The Conceptual Ambiguity of AI Adoption: A Construct Clarification and Layered Taxonomy

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DOI: https://dx.doi.org/10.47772/IJRISS.2026.100400567

Received: 23 April 2026; Accepted: 28 April 2026; Published: 19 May 2026

ABSTRACT

Artificial intelligence (AI) adoption has become a central topic in organisational research, particularly as firms increasingly invest in AI-enabled systems to improve decision-making, automate processes, enhance productivity, and support new forms of value creation. However, the construct of "AI adoption" remains inconsistently defined and operationalised across the literature. This lack of construct clarity creates difficulty in comparing findings, developing cumulative theory, and identifying the specific organisational effects of learning-based AI capability. This study aims to clarify how AI adoption is used in organisational research and to distinguish learning-based AI capability from related distinct technological layers. Using a targeted qualitative literature review, the study examines scholarly articles published between 2019 and 2026 that address organisational, managerial, or firm-level AI adoption, readiness, implementation, or utilisation. Each paper was analysed according to the technological artefact examined, the extent to which AI was explicitly defined, and whether the study distinguished AI capability from broader digital technologies. The findings show that 45% of the reviewed corpus examined bounded AI applications such as machine learning, natural language processing, computer vision, or predictive algorithms. The remaining studies focused on AI-adjacent digital infrastructure, automation without learning, or standard enterprise digitalisation. In response, the study develops a layered taxonomy of organisational AI adoption and proposes boundary criteria for identifying AI capability. The study concludes that clearer operationalisation of AI adoption is necessary to improve measurement precision, reduce conceptual ambiguity, and support more consistent future research on AI adoption in organisational settings.

Keywords: Artificial Intelligence, AI adoption, organisational, technology adoption, digitalisation

INTRODUCTION

Artificial intelligence (AI) is widely recognised as a general-purpose technology capable of driving widespread operational improvements and entirely new business opportunities for organisations (Jöhnk et al., 2021). Across industries, firms are actively investing in AI-enabled systems to augment human capabilities, enhance decision-making, and develop novel forms of value creation. Because AI functions as a general-purpose technology, its integration fundamentally alters work practices, processes, and entire business models, differentiating it from traditional, single-use IT implementations (Jöhnk et al., 2021).

Despite this growing strategic interest, the exact meaning of "AI adoption" within the literature remains unclear (Uren & Edwards, 2023). In contemporary organisational research, AI is frequently entangled with broader concepts such as general digitalisation, digital transformation, Industry 4.0, and standard workflow automation. Because these terms are often used interchangeably, the actual technological referent of what constitutes "AI adoption" is often conceptually ambiguous. This lack of clarity is further exacerbated by the multidisciplinary nature of AI research, which brings together multiple, often conflicting, perspectives (Uren & Edwards, 2023).

This operational inconsistency makes it difficult to compare findings across studies. When studies treat digital infrastructure, rule-based automation, and learning-based AI systems as equivalent, it becomes difficult to build cumulative knowledge about the specific organisational effects of AI. Consequently, current research often yields various jumbled readiness factors without a structured conceptualisation of technology adoption from an organisational perspective (Jöhnk et al., 2021). Without clearer boundaries, it is difficult to determine how AI-specific capabilities, rather than broader digital technologies, contribute to organisational change across different layers of the firm (Plekhanov et al., 2023).

To address this theoretical gap, this paper offers a construct clarification of organisational AI adoption by developing a layered taxonomy and boundary criteria for identifying learning-based AI capability. The core research question asks: How is "AI adoption" being used in organisational literature? Drawing on a targeted qualitative literature review of 29 scholarly articles, this study identifies recurring patterns of conceptual ambiguity and proposes a layered operationalisation of organisational AI adoption. By adapting existing multi-layered models of the firm, the proposed framework distinctly separates bounded AI applications from AI-adjacent digital infrastructure, automation without learning, and standard enterprise digitalisation.

The remainder of the paper proceeds as follows. Section 2 reviews prior literature on organisational AI adoption, highlighting the conceptual overlap with digitalisation and the critical need for greater construct clarity. Section 3 explains the methodological approach of the study. Section 4 presents the findings of this review, mapping the distribution of AI operationalisation across the literature and exposing patterns of conceptual ambiguity. Finally, Section 5 develops a layered conceptualisation of organisational AI adoption and discusses its implications for both future research and practical technological progression, followed by concluding remarks in Section 6.

LITERATURE REVIEW

Organisational AI adoption research

A considerable amount of literature investigates organisational artificial intelligence (AI) adoption, conceptualising it as a General Purpose Technology (GPT) capable of driving significant performance improvements and novel business models (Jöhnk et al., 2021). However, successfully adopting AI poses critical challenges, and evidence suggests that most organisations struggle to advance beyond initial pilot phases into core operations (Jöhnk et al., 2021). Consequently, recent scholarship emphasises that AI adoption should not be viewed as a discrete, single-point-in-time event, but rather as an ongoing, highly complex sociotechnical journey (Uren & Edwards, 2023). To navigate this, the concept of "readiness" has emerged as a central construct, highlighting readiness dimensions spanning strategic alignment, resources, knowledge, culture, and data (Jöhnk et al., 2021). Furthermore, Uren & Edwards, (2023) extend this discussion through the People, Processes, Technology, and Data (PPTD) model.

AI Adoption and digitalisation: unclear boundary

Despite the growing body of AI-specific research, the conceptual boundaries between AI adoption, general digitalisation, Industry 4.0, and broader technological automation remain unclear (Plekhanov et al., 2023; Uren & Edwards, 2023). Studies frequently use terms like digitisation, digitalisation, and digital transformation interchangeably, often treating AI merely as another infrastructural component within this broader spectrum (Holmström, 2022). However, conflating AI with standard digital automation is deeply problematic. AI possesses distinctive characteristics, particularly its autonomous agency, learning capabilities, and "black-box" algorithmic nature, which sharply differentiate it from traditional, easier-to-use digital technologies (Holmström, 2022; Jöhnk et al., 2021) . The integration of these intelligent systems creates profound sociotechnical challenges that fundamentally alter work practices, human roles, and decision-making, uniquely differentiating AI integration from prior industrial or technological revolutions (Uren & Edwards, 2023).

The need for construct clarity in AI adoption research

This conceptual entanglement highlights a significant gap in the literature: an overarching construct clarity problem regarding how AI adoption is operationalised and measured. The multidisciplinary nature of the field has fostered definitional ambiguity (Uren & Edwards, 2023), leading to what Information Systems literature describes as "various jumbled readiness factors" that lack a structured conceptualisation (Jöhnk et al., 2021). A primary reason for this ambiguity is that extant literature predominantly treats the firm as a single, uniform unit of analysis, lacking an informed understanding of how digital and AI advancements dynamically impact distinct structural layers of the organisation (Plekhanov et al., 2023). As Plekhanov et al., (2023) argue in the broader digital context, navigating this complexity requires moving towards a multi-layered model that divides the firm into its organisational core, organisational periphery, and external environment (Plekhanov et al., 2023).

While this layered perspective effectively unpacks digital transformation, it has not yet been purposefully adapted to operationalise AI adoption specifically. Without a precise, layered operationalisation, research remains hampered by conceptual ambiguity, unable to accurately distinguish where general digitalisation ends and true AI capability begins. Therefore, a more precise operationalisation is needed to adequately frame, identify, and measure organisational AI adoption. This gap motivates the study's methodological approach and informs the development of a layered view of organisational AI.

METHODOLOGY

Review design

To examine how organisational AI adoption is operationalised in the literature, a targeted qualitative literature review of 29 academic papers was conducted. The primary objective of this review was not to assess effect sizes or performance outcomes, but to analyse the technological referent associated with the label of AI adoption.

Paper selection and analytical procedure

The source corpus comprised 29 recent scholarly articles published between 2019 and 2026. The review was designed as a targeted qualitative literature review rather than an exhaustive systematic review. Papers were selected purposively to capture studies that explicitly addressed organisational, managerial, or firm-level AI adoption, implementation, readiness, or utilisation. The search focused on peer-reviewed journal articles identified through academic databases and publisher platforms using combinations of terms including 'artificial intelligence adoption', 'AI readiness', 'organisational AI adoption', 'AI implementation', 'SMEs', 'TOE framework', and 'digital transformation'. The purpose of selection was conceptual coverage rather than statistical representativeness. The inclusion logic deliberately targeted studies investigating the managerial and organisational adoption or implementation of artificial intelligence. Consequently, the sample encompasses both empirical studies, including quantitative surveys and qualitative case studies, and review papers across multiple industries. Highly technical computer science papers focused purely on algorithm architecture were excluded, as were studies that discussed AI only at a societal, ethical, or policy level without examining organisational adoption, implementation, or readiness.

To prevent conceptual conflation and ensure analytical rigour, a structured data extraction protocol was employed. Each paper was examined for (i) whether AI was explicitly defined, (ii) the technology actually studied, and (iii) the degree to which the paper distinguished AI capability from broader digital technologies. Furthermore, the protocol captured the exact terminology authors used to denote AI alongside recurrent "boundary signals". For instance, signals of genuinely bounded AI capabilities included explicit references to model training, predictive classification, and machine learning algorithms. Conversely, signals of general digitalisation included implementation language surrounding legacy systems, enterprise resource planning (ERP), and workflow automation. This extraction assessed whether each study's theoretical claims about AI adoption matched the technology it actually examined.

Classification Framework

Following data extraction, each paper was classified through an interpretive coding based on the dominant technological artefact examined in the study. To reduce subjectivity, classification was guided by explicit boundary indicators, including whether the study referred to learning mechanisms, predictive or classificatory inference, identifiable AI artefacts, enabling data infrastructure, rule-based automation, or general enterprise digitalisation. Each study was assigned to the operational layer that best reflected the dominant technological artefact examined in the analysis, rather than the label used by the authors. This distinction was necessary because several studies used the term ‘AI adoption’ while empirically examining infrastructure, automation, or broad digital transformation. Initially, papers were grouped according to whether they examined: (i) a clearly identifiable learning-based AI system, (ii) AI-enabling infrastructure such as data platforms, cloud systems, or IoT, (iii) automation based on predefined rules, or (iv) general enterprise digitalisation without a specific AI artefact.

Based on this analysis, the literature was classified into four operational layers: 1. bounded AI applications, 2. AI-adjacent digital infrastructure, 3. Automation without learning, and 4. standard enterprise digitalisation. Adapting the approach used by Plekhanov et al., 2023 to unpack digital transformation, this mapping protocol ensured that classification was predicated upon the actual technologies evaluated in the studies, rather than relying solely on the introductory definitions provided by the authors.

FINDINGS

To examine how AI adoption is operationalised in organisational research, the reviewed corpus of 29 studies was analysed according to the technological artefact investigated in each paper. Specifically, the analysis examined whether studies operationalised AI as a learning-based AI application, enabling digital infrastructure, rule-based automation, or general enterprise digitalisation. This classification allows a clearer understanding of how the term “AI adoption” is applied across organisational studies.

Distribution of AI operationalisation across reviewed studies

The results reveal considerable variation in how AI adoption is conceptualised. Of the 29 reviewed papers, 13 studies (45%) examine bounded AI applications, where the technology under investigation consists of identifiable learning-based systems such as machine learning models, natural language processing tools, computer vision systems, or predictive algorithms. These studies explicitly describe the learning capability of the technology and specify the mechanisms through which data-driven inference or prediction occurs (Demlehner et al., 2021; Hradecky et al., 2022; Chatterjee et al., 2021; Kinkel et al., 2022; Patnaik & Bakkar, 2024; Radhakrishnan et al., 2022; Van Phuoc, 2022; Horani et al., 2023; Uren & Edwards, 2023; Chen et al., 2023; Badghish & Soomro, 2024; Peretz-andersson et al., 2024; Yang et al., 2024).

A further 9 studies (31%) focus on AI-adjacent digital infrastructure, where AI is discussed alongside enabling technologies such as big data platforms, cloud computing systems, and Internet of Things architectures. While these technologies provide the data environment required for AI systems, the studies do not examine the deployment of a specific learning-based AI capability (Ghobakhloo & Ching, 2019; Dwivedi et al., 2021; Hansen & Bøgh, 2021; Jamwal et al., 2022; Kurup & Gupta, 2022; Ghani et al., 2022; Polisetty et al., 2023; Abaddi, 2025; Alkhatib, 2026).

A further 6 studies (21%) investigate standard enterprise digitalisation, where the technologies discussed involve enterprise systems, digital platforms, or organisational modernisation initiatives labelled as AI adoption. In these cases, the technological artefact is either unspecified or unrelated to learning-based AI capabilities (Wang et al., 2022; Kim & Seo, 2023; Merhi & Harfouche, 2023; Barata et al., 2024; Enshassi et al., 2025; Tiago & Almeida, 2026)

Finally, only 1 study (3%) examines automation without learning, analysing automated processes or rule-based task execution without the presence of adaptive learning models. Although such systems may improve operational efficiency, they do not demonstrate the inferential capabilities associated with artificial intelligence (Chaves & Gil-cordero, 2026).

These findings indicate that organisational AI adoption research encompasses multiple technological layers, ranging from digital infrastructure and automation to fully developed AI capabilities. Table 1 highlights the distribution of these operational layers across the reviewed studies. The table shows that less than half of the reviewed papers examined bounded learning-based AI applications. The remaining studies used the language of AI adoption while focusing on infrastructure, automation, or general enterprise digitalisation. This distribution supports the central argument that AI adoption is frequently operationalised across different technological layers.

Table 1 Distribution of operational layers across reviewed studies.

Layer	**Description**	**Number of papers**	**%**
Bounded AI applications	Clearly specified AI artefacts such as Machine Learning (ML), Deep Learning (DL), Computer Vision (CV), Natural Language Processing (NLP), predictive models	13	45
AI-adjacent digital infrastructure	AI bundled with big data, IoT, cloud, or Industry 4.0 infrastructure	9	31
Automation without learning	Rule-based automation without explicit learning or model adaptation	1	3
Standard enterprise digitalisation	Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), Manufacturing Execution System (MES), e-commerce, or vague "AI adoption" without a clear artefact	6	21
Total		**29**	**100%**

Patterns of conceptual ambiguity in AI adoption research

Analysis of the reviewed studies reveals several recurring patterns that blur the boundaries of organisational AI adoption research (Jöhnk et al., 2021; Uren & Edwards, 2023). First, AI is frequently bundled within broader Industry 4.0 or digital transformation frameworks (Chatterjee et al., 2021; Polisetty et al., 2023). In these studies, AI appears as one element within a larger technological suite that may include IoT devices, cloud platforms, robotics, or advanced manufacturing technologies (Barata et al., 2024; Wang et al., 2022). Because these technologies are analysed collectively, the specific capabilities of AI systems are rarely isolated.

Second, AI is often conflated with its underlying data infrastructure (Holmström, 2022). Several studies treat technologies such as big data platforms, data lakes, or IoT sensor networks as evidence of AI adoption (Ghobakhloo & Ching, 2019; Hansen & Bøgh, 2021; Kurup & Gupta, 2022). While such infrastructure is necessary for training and operating machine learning systems, it does not itself represent the deployment of AI capability.

Third, rule-based automation is sometimes interpreted as AI adoption. Some studies describe automated processes or workflow systems as AI-enabled even when the system operates through predefined rules rather than learning from data (Chaves & Gil-cordero, 2026). This blurs the distinction between automation and learning-based artificial intelligence.

Fourth, survey-based measures of AI adoption frequently lack a clear technological referent. In several studies, managers are asked to report organisational readiness for "AI adoption" or intentions to adopt AI technologies without specifying the type of AI system under consideration (Abaddi, 2025; Chaves & Gil-cordero, 2026; Ghani et al., 2022; Merhi & Harfouche, 2023; Tiago & Almeida, 2026; Kim & Seo, 2023). When respondents interpret the construct differently, the resulting measures may capture perceptions of digital transformation rather than actual AI capability.

Taken together, these patterns suggest that the concept of AI adoption is often applied across multiple technological layers without clear differentiation. This lack of construct clarity complicates comparisons across studies and limits the cumulative development of knowledge on organisational AI adoption (Jöhnk et al., 2021; Uren & Edwards, 2023).

The following section addresses this issue by proposing a layered conceptualisation that distinguishes enabling infrastructure, automation capability, and AI capability within organisational contexts (Plekhanov et al., 2023).

INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue IV April 2026

DISCUSSION

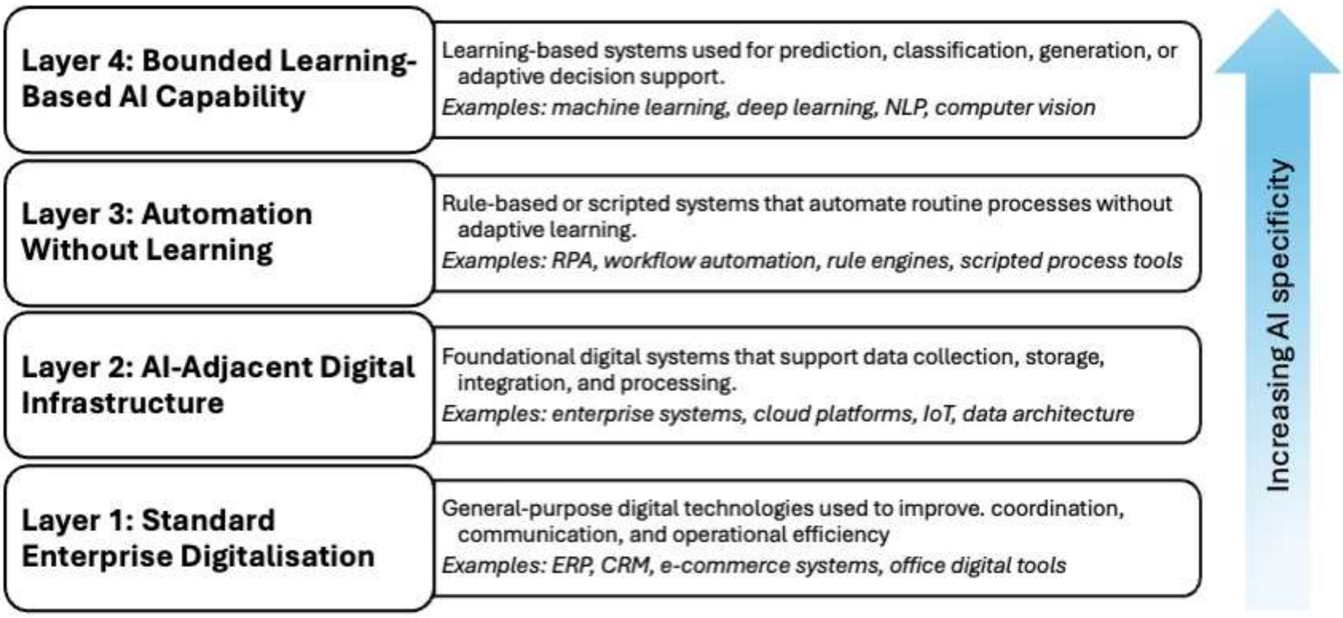
A layered view of Organisational AI Adoption

The findings presented in Section 4 indicate that studies labelled as examining "AI adoption" frequently analyse different types of technologies. Some studies focus on learning-based AI applications such as machine learning models or computer vision systems (e.g., Demlehner et al., 2021; Kinkel et al., 2022; Patnaik & Bakkar, 2024), while others analyse enabling digital infrastructure, rule-based automation, or broader digital transformation initiatives (e.g., Enshassi et al., 2025; Ghobakhloo & Ching, 2019; Wang et al., 2022). This variation suggests that AI adoption is not always used to describe the same organisational capability. In some studies, the term refers to learning-based AI systems. In others, it refers to infrastructure, automation, or general digitalisation (Plekhanov et al., 2023; Uren & Edwards, 2023).

These findings support the need for a clearer conceptualisation of AI adoption that distinguishes between different stages of technological capability within organisations (Jöhnk et al., 2021). Rather than treating AI adoption as a single event, organisational AI capability can be understood as developing through layered technological progression (Plekhanov et al., 2023; Uren & Edwards, 2023). Foundational digital infrastructure, particularly data architectures, enterprise systems, and IoT platforms, provides the technical environment required for data collection and integration (Hansen & Bøgh, 2021; Holmström, 2022). Building on this infrastructure, organisations often implement automation mechanisms that standardise processes and enable efficient execution of routine tasks (Wang et al., 2022). Only when sufficient data availability, process stability, and computational capacity exist can organisations deploy learning-based AI systems capable of prediction, classification, or adaptive decision support (Chen et al., 2023; Dwivedi et al., 2021).

Figure 1 illustrates the proposed layered conceptualisation of organisational AI adoption. The figure separates foundational digital infrastructure, automation capability, and bounded AI capability as analytically distinct layers. Its purpose is not to present a fixed maturity sequence, but to clarify that studies labelled as AI adoption may examine different levels of technological capability. This proposed layered model does not imply that all organisations follow a rigid linear pathway. However, the findings suggest that many organisations, particularly SMEs, develop the technological foundations required for AI through incremental digitalisation and automation efforts (Chaves & Gil-cordero, 2026; Ghobakhloo & Ching, 2019; Kurup & Gupta, 2022).

Figure 1: Layered Model of Organisational AI Adoption



Operational Layers of AI Adoption

The layered model also provides a framework for interpreting the diverse operationalisations observed in the

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reviewed literature. The findings demonstrate that studies in AI adoption frequently analyse technologies that belong to different layers of organisational capability. By distinguishing these layers, the proposed framework clarifies how different studies relate to one another within the broader field of organisational AI research.

The first layer corresponds to bounded AI applications, where organisations deploy learning-based systems such as machine learning algorithms, natural language processing tools, or computer vision applications (Badghish & Soomro, 2024; Demlehner et al., 2021; Kinkel et al., 2022; Patnaik & Bakkar, 2024). Studies in this category directly investigate AI capability and its organisational implications (Chen et al., 2023; Peretz-andersson et al., 2024).

The second layer consists of AI-adjacent digital infrastructure, including technologies such as big data platforms, cloud computing architectures, and IoT data pipelines (Ghobakhloo & Ching, 2019; Hansen & Bøgh, 2021; Kurup & Gupta, 2022). Although these technologies enable AI development, they primarily support data availability and system integration rather than performing intelligent inference themselves (Holmström, 2022).

The third layer captures automation without learning, where organisations implement rule-based process automation or scripted workflows (Chaves & Gil-cordero, 2026). These systems enhance operational efficiency but rely on deterministic logic rather than adaptive learning.

Finally, the fourth layer represents standard enterprise digitalisation, where organisations implement enterprise systems, digital platforms, or general digital transformation initiatives that are sometimes described as AI adoption despite lacking learning-based capabilities (Barata et al., 2024; Enshassi et al., 2025; Kim & Seo, 2023).

By organising the literature according to these operational layers, the framework clarifies why studies labelled as AI adoption often report different determinants, challenges, and outcomes (Jöhnk et al., 2021). Researchers may in fact be examining different technological strata rather than the same phenomenon (Plekhanov et al., 2023).

Table 2 Taxonomy of operational layers in organisational AI adoption research

Operational Layer	Description	Technologies Examined	Studies
Layer 1: Standard Enterprise Digitalisation	Represents broad digital transformation initiatives, routine business software, and abstract technology adoption. In many of these studies, "no specific AI application or model is examined," treating AI instead as a generic organisational capability.	General digital technologies, smart manufacturing systems, SEO, email marketing, conversion rate optimization.	(Wang et al., 2022; Kim & Seo, 2023; Merhi & Harfouche, 2023;Barata et al., 2024; Enshassi et al., 2025; Tiago & Almeida, 2026)
Layer 2: AI-Adjacent Digital Infrastructure	Encompasses the foundational technical architecture and data pipelines necessary to support AI systems. These technologies are critical for data collection but support system integration rather than performing intelligent inference themselves.	Industrial Internet of Things (IIoT), smart sensors, Enterprise Resource Planning (ERP), data analytics platforms.	(Ghobakhloo & Ching, 2019; Dwivedi et al., 2021; Hansen & Bøgh, 2021; Jamwal et al., 2022; Kurup & Gupta, 2022; Ghani et al., 2022; Polisetty et al., 2023; Abaddi, 2025; Alkhatib, 2026).
Layer 3: Automation without learning	Captures systems designed to standardise and execute routine organisational processes using deterministic logic. These	Customer service chatbots, automated networks, rule-based engines, robotic	(Chaves & Gil-cordero, 2026)

	technologies function through scripted workflows and predefined rules rather than autonomously improving through data-driven learning.	process automation (RPA), CRM analytics.	
Layer 4: Bounded AI Capability	Represents the deployment of specific, learning-based algorithms capable of pattern recognition, prediction, and adaptive inference without predetermined rules. Studies here isolate advanced computational capabilities that process data to achieve goals and adapt over time.	Machine Learning (ML), Natural Language Processing (NLP), Computer Vision (CV), Deep Learning, Artificial Neural Networks (ANN).	(Demlehner et al., 2021; Hradecky et al., 2022; Chatterjee et al., 2021; Kinkel et al., 2022; Patnaik & Bakkar, 2024; Radhakrishnan et al., 2022; Van Phuoc, 2022; Horani et al., 2023; Uren & Edwards, 2023; Chen et al., 2023; Badghish & Soomro, 2024; Peretz-andersson et al., 2024; Yang et al., 2024)

Table 2 clarifies how each operational layer differs in terms of technological capability. Bounded AI capability refers to systems with learning and inference functions, whereas AI-adjacent infrastructure provides the data and technical conditions that may support AI but does not itself perform intelligent inference. Automation without learning relies on predefined rules, while standard enterprise digitalisation refers to broader digital systems or transformation initiatives without a clearly specified AI artefact.

Boundary criteria for identifying AI capability

Building on this layered conceptualisation, the study proposes a set of boundary criteria that can help researchers distinguish learning-based AI capability from broader forms of digital transformation (Plekhanov et al., 2023; Uren & Edwards, 2023). These criteria aim to improve construct clarity and support more consistent operationalisation of AI adoption in future empirical studies (Jöhnk et al., 2021).

First, AI adoption should involve the presence of an inference capability, meaning that the system performs prediction, classification, recommendation, or decision support beyond deterministic rule-based logic (Chen et al., 2023; Peretz-andersson et al., 2024). Second, the system should demonstrate an explicit or implied learning mechanism, where models improve through pattern recognition from data rather than fixed programmed rules (Demlehner et al., 2021; Hansen & Bøgh, 2021). Third, data infrastructure alone should not be treated as AI adoption, as technologies such as IoT platforms or big data architectures represent enabling conditions rather than AI capability itself (Ghobakhloo & Ching, 2019; Holmström, 2022).

In addition, empirical studies should ensure that the AI artefact is clearly identifiable, specifying the type of system under investigation, such as predictive maintenance models, NLP-based chatbots, or computer vision inspection tools (Jamwal et al., 2022; Kinkel et al., 2022; Patnaik & Bakkar, 2024). Measurement instruments should also correspond to the technological artefact being examined. Survey measures of AI adoption or readiness without a defined referent risk capturing perceptions of digital transformation rather than actual AI capability (Abaddi, 2025; Kim & Seo, 2023; Tiago & Almeida, 2026).

Finally, researchers should distinguish AI capability adoption from digital readiness, recognising that organisations may possess advanced digital infrastructure without yet deploying learning-based AI systems (Jöhnk et al., 2021; Uren & Edwards, 2023).

Implications

The proposed taxonomy has several implications for organisational research on AI adoption. First, it suggests that the construct of AI adoption should be conceptualised as a multi-layered technological progression rather than a singular organisational event (Plekhanov et al., 2023; Uren & Edwards, 2023). Treating infrastructure development, automation capability, and learning-based AI deployment as equivalent phenomena may obscure important differences in adoption drivers and organisational outcomes (Holmström, 2022; Jöhnk et al., 2021).

Second, the framework highlights the need for greater precision in empirical research design (Plekhanov et al., 2023). Studies examining AI adoption should explicitly specify the technological artefact under investigation and clarify whether the analysis concerns enabling infrastructure, automation capability, or learning-based AI systems (Jöhnk et al., 2021; Uren & Edwards, 2023).

Third, the layered perspective is particularly relevant in SME contexts. Resource-constrained organisations often develop digital infrastructure and automation capabilities incrementally before deploying learning-based AI systems (Ghobakhloo & Ching, 2019; Hansen & Bøgh, 2021; Kurup & Gupta, 2022). Interpreting these intermediate stages as "AI adoption" may overstate the level of technological capability within such organisations (Holmström, 2022). Overall, this taxonomy provides a clearer basis for future research on organisational AI adoption and helps explain why existing studies often report divergent findings (Jöhnk et al., 2021; Uren & Edwards, 2023).

CONCLUSION

Despite the growing strategic importance of artificial intelligence, organisational research frequently uses the term "AI adoption" inconsistently. The literature often entangles true AI capabilities with broader technological paradigms such as general digitalisation, Industry 4.0, and standard workflow automation. This review indicates that organisational AI adoption is often operationalised inconsistently across studies, which complicates comparison and weakens construct clarity.

To address this gap, this study conducted a targeted qualitative literature review of 29 recent empirical and review papers to examine how AI adoption is practically operationalised. The analysis revealed considerable variation between theoretical definitions and the actual technologies studied. While a specific subset of studies successfully isolated learning-based AI applications, the majority of the literature measured underlying data infrastructure, rule-based automation, or standard enterprise digitalisation. These recurring patterns confirm that the concept of AI adoption is frequently applied across multiple technological strata without clear differentiation.

In response to these findings, this paper proposes a layered conceptualisation of organisational AI adoption that separates the construct into four distinct operational layers. By distinguishing bounded AI capability from AI-adjacent digital infrastructure, rule-based automation, and standard enterprise digitalisation, the framework clarifies how organisations, particularly SMEs, develop technological capabilities incrementally. Furthermore, the study established boundary criteria requiring evidence of inference capability, explicit learning mechanisms, and identifiable technological artefacts to separate true AI from broader digital readiness. Ultimately, this layered framework provides a clearer conceptual foundation for achieving greater empirical precision in future research.

Limitations and Future Research

This study is subject to several methodological limitations. First, the study is based on a targeted qualitative literature review of a purposive sample of 29 papers rather than an exhaustive systematic review. The findings should therefore be interpreted as a construct clarification exercise rather than as a complete mapping of all AI adoption literature. Consequently, the classification of studies into operational layers involved interpretive judgement regarding the technological referent examined in each paper. To reduce this limitation, the classification was guided by boundary criteria such as evidence of learning capability, inference, identifiable AI artefacts, data infrastructure, rule-based automation, and general digitalisation. Furthermore, the scope of the study was deliberately restricted to organisational AI adoption literature, explicitly excluding highly technical or purely algorithmic research.

Conceptually, it is important to acknowledge that the proposed layered model of organisational AI adoption is a conceptual framework rather than an empirically tested model. While the taxonomy disaggregates the construct into distinct technological layers, the relationships and boundaries between these layers have not been empirically validated in this study.

These limitations present clear and actionable directions for future research. Future research should test the proposed taxonomy using larger samples, systematic review procedures, expert validation, or empirical survey instruments that measure specific technological artefacts rather than abstract AI readiness. By applying the proposed boundary criteria in future empirical designs, researchers can accurately isolate learning-based AI capabilities from broader digital transformation initiatives, paving the way for a more rigorous and cumulative understanding of organisational AI adoption.

ACKNOWLEDGEMENTS

The author would like to acknowledge the support of Universiti Teknologi MARA (UiTM), Cawangan Selangor, Kampus Puncak Alam and Faculty of Art & Design, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia for providing support on this research.

Conflict Of Interest Statement

The author agrees that this research was conducted in the absence of any personal, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

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