: The resilience Management fuzzy Controller. *2016 Ieee Congress on Evolutionary Computation (Cec)*, Vancouver, BC, Canada. (pp. 2313–2320). https://doi.org/10.1109/CEC.2016.7744074

Chen, L.-T., & Chen, J.-M. (2008). Collaborative marketing and production planning with IFS and SFI production styles in an ERP system. *Journal of the Chinese Institute of Industrial Engineers*, *25*(4), 337–346. https://doi.org/10.1080/10170660809509097

Chen, S.L., & Chen, H.H. (2013). Organizational forms for collaborative learning at different structures of social networks: China as an example. *Proceedings of the 10th International Conference on Innovation and Management*, Tapei, Taiwan (pp. 480–486).

Chen, H., Chiang, R.H., & Storey, V.C. (2012). Business intelligence and analytics: From big data to big impact. *Mis Quarterly*, *36*(4), 1165–1188. https://doi.org/10.2307/41703503

Cheung, S.T., Jayawickrama, U., Olan, F., & Subasinghage, M. (2023a, May 30). Check for. Decision support systems XIII. Decision support systems in an uncertain world. The Contribution of Digital Twins: 9th International Conference on Decision Support System Technology, ICDSST 2023, Albi, France. June 1, 2023, Proceedings

Cheung, S.T., Jayawickrama, U., Olan, F., & Subasinghage, M. (2023b). An investigation on cloud ERP adoption using Technology-Organisation-Environment (TOE) and Diffusion Of Innovation (DOI) theories: A systematic Review. International Conference on Decision Support System Technology, Albi, France.

Cheung, S.T., Jayawickrama, U., Olan, F., Subasinghage, M., Liu, S., Zaraté, P., Kamissoko, D., Linden, I., & Papathanasiou, J. (2023). An investigation on cloud ERP adoption using Technology-Organisation-Environment (TOE) and Diffusion Of Innovation (DOI) theories: A systematic Review. In: *Decision support systems XIII. Decision support systems in an uncertain world: The contribution of digital twins* (pp. 235–251). https://doi.org/10.1007/978-3-031-32534-2_17

Choudri, B.S., Baawain, M., Al-Sidairi, A., Al-Nadabi, H., & Al-Zeidi, K. (2016). Perception, knowledge and attitude towards environmental issues and management among residents of Al-Suwaiq Wilayat, sultanate of Oman. *International Journal of Sustainable Development and World Ecology*, *23*(5), 433–440. https://doi.org/10.1080/13504509.2015.1136857

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management*, *60*, 102383. https://doi.org/10.1016/j.ijinfomgt.2021.102383

Cunningham, J.A., Damij, N., Modic, D., & Olan, F. (2023). MSME technology adoption, entrepreneurial mindset and value creation: A configurational approach. *The Journal of Technology Transfer*, 1–25. https://doi.org/10.1007/s10961-023-10022-0

Dao, V., Langella, I., & Carbo, J. (2011). From green to sustainability: Information technology and an integrated sustainability framework. *Journal of Strategic Information Systems*, *20*(1), 63–79. https://doi.org/10.1016/j.jsis.2011.01.002

De Santis, E., Rizzi, A., & Sadeghian, A. (2017). Hierarchical genetic optimization of a fuzzy logic system for energy flows management in microgrids. *Applied Soft Computing Journal*, *60*(C), 135–149. https://doi.org/10.1016/j.asoc.2017.05.059

DiVaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *Journal of Business Research*, *121*, 283–314. https://doi.org/10.1016/j.jbusres.2020.08.019

DiVaio, A., Palladino, R., Pezzi, A., & Kalisz, D.E. (2021). The role of digital innovation in knowledge management systems: A systematic literature review. *Journal of Business Research*, *123*, 220–231. https://doi.org/10.1016/j.jbusres.2020.09.042

Dwivedi, Y.K., Hughes, D.L., Coombs, C., Constantiou, I., Duan, Y., Edwards, J.S., Gupta, B., Lal, B., Misra, S., Prashant, P., Raman, R., Rana, N.P., Sharma, S.K., & Upadhyay, N. (2020). Impact of COVID-19 pandemic on information management research and practice: Transforming education, work and life. *International Journal of Information Management*, *55*, 102211. https://doi.org/10.1016/j.ijinfomgt.2020.102211

García-Sánchez, E., García-Morales, V.J., & Bolívar-Ramos, M.T. (2017). The influence of top management support for ICTs on organisational performance through knowledge acquisition, transfer, and utilisation. *Review of Managerial Science*, *11*(1), 19–51. https://doi.org/10.1007/s11846-015-0179-3

Hajek, P., & Prochazka, O. (2016). Interval-valued fuzzy cognitive maps for supporting Business decisions. *2016 Ieee International Conference on Fuzzy Systems (Fuzz-Ieee)*, Vancouver, BC, Canada. (pp. 531–536). https://doi.org/10.1109/FUZZ-IEEE.2016.7737732

Huang, M.-H., & Rust, R.T. (2018). Artificial intelligence in service. *Journal of Service Research*, *21*(2), 155–172. https://doi.org/10.1177/1094670517752459

Hu, C.K., Liu, F.B., & Hu, C.F. (2017). Efficiency measures in fuzzy data envelopment analysis with common weights. *Journal of Industrial and Management Optimization*, *13*(1), 237–249. https://doi.org/10.3934/jimo.2016014

Ikujiro, N. (1994). A dynamic theory of organizational knowledge creation. *Organization Science*, *5*(1), 14–37. https://doi.org/10.1287/orsc.5.1.14

Jayawickrama, U., Liu, S., & Hudson Smith, M. (2017). Knowledge prioritisation for ERP implementation success: Perspectives of clients and implementation partners in UK industries. *Industrial Management & Data Systems*, *117*(7), 1521–1546. https://doi.org/10.1108/IMDS-09-2016-0390

Jayawickrama, U., Liu, S., & Smith, M.H. (2016). Empirical evidence of an integrative knowledge competence framework for ERP systems implementation in UK industries. *Computers in Industry*, *82*, 205–223. https://doi.org/10.1016/j.compind.2016.07.005

Jiang, J., Wang, S., & Zhao, S. (2012). Does HRM facilitate employee creativity and organizational innovation? A study of Chinese firms. *The International Journal of Human Resource Management*, *23*(19), 4025–4047. https://doi.org/10.1080/09585192.2012.690567

Jordan, S.L., Ferris, G.R., & Lamont, B.T. (2019). A framework for understanding the effects of past experiences on justice expectations and perceptions of human resource inclusion practices. *Human Resource Management Review*, *29*(3), 386–399. https://doi.org/10.1016/j.hrmr.2018.07.003

Jung, Y.H., & Takeuchi, N. (2010). Performance implications for the relationships among top management leadership, organizational culture, and appraisal practice: Testing two theory-based models of organizational learning theory in Japan. *The International Journal of Human Resource Management*, *21*(11), 1931–1950. https://doi.org/10.1080/09585192.2010.505093

Karatop, B., Kubat, C., & Uygun, O. (2015). Talent management in manufacturing system using fuzzy logic approach. *Computers & Industrial Engineering*, *86*, 127. https://doi.org/10.1016/j.cie.2014.09.015

Keshtkar, A., & Arzanpour, S. (2017). An adaptive fuzzy logic system for residential energy management in smart grid environments. *Applied Energy*, *186*(P1), 68–81. https://doi.org/10.1016/j.apenergy.2016.11.028

Klashanov, F. (2018). Fuzzy logic in construction management. *MATEC Web of Conferences*, 170. https://doi.org/10.1051/matecconf/201817001111

Klein, H.J., & Potosky, D. (2019). Making a conceptual contribution at human Resource Management Review. *Human Resource Management Review*, *29*(3), 299–304. https://doi.org/10.1016/j.hrmr.2019.04.003

Kroll, A. (2015). Exploring the link between performance information use and organizational performance: A contingency approach. *Public Performance & Management Review*, *39*(1), 7–32. https://doi.org/10.1080/15309576.2016.1071159

Landay, K., & Harms, P.D. (2019). Whistle while you work? A review of the effects of music in the workplace. *Human Resource Management Review*, *29*(3), 371–385. https://doi.org/10.1016/j.hrmr.2018.06.003

LIKENS, J. (1978). *Organizational formality and performance in motor-carrier industry-wyckoff, dd*. SPRINGER VERLAG. (175 FIFTH AVE, NEW YORK, NY 10010).

Long, R.J. (1978). The effects of employee ownership on organizational identification, employee job attitudes, and organizational performance: A tentative framework and empirical findings. *Human Relations*, *31*(1), 29–48. https://doi.org/10.1177/001872677803100102

Malik, A., Froese, F.J., & Sharma, P. (2020). Role of HRM in knowledge integration: Towards a conceptual framework. *Journal of Business Research*, *109*, 524–535. https://doi.org/10.1016/j.jbusres.2019.01.029

Malik, A., Pereira, V., & Tarba, S. (2017). The role of HRM practices in product development: Contextual ambidexterity in a US MNC's subsidiary in India. *The International Journal of Human Resource Management*, *30*(4), 536–564. https://doi.org/10.1080/09585192.2017.1325388

Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., Ko, R., & Sanghvi, S. (2017). Jobs lost, jobs gained: Workforce transitions in a time of automation. *McKinsey Global Institute*, *150*(1), 1–148.

Martínez-López, F.J., & Casillas, J. (2013). Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. *Industrial Marketing Management*, *42*(4), 489–495. https://doi.org/10.1016/j.indmarman.2013.03.001

Mattsson, B., Fischborn, M., Brunson, M., & Vacik, H. (2019). Introducing and evaluating a knowledge transfer approach to support problem solving in and around protected areas. *Ambio*, *48*(1), 13–24. https://doi.org/10.1007/s13280-018-1048-5

Moraga, C., Trillas, E., & Guadarrama, S. (2003). Multiple-valued logic and Artificial intelligence fundamentals of fuzzy control revisited. *The Artificial Intelligence Review*, *20*(3/4), 169–197. https://doi.org/10.1023/B:AIRE.0000006610.94970.1d

Narayanamurthy, G., & Tortorella, G. (2021). Impact of COVID-19 outbreak on employee performance–moderating role of industry 4.0 base technologies. *International Journal of Production Economics*, *234*, 108075. https://doi.org/10.1016/j.ijpe.2021.108075

Nonaka, I., & Von Krogh, G. (2009). Perspective—tacit knowledge and knowledge conversion: Controversy and advancement in organizational knowledge creation theory. *Organization Science*, *20*(3), 635–652. https://doi.org/10.1287/orsc.1080.0412

Olan, F., Arakpogun, E.O., Suklan, J., Nakpodia, F., Damij, N., & Jayawickrama, U. (2022). Artificial intelligence and knowledge sharing: Contributing factors to organizational performance. *Journal of Business Research*, *145*, 605–615. https://doi.org/10.1016/j.jbusres.2022.03.008

Olan, F., Liu, S., Neaga, I., & Alkhuraiji, A. (2016). How knowledge sharing and business process contribute to organizational performance: Using the fsQCA approach. *Journal of Business Research*, *69*(11), 5222–5227. https://doi.org/10.1016/j.jbusres.2016.04.116

Olan, F., Liu, S., Neaga, I., Chen, H., & Nakpodia, F. (2019). How cultural impact on knowledge sharing contributes to organizational performance: Using the fsQCA approach. *Journal of Business Research*, *94*, 313–319. https://doi.org/10.1016/j.jbusres.2018.02.027

Olan, F., Liu, S., Suklan, J., Jayawickrama, U., & Arakpogun, E.O. (2022). The role of Artificial intelligence networks in sustainable supply chain finance for food and drink industry. *International Journal of Production Research*, *60*(14), 4418–4433. https://doi.org/10.1080/00207543.2021.1915510

Onjewu, A.-K.E., Olan, F., Nguyen, S., Paul, H.T.T., & Nguyen, H.T.T. (2023). The effect of government support on bureaucracy, COVID-19 resilience and export intensity: Evidence from North Africa. *Journal of Business Research*, *156*, 113468. https://doi.org/10.1016/j.jbusres.2022.113468

Pak, K., Kooij, D.T., De Lange, A.H., & Van Veldhoven, M.J. (2019). Human resource management and the ability, motivation and opportunity to continue working: A review of quantitative studies. *Human Resource Management Review*, *29*(3), 336–352. https://doi.org/10.1016/j.hrmr.2018.07.002

Patnaik, D. (2015). Theorizing change in artificial intelligence: Inductivising philosophy from economic cognition processes. *AI & SOCIETY*, *30*(2), 173–181. https://doi.org/10.1007/s00146-013-0524-5

Pavlou, P.A. (2018). Internet of things – will humans be replaced or augmented? *GfK Marketing Intelligence Review*, *10*(2), 42–47. https://doi.org/10.2478/gfkmir-2018-0017

Prasad, B., & Prasad, B. (2008). *Soft computing applications in industry*. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-77465-5

Prentice, C., Dominique Lopes, S., & Wang, X. (2020). Emotional intelligence or artificial intelligence– an employee perspective. *Journal of Hospitality Marketing & Management*, *29*(4), 377–403. https://doi.org/10.1080/19368623.2019.1647124

Rai, R.K. (2011). Knowledge management and organizational culture: A theoretical integrative framework. *Journal of Knowledge Management*, *15*(5), 779–801. https://doi.org/10.1108/13673271111174320

Riemann, A. (1978). Organizational forms of multi-farm work performance-development, presentation, evaluation].[German]. *Landtechnik*.

Robbins, S. (2020). AI and the path to envelopment: Knowledge as a first step towards the responsible regulation and use of AI-powered machines. *AI & SOCIETY*, *35*(2), 391–400. https://doi.org/10.1007/s00146-019-00891-1

Robbins, S.A. (2019). AI and the path to envelopment: Knowledge as a first step towards the responsible regulation and use of AI-powered machines. *AI&Society: The Journal of Human-Centered Systems and Machine Intelligence*, *35*(2), 391–400. urn:issn. https://doi.org/10.1007/s00146-019-00891-1

Schmidpeter, R., & Osburg, T. (2013). *Social innovation: solutions for a sustainable future*. Dordrecht: Springer.

Sharma, S., & Harsh, O.K. (2017). Role of explicit knowledge Management and reuse in higher educational environment. *International Journal of Advanced Computer Science & Applications*, *8*(1), 193–197. https://doi.org/10.14569/IJACSA.2017.080125

Shipley, M., Johnson, M., Pointer, L., & Yankov, N. (2013). A fuzzy attractiveness of market entry (FAME) model for market selection decisions. *The Journal of the Operational Research Society*, *64*(4), 597–610. https://doi.org/10.1057/jors.2012.59

Shirouyehzad, H., Mokhatab Rafiee, F., & Berjis, N. (2017). Performance evaluation and prioritization of organizations based on knowledge management and safety management approaches using DEA: A case study. *Journal of Modelling in Management*, *12*(1), 77–95. https://doi.org/10.1108/JM2-03-2015-0010

Soriano, D.R., & Huarng, K.-H. (2013). Innovation and entrepreneurship in knowledge industries. *Journal of Business Research*, *66*(10), 1964–1969. https://doi.org/10.1016/j.jbusres.2013.02.019

Spanaki, K., Papadopoulos, T., Jayawickrama, U., Olan, F., & Liu, S. (2023). Fake news, misinformation, and supply chain disruptions: The role of emerging technologies. *Annals of Operations Research*, *327*(2), 1–4. https://doi.org/10.1007/s10479-023-05498-w

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*, *61*(4), 15–42. https://doi.org/10.1177/0008125619867910

Torresen, J. (2018). A Review of future and ethical perspectives of robotics and AI.(Report). *Frontiers in Robotics and AI*, *4*, 4. https://doi.org/10.3389/frobt.2017.00075

Troth, A.C., & Guest, D.E. (2020). The case for psychology in human resource management research. *Human Resource Management Journal*, *30*(1), 34–48. https://doi.org/10.1111/1748-8583.12237

Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. *International Journal of Information Management Data Insights*, *1*(1), 100002. https://doi.org/10.1016/j.jjimei.2020.100002

Von Krogh, G., Nonaka, I., & Aben, M. (2001). Making the most of your company's knowledge: A strategic framework. *Long Range Planning*, *34*(4), 421–439. https://doi.org/10.1016/S0024-6301(01)00059-0

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *The International Journal of Human Resource Management*, *33*(6), 1237–1266. https://doi.org/10.1080/09585192.2020.1871398

Wales, W., Monsen, E., & McKelvie, A. (2011). The organizational pervasiveness of entrepreneurial orientation. *Entrepreneurship Theory and Practice*, *35*(5), 895. https://doi.org/10.1111/j.1540-6520.2011.00451.x

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J.R., & Tchatchouang Wanko, C.E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal*, *26*(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411

Williams, C.J. (2009). *A Review of: "moral machines: Teaching robots right from wrong by W. Wallach and C. Allen"* (Vol. 2009). Oxford University Press. ISBN: 9-780195-374049. In (Vol. 27, pp. 243-248)

Woodside, A.G. (2013). Moving beyond multiple regression analysis to algorithms: Calling for adoption of a paradigm shift from symmetric to asymmetric thinking in data analysis and crafting theory. *Journal of Business Research*, *66*(4), 463–472. https://doi.org/10.1016/j.jbusres.2012.12.021

Wright, S.A., & Schultz, A.E. (2018). The rising tide of artificial intelligence and business automation: Developing an ethical framework. *Business Horizons*, *61*(6), 823–832. https://doi.org/10.1016/j.bushor.2018.07.001

Zahraee, S., Assadi, M.K., & Saidur, R. (2016). Application of artificial intelligence methods for hybrid energy system optimization. *Renewable and Sustainable Energy Reviews*, *66*, 617–630. https://doi.org/10.1016/j.rser.2016.08.028

Zhang, H.Y., Ji, P., Wang, J.Q., & Chen, X.H. (2017). A novel decision support model for satisfactory restaurants utilizing social information: A case study of TripAdvisor.com. *Tourism Management*, *59*, 281–297. https://doi.org/10.1016/j.tourman.2016.08.010

Zhao, G., Olan, F., Liu, S., Hormazabal, J.H., Lopez, C., Zubairu, N., Zhang, J., & Chen, X. (2022). Links between risk source identification and resilience capability building in agri-food supply chains: A comprehensive analysis. *Ieee Transactions on Engineering Management*, 1–18. https://doi.org/10.1109/TEM.2022.3221361