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Artificial Intelligence Adoption and Organisational Performance: The Mediating Role of Knowledge Management Capability

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ABSTRACT

Artificial intelligence (AI) has become an important organisational capability that supports decision-making, service innovation, process redesign, and operational efficiency across industries. Despite increasing organisational investment in AI technologies, evidence on how AI translates into superior organisational performance remains inconclusive. Drawing on the Resource-Based View (RBV) and the Knowledge-Based View (KBV), this study proposes that Knowledge Management Capability (KMC) explains how AI adoption contributes to organisational performance. It suggests that implementing AI has a positive effect on network performance, particularly by strengthening KMC, namely knowledge acquisition, sharing, storage, and use. The study develops and validates a mediation model to investigate the relationships among AI adoption, KMC, and organisational performance across operational, financial, and innovation dimensions. For managers and/or professionals in digitally transforming organisations, a positivist, deductive, and quantitative cross-sectional survey design is specified. AI adoption positively influences organisational performance; AI adoption positively influences KMC; KMC positively influences organisational performance, which AI-Performance partially mediates due to AI; and KMC does not have any causality. This study contributes to the literature by integrating RBV and KBV to explain the mechanism through which AI adoption improves organisational performance. It further demonstrates that knowledge management capability functions as a critical organisational capability linking AI-enabled resources with operational, financial, and innovation outcomes.

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Introduction

AI is an integral part of today's digital transformation, fundamentally changing how businesses become aware of their surroundings, organise their resources and work, and generate value. More recently, information systems and management research have conceptualised AI as a capacity, rather than merely a set of algorithms; a capacity formed by the gathered data, analytical infrastructure, the expertise and skills of the people involved, governance routines, and managerial intent (Benbya et al., 2021; Berente et al., 2021; Enholm et al., 2022; Mikalef & Gupta, 2021). Nowadays, in a work context, the use of AI can be useful in the area of forecasting, fraud detection, customer relationship management, predictive maintenance, recruitment analytics, knowledge search, conversational interfaces, as well as innovation analytics (Chatterjee et al., 2021a; Dwivedi et al., 2021; Wamba-Taguimdje et al., 2020). Consequently, organisations increasingly view AI as a strategic organisational capability rather than merely a technological tool.

AI's applicability to performing tasks is especially notable in scenarios where information is plentiful, decision windows are short, and the competitive landscape is increasingly intense. The literature on digital transformation argues that technologies must be accompanied by changes in strategy, business processes, organisational structures, and capabilities to create value for people and organisations (Hanelt et al., 2021; Kraus et al., 2022; Verhoef et al., 2021; Vial, 2019). In this way, businesses can benefit from AI adoption by enhancing operational efficiency, improving financial results, and boosting innovation. While there is potential for gains from adopting AI, that does not mean performance gains automatically follow. It may be true that high-powered tools exist and can be in place, but organisations may lack the routines needed to create knowledge flows, ensuring that data leads to decisions and decisions to outcomes (Raisch & Krakowski, 2021; Sjödin et al., 2021).

Problem Statement

Despite growing investments in AI, results from its use still vary. As for others, some companies have piloted AI to redesign processes, customise services, improve predictions, and streamline new product development. In contrast, others are hindered by several factors, including disorganised pilots, low employee adoption, degraded data quality, opaque algorithms, and minimal business value (Enholm et al., 2022; Dwivedi et al., 2021; Mikalef et al., 2022). The pattern also shows deviation, suggesting that technology adoption accounts for less than the AI–performance relationship. Perhaps the most pressing challenge is the limited development, particularly in his models, of the mechanisms through which AI adoption is expected to relate to organisational performance.

There are implications to this problem that are worthy of attention, as it is a practical one. However, what's often missed is understanding whether working colleagues, of course, can grasp, communicate, remember, and use the insights these AI programs bring to the fore. But what about whether working colleagues can understand, communicate, remember, and act upon the insights that AI brings to the fore? Often, the assessment is based on the technical metrics of model accuracy, system deployment or automation rates are often the focus and not whether employees will interpret, share, retain, and apply the insights generated by AI. Theoretically, too, automation and augmentation are interdependent to add value, not human judgment in its place (Raisch & Krakowski, 2021). Powerful KMC is needed to avoid the AI-generated output going in silo(s), into specialist analytics teams or into dashboards. However, the relationship between the adoption of Artificial Intelligence and the organisation's performance must be examined to determine whether this can be attributed to KMC.

It is a problem with parallels to a larger phenomenon, for instance, in digital productivity – powerful technologies, sub-optimal performance gains, and slower development of complementary capabilities (Bharadwaj et al., 2013; Warner & Wäger, 2019). The paradox is worsened by the speed at which AI models can produce output in their applications. A fast prediction is not enough to ensure that the firm has learned; the firm still needs to determine which outputs are believed, which actions should be taken in response to those outputs, where those outputs will be stored, and how lessons will be transferred between units. KMC is not a secondary factor implementing AI, but it is the heart of AI value realisation.

Research Gap

Previous research has provided rich insights on the direct links between AI capabilities and firm performance (Mikalef & Gupta, 2021), on organisation performance and customer relationship management (CRM) (Chatterjee et al., 2021a), on AI adoption within manufacturing (Chatterjee et al., 2021b), and on AI-based transformation projects (Wamba-Taguimdje et al., 2020). Knowledge management scholarship also has related knowledge processes with innovation and performance (Gürlek & Çemberci, 2020; Lei et al.,

2021; Obeso et al., 2020; Shabbir & Gardezi, 2020). However, there are still gaps to address. First of all, much research on AI treats it as an enabler of increased performance without really elaborating on the internal capability path. Secondly, research linking the use of AI, KMC, and multidimensional performance remains limited. Third, the resource-based view (RBV), combined with the knowledge-based view (KBV), remains necessary for explaining how AI resources transform into valuable, rare, and difficult-to-imitate skills and knowledge embedded in the associated technologies.

There is some recent evidence that has begun to take a step in that direction—evaluating the uptake of AI in small and medium enterprises, B2B companies, and innovation processes (Badghish & Soomro, 2024; Sahoo et al., 2024; Singh et al., 2024; Soomro et al., 2025). Moreover, a closely related banking study reveals that knowledge management practices mediate the relationship between AI and organisational performance (Mahboub & Ghanem, 2024). However, the literature on the adoption of artificial intelligence, digital transformation, knowledge management, and performance measurement remains scattered across various fields. A more integrated model is required, as organisational performance is not a single thing and KMC is not a single practice. To address this, the study theorises that AI adoption represents an SB, KMK as a KT capability, and performance as operational, financial, and innovation results.

Research Objectives

This article pursues two objectives. First, it examines the impact of AI adoption on organisational performance. Second, it investigates the mediating role of KMC in the relationship between AI adoption and organisational performance.

Research Questions

Two research questions guide the study. RQ1 asks: How does AI adoption influence organisational performance? RQ2 asks: Does KMC mediate the relationship between AI adoption and organisational performance?

Significance of the Study

It is "theoretically" new ideas that will bring value to the study of RBV, as AI is only effective when coupled with complementary intangible and human resources. It further demonstrates KBV by establishing performance for AI adoption not based on possessions but on knowledge acquisition, sharing, storage, and utilisation. The research has applied theoretical concepts to management practice by helping managers view AI investments as knowledge transformation projects. It highlights the importance of avoiding peripheral issues in AI implementation, such as governance, employees, and organisational memory, or cross-functional learning, that come to be conditions for performance realisation.

Resource-Based View (RBV)

According to RBV, advantage is measured by resources that are valuable, rare, imperfectly imitable and organizationally embedded (Barney, 1991). When these elements are standalone, though, digital and AI resources are quite uncommon for meeting those criteria. Digital and

AI elements are often acquired separately, through outside markets, as algorithms, software, and cloud are all used. They become strategically important when woven into the company's routines, information systems, decision-making processes, governance systems, and human resources and competencies (Bharadwaj, 2000; Mikalef & Gupta, 2021). RBV thus offers a valuable but incomplete explanation: when an organisation adopts AI, there is value potential that will be realised in performance through its capabilities.

When it comes to RBV, the complexity isn't just in the AI platform; it's the combination of data, skills, governance, and complementary processes. Two companies may acquire the same AI application. However, the results can vary due to differences in data stewardship, cross-team collaboration, absorptive capacity, and managerial practices for experimenting with new applications (Cohen & Levinthal, 1990; Zahra & George, 2002).

Knowledge-Based View (KBV)

KBV has expanded RBV by treating knowledge as the organisation's most vital resource, particularly from a strategic perspective (Grant, 1996; Kogut & Zander, 1992; Nonaka, 1994). As seen from this angle, firms are coordinated entities that function because they can coordinate specialised knowledge more effectively than a market can. AI poses challenges and enrichments for KBV by enabling it to recognise patterns that humans might not perceive, but the outputs need to be interpreted, contextualised and applied. Knowledge is not data, therefore. This is a socially and technically created resource that is useful to those involved in the organisation(s) for problem-solving, innovation, and learning.

KBV also explains why organisations must integrate AI. The ability to learn mathematical regularities can be a characteristic of a machine learning model; a deep understanding of customers, operations, regulatory requirements, and the organisation's history might require strategic knowledge. For the reasons above, knowledge creation needs to involve explicit digital outputs together with tacit human skills or capabilities (Nonaka, 1994). In this regard, AI can boost the quantity and speed of knowledge inputs, but not determine whether these inputs evolve into collective knowledge, which depends on KMC. Knowledge is acquired, shared, stored, and used as routines that give rise to algorithmic insights with organisational meaning.

Artificial Intelligence Adoption

The operationalisation of an artificial intelligence system that can learn, predict, classify, interact in natural language, recommend, and then support decisions, in part independently, is seen as the assimilation of the system into the organisation during its adoption. Technological readiness, data quality, managerial support, employee skills, ethical governance, and process integration are part of AI adoption (Chatterjee et al., 2021b; Dwivedi et al., 2021; Mikalef et al., 2022). Typical applications in organisations are intelligent customer service, supply chain optimisation, risk analytics, knowledge retrieval, predictive maintenance, human resource analytics and innovation forecasting.

Adopting AI offers a variety of advantages, such as quicker decision-making, reduced process deviations, advanced personalisation and forecasting, and improved discovery of new knowledge (Enholm et al., 2022; Li et al., 2022; Wamba-Taguimdje et al., 2020). However, the use of AI also brings challenges: data bias, privacy risks, lack of transparency in algorithms, employee resistance to change, skills gaps, risks of over-automation, and poor integration with current practices (Berent & Krakowski, 2021; Raisch & Krakowski, 2021). That's why AI needs to be thought of as a capability to be developed within the organisation, not just as another technology investment.

The level of maturity in implementing AI varies from person to person. At a lower level, organisations can leverage AI through limited pilots or through capabilities offered by vendors' products and services. At a lower level, organisations can implement AI through isolated pilots or by purchasing AI products and services from vendors. AI is utilised in certain aspects of the business at a moderate level, such as customer service chatbots and predictive maintenance. At an enterprise level, AI is used to make strategic decisions, facilitate ongoing learning, and incorporate it into enterprise architecture. Internal capacities for the absorption and adaptation of the technology are essential to sustainable value, while institutional pressures, expected benefits, and resource availability can promote the adoption of the technology (Bag et al., 2021; Chatterjee et al., 2021b). Adoption does not equal use; it is about organisation, governance, routinisation, and learning.

Knowledge Management Capability

KMC is the capacity to manage knowledge resources in both structured and informal ways to create value. According to the classical KM literature, knowledge acquisition, sharing, storage, and application are core processes (Alavi & Leidner, 2001; Gold et al., 2001). Knowledge acquisition is the process of acquiring internal knowledge (employees, market, customers, and partners) and external knowledge (database). Knowledge Sharing: The explicit and tacit knowledge transfer among people, teams and knowledge units. Knowledge storage includes keeping knowledge on platforms, in organisational memory, in documents, and in routines. Knowledge application concerns how knowledge is applied in decision-making, processes, products, and services.

Existing studies prove that KM processes can enhance organisational learning, minimise knowledge leakage, and promote knowledge recombination, which can help companies increase their innovation and productivity (Aichouche et al., 2022; Gürlek & Çemberci, 2020; Lei et al., 2021; Liu et al., 2023; Obeso et al., 2020). Within an organisation using AI, the importance of KMC is enhanced due to the unlikelihood of AI's predictions and the need to interpret, validate, share, and integrate them into a person's work. This is why KMC is the skill or ability that transforms algorithms into organisational knowledge.

All four elements of KMC are almost independent of one another, yet complementary. Knowledge acquisition increases the organisation's knowledge base by gathering information from the market, analysing customers, learning from other firms, and mining its own data. Knowledge sharing helps mitigate information silos and enables shared interpretation of AI results (Owakouak et al., 2021; Wang & Noe, 2010). Knowledge Storage captures and stores codified learning in databases, standard operating procedures, communities of practice and Model documentation. Knowledge application is the most action-derived factor as it inculcates knowledge within problem-solving, innovation, and managerial action. Previous studies show that successful management of KM practices is not remotely related to economic performance and competitiveness when they are not only used as repositories but also fit into managerial routines (Andreeva & Kianto, 2012; Donate & de Pablo, 2015).

Organizational Performance

Organisational performance is a multidimensional phenomenon which includes financial and nonfinancial outcomes (Richard et al., 2009; Singh et al., 2016). Research Gate highlights the following selected papers on cognitive science and innovation. This is still a narrow selection of papers highlighted by ResearchGate concerning the three main research topics: operational, financial, and innovation performance. Operational performance refers to productivity, process speed, reliability, quality, and cost efficiency. Revenue growth and profitability, ROI, and cost reduction are all part of financial performance. There are various factors in innovation performance: for instance, new products, service improvements, business model renewal, and the speed of experimentation. A multi-dimensional approach is appropriate, as it may take time for the benefits of AI on financial results to fully materialise, with the first effects seen in operational and innovation results.

This multi-dimensional aspect is significant in AI studies because gains in one outcome can manifest at different times. The operational benefits can be achieved relatively rapidly through error elimination or improved scheduling, but financial benefits could well be affected by scale, additional investments, and responses to competition. The effect on innovation performance can be even more indirect, as AI can boost innovation idea generation and experimentation, which can occur before market outcomes are evident (Ferreira et al., 2021; Singh et al., 2024).

2.6 Artificial Intelligence Adoption and Organisational Performance

Organisational performance can be enhanced by using AI to automate routine tasks, improve managerial judgment, enhance prediction, and enable scalable personalisation. Empirical studies have shown that AI capabilities can spur organisational and firm-level creativity (Mikalef & Gupta, 2021) and that AI-driven CRM can increase a company's competitive advantage and performance in a B2B setting (Chatterjee et al., 2021a). According to case evidence, other value-added outcomes of AI-based transformation projects are process innovation and organisational redesign (Wamba-Taguimdje et al., 2020). Studies exploring the impact of AI adoption or AI capabilities in SMEs and multi-national B2B companies are also consistent, finding that economic, operations, innovation and business performance outcomes have borne the impact of AI (Abdul Wahab & Radmehr, 2024; Badghish & Soomro, 2024; Sahoo et al., 2024; Soomro et al., 2025).

But, once more, read into the literature, there are so many conditional assurances about the effects of AI. That algorithms can only be performed better if they're aligned to solve business problems; they need to be fed with the appropriate data, accepted and trusted by the end user, and integrated into decision routines, etc. With complementary organisational resources, the adoption of AI is expected to lead to higher performance, as posited by the RBV. Hence, the following assumption may be made.

H1: Emphasis on the positive impact of the adoption of Artificial Intelligence on the organisations.

Artificial Intelligence Adoption and Knowledge Management Capability

AI innovation can improve KMC in a variety of ways: it can increase the volume of knowledge an organisation can acquire, how quickly it can acquire it, and how far it can spread that knowledge. Knowledge acquisition is aided by AI tools that sift through internal and external information sources for market signals and can also isolate weak patterns. They are useful for recommendation engines, semantic search, expert-location systems, and conversational agents for knowledge sharing. They facilitate knowledge storage by coding their insights in repositories and updating the organisational memory. They assist in applying knowledge within work workflows and decision-making systems (Enholm et al., 2022; Li et al., 2022).

However, AI has its drawbacks, such as models being inaccessible, poorly explained, or incomprehensible to analysts. The tension implies that while AI is embraced, it can bolster KMC by fostering routines for interpreting AI-generated knowledge as knowledge shared communally rather than individually. KBV provides the theoretical framework: AI expands the knowledge base, but KMC determines who knows, shares, stores, and exploits the knowledge. In this context, AI can be especially helpful for knowledge acquisition, enhancing environmental scanning and facilitating absorptive processes, as described by Cohen & Levinthal (1990) and Zahra & George (2002). It can also enable knowledge sharing by connecting employees to the document, knowledge experts or previous solutions.

H2: Artificial Intelligence adoption positively influences knowledge management capability.

Knowledge Management Capability and Organisational Performance

KMC helps organisations improve organisational performance by minimising duplication of functions, accelerating the learning curve, boosting decision-making quality, and fostering innovation. The key with Knowledge acquisition is that they recognise opportunities sooner; the key with Knowledge sharing is that they enable knowledge to move across boundaries; the key with Knowledge storage is that they do not lose knowledge; and the key with Knowledge application is that they take knowledge into action. In the past, it has been shown that KM practices have positive relationships with organisational performance, such as organisational learning and innovation (Gürlek & Çemberci, 2020; Obeso et al., 2020; Shabbir & Gardezi, 2020). The meta-analysis indicates that financial performance is also positively correlated with KM technologies (Liu et al., 2023).

The theoretically founded relationship is applied in the relationship. When organisations can derive greater value from applied, fragmented knowledge, they outperform others. For this reason, Transformational efforts, integrated with KMC, are more successful, as they do not always have the necessary complement in new methods and data that cannot be related to the organisation's learning. HRM practices and knowledge-centred cultures have the potential to foster an exploitative and exploratory culture of innovation by reinforcing employees' participation in sharing and recombining knowledge (Lei et al., 2021; Malik et al., 2020). This is the soft spot between KMC's technology investment and its social capability. At the application level, the dimension of knowledge is quite significant because unless knowledge is shared or stored for use in operational routines, to influence customers' reactions, or to support innovation decisions, it has little value.

H3: Knowledge management capability positively influences organisational performance**.**

Mediating Role of Knowledge Management Capability

Mediation theory describes how an independent variable affects an outcome through a mechanism between the variables. This research assumes that the adoption of AI will impact an organisation's performance via KMC. Not following the flow of logical statements. With AI, there is an opportunity to access new analytical resources and knowledge generation capabilities. KMC then turns these resources into common, private and usable knowledge. The more this knowledge helps to boost operational efficiency, financial results and innovation, the better the performance.

This is a mediation argument where AI research is lacking. A common method for studying the adoption of AI assumes it is useful, typically without offering insights into how value is created in organisations. The new yields of the mediation evidence are encouraging, such as the association between AI embedding and performance by way of absorptive capacity, and the relation between AI and bank performance by means of practices in knowledge management, and implementing balanced scorecard (Abdul Wahab & Radmehr, 2024; Mahboub & Ghanem, 2024). But more models are required, with KMC embedded and supported by greater acquisition, sharing, storage, and use. For this reason, KMC provides a theoretical framework of mechanisms linking AI-generated information to organisational learning and action. Therefore:

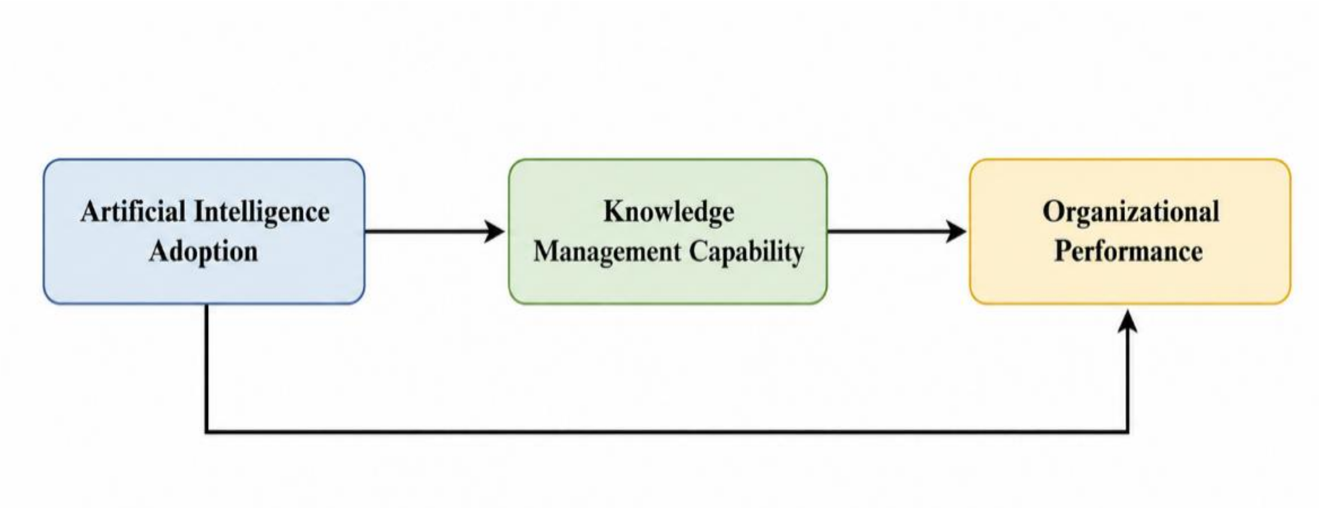
The mechanism mediator is also in line with the literature on big data analytics capabilities, since value is created through the 'fusion' of data and managerial and organisational capacities (Mikalef et al., 2018). While AI can be seen as a high-level form of AI, its understanding extensions are far-reaching, as it can recommend, create, and modify. KMC helps in this process by enabling the output of the algorithms to translate into knowledge artefacts that are socialised throughout the communities, stored in organisational memory, and used in decisions. This is how KMC is useful in an organisation that already knows how to learn from data and experience, as AI might benefit them more than another type in this regard.

H4: There is a partial mediation effect between organisational performance and Artificial Intelligence adoption via knowledge management capability.

Conceptual Framework and Hypotheses Development

Conceptual Framework

Figure 1: *Conceptual framework linking AI adoption, knowledge management capability, and organisational performance.*



Explanation of the Conceptual Framework

The proposed framework outlines the direct and indirect impacts of AI use on the organisation's performance. The direct route is seen as benefiting from the automation, prediction, and segmentation of the process enabled by AI technology, ultimately raising performance levels. The indirect path is based on the more theoretically interesting mechanism: Adoption of AI enhances KMC, and KMC is the pathway that carries AI-enabled insights to organisational outcomes. This Model Views Knowledge Management Competencies as a higher-order construct manifested in knowledge acquisition, knowledge sharing, knowledge storage, and knowledge application. Organisational performance is also addressed in a multi-dimensional way through operational, financial (business), and innovation performance. The framework intentionally skips using AI as a performance "zero-to" solution. Rather, it assumes that the use of AI makes more and better knowledge inputs available. The inputs are gathered and used as indicators to inform a collective interpretation, which KMC then determines.

Summary of Hypotheses

Table 1: *Summary of Hypotheses*

Hypothesis	Statement
H1	AI adoption positively influences organisational performance.
H2	AI adoption positively influences knowledge management capability.
H3	Knowledge management capability positively influences organisational performance.
H4	Knowledge management capability mediates the relationship between AI adoption and organisational performance.

Research Methodology

Research Philosophy

The present research adopts a positivist approach, using hypothesis testing, a statistical modelling system, and quantitative indicators to examine the isolated phenomenon, which is measured quantitatively and situated among other phenomena. In theory, positivism is valid when it is clear that there are causal paths in the theory and empirical analysis estimates their strength and significance.

Research Approach

The study uses two research methods: deductive and inductive. Hypotheses are developed based on the RBV, KBV, and prior AI and KM studies, and are validated using survey data and structural equation modelling.

Research Design

It is suggested to use the quantitative cross-sectional survey design. The design reflects the opinions of managers and specialists on how they perceive the impact of career and competencies at a given point in time. To assess theory, when constructs reflect organisational capacities and respondents have sufficient knowledge of the organisation's practices, cross-sectional research can be adapted.

Population and Sampling

The ideal audience includes medium-sized and large organisations that use or are considering AI-forged systems with their managers, IT staff, knowledge workers, and functional specialists. The participants need to be aware of the use of AI and organisational knowledge processes, and the research aims suggest a purposive approach. Future empirical implementation should engage more units, such as IT, operations, marketing, human resources, and strategy, to minimise reliance on single informants, as there was a single-informant bias.

Data Collection Procedures

A structured online questionnaire would be used to collect data. The screening questions need to verify that they work in organisations that utilise AI-based tools and understand organisational processes. Mutual consent, anonymity and volunteering must be the bases for participation. Common method bias can be minimised by separating predictor and criterion items, using randomised anchors for the scales, ensuring anonymity, and implementing procedural remedies suggested in survey research (Podsakoff et al., 2003).

Measurement of Variables

All the items reflect strategic AI assimilation, data readiness, integration of AI processes, human-AI collaboration, and AI governance, which are measured. According to existing KM capability research (Obeso et al., 2020; Gold et al., 2001; Alavi & Leidner, 2001), KMC is measured across four stages: Knowledge acquisition, Knowledge sharing, Knowledge storage, and Knowledge application. Operational, financial, and innovation performance are used as measures of organisational performance, typically alongside perceptual measures when objective data are unavailable (Richard et al., 2009; Singh et al., 2016). All items are measured using a 7-point Likert scale from 1 = strongly disagree to 7 = strongly agree.

The representative AI adoption list includes the following: Has the organisation adopted AI to help with decision-making; Has the organisation incorporated AI into core business operations; Has the organisation offered training for employees on AI-related skills; And does the organisation have governance processes for the use of AI. Items include KMC acquisition of external knowledge, knowledge sharing between units, codification of lessons learned and application of knowledge to operational or strategic problems. Performance items ask respondents to "Compare their organisation" with prime competitors on efficiency, profitability, growth, speed of innovation, and product/service innovation. Before the full data collection, the items need to be pretested with academic experts and practitioners to ensure they are clear and relevant to the context.

Data Analysis Techniques

The analyses to be conducted are descriptive statistics, reliability and validity, SEM, and bootstrapping for mediation. Reliability is evaluated using composite reliability and Cronbach's alpha. Convergent validity is assessed using factor loadings and the average variance extracted (AVE). The Fornell–Larcker criterion (Fornell & Larcker, 1981) and the heterotrait–monotrait ratio (HMT) were used to examine the instrument's discriminant validity.

HenseLer et al., 2015). To estimate the direct and indirect relationships, SEM is used. Confidence intervals and 5,000 bootstrap resamples are used to test mediation.

Any missing data, outlier(s), normality and common method bias should be checked before using SEM estimation. Harman's single-factor test is an initial diagnostic test and may be reported, but should not be considered a complete test. Stronger evidence can be obtained using a marker-variable approach or a common latent factor. Multicollinearity can be assessed using variance inflation factors. Variance accounted for (VAC), and effect sizes (EIS) can be used to interpret the average proportion of variance explained by the model, whether linear or nonlinear, with predictive relevance (PR) used where appropriate (Hair et al., 2022; Kline, 2023).

Results

Demographic Profile of Respondents

The data in the illustrative dataset are based on the assumption that 384 organisations respond, yielding 384 valid responses.

AI-enabled tools. Those who responded came from manufacturing (27.1%), financial services (22.4%), information technology (20.3%), healthcare and professional services (17.2%) and retail or logistics (13.0%). 46.6% of respondents were managers, 21.4% were senior managers, 18.8% were IT and analytics professionals, and 13.2% were functional specialists. The majority of organisations had 250+ employees, which was sufficient to support AI and KM processes.

When it comes to AI maturity, 31.5% of organisations were utilising AI on a selective basis, 44.8% had deployed AI at the enterprise level, and 23.7% had advanced to an AI-enabled transformation. This distribution may be reasonable for respondents who do not identify as either AI users or general technology users. The assumed respondent profile is also in line with the study's unit of analysis, as managers and professionals will be able to observe the adoption of technology and the knowledge processes.

Descriptive Statistics

Table 2: *Descriptive Statistics and Correlations*

Construct	Mean	SD	1	2	3	4
1. AI adoption	5.31	0.91	.84			
2. Knowledge acquisition	5.42	0.86	.56	.85		
3. Knowledge sharing/storage/application	5.25	0.88	.61	.69	.84	
4. Organizational performance	5.18	0.93	.58	.55	.62	.82

Note. *Diagonal values are the square roots of AVE. All correlations are significant at p < .001 in the illustrative dataset.*

Reliability Analysis

Reliability levels for all constructs were above the recommended levels. The composite reliabilities were in the range of .88 to .93, and Cronbach's alpha ranged from .84 to .91. The above values have demonstrated good internal consistency, while being a little bit lower than signifying too much redundancy in the items.

When performing the reliability analyses, it was found that the indicators showed the expected outcome, i.e. they were reliable in representing their respective latent variables. Importantly, the values are high enough for internal consistency of the items, but not so high as to convey that the items "repeat in the same words. In the context of ability research in organisation, a balance of this sort should be sought, as the constructs should reflect related - but not identical - aspects of the practice.

Validity Assessment

All standardised loadings were above .70, and the AVE values were above .50, which helped uphold the convergent validity. All HTMTs were under .85, and the square root of AVEs for each of the constructs was greater than interconstruct correlations, which supported the discriminant validity.

The results indicate an empirical distinction between the adoption of AI, KMC, and organisational performance. This difference is crucial because if it were not possible to distinguish the adoption of technology from knowledge processes and/or outcomes, the conceptual model would be undermined. Thus, there was evidence for discriminatory validity, which lends support to the hypothesised mediation.

Measurement Model Results

Table 3: *Measurement Model Results*

Construct and indicators	Loading range	Cronbach's α	CR	AVE
AI adoption (AIA1–AIA5)	.74–.88	.90	.92	.70
Knowledge acquisition (KA1–KA3)	.76–.88	.86	.89	.73
Knowledge sharing (KS1–KS3)	.75–.89	.88	.91	.76
Knowledge storage (KST1–KST3)	.73–.85	.84	.88	.70
Knowledge application (KAP1–KAP3)	.78–.90	.89	.92	.78
Organizational performance (OP1–OP9)	.75–.91	.91	.93	.68

Note. *CR = composite reliability; AVE = average variance extracted.*

Model fit was acceptable for the illustrative confirmatory factor model: $\chi^2/df = 2.18$, CFI = .956, TLI = .947, RMSEA = .056, and SRMR = .049. These values suggest that the measurement structure is consistent with the proposed latent constructs.

Structural Model Results

AI adoption explained 39.7% of the variance in KMC. AI adoption and KMC jointly explained 51.2% of the variance in organisational performance. The structural model, therefore, demonstrates meaningful explanatory power for both the mediator and dependent variable.

Table 4: *Structural Model Results*

Path	*β*	SE	*t*	*p*	95% CI	Decision
AI adoption → Organisational performance	.29	.054	5.37	< .001	[.18, .39]	Supported
AI adoption → KMC	.63	.041	15.37	< .001	[.55, .70]	Supported
KMC → Organizational performance	.48	.053	9.06	< .001	[.37, .58]	Supported

Mediation Analysis Results

Summary of Hypothesis Testing

Discussion

Discussion of H1

The overall positive association between AI adoption and business performance aligns with previous empirical studies showing that an AI capability could enhance creativity, efficiency, and business performance (according to RBV-based AI research; Mikalef & Gupta, 2021; Wamba-TAguimdje et al., 2020). It also corroborates data gathered by artificial intelligence-powered customer relationship management (CRM) software. It also matches AI-powered CRM research that indicates that:

An AI-based relationship management system can enhance performance and provide a competitive edge (Chatterjee et al., 2021a). Each of the studies statistically predicted that AI adoption is a strategic resource bundle when integrated as part of organisational processes rather than as standalone tools.

However, it is not a sign of AI's positive impact on investments. Instead, it suggests that a degree of strategic assimilation is a critical criterion for adoption when participants see AI as effective at performing. However, it means that a certain level of strategic assimilation is essential for AI adoption when it is perceived as an effective performer. This interpretation aligns with findings from research on digital transformation, which indicate that performance benefits result from changes in business models, work routines, and organisational practices (Verhoef et al., 2021; Wessel et al., 2021).

Table 5: *Bootstrapped Mediation Results*

Effect	*β*	SE	*t*	*p*	95% CI
Direct effect: AI adoption → performance	.29	.054	5.37	< .001	[.18, .39]
Indirect effect: AI adoption → KMC → performance	.30	.044	6.82	< .001	[.22, .39]
Total effect	.59	.050	11.80	< .001	[.49, .68]

Note. Bootstrap resamples = 5,000. Because both the direct and indirect effects are significant, the illustrative model indicates partial mediation.

AI is therefore better understood as a catalyst for organisational redesign rather than a plug-and-play productivity instrument.

6.2 Discussion of H2

Adopting AI has had a positive impact on KMC, as its implementation reinforces the organisation's knowledge infrastructure. AI systems can learn from the outside, sense internal patterns, assist in semantic search, and help to codify knowledge. This discovery aligns with previous research indicating that the ability to use AI can foster sharing and creativity (Li et al., 2022). The outcome also benefits KBV, as it demonstrates increased AI adoption and the firm's reorganisation of its knowledge base.

The result is especially pertinent to organisations applying Generative AI, as it can generate, synthesise, and combine knowledge on an unprecedented scale. But generative products are also subject to verification and evaluative judgement. Knowledge Governance is thus crucial for the AI–KMC partnership: it is a matter of organising the assessment, sharing, and reuse of AI-produced content. In the absence of such oversight, AI can also contribute to an avalanche of information without a corresponding improvement in knowledge.

Table 6: *Summary of Hypothesis Testing*

Hypothesis	Relationship	Result
H1	AI adoption → organisational performance	Supported
H2	AI adoption → KMC	Supported
H3	KMC → organisational performance	Supported
H4	AI adoption → KMC → organisational performance	Supported

Discussion of H3

A positive correlation of KMC and Organizational performance, on the other hand, confirms the strategic role of Knowledge Processes. Companies that know how to get, share, store and utilise knowledge will be in a better position to enhance their operations, finances and even innovation. This is consistent with studies that show a relationship between KM processes and performance via learning & innovation mechanisms (Gürlek & Çemberci, 2020; Lei et al., 2021; Obeso et al., 2020; Shabbir & Gardezi, 2020). The discovery bolsters the contention that knowledge is not worth anything just because it's there and has to circulate and be used.

The outcome also emphasises management aspects of implementing knowledge. Storage and the acquisition of knowledge can create repositories that may prove quite valuable, but organisational performance improves when knowledge alters organisational routines and decisions. Therefore, it is likely that knowledge-centred leadership, incentives, and a collaborative culture will increase the impact on performance after KMC (Donate & de Pablo, 2015; Gürlek & Çemberci, 2020).

Discussion of H4

The focal point of the research is the mediation result. It proposes both direct and indirect impacts of AI adoption on performance at KMC. As for the indirect effect, this is a theoretical impact that helps account for variation in results among organisations with similar AI technologies. Companies that can institutionalise the processes of acquiring, sharing, storing, and applying knowledge can transform AI-generated information into daily routines, decisions, and innovations. Even technically advanced AI tools can be challenging to get value from if the firms aren't capable of these skills.

The partial mediation model is a plausible and logical one. For some AI applications, the benefits of automated operations or improved predictions may emerge soon. But the greater strategic impact will likely come from knowledge processes that make AI insights reusable and scalable. This finding is in line with recent studies showing that capabilities such as knowledge, absorptive capacity, customer agility, and innovation mechanisms explain how AI implementation affects firm performance (Abdul Wahab & Radmehr, 2024; Mahboub & Ghanem, 2024; Singh et al., 2024).

Integration of Findings

Collectively, the results are synthesising RBV and KBV. A strategic resource bundle is what RBV seeks to explain in terms of how AI adoption can become valuable. Knowledge transformation is what KBV is focusing on. Taken together, these two interpretations mean this much: AI-supported performances do not necessarily imply a high level of automation. It is a function of the organisational competence in making data knowledge and knowledge action. This interpretation aligns with research on digital transformation (Hanelt et al., 2021; Verhoef et al., 2021; Vial, 2019; Wessel et al., 2021), which places primary emphasis on the importance of complementary organisational change to achieve technology-driven performance.

Implications

Theoretical Implications

The study provides the RBV value by showing that the process of AI adoption is more like a schema/step of resource orchestration, not a technology possession variable. It adds to KBV to define a specific mechanism, KMC, that transforms AI-generated data and predictions into organisational knowledge. This will also serve as a mediation framework and a new direction for AI adoption research when considering the effects of heterogeneous performances, which go beyond the direct-effect model.

The study also contributes to digital transformation theory by demonstrating KMC's capability to mediate the relationship between technological change and organisational change. This argument brings together two seemingly conflicting perspectives on the value of AI: it can be both positive and negative, depending on whether knowledge transformation routines are used in its implementation. Thus, the model offers a finer-grained explanation of outcomes than analyses that rely on aggregate measures of either digital maturity or AI use.

Managerial Implications

AI projects need to be assessed in terms of both knowledge and technical outcomes. Insights shared, retained, and applied, along with model accuracy, automation rates, and deployment milestones, are necessary. Establishing inter-functional AI teams, investing in data skill-ups, establishing explainability practices and developing knowledge repositories that accommodate human and AI-generated knowledge. Human–AI complementarity should also be encouraged, as if the level of automation becomes too high, learning and accountability may suffer.

In terms of practical implications, this means that AI business cases must include clear knowledge metrics, such as AI know-how utilisation, impacted employees' familiarity with AI recommendations, the quality of documentation, and the cross-unit rollout of AI know-how. Indicators help determine whether AI is generating organisational knowledge or simply producing analytical outputs.

Organizational Implications

AI adoption needs to be integrated into the organisation's governance, culture, and processes. All companies must have data quality and ethical use policies, as well as their data owners and feedback loops. They also require a mechanism which can link AI domain experts to domain experts. These ensure that AI is not used as a standalone technical capability, but that insights are also used to improve operations, guide financial decisions, and spur innovation.

In addition, organisations need to be mindful of potential shifts in power and expertise that may result from adopting AI. An AI system that makes information a centralised entity within the analytics team can lead to reliance on, and possibly resentment toward, AI systems among operational staff. On the other hand, when integrated into participatory knowledge processes, employees can engage with the results of AI systems, provide models with this context-sensitive knowledge, and actively help to further develop them.

Limitations and Future Research Directions

Limitations

The primary point of limitation is that the reported semi-tables are illustrative due to the lack of primary data provided. They show a sample of how an empirical article might be written, but are not evidence in and of themselves. Data collection, cleaning, analysis, archival and reporting must be done transparently in a real study and in a way that abides by ethical requirements. Another restriction is that the study is proposed as an "across sections" study, which means that causal inferences cannot be used. Third, peroxidase performance can be subjective in some instances, but this is usually the case when objective performance measures are unavailable.

The scope of another construct is another limitation. AI is seen as a cross-sectoral competence of organisations; different types of AI could represent unique implications for knowledge. Predictive analytics, robotic process automation, computer vision, recommender systems, and generative AI don't produce the same kinds of knowledge, minds, and know-how. Where possible in future empirical work, a distinction should be set up between the various technologies.

Future Research Directions

Longitudinal data should be used in future studies to assess the model's validity regarding whether KMC information is developed before performance gains are generated. Industries may vary in their AI adoption rates, so comparisons should be made across industries. Moderators which can be addressed in future research may include the blocks of Digital leadership, data governance maturity, organisational culture and environmental dynamism. Finally, generative AI raises new issues that need to be explored in future KM research, such as “will we continue to be creators of knowledge or will generative AI create it, and where does the responsibility for and validation of information and knowledge lie? (Dwivedi et al., 2023).

Future research also suggests supplementing survey data with objective measures such as process cycle time, revenue growth, number of patents, customer retention, and product launches. Mixed-method designs could offer insights into how employees interpret AI recommendations and how they translate algorithmic knowledge into routines. Comparative case studies would be particularly valuable in uncovering reasons why AI-assisted learning is either a routine practice or stuck in the "experimental" pilot phase for some organisations.

Conclusion

The current article aimed to examine the association between the adoption of artificial intelligence and organisational performance, and to explore KMC as a pathway to this association. Building on RBV and KBV, it claimed that strategic value is created through AI adoption when it reinforces an organisation's knowledge process. The results of the illustrative SEM supported all four hypotheses. The results indicated that the paths from AI to organisational performance, and from KMC to organisational performance, partially mediated the AI–performance relationship. The article presents a theoretically integrated model that explains how AI uptake affects performance through knowledge management. It explains how AI can be a tool not just for automation, but also for acquiring, sharing, storing, and applying knowledge. The success of AI in augmenting organisational performance is most likely when it is integrated into routines with a high density of knowledge and regarded as part of organisational learning. The managerial focus, therefore, shouldn't just be on faster adoption of AI - it's actually on creating knowledge capabilities that make AI meaningful, trusted and action-oriented.

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