New Trends Towards AI, Agility and Maturity in Learning Organisations: A Scoping Review

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Abstract: Technology adoption plays a central role in the success of organisations, where organisational maturity can only be achieved based on learning organisation principles and agile teams for cross-functional collaboration. These constructs are seldom examined in tandem, and are more often approached as separate aspects in the complex adaptive systems in today's organisations. Recent AI developments necessitate a re-evaluation of how learning organisations are optimised in digitally transformed environments. Knowledge management (KM) has evolved into a strategic enabler of organisational learning and adaptive capacity. This paper reports on findings of a scoping review that explored trends in organisational maturity, conceptualised as the extent to which organisations institutionalise continuous learning, reflective practice, and knowledge integration across systems, culture, and leadership. Databases Google Scholar, Scopus, Web of Science and ProQuest Central were searched and sources published from 2009 to 2025 were selected for thematic analysis. Using the PRISMA-ScR reporting guidelines and Covidence for data extraction, 37 articles were selected and analysed to identify trends and gaps in research. Findings indicate that sustainable competitive advantage emerges when organisational maturity, AI integration, and continuous learning are aligned to support anticipatory, evidence-based decision-making in complex environments.

Keywords: Agile organisations, Learning organisations, Organisational maturity, AI in learning organisations, Complex adaptive systems, Competitive advantage

1. Introduction

KM has evolved from a document-centric function to a strategic enabler of excellence in organisations (Sorenko, 2021, Rehman, 2025) where organisational learning and adaptive capacity cannot be negated. Learning organisations can be conceptualised as complex adaptive systems (CAS) characterised by continuous interaction, feedback, and evolution. Within this context, KM processes enable organisational learning through dynamic knowledge creation and sharing (Nonaka & Takeuchi, 1995). The integration of artificial intelligence enhances these processes by strengthening feedback loops, enabling real-time decision-making, and supporting adaptive capacity, thereby advancing organisational maturity Studying learning organisations, as a part of KM, as explained by Senge (1990), and later by authors including Shih-Wei et al (2020), Titihalawa et al. (2025) and others, focus on the continuous, adaptive, and generative learning to sustain performance. This offers organisations the means to support and nurture learning at individual, team, and systemic levels Employees could collectively enhance their capability to create desired results. on how technology and the level of its adoption play a cardinal role in and levels of maturity in organisations, in general. In a constantly and disruptively technological world these constructs should not be studies and implemented in isolation, and with considering organisational maturity and agility (Lu, 2024; Steegh, Van De Voorde & Paauwe, 2025). Agility is the capability to quickly adjust to changes, such as currently being experienced by AI developments, and these strategies aim to sustain competitive advantages (Ehiorobo, 2020). However, organisational agility can only be achieved through KM practitioners and their ability to recognise and respond to changes and challenges (Devarakonda, 2019; Munteanu et al., 2020). Agile teams and organisations, organisational maturity, and learning organisations share key features that enhance organisational effectiveness and adaptability. Steegh, Van De Voorde and Paauwe (2025) add that cross sectional collaboration and hierarchical differentiation in agile teams lead to shared leadership, where team reflexivity and feedback add to its effectiveness. Agile organisations focus on quick responsiveness through iterative processes.

In addition, organisational maturity reflects a company's ability to evolve its practices and processes within the complexities posed by disruptive technologies such as AI innovations (Ross, 2019). Organisations that may have reached maturity before these disruptions, are now faced with a new wave of developments to stay abreast of the maturity curve. Recent AI innovations and developments necessitate a re-evaluation of what must be considered in optimising learning organisations.

2. Background

Technology and the level of its adoption and implementation plays a cardinal role in learning organisations and levels of maturity in organisations, in general. Yet, these constructs are often studied in isolation. Recent AI innovations and developments necessitate a further re-evaluation of factors to considered in optimising learning organisations. Drawing on principles of organisational learning, this paper reports on a scoping review as explained by Tricco et al., (2018), of recent trends looking at organisational maturity, seen as the extent to which organisations institutionalise continuous learning, reflective practice, and knowledge integration across levels. Does it reflect the depth of collective learning embedded in systems, culture, and leadership practices in a digitally changed world? How can mature organisations cultivate learning cultures characterised by psychological safety, feedback loops, cross-functional collaboration, and mechanisms for converting tacit knowledge into shared organisational memory? In this context, KM is not merely the storage of information but a dynamic process of knowledge creation as explained by Nonaka, sense-making, and strategic alignment. The value of AI may still be unexplored, while it enhances this learning ecosystem by augmenting organisational foresight and forecasting capability. Organisational maturity refers to the degree to which an organisation has developed structured processes, governance, technology and knowledge systems, leadership capacity, whilst subscribing to a learning culture. As complex systems, organisational maturity and forecasting depend on an organisation's ability to systematically use knowledge, data, and learning processes to anticipate and shape future outcomes rather than merely react to them. More advanced AI applications, including scenario modelling, pattern recognition across weak signals, and knowledge graph integration, enable double-loop learning by revealing structural inefficiencies and hidden assumptions embedded in organisational data. When integrated within reflective governance frameworks, AI can even contribute to triple-loop learning by informing strategic reorientation and policy redesign. However, the effectiveness of AI-driven forecasting depends on organisational learning maturity. Without strong feedback mechanisms, ethical reflexivity, and knowledge-sharing norms, AI risks reinforcing existing biases and silos. How do recent studies approach the understandings of learning-oriented organisations to position AI as a cognitive partner within a socio-technical system to capitalise on collective intelligence, and adaptive strategy? The paper argues that AI-enabled forecasting represents not merely technological advancement but an extension of organisational learning capability. Utilising the PRISMA Scoping Review Extension (PRISMA-ScR) (Tricco et al., 2018) as reporting guideline and the Covidence tool for data extraction, a total of 57 articles were analysed, and qualitative data were extracted were thematically coded and analysed further. Based on the findings of the scoping review, this paper explores existing trends, assumptions and governance structures, to see how organisational maturity is viewed. Some studies argue that agile organisations link better to the concept of both learning organisations and organisational maturity. Findings are that sustainable competitive advantage emerges when organisational maturity, AI integration, and continuous learning are aligned to support anticipatory, evidence-based decision-making in complex environments. Studies further advocate the need for a shift in approaches where long-term prediction accuracy must reconsider a more agile and adaptive approach towards better foresight and rapid learning.

Though KM studies in technology adoption, maturity and agility of organisations always underpinned the aims and efforts of learning organisations, recent AI developments and innovations beg new answers and asks: (1) how can organisations continue to cultivate learning cultures to maintain maturity levels amidst the demands and possibilities arising from AI innovation? The value of AI may still be unexplored (Vinning et al. , 2025), while it enhances this learning ecosystem by augmenting organisational foresight and forecasting capability. This paper looks at research published around these issues.

3. Research Design

Guided by the PRISMA Extension for Scoping Reviews protocol (PRISMA-ScR), (see Tricco et al., 2018; Page et al, 2020), this scoping review explored the role that AI. It examined the current trends, gaps, as well as reported best practices in recent reported studies. The selected databases provided 57 hits and qualitative thematic analysis was used to identify themes observed in current research.

3.1 The Search Strategy

Peer-reviewed articles and book chapters in English, published between 2019 and 2025, were considered for inclusion in this study. The following constructs were used to filter the results: (1) Learning organisations; (2) Agile organisations and discussion including AI impacting change (3) Maturity in organisations including changes of digital transformation. Based on the recent escalation AI and GenAI developments (as reported by Floridi, 2019 and others), the study is limited to research reported during the last seven years at the time of this study.

The search strategy covers learning organisations in the pursuit of agility and maturity in terms of AI incorporation. The study does not consider organisation learning, which for the purpose of this study is considered to be the ongoing processes through which organisations acquire, share, and apply knowledge from experiences, while a learning organisation is the structural and cultural model where business organisations set out to instil continuous, adaptive, and generative learning to improve performance. (Senge, 1990). For the latter, employees collectively enhance their capability to create desired results. It is built on five core disciplines: systems thinking, personal mastery, mental models, shared vision, and team learning.

The databases included in this study are Google Scholar, Scopus and ProQuest. Databases were queried from January 2025 to May 2025. A combination of the following keywords was used: “artificial Intelligence”, “digital transformation”, “AI transformation”, “learning organisations”, “agility”, “agile organisations”, “complex systems”, “adaptive complex systems” and “organisational maturity” as systematically as possible within the search functionality and capabilities of each website. Search terms used included: Learning organisations AND complex adaptive systems OR CAS; agility OR agile organisations OR agile teams AND learning organisations AND Organisational maturity; AI OR AI application AND learning organisations.

3.2 The Selection of Sources of Evidence

These results of each search were filtered according to document type, publication date, and then further refined to look for aspects such as Information or research ethics. A data log of the search strategies and complete results, with links, were recorded in Excel. This study focuses mainly on businesses as learning organisations being a subset of KM. As educational institutions approach this topic differently, studies primary focusing on AI in education, teaching and learning were excluded.

3.3 Inclusion and Exclusion Criteria

Studies included in the literature search met the following inclusion and exclusion criteria:

Inclusion criteria: Reported studies focusing on business organisations and learning organisations. Studies reported in full-text, peer-reviewed journal articles and conference papers between 2019 and 2025, covering concepts of in the titles, abstracts, or keywords were identified and included. Only studies in English were considered and selected.

Exclusion criteria: Studies not in learning organisations or industries. Non-peer reviewed sources were excluded. The following document types were excluded: books, book chapters, grey literature, articles with abstracts only, patents, and reports, and duplicate studies found in the databases. Studies in other languages that are not English were excluded. Studies on organisational learning without focussing on learning organisations where excluded.

3.4 Knowledge Synthesis

The PRISMA extension for scoping reviews (PRISMA-ScR) was published in 2018, and an updated checklist of 20 essential reporting items was revised in 2021 (Page et al., 2021). This scoping review synthesizes evidence selected to assess the extent of literature covered on this topic. This study indicates whether further research in terms of recommending systematic reviews of the literature are feasible. The PRISMA-ScR flowchart presented in Figure 1 explains the identification, screening, inclusion/exclusion, and extraction for this scoping review. It outlines each step taken, which enhances not only the transparency, but also the reproducibility and rigour of the review process followed.

The review included searches in ProQuest (n=667); Scopus (n=14); Web of Science (n=36) and Google Scholar (n=857), totalling 1574, records included in the initial abstract screening. Twenty-six (26) duplicate records were removed. Of the 1078 studies screened, based on their titles and abstracts, 454 were excluded as they did not meet the inclusion criteria, leaving 624 studies. Full-text reviews followed, and 26 studies were excluded. Reasons included: Reason 1: wrong outcomes (n=11), Reason 2: wrong population (n=1), Reason 3: no full-text available (6), and Reason 4: wrong publication type (n=1). Once the full-text screening was completed, 57 studies were included for extraction. The studies were exported an Excel spreadsheet and thematically data analysed.

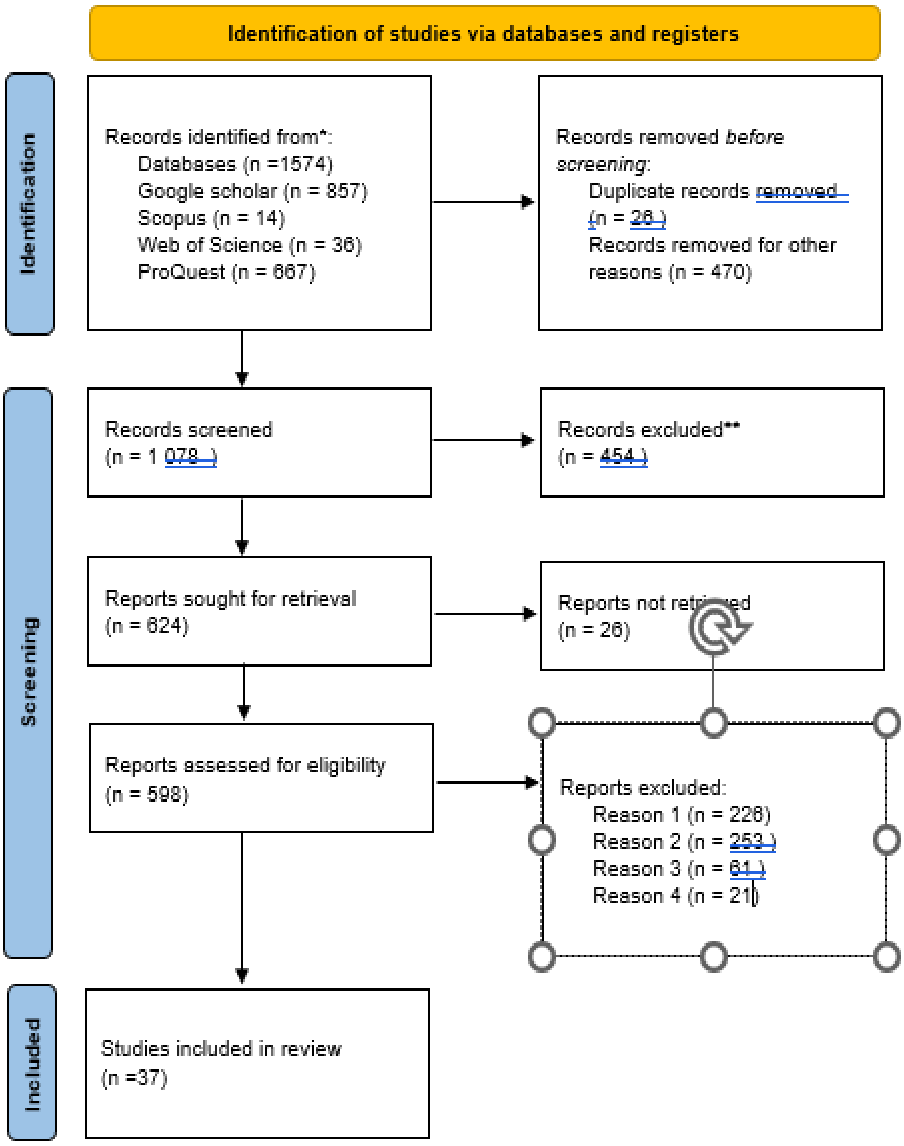

Figure 1: PRISMA 2020 Flow Chart

4. Presentation and Discussion of Findings

In Table 1, the different research methods used in the studies analysed are summarised. Industries in these studies ranged from hotels, marketing to supply chain organisations. Countries where this research originated include Poland, China, USA, Germany, Norway, Portugal

4.1 Trends, Themes and Gaps Identified

Although this study can report on an exponential increase in research from 2019 to date, selected studies report a general gap on the topic and add that there remains a paucity in literature, particularly addressing topics of AI as relating to maturity models (Ellefsen, 2019).

Table 1: Summary of Search Results

Research Method	Trends and Gaps	Themes	Authors
• Multiple case studies • Systematic reviews • Critical reviews • Surveys	1. AI readiness models 2. Leadership mindsets 3. AI maturity	**LO, KM & CAS**	Korecki (2023); Nault & Ruhi (2024); Nimmi, Vilone & Jagathyraj (2022); Rahman, Dzunur'aini, & Nur'aini (2022); Taherdoost & Madanchian (2023); Usmani, & Priyadarshini (2025); Riaz, Morgan & Kimberley (2023);
		OA, leadership and LO	Steegh, Van De Voorde and Paauwe (2025); Olan et al., 2022); Row & Brook (2022); Shafiabady et al., (2023); Titihalawa (2025); Armanious & Padgett (2021); Ehiorobo (2020); Eliane & Scafuto, (2022); Kucharska (2025); Ratajczak, (2023); .
		AI in LO, Performance	Li, K. C., & Wong, B. T. M. (2023); Majeed & Ravindran (2026); Li & Wong (2023); Morandini e. al., (2023); Ranjan et al., (2024); Reichl & Gruenbichle (2023);
		AI readiness, digital transformation and OM	Cardoso E, and Su X. (2022); Chandrakasan et al., (2023), (2023Lichtenhaler (2025); Anna (2025); Ellefsen(2019); Felemban, Sohail, & Ruikar (2024); Alavi, Leidner, & Mousavi. (2024); Lech & Werbinska-Wojciechowska Sylwia; Mielcarek, et al., (2025); Reichl & Gruenbichler (2023); Robertson (2022); Sadiq (2021); Usmani & Priyadarshini (2025); Vining (2025);

Studies (Shih-Wei et al., 2020; Titihalawa et al., 2025; Alavi, Leidner, & Mousavi, 2024) confirm that KM as a discipline has evolved into a field where the systematic creation, sharing, application, and governance of organisational knowledge is transitioning. Rooted in the seminal work of Peter Senge, learning organisations are characterised by systems thinking, shared vision, and collective learning practices that enable organisations to respond proactively to environmental change, where AI is now part of technological transformation. Learning organisations amidst these developments are dependent on systems that are adaptive, and responsive to rapid technological change, exhibiting properties such as self-organisation, co-evolution, and path dependency

4.2 Learning Organisations, Agility and Leadership

Boerma, De Laat and Vermeulen (2024) hail the benefit for organisations to pay attention to organisational agility in learning, as profound technological, occupational and societal changes are a constant. Learning as part of organisational agility however is an under researched area of attention. Agility and learning organisations form significant tangents where formal and informal learning can take place. (Boerma, De Laat and Vermeulen, 2024; Kucharska et al., 2025). Both learning organisations and agile organisations display the ability to be responsive to changes. Kucharska et al (2025) state that leaders with an agile mindset develop their competencies and tacit knowledge through continuous informal learning practices such as experiential learning, critical thinking, feedback, mentoring, and supportive organizational cultures that foster agility and adaptability (Kucharska, 2025). Chandrakasan et al.,(2025) lament that the lack of the appropriate leadership styles to prosper observed in a Malaysian study is causing many organisations

4.3 How AI Strengthens Learning Organisations

Lichtenthaler (2025) states that AI management focusses mostly on consists of the strategies, processes, practices, activities, and tools, for achieving consistent access and using AI intelligence for better performance and forecasting. AI innovations enable organisations to capture, analyse, and leverage organisational knowledge at scale. By automating routine tasks and providing data-driven insights, AI allows employees to focus on higher-value learning and strategic thinking. This creates a feedback loop where organisations continuously improve their practices based on AI-generated intelligence, directly supporting the learning organisation model.

4.4 Factors Associated with AI Weaknesses

The findings of this scoping review are affirmed by a later study of Litvinenko (2026) stating that there are weaknesses in applying and utilising AI in organisations for learning. Currently barriers caused by context blindness, bias, and the black-box nature of AI, overreliance and cognitive deskilling, limited cross-domain transfer, and psychological or power-related barriers to codification and sharing – factors that can weaken AI's benefits if unmanage. Alavi, Leidner and Mousavi (2024) note that particularly GenAI has the propensity to reduce human interaction and socialisation. This may exclude more junior staff from learning**.**

4.5 AI's Role in Advancing Organisational Maturity

Studies (Ellefsen et al., 2019) state that there are many instances where organisations fall behind with digital transformation and organisational maturity as so far AI is concerned. Organisations that are AI-mature significantly outperform early-stage AI implementers, but many companies struggle to advance from AI pilots to enterprise-wide AI adoption. AI maturity involves developing organizational capabilities to effectively implement, manage, and scale AI solutions.

4.6 Accelerating Agile Practices with AI

Shafiyabadi et al.; (2023) state that AI should be employed to predict organisational agility and responsiveness. This would enable agile teams to move faster while maintaining quality. AI tools accelerate agile methodologies by automating code generation, backlog management, testing, and other iterative processes. AI tools used include Machine Learning (ML) methods e.g., Support Vector Machine (SVM), Decision Trees (DT), and K-Nearest Neighbours (KNN).

4.7 New Maturity Models

Usmani et al., (2025) questions India's readiness to reap the benefits of incorporation AI effectively, and state that there is a paucity of proven and updated models and frameworks to guide organisations. One of the few alternative models of maturity that addresses AI is offered by Lichtenhaler (2025), describing thee 6 levels of existing transformation in organisations:

- *Level 0: Isolated Ignorance* – AI is ignored;
- *Level 1: Initial Intent* – Preliminary experimentation with AI technology; .
- *Level 2: Independent Initiative* – Multiple, uncoordinated AI activities focused on efficiency;
- *Level 3: Interactive Implementation* – Coordinated AI usage integrated with human intelligence;
- *Level 4: Interdependent Innovation* – Strategy, combined with innovation;
- *Level 5: Integrated Intelligence* – Seamless, sustainable AI-human collaboration and learning.

However, most studies analysed for AI-readiness as part of learning organisation strategies and technological maturity, has yet to be realised.

5. Conclusion

The findings of this scoping review indicate that organisational maturity, organisational agility, and AI adoption should not be approached as separate organisational factors. These are interdependent constructs within contemporary learning organisations. Learning organisations function as complex adaptive systems in which knowledge creation, sharing, and continuous learning are enabled through dynamic interactions, feedback mechanisms, and adaptation. Within this environment, AI increasingly serves as a critical enabler of organisational learning by strengthening KM processes, supporting real-time decision-making, and enhancing adaptive capacity. At the same time, agile organisational practices provide the much-needed flexibility and responsiveness required to navigate rapidly changing technological faced by organisations today. All while organisational maturity provides the structures, capabilities, and governance mechanisms necessary to institutionalise learning and innovation. Collectively, these constructs share common foundations, including continuous improvement, collaboration, knowledge sharing, strategic alignment, and adaptive leadership. Lichtenhaler, (2025) further underpins the risk of ignoring the importance of AI adoption in learning organisations. While Shih-Wei and Lamb (2020) add and remind that older models of maturity can no longer answer to the demands of new developments, and AI-maturity models require urgent attention The findings further suggest that organisations are beginning to assess AI maturity and develop pathways towards enterprise-wide AI integration, although adoption remains uneven and relatively slow.

New trends that this study was able to identify are that there are efforts to assess organisation's current AI maturity levels and develop a roadmap to advance from pilots to enterprise-wide integration, but that these are slow on the uptake. It is evident that AI integration could potentially strengthen organisational agility by equipping employees and managers with real-time insights, predictive analytics, and intelligent decision-support capabilities. In turn, responsiveness and adaptability will improve. There is a need for deeper studies and full-scale systematic literature reviews on the intersection of the practicalities of agility, maturity and the changing landscape of learning organisations. In particular, leadership styles have been identified as a concern and a gap requiring further empirical research to enhance new skills to manage AI-driven decision-making.

This study concludes by highlighting the need for further research to examine the intersection of organisational maturity, agility, and AI-enabled learning in a more integrated manner. To this end, attention should be given to emerging leadership capabilities, governance models, and organisational competencies required to support AI-driven decision-making and sustainable organisational learning. Understanding these relationships will be essential for developing organisations that are resilient, innovative, and capable of thriving in increasingly complex and technology-mediated environments.

Ethics Declaration: This study used secondary data and no ethical clearance was required.

AI Declaration: For this research, the grammar assistant software tool Grammarly was used for editing purposes.

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