

Systematic Review

AI-Based Personalized Learning for Professional Development: A Systematic Review and Cross-Sector Comparison of Knowledge-Intensive Organizations and Educational Organizations Using the Nine-Cell Model

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Abstract

The rapid integration of artificial intelligence (AI) into learning environments has driven the development of personalized learning models, yet systematic cross-sector comparisons remain limited. This systematic literature review addresses this gap by comparing AI-based personalized learning models in knowledge-intensive organizations and educational organizations, using the Nine-Cell Model as an integrative analytical framework. Following PRISMA 2020 guidelines, 43 peer-reviewed studies (2017–2026) were analyzed. The findings indicate that while both sectors rely on shared AI infrastructures (e.g., adaptive algorithms), they diverge substantially: organizational models prioritize competency development and training transfer aligned with strategic goals, whereas educational models emphasize mastery of disciplinary knowledge through structured assessments. Furthermore, managerial involvement is a key differentiator, with managers in organizations acting as active learning architects, while educational leaders primarily enable self-directed learning conditions. Across both sectors, alignment with the Nine-Cell Model is strong in knowledge acquisition but critically weak in cultivating professional values and ethics. This review advances the field by foregrounding the underexamined managerial role and demonstrating the need to shift from defensive to generative ethics in AI-based professional development.

Keywords: artificial intelligence; personalized learning; knowledge-intensive organizations; educational organizations; professional development; Nine-Cell Model; human capital development; managerial roles; systematic review; PRISMA

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1. Introduction

Recent years have witnessed a substantial shift toward technology-enhanced learning, a trend significantly intensified by the period of the COVID-19 pandemic (Hariyanto et al., 2025). The integration of artificial intelligence (AI) into learning environments has fundamentally altered instructional practices, enabling systems that analyze learner data and adapt content, pacing, and feedback in real time (Farhood et al., 2025). This transformation spans both workplace and academic settings, where AI applications increasingly

tailor learning experiences to individual needs and organizational objectives (Kazanci Yabanova, 2025; Ubada-García et al., 2025).

The literature identifies two primary contexts for AI-driven personalized learning (Farhood et al., 2025; Tusquellas et al., 2024). For the purpose of this review, “knowledge-intensive organizations” encompass corporate, technological, and professional service environments driven by continuous workforce training. Conversely, “educational organizations” specifically refers to higher education institutions focusing on adult learners, as K-12 settings were intentionally excluded to maintain comparability in professional development. Knowledge-intensive organizations prioritize competency development aligned with organizational goals and career advancement, while educational organizations operate within structured curricula oriented toward knowledge mastery and credentials (Farhood et al., 2025; Hariyanto et al., 2025; Tusquellas et al., 2024; Kazanci Yabanova, 2025). These sectors differ in learner motivation, time constraints, evaluation criteria, and managerial support (Kauffeld et al., 2025; Ventista & Brown, 2023). Yet existing reviews have largely examined each context in isolation, leaving systematic cross-sector comparison infrequent (Fortuna et al., 2025; Ekuma, 2023). Precisely because these sectors are grounded in divergent theoretical frameworks such as adult learning and human resource development in organizations—compared to constructivist and mastery-based theories in higher education—a cross-sector comparison is theoretically vital. It allows us to investigate how identical AI technologies (e.g., adaptive algorithms) are differently pedagogically repurposed, shaped, and constrained by distinct institutional logics. Moreover, the role of managers in supporting AI-based personalized learning remains underexplored in both sectors (Bevilacqua et al., 2025).

To enable systematic cross-sector comparison, this study adopts the Nine-Cell Model for Personalized Professional Learning as its analytical framework. The model integrates three professional competencies: systematic knowledge and intellectual skills; creating new knowledge and lifelong learning; and norms, values, and code of ethics, with three job-related components: means of action, networks of action, and role constraints. The resulting nine-cell matrix provides a structured lens for examining personalized learning across diverse organizational contexts, with recent empirical validation in teacher professional development research (Avidov-Ungar, 2025). Although not originally designed for AI contexts, this model is particularly suited for our review because AI increasingly functions as a pedagogical agent. The Nine-Cell framework provides a powerful diagnostic lens to assess whether AI-driven systems support holistic professional development across all nine dimensions, or if they narrowly restrict learning solely to technical knowledge acquisition. This review contributes to the literature in four ways: (1) by offering a systematic cross-sector comparison of AI-based personalized learning models in knowledge-intensive organizations and in educational organizations; (2) by foregrounding the underexplored managerial dimension in AI-driven personalization; (3) by operationalizing the Nine-Cell Model as an integrative analytical framework for reviewing AI-based professional learning and (4) by inductively generating preliminary conceptual frameworks regarding managerial mediation and ethical orientations to guide future empirical research. Guided by these contributions, this systematic review was conducted following PRISMA 2020 guidelines (Page et al., 2021). The overarching research question is: What similarities and differences characterize AI-based personalized learning models in knowledge-intensive organizations compared with educational organizations, and how do these patterns align with the Nine-Cell Model?

Three sub-questions guide the analysis:

RQ1. *What organizational and pedagogical characteristics define AI-based personalized learning models in each sector?*

RQ2. How does the literature describe managerial actions supporting AI-based personalized learning across both sectors?

RQ3. How do models in each sector align with the Nine-Cell Model?

2. Methodology

This systematic literature review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines (Page et al., 2021). The protocol was developed before the search and guided all methodological decisions. The PRISMA 2020 flow diagram is presented in Figure 1, and the complete PRISMA 2020 framework checklist is included in Appendix A.

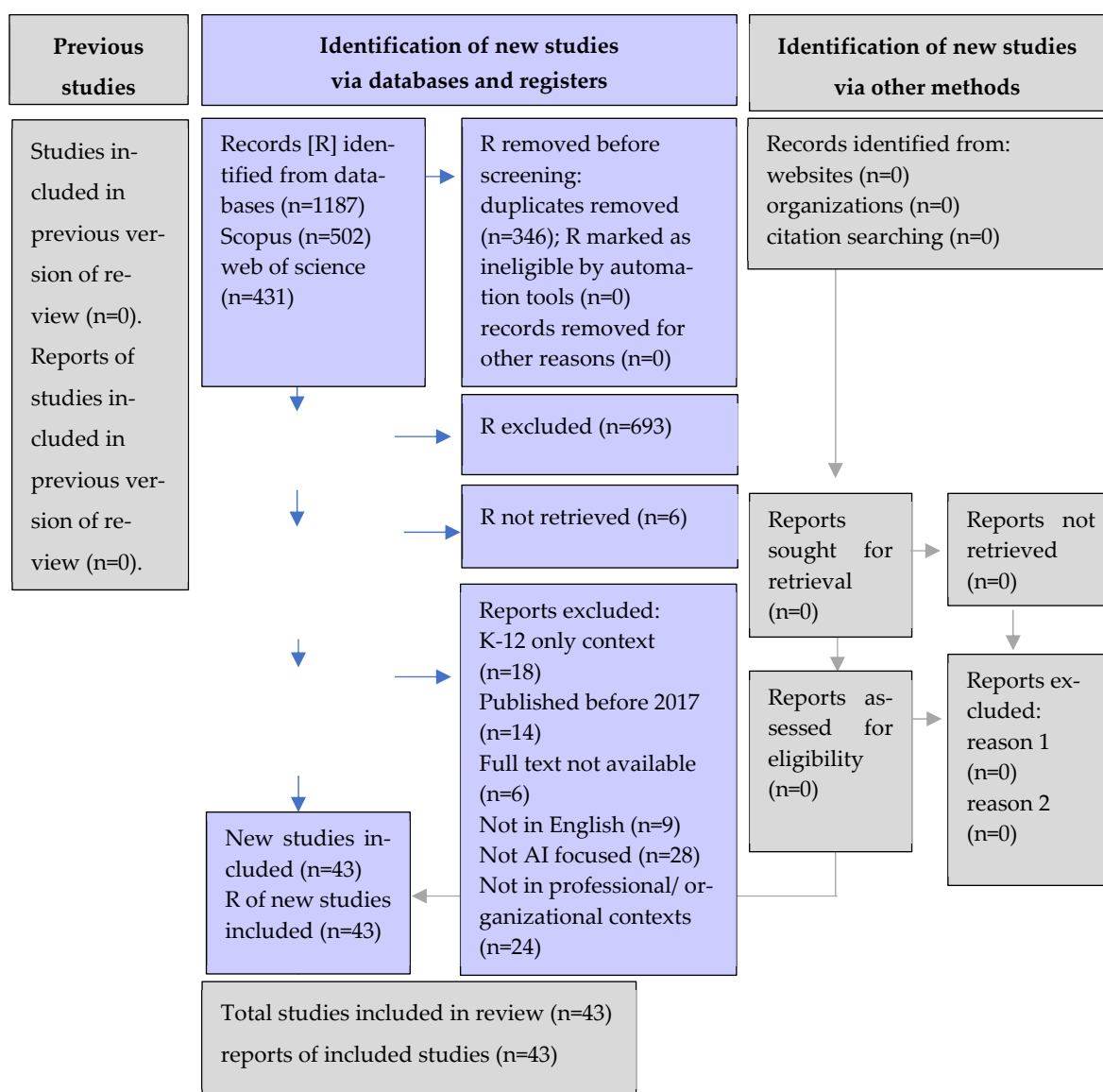


Figure 1. PRISMA process diagram.

The screening process also followed PRISMA 2020 guidelines (Page et al., 2021). Initial title and abstract screening were conducted by a research assistant based on predefined inclusion and exclusion criteria. Full-text review was then performed independently by the first and second authors. Discrepancies were resolved through discussion until consensus was reached.

2.1. Search Strategy

A comprehensive search was conducted across three major electronic databases: Scopus, Web of Science and IEEE Xplore. The search was performed in January 2026. Table 1 presents the characteristics of the studies included in the systematic review.

Table 1. Boolean Search Query Structure.

Concept	Search Terms
AI Technology	"artificial intelligence" OR "machine learning" OR "natural language processing" OR "generative AI" OR "adaptive system*" OR "intelligent tutor*" OR "recommender system*"
Personalization	"personali*" OR "adaptive learning" OR "individuali*" OR "tailored" OR "customiz*" OR "learner model*" OR "learning path*"
Professional Context	"professional development" OR "workforce development" OR "employee training" OR "corporate learning" OR "workplace learning" OR "human resource development" OR "HRD" OR "talent development" OR "adult learning" OR "lifelong learning"
Organizational Context	"knowledge-intensive organization*" OR "knowledge-based organization*" OR "knowledge work*" OR "professional service*" OR "educational organization*" OR "education sector" OR "higher education institution*" OR "academic institution*"
Boolean Logic	(AI Technology) AND (Personalization) AND (Professional Context) AND (Organizational Context)

2.2. Eligibility Criteria

2.2.1. Inclusion Criteria

- Peer-reviewed journal articles published between 2017 and 2026;
- Empirical studies (quantitative, qualitative, or mixed methods) and systematic reviews;
- Focus on AI-driven personalization in learning contexts;
- Application to professional development, workforce training, or adult learning;
- Published in English;
- Full text available.

2.2.2. Exclusion Criteria

- Dissertations;
- Studies focused exclusively on K-12 education without professional relevance;
- Studies on educational technology without clear AI components;
- Opinion pieces, editorials;
- Studies not available in English;
- Peer-reviewed journal articles published before 2017.

2.3. Data Collection Process

The following data items were extracted from each included study:

- Study characteristics (authors, year, journal, country);
- Research design and methodology;
- Sample characteristics (size, professional context, demographics);
- AI technologies and personalization approaches;
- Learning outcomes and effectiveness measures;
- Implementation factors and challenges;

- Key findings and conclusions.

Because the review addresses a relatively understudied topic, our initial search yielded a higher proportion of systematic reviews than empirical studies. To account for this in a controlled manner, a differentiated synthesis approach was adopted. To address the conceptual heterogeneity arising from the inclusion of diverse study designs, a differentiated synthesis approach was adopted. Different evidence types were weighted according to their methodological strengths: systematic reviews and conceptual papers were primarily utilized to map broad cross-sector patterns and theoretical frameworks, whereas empirical studies were prioritized for extracting specific AI mechanisms, managerial actions, and concrete learning outcomes. This weighting strategy ensured that theoretical concepts were consistently grounded in empirical evidence, thereby strengthening the analytical consistency of the review.

2.4. Data Analysis and Synthesis

To ensure the reliability and replicability of the findings, the data analysis and thematic synthesis were conducted through a structured, multi-stage approach. Two independent researchers performed the data extraction and coding using a standardized coding template to minimize potential bias. The analysis followed an inductive coding approach: first, initial open codes were generated through a close reading of the included texts. These initial codes were then iteratively compared, refined, and merged into higher-level categories. Finally, overarching themes were derived from these categories to capture the broader patterns in the data. To establish reliability, both researchers independently coded the data and cross-checked their findings. Any discrepancies or disagreements during the coding process were resolved entirely through collaborative discussion between the two researchers until a mutual consensus was reached. All coding templates and decision rules were systematically documented to ensure full transparency and replicability of the study.

3. Results

The results are organized in two parts. Table 2 presents the background characteristics of the 43 studies included in this review, summarizing their distribution by research design, sector, geographic region, and publication year. The thematic findings are then presented in Section 3.1, structured according to the research questions guiding this review.

Table 2. Summary of background characteristics of analyzed studies ($N = 43$).

Category	Studies (n)	Proportion (%)
By sector		
Education sector	25	58.1%
Knowledge-intensive organizations	18	41.9%
By study type		
Systematic/scoping literature reviews	21	48.8%
Meta-analysis	1	2.3%
Theoretical/conceptual	2	4.7%
Quantitative/quasi-experimental	12	27.9%

Qualitative/case studies	2	4.7%
Mixed methods	5	11.6%
By region		
Asia (China, India, Indonesia, Kazakhstan, South Korea)	11	25.6%
Europe (UK, Germany, Spain, Netherlands, Italy, Czech Republic, Greece, Russia, Serbia, Slovenia, Switzerland)	18	41.8%
North America (USA & Mexico)	8	18.6%
Middle East (Israel, Saudi Arabia, Turkey)	4	9.3%
Oceania (Australia)	2	4.7%
By year		
2017–2021	6	14%
2022–2023	11	25.6%
2024–2026	26	60.4%

Note: Each source was classified into one primary category per dimension. Marginal totals may vary slightly across dimensions due to dual classifications or multi-national authorship.

3.1. Findings by Research Question

The results section presents the findings from this systematic literature review, analyzing all included studies in relation to each research question. The analysis proceeds as follows: Section 3.1.1 provides an overarching synthesis of similarities and differences between AI-based personalized learning models in knowledge-intensive organizations and educational organizations. Sections 3.1.2 examines model characteristics (RQ1), Section 3.1.3 analyzes managerial roles (RQ2) and Section 3.1.4 addresses alignment with the Nine-Cell Model (RQ3). Throughout the analysis, findings from both sectors are compared to illuminate convergences and divergences in how AI-based personalization is conceptualized and enacted.

3.1.1. Overarching Question: Cross-Sector Comparison

The synthesis of all 43 included studies reveals that AI-based personalized learning in knowledge-intensive organizations and educational organizations shares a common technological foundation yet operates through distinct institutional logics. Both sectors employ adaptive algorithms, real-time feedback mechanisms, and learning analytics to monitor progress and tailor content to individual learners (Hariyanto et al., 2025; Pavlakou et al., 2025; Vorobyeva et al., 2025). In each context, AI technologies such as machine learning and natural language processing serve as enabling infrastructure for personalization. Both sectors have also shifted from standardized training models toward individualized architectures, a transition accelerated by the COVID-19 pandemic and the shift to remote and hybrid learning (Hariyanto et al., 2025; Kazanci Yabanova, 2025). Despite this shared infrastructure, however, the two sectors diverge along four axes: purpose, data ecosystems, temporal structures, and governance.

The overarching purpose of personalization differs between the two sectors. Whereas knowledge-intensive organizations, models orient toward competency alignment, career

progression, and employee retention (Tusquellas et al., 2024; Pavlakou et al., 2025), educational models focus on knowledge mastery and credential attainment within structured curricula (Farhood et al., 2025; Bernacki et al., 2021). The data ecosystems that support personalization reflect this distinction: organizational systems integrate a broad range of inputs including performance reviews, competency frameworks, and strategic workforce needs (Tusquellas et al., 2024; Hemmler et al., 2023), while educational platforms rely primarily on academic performance indicators and engagement metrics (Wang et al., 2024; Merino-Campos, 2025). Similarly, AI-mediated personalized learning paths have been found to remain concentrated in higher education settings, with significant opportunities for further development in workplace and informal learning contexts, a pattern consistent with the cross-sector asymmetry identified in this review (Bayly-Castaneda et al., 2024).

The temporal dimension presents a further contrast. In organizational contexts, learning operates as a continuous, open-ended process embedded within daily work routines (Kauffeld et al., 2025; Kazanci Yabanova, 2025), whereas in educational organizations, learning is typically bounded by semester or course cycles (Merino-Campos, 2025; Farhood et al., 2025). Both sectors confront overlapping implementation challenges, including data privacy, algorithmic bias, infrastructure limitations, and the need for human oversight (Hariyanto et al., 2025; S. Kim et al., 2024; Dima et al., 2024). Yet these challenges manifest differently in each sector: organizations face issues of HR system integration and employee trust in algorithmic decision-making (Ubeda-García et al., 2025), while educational organizations center on student data protection and equitable access to technology (Vorobyeva et al., 2025; Luo et al., 2025).

The organizational and pedagogical characteristics that define each sector are examined in detail in Section 3.1.2 (RQ1). The distinct managerial roles in each context are analyzed in Section 3.1.3 (RQ2), and the alignment of cross-sector patterns with the Nine-Cell Model is addressed in Section 3.1.4 (RQ3).

Key finding: Despite sharing a common adaptive technology infrastructure, the two sectors diverge in the purpose, data ecosystems, temporal structures, and governance of personalization. The findings indicate that each sector adapted AI tools to its pre-existing institutional logic rather than converging toward shared models, suggesting that personalization is shaped more by context than by algorithmic capability.

3.1.2. Sub-Question 1: Model Characteristics

Building on the broad cross-sector patterns identified above, this subsection turns to the specific organizational and pedagogical characteristics defining AI-based personalized learning in each sector. The analysis moves beyond the shared technological infrastructure to examine the theoretical foundations, empirical mechanisms, and institutional structures that shape how personalization operates in practice.

In knowledge-intensive organizations, AI-based personalized learning models prioritize competency development aligned with strategic business objectives, career trajectory planning, and workforce adaptability (Tusquellas et al., 2024; Kazanci Yabanova, 2025). The pedagogical design of these models draws on adult learning theory, workplace learning research, and human resource development (HRD) frameworks, reflecting the motivational profiles and learning needs of professional learners (J. Kim et al., 2025; Kauffeld et al., 2025).

Technologically, organizational learning systems draw on a broad data ecosystem, integrating performance, competency, and career data to construct individualized pathways (Hemmler et al., 2023; Tusquellas et al., 2024). What distinguishes these systems at the model level is their use of AI to contextualize content in relation to professional development needs. Research on AI-powered learning for working adults indicates that learners value personalized, mastery-based approaches that adapt content to their professional

goals and pacing needs, viewing such systems as conducive to sustained engagement and meaningful learning (J. Kim et al., 2025). The integration of AI with existing HR systems represents a further organizational characteristic. In this context, personalization must align with broader talent management processes, from recruitment and retention to succession planning (Rozman et al., 2022; Nawaz et al., 2024).

A further distinguishing feature of organizational models is their emphasis on training transfer and knowledge sharing as key outcomes. Unlike educational organizations, where assessment is the primary feedback mechanism, organizational models evaluate learning effectiveness through observable changes in workplace behavior and task performance. Knowledge sharing with colleagues serves as an additional outcome measure (Kauffeld et al., 2025; Mehner et al., 2025; de Jong et al., 2025). Both peer and supervisor support have been found to function as significant contributing factors for training transfer and knowledge sharing, underscoring the social embeddedness of learning in organizational contexts (Mehner et al., 2025). The centrality of transfer outcomes, rather than assessment scores, marks a fundamental departure from educational models and reflects the applied orientation of workplace learning.

In contrast, in educational organizations, AI-based personalized learning models are predominantly structured around adaptive content delivery systems, designed to support student mastery of disciplinary knowledge. These systems typically employ machine learning algorithms that analyze learner performance data to adjust content difficulty, sequencing, and pacing in real time (Hariyanto et al., 2025; Farhood et al., 2025; Wang et al., 2024). Pedagogically, the models are grounded in constructivist (learner-centered) and mastery-based learning theories. While empirical evidence suggests that adaptive e-learning models can produce measurable improvements in learning outcomes (Arsovic & Stefanovic, 2020), the validity of these findings is sometimes limited by small sample sizes and specific localized contexts, necessitating a critical and cautious interpretation. Existing empirical evidence supports the pattern that adaptive e-learning models have been shown to produce measurable improvements in learning outcomes compared to non-adaptive alternatives (Arsovic & Stefanovic, 2020). Machine-learning-based predictive interventions delivering “just-in-time” support also yielded statistically significant improvements in pass rates among undergraduate STEM students (Hasan & Khan, 2023). In the context of language learning, while a controlled experiment suggested that AI-mediated instruction produced higher English achievement scores and increased motivation (L. Wei, 2023), the relatively small sample size of 60 university students limits the generalizability of these claims. This underscores the need for larger-scale empirical validations before drawing definitive conclusions about the impact of AI on complex metacognitive processes. A defining pedagogical characteristic in education is the emphasis on formative assessment as the primary mechanism for personalization. AI tools in this sector function primarily as assessment engines, continuously evaluating learner understanding and adjusting instructional pathways accordingly (Luo et al., 2025; Vorobyeva et al., 2025). The role of AI-driven chatbots has also expanded within educational models. Although some studies report that chatbot-assisted in-class debates enhance students’ argumentation skills and motivation (Guo et al., 2023; J. W. Han et al., 2022), these claims often stem from short-term quasi-experimental designs, indicating a need for more robust longitudinal evidence to firmly establish their reliability. These findings suggest that AI tools in education serve not only as content delivery mechanisms but also as pedagogical agents that support higher-order cognitive processes. Institutionally, higher education AI systems operate within relatively bounded structures. The learner population tends to be relatively homogeneous in terms of age and educational stage. Evaluation criteria are standardized around academic achievement metrics such as grades, test scores, and course completion (Wang et al., 2024; Bernacki et al., 2021). Infrastructure constraints also shape model de-

sign. In settings with limited resources, the successful integration of technology-enhanced learning depends on pedagogical, cultural, and institutional factors that extend well beyond the technical capacity of the AI system itself (Heinrich et al., 2020). These bounded conditions contrast with the continuous, strategically embedded structures described above in organizational contexts.

In summary, organizational and educational models share a common technological infrastructure of adaptive algorithms and learning analytics, yet they ground their personalization in different theoretical traditions and pursue different goals. Organizational models draw on adult learning theory and HRD scholarship, positioning AI as a tool that contextualizes learning to career goals within broader talent management systems. Educational models draw on learner-centered pedagogy and formative assessment to function primarily as adaptive assessment engines. Both approaches yield measurable learning gains, but the mechanisms and evaluation criteria remain specific to each sector.

Key finding: Organizational models position AI as a career-contextualization tool informed by adult learning and HRD frameworks, while educational models function as adaptive assessment engines grounded in constructivist pedagogy. Temporal asymmetry persists: organizational learning operates as a continuous, work-embedded process, while educational AI remains bounded by course cycles.

3.1.3. Sub-Question 2: The Role of Managers

The literature that was reviewed reveals that managerial roles in supporting AI-based personalized learning differ substantially between knowledge-intensive and educational organizations (Bevilacqua et al., 2025; Darling-Hammond et al., 2017; Kauffeld et al., 2025). This section examines how managers in each sector are described as facilitating, shaping, or constraining the implementation of personalized learning for human capital development.

In knowledge-intensive organizations, several studies position managers as active agents in shaping personalized learning pathways (Bevilacqua et al., 2025; Hossain et al., 2025; Pavlakou et al., 2025). This role extends beyond administrative oversight to include the strategic alignment of individual learning goals with organizational objectives (Kauffeld et al., 2025). Managers are also involved in selecting and endorsing learning content, as well as in creating supportive conditions for learning transfer (Bevilacqua et al., 2025; Hossain et al., 2025). Three clusters of managerial involvement with AI have been identified: cultivating AI leadership skills, driving organizational adoption of AI, and deploying AI for strategic decision-making (Bevilacqua et al., 2025). This indicates that effective managerial support for personalized learning requires leaders who understand AI capabilities and can integrate them into broader talent development strategies.

In the organizational literature, a managerial mindset emerges as a critical variable. A goal-oriented leadership app combined with a leaders' growth mindset (defined as leadership self-efficacy and motivation to lead) was found to significantly enhance training transfer (Guntner et al., 2025). These results indicate that the effectiveness of personalized learning supported by technology depends not only on the design of the AI system but also on the psychological orientation and active engagement of the supervising manager (Guntner et al., 2025). Leaders managing AI environments have been found to require dynamic managerial capabilities, including the ability to sense opportunities, seize strategic advantages, and reshape organizational resources in response to technological change (Hossain et al., 2025).

Beyond the individual mindset, social support structures also play a central role in organizational personalized learning. Both supervisor and peer support have been identified as significant contributing factors for training transfer and knowledge sharing (Mehner et al., 2025). This aligns with the argument that learning in organizations is a

social process. It requires integration across formal, informal, and self-regulated learning pathways (Kauffeld et al., 2025). Managers, in this view, serve a connective function, linking individual learning pathways with organizational knowledge networks (Kauffeld et al., 2025; Pavlakou et al., 2025). AI-based learning systems in organizations have produced measurable improvements in training efficiency and talent retention. This is particularly true when managers endorse these systems and align them with organizational culture (Pavlakou et al., 2025).

In educational organizations, the managerial role takes different forms. The literature describes school leaders, department heads, and program directors primarily as facilitators of structural conditions rather than direct shapers of individual learning pathways (Darling-Hammond et al., 2017; Ventista & Brown, 2023). Key characteristics of effective professional development include sustained duration, content focus, active learning, collaboration, and coherence with institutional priorities. Although this framework predates the current wave of AI adoption, its principles continue to shape how educational leaders approach personalized learning (Darling-Hammond et al., 2017). Evidence from the educational sector indicates that continuous, collaborative, and sustained professional development produces the most significant positive outcomes for student learning (Ventista & Brown, 2023). These findings underscore the importance of managerial decisions regarding time allocation, resource provision, and the design of collaborative structures (Ventista & Brown, 2023). Educational leaders might support personalized professional learning by enabling teachers to self-assess their competencies across the dimensions of the Nine-Cell Model and to set individualized development goals accordingly. In this framework, the managerial role shifts from direct instruction to supportive guidance, providing the structural and cultural conditions for self-directed professional growth (Avidov-Ungar, 2024).

The literature also identifies challenges specific to AI for educational leaders. Pedagogical challenges in integrating AI-based personalization have been found to precede and often outweigh technical ones, suggesting that educational leaders must prioritize pedagogical readiness alongside technological infrastructure (Vorobyeva et al., 2025). Educational leaders also face particular challenges related to educator preparedness, scalability constraints, and the need for ethical frameworks governing AI use in learning contexts (Fortuna et al., 2025). These challenges require managerial competencies that extend beyond traditional administrative skills to include digital literacy, ethical reasoning, and the capacity to navigate institutional change (Kazanci Yabanova, 2025; Vorobyeva et al., 2025; Fortuna et al., 2025).

Comparison between the two sectors reveals a notable difference in managerial involvement. Managers in organizations actively shape and align learning pathways with strategic objectives, and create supportive conditions for transfer and application (Bevilacqua et al., 2025; Kauffeld et al., 2025; Guntner et al., 2025; Pavlakou et al., 2025; Hossain et al., 2025), whereas educational leaders primarily design structural conditions that enable self-directed professional learning (Darling-Hammond et al., 2017; Ventista & Brown, 2023). Both sectors recognize the critical importance of managerial support, but the mechanism and focus of that support differ.

Key finding: Managers in knowledge-intensive organizations actively shape learning pathways and align them with strategic objectives, while educational leaders primarily create structural conditions for self-directed professional growth. Managerial mindset, particularly growth orientation and leadership self-efficacy, emerged as a significant predictor of training transfer. A gap exists in the educational literature, where managerial roles are examined largely in pre-AI contexts. To facilitate comparison between the two sectors, Table 3 summarizes the key characteristics of AI-based personalized learning in knowledge-intensive organizations and educational organizations.

Table 3. Cross-Sector Comparison of AI-Based Personalized Learning.

Comparison	Educational Organizations	Knowledge-Intensive Organizations
Goals and Orientation		
Overarching purpose	Knowledge mastery and credential attainment within structured curricula	Competency alignment with strategic objectives, career progression, and employee retention
Theoretical foundation	Constructivist and mastery-based learning theories emphasizing learner-centered progression	Adult learning theory, workplace learning, and HRD frameworks reflecting professional learner profiles
Success metrics	Grades, test scores, course completion rates, and formative assessment indicators	Training transfer, workplace behavior change, knowledge sharing, and talent retention
Data and Technology		
Data sources	Academic performance indicators, learning style assessments, and engagement metrics	Performance reviews, competency frameworks, career aspirations, and labor market signals
Dominant AI types	Adaptive content delivery, intelligent tutoring systems, AI chatbots, recommendation engines	Generative AI for career-contextualized content, competency mapping tools, AI-integrated HR platforms
Personalization mechanism	Algorithms adjust content difficulty, sequencing, and pacing based on real-time learner performance	Generative AI contextualizes learning material to individual career goals and competency gaps
Temporal and Structural Dimensions		
Temporal structure	Bounded by semester or course cycles	Continuous, open-ended process embedded within daily work routines
Learner agency	Structured progression within fixed curricula; learner choice constrained by institutional requirements	Greater self-direction in choosing learning pathways, with managers as active co-shapers of trajectories
Institutional structure	Relatively homogeneous learner population; standardized evaluation; infrastructure constraints shape design	Heterogeneous workforce; integration with talent management, recruitment, succession planning
Managerial Role		
Primary managerial function	Facilitators of structural conditions enabling self-directed professional learning	Active agents shaping personalized learning pathways and aligning them with organizational strategy
Managerial mindset	Emphasis on pedagogical readiness and institutional coherence; supportive guidance for self-assessment	Growth mindset (leadership self-efficacy, motivation to lead) and dynamic managerial capabilities
Social support mechanisms	Communities of practice, peer observation, collaborative professional learning networks	Supervisor and peer support as predictors of training transfer; managers linking individual pathways with organizational networks
Challenges		
Ethics and governance	Concerns center on student data protection, algorithmic transparency, and equitable access to AI tools	Concerns focus on algorithmic bias in talent management, employee trust, and risk of reinforcing structural inequalities
Implementation challenges	Educator preparedness, scalability constraints, pedagogical challenges preceding technical ones, and resource limitations	Integration with existing HR infrastructure, alignment with organizational culture, and ensuring managerial endorsement

3.1.4. Sub-Question 3: Model Evolution and Alignment with the Nine-Cell Model

This section examines how AI-based personalized learning models in both sectors align with the dimensions of the Nine-Cell Model which crosses three professional competencies (systematic knowledge and intellectual skills; creating new knowledge and life-long learning; norms, values, and code of ethics) with three job-related components (means of action, networks of action, and role constraints). The resulting matrix provides a structured lens for analyzing personalization across professional contexts (Avidov-Ungar, 2024, 2025).

The first dimension—systematic knowledge and intellectual skills—is well represented across the two sectors, though the emphasis varies. In organizational contexts, this component takes the form of competency-based training aligned with job performance standards and strategic objectives (Tusquellas et al., 2024; Morandini et al., 2023). In educational organizations, the focus falls on disciplinary and pedagogical knowledge acquisition through adaptive content delivery and mastery-based assessment cycles (Farhood et al., 2025; Wang et al., 2024; Alsadoon, 2020). Both sectors employ AI to support the acquisition of systematic knowledge, yet the knowledge domains differ: professional competencies and technical skills in organizations versus academic disciplines in education.

The second dimension—creating new knowledge and lifelong learning—encompasses the capacity to identify problems, generate original solutions, and engage in continuous self-directed inquiry. This dimension receives uneven attention across sectors. In organizational contexts, it is addressed through experiential learning, reflective practice, and self-regulated learning embedded within daily work activities (Kauffeld et al., 2025; Hemmler et al., 2023). Research on AI-powered adult learning further suggests that cognitive interaction with AI tools, including metacognitive monitoring and the formulation of quality questions, supports deeper engagement with learning content when aligned with professional goals. These findings indicate that organizational models support knowledge creation by connecting learning to authentic professional challenges (J. Kim et al., 2025). In educational organizations, AI tools support this area through platforms that promote independent inquiry, problem-solving, and creative thinking (Hasan & Khan, 2023; Bernacki et al., 2021). Although some experimental evidence points to ChatGPT improving creative problem-solving and AI-supported debates fostering argumentation skills (Urban et al., 2024; Guo et al., 2023), these findings are largely derived from short-term, controlled academic tasks. Consequently, their long-term applicability to complex, real-world professional environments needs to be more rigorously established.

The third dimension—norms, values, and code of ethics—is the least explicitly addressed in either sector. In organizational contexts, ethical concerns center on algorithmic bias in talent management, employee trust in AI-based decision-making, and the potential for personalization to reinforce structural inequalities (S. Kim et al., 2024; Dima et al., 2024; Ubada-García et al., 2025). In educational organizations, such considerations appear primarily around data privacy, algorithmic transparency, and equitable access (Vorobyeva et al., 2025; Fortuna et al., 2025). Several studies further note the risk that AI systems may narrow learning opportunities if not governed by robust ethical frameworks (Hariyanto et al., 2025; Luo et al., 2025). A pattern common to both sectors is that ethics is framed primarily as a constraint on AI implementation rather than as a learning outcome that AI systems actively cultivate (Vorobyeva et al., 2025; S. Kim et al., 2024). This gap is theoretically consequential relative to the Nine-Cell Model, which positions norms and values as a component of professional development that personalized learning should foster, not merely safeguard through governance mechanisms (Avidov-Ungar, 2024).

Turning to the job-related components, means of action is the most extensively supported area in both sectors. In organizational contexts, relevant tools include competency mapping systems, career-aligned learning pathways, and AI-integrated HR platforms that

support skill development and knowledge transfer (Tusquellas et al., 2024; Rozman et al., 2022; Nawaz et al., 2024). The breadth of these resources is generally greater in corporate environments, reflecting the wider array of data sources and integration points available (Tusquellas et al., 2024; Pavlakou et al., 2025). In education, AI serves as a primary means of action by providing adaptive content, automated assessment, and data-informed feedback that enhance pedagogical knowledge and instructional skills (Luo et al., 2025; Hariyanto et al., 2025; Vorobyeva et al., 2025). Tools such as intelligent tutoring systems, chatbots, and recommendation engines function as actionable resources that practitioners deploy in daily work (Tapalova & Zhiyenbayeva, 2022; X. Wei et al., 2021). Evidence from language instruction further indicates that AI platforms can produce gains not only in domain-specific knowledge but also in learner motivation and self-regulation (L. Wei, 2023).

Networks of action, defined as patterns of cooperation, communicative awareness, and knowledge transmission, are addressed through different mechanisms in each sector. In organizational contexts, such networks are supported through cross-departmental team learning, knowledge-sharing platforms, and socially embedded learning processes (Mehner et al., 2025; H. Han et al., 2023; Kauffeld et al., 2025). Training participation has been shown to expand professional knowledge networks, with peer and supervisor relationships serving as central channels for effective knowledge transfer (Mehner et al., 2025). The organizational literature thus portrays these networks as integral to the learning process itself rather than as peripheral supports (Kauffeld et al., 2025). In educational organizations, collaborative professional learning is sustained through communities of practice, peer observation, and professional learning networks (Ventista & Brown, 2023; Darling-Hammond et al., 2017; Avidov-Ungar, 2025). AI tools increasingly facilitate such collaboration, as demonstrated by chatbot-supported debate activities that strengthened student argumentation (Guo et al., 2023).

Role constraints, defined as commitment to values, ethics, and rules of conduct, emerge as the component most weakly addressed by AI-based personalization across the two sectors. In organizational contexts, these constraints appear through compliance requirements, professional standards, and the ethical governance of AI systems (S. Kim et al., 2024; Dima et al., 2024). Ensuring fairness, inclusion, and ethical conduct in AI-based skill development remains a persistent challenge, particularly across dimensions of age, gender, and cultural diversity (Morandini et al., 2023). In educational organizations, institutional constraints shape AI integration through curricular requirements, standardized assessment mandates, and regulatory frameworks governing student data (Farhood et al., 2025; Heinrich et al., 2020; Merino-Campos, 2025), emphasized that professional growth requires engagement with role constraints, including developing leadership capacity and aligning personal development with institutional goals (Avidov-Ungar, 2024, 2025). The limited attention to this component suggests that current AI-based personalization models prioritize knowledge and skill acquisition over the cultivation of professional values and ethical reasoning.

In sum, both sectors demonstrate strong alignment with the systematic knowledge and means of action dimensions of the Nine-Cell Model, reflecting a natural fit between AI capabilities and structured knowledge delivery. The dimension of creating new knowledge receives moderate support through distinct approaches in each sector. Organizations emphasize experiential and reflective methods (Kauffeld et al., 2025; Hemmler et al., 2023). Educational organizations, by contrast, rely on creative and inquiry-based tools (Urban et al., 2024; Guo et al., 2023). Networks of action are supported through knowledge-sharing platforms in organizations and collaborative professional communities in education. The dimensions of norms, values, and role constraints are the least de-

veloped, representing a gap that the Nine-Cell Model helps identify as essential for holistic professional development (Avidov-Ungar, 2024).

Key finding: Alignment with the Nine-Cell Model is strongest in the systematic knowledge and means of action dimensions, yet substantially weak in norms/values and role constraints. Ethics is framed across both sectors as a constraint on AI implementation rather than as a learning outcome, and none of the reviewed studies explicitly described AI-based personalization systems designed to cultivate professional values as a primary learning objective. This gap highlights a partial conception of professional development in current models. Table 4 summarizes the alignment between the findings of the systematic review and the dimensions of the Nine-Cell Model, highlighting similarities and differences across organizational and educational contexts.

Table 4. Alignment of AI-Based Personalized Learning with the Nine-Cell Model.

Nine-Cell Dimension	Coverage	Knowledge-Intensive Organizations	Educational Organizations
Professional Competencies			
Systematic knowledge and intellectual skills	High	Competency-based training aligned with job performance standards and strategic objectives	Adaptive content delivery and mastery-based assessment targeting disciplinary knowledge
Creating new knowledge and lifelong learning	Medium	Experiential and reflective learning within daily work; generative AI contextualized to career goals facilitating deeper engagement	Tools promoting inquiry, problem-solving, and creative thinking; ChatGPT improving creative performance
Norms, values, and code of ethics	Low	Ethical concerns focused on algorithmic bias, employee trust, and structural inequalities; treated as governance issue, not developmental goal	Ethics addressed as implementation constraints (data privacy, transparency, equitable access) rather than as learning outcomes
Job-Related Components			
Means of action	High	Competency mapping, career-aligned learning pathways, AI-integrated HR systems; broader array of data sources and integration points	AI as primary means: adaptive content, automated assessment, data-driven feedback, ITS, chatbots, recommendation engines
Networks of action	Medium	Cross-departmental team learning, knowledge-sharing platforms; peer and supervisor relationships as central transfer channels	Collaborative learning through communities of practice, peer observation, and AI-facilitated debates
Role constraints	Low	Compliance requirements, professional standards, ethical AI governance; limited attention to cultivating professional values through personalized learning	Institutional constraints via curricular requirements, assessment mandates, data regulations; limited development of leadership capacity through AI

4. Discussion

This systematic review compared AI-based personalized learning models across knowledge-intensive organizations and educational organizations, using the Nine-Cell Model as an integrative analytical lens (Avidov-Ungar, 2024). The findings reveal both convergence and divergence in how personalization is conceptualized, enacted, and governed in each sector. This section interprets the principal findings in relation to three areas: the theoretical contribution of the cross-sector comparison, managerial mediation of AI-based personalization, and the diagnostic value of the Nine-Cell Model.

The cross-sector comparison reveals a key distinction in how personalization operates. In knowledge-intensive organizations, personalization is structured around alignment and transfer: AI systems identify competency gaps, map content to career trajectories, and evaluate effectiveness through workplace behavior change (Tusquellas et al., 2024; Kauffeld et al., 2025; Hemmler et al., 2023). Integration with HR and talent management systems extends personalization beyond individual skill acquisition to encompass workforce planning and succession strategies (Nawaz et al., 2024; Rozman et al., 2022). In educational organizations, personalization is organized around mastery and assessment. AI tools adapt content difficulty, sequencing, and feedback in response to learner performance data, with evaluation centered on academic achievement metrics (Farhood et al., 2025; Wang et al., 2024). These empirical patterns, documented in Section 3.1.2, suggest that the two sectors are developing functionally distinct personalization architectures despite relying on comparable AI infrastructure.

These sectors operate according to different logics. In organizations, personalization serves a strategic function, synchronizing individual development with collective objectives (Bevilacqua et al., 2025; Rozman et al., 2022). In education, it serves a pedagogical function, calibrating instruction to the cognitive state and trajectory of each learner (Vorobyeva et al., 2025; Luo et al., 2025). Although the technological infrastructure is similar, the purposes, data ecosystems, and evaluation criteria differ substantially. This finding suggests that personalization is not a unitary construct, but a family of practices shaped by institutional context. Previous reviews examining personalization within a single sector have been unable to identify these cross-sector patterns (Bayly-Castaneda et al., 2024; Fortuna et al., 2025; Ekuma, 2023; Farhood et al., 2025). This comparison shows that insights from one sector are not directly transferable without accounting for the distinct logic governing each context, and that effective personalization requires sector-specific design principles rather than a universal framework.

The observed sectoral differences are not merely operational; they stem fundamentally from the distinct learning theories that govern each context. Educational organizations are inherently guided by constructivist pedagogy and mastery-based learning. This theoretical foundation explains why AI systems in this sector are, by nature, more assessment- and curriculum-oriented, focusing on individual cognitive progression. Conversely, knowledge-intensive organizations operate under the paradigms of adult learning theory, workplace learning, and Human Resource Development (HRD). These frameworks emphasize the social and applied nature of learning, which explains why organizational AI models prioritize competency development, transfer of training, and strategic alignment over standardized assessment.

The findings indicate that managerial involvement constitutes a critical mediating factor in both sectors, though its nature differs between contexts. In knowledge-intensive organizations, managers function as active architects of personalized learning. They align pathways with strategic objectives and build trust in AI systems through active endorsement (Bevilacqua et al., 2025; Kauffeld et al., 2025; Hossain et al., 2025). The effectiveness of this role is mediated not only by organizational structures but also by the managerial mindset, particularly leadership self-efficacy and growth orientation (Guntner et al.,

2025). This finding contributes to HRD scholarship by demonstrating that the psychological disposition of managers shapes the outcomes of technology-mediated learning, rather than just its implementation. Action learning approaches further bridge individual skill development and organizational knowledge building through structured reflection and collaborative problem-solving (H. Han et al., 2023).

In educational organizations, leaders operate primarily as enablers of structural and cultural conditions. Rather than shaping individual pathways, they design institutional frameworks supporting self-directed professional growth: time allocation, resource provision, collaborative structures, and coherence with priorities (Darling-Hammond et al., 2017; Ventista & Brown, 2023). The educational findings reinforce the notion that institutional readiness, rather than algorithmic sophistication, remains the primary determinant of effective AI integration. This underscores the managerial function of creating favorable structural and cultural conditions (Heinrich et al., 2020).

As a preliminary reflection derived from this qualitative synthesis, four provisional components of managerial mediation emerge: (1) enabling conditions, including resource allocation and time structures; (2) strategic action, aligning learning with institutional goals; (3) trust and endorsement mechanisms; and (4) governance of ethical and equitable AI use. This four-component framework is not a fully developed theory but rather offers a structured proposition for future research. In organizational contexts, strategic action and trust carry greater weight. In contrast, enabling conditions and governance are more prominent in educational organizations (Kazanci Yabanova, 2025; Vorobyeva et al., 2025). This four-component framework offers a structured lens for future research examining the conditions under which managerial mediation enhances or constrains AI-based personalization.

Consequently, the Nine-Cell Model functions as more than a descriptive classificatory framework; it serves as a theory-building mechanism (Avidov-Ungar, 2024, 2025). By analyzing the findings through this model, we advance theoretical understanding by demonstrating how the dominant learning theories in each sector create specific developmental ‘blind spots.’ For instance, the strong constructivist focus in education (e.g., Bernacki et al., 2021; Farhood et al., 2025) explains its theoretical neglect of organizational dimensions such as ‘role constraints.’ More importantly, the model reveals that both constructivist and HRD paradigms (e.g., Kauffeld et al., 2025; J. Kim et al., 2025) currently fail to adequately conceptualize professional identity and ethics as core learning outcomes, treating them instead as external regulatory issues. Thus, the model builds theory by highlighting exactly where current learning paradigms must evolve to support holistic, AI-based professional development (Avidov-Ungar, 2025).

Alignment is strongest in the knowledge-oriented and tool-oriented cells of the model, confirming that AI capabilities map most readily onto structured content delivery and skills-based training. Moderate alignment characterizes the dimensions of creating new knowledge and networks of action, while norms, values, and role constraints receive weak attention. The strong representation of knowledge and means of action reflects a natural affinity between AI capabilities and structured content delivery. Adaptive algorithms excel at adjusting difficulty, sequencing material, and providing data-informed feedback (Hariyanto et al., 2025; Tusquellas et al., 2024). AI systems are beginning to support higher-order processes such as creative problem solving, collaborative argumentation, and reflective practice, but these applications remain secondary to knowledge delivery (Urban et al., 2024; Guo et al., 2023; Kauffeld et al., 2025).

The most consequential finding concerns the dimensions of norms, values, and role constraints. These represent essential components of professional development: ethical reasoning, professional autonomy, and the capacity to exercise leadership within institutional constraints (Avidov-Ungar, 2024, 2025). The findings confirm what the Nine-Cell

Model would predict: when ethical dimensions are treated solely as regulatory guardrails, they remain external to the learning process rather than integral to professional growth. Building on this pattern, and while recognizing the need for further conceptual and empirical development, we propose a preliminary conceptual distinction between two orientations toward ethics in AI-based personalized learning. The first, which we term ‘defensive ethics’, refers to approaches that frame ethics as a constraint on system implementation, focusing on preventing harm through regulatory safeguards such as bias audits, data privacy protocols, and algorithmic transparency requirements. The second, which we term ‘generative ethics’, refers to approaches that position ethics as an active learning outcome, aiming to cultivate professional judgment, value-laden reflection, and ethical reasoning as core components of personalized development. The reviewed literature across both sectors operates almost exclusively within a defensive ethics orientation, addressing ethical concerns through governance mechanisms rather than through learning design.

The Nine-Cell Model calls attention to this gap by positioning norms, values, and role constraints as professional competencies that personalized learning should actively develop. Current AI systems, however, lack the design architecture to prompt value-laden reflection or facilitate dialogue about professional role tensions (Avidov-Ungar, 2025). This suggests a need to shift from defensive to generative ethics in the design of AI-based personalized learning across both sectors. Without such a shift, current models risk producing technically competent professionals who lack normative foundations for responsible practice. The identification of this pattern validates the diagnostic utility of the Nine-Cell Model, revealing blind spots that would not be visible through a purely technological or sector-specific analysis.

4.1. Implications

In knowledge-intensive organizations, the implications center on three priorities. First, algorithmic transparency and trust: employees and managers must be able to understand and interrogate the logic of AI-driven pathways (Ubeda-García et al., 2025; S. Kim et al., 2024). Second, bias detection and mitigation: AI systems personalizing learning from historical data risk perpetuating inequalities related to age, gender, and cultural background, requiring regular audits and fairness criteria (S. Kim et al., 2024; Morandini et al., 2023). Third, positioning managers as active learning architects who participate in designing, endorsing, and evaluating personalized pathways, which requires developing managerial competencies in AI literacy and ethical governance (Bevilacqua et al., 2025; Guntner et al., 2025). Fourth, the shift from defensive to generative ethics identified in this review calls for the design of AI learning modules that actively engage employees in ethical reasoning and value-based decision making, rather than limiting ethical engagement to compliance training.

In educational organizations, the predominant use of AI for assessment and content delivery limits the scope of personalization. The findings suggest a shift from AI as an efficiency mechanism toward AI as a tool that expands learning opportunities, including inquiry-based activities, collaborative learning, and engagement with professional values (Avidov-Ungar, 2024, 2025). Evidence indicates that AI tools can support higher-order processes such as argumentation and creative problem solving, yet these remain peripheral in most educational AI models (Guo et al., 2023; Urban et al., 2024). Pedagogical readiness often lags behind technological capacity, suggesting that institutional investment in digital pedagogy and ethical AI governance is at least as important as investment in infrastructure (Vorobyeva et al., 2025; Fortuna et al., 2025). Similarly, a shift from defensive to generative ethics in educational AI requires moving beyond data privacy safeguards toward learning designs that foster teachers’ ethical reasoning and professional identity

development. The Nine-Cell Model provides a practical self-assessment tool that educational leaders can use to diagnose gaps and design pathways addressing the full range of professional competencies. By illuminating these cross-sectoral dynamics, this review directly contributes to the core scope of Education Sciences. It provides educational researchers, technologists, and policymakers with a comprehensive, theory-grounded framework to advance AI-driven pedagogical innovation and holistic professional development across diverse learning environments.

4.2. Limitations

Several limitations should be noted. First, the search was restricted to peer-reviewed English-language articles indexed in Scopus, Web of Science, and IEEE Xplore, potentially excluding relevant studies in other languages or databases. Second, the evidence base remains in an emergent and relatively immature stage. The somewhat small and uneven sample of 43 studies, with a significant majority published very recently (2024–2026), reflects a nascent field. Consequently, the broad cross-sector patterns identified in this review should be interpreted cautiously as early indicators rather than definitive or fully mature conclusions; the rapid pace of AI development means these models are still evolving and new evidence may quickly alter current understandings. Third, the inclusion of diverse study designs generates conceptual heterogeneity. Although we applied a differentiated weighting strategy to synthesize empirical and conceptual evidence, the qualitative synthesis does not permit statistical aggregation of effect sizes, and the alignment analysis with the Nine-Cell Model remains subject to interpretive variability. Furthermore, because nearly half of the included studies (48.8%) are systematic or scoping reviews rather than primary empirical studies, this composition may have influenced the synthesis and should be taken into consideration when interpreting the broad cross-sector findings. Fourth, the categorization into organizational and educational sectors simplifies a landscape in which hybrid contexts, such as corporate universities, may blur boundaries. Fifth, the conceptual frameworks proposed in this review, including the defensive-generative ethics distinction and the four-component model of managerial mediation, emerged from qualitative synthesis and have not yet been empirically validated. Future research should examine these contexts and test the robustness of the patterns and frameworks proposed here.

5. Conclusions

This systematic review, guided by three research questions and framed by the Nine-Cell Model, analyzed 43 studies following PRISMA 2020 guidelines. Based on the current exploratory synthesis, three principal conclusions provisionally emerge. First, the review points to two distinct logics of personalization.

Organizational models are structured around strategic alignment and transfer to practice, while educational models center on disciplinary mastery and formative assessment. These logics caution against treating personalization as a context-free construct. Second, managerial involvement is a pivotal mediating variable. In organizations, managers actively shape learning pathways; in education, they create structural and cultural conditions for self-directed growth. As a preliminary conceptual reflection, four provisional components of managerial mediation emerged: enabling conditions, strategic action, trust and endorsement, and ethical governance. These components apply across both sectors, though with varying emphasis. Third, the Nine-Cell Model reveals a consequential gap: both sectors engage strongly with knowledge-oriented and tool-oriented dimensions but largely neglect the cultivation of professional values, ethical reasoning, and role identity. This gap points toward a more holistic conception of personalized learning that

encompasses not only what professionals know and can do, but also who they aspire to become and how they navigate ethical demands.

These conclusions suggest that the field stands at a critical juncture. The technological capacity to personalize at scale is established. The challenge ahead is to broaden personalization to encompass the full range of professional competencies identified by the Nine-Cell Model. This requires positioning managerial mediation, ethical governance, and institutional context as central to the design and evaluation of AI-based learning systems. Future research should pursue longitudinal and cross-sector empirical studies that test the conceptual frameworks proposed here. Particular attention is warranted to AI architectures that actively support the value-oriented and relational dimensions this review has identified as critically underdeveloped.

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Appendix A. PRISMA 2020 Checklist

Item #	Section and Topic	Checklist Item
1	Title	Title page
2	Abstract	Abstract
3	Introduction	Introduction
4	Objectives	Introduction-research questions
5	Methods/Eligibility criteria	Methodology
6	Information sources	Methods-Search Strategy
7	Search strategy	Methodology-Search terms Table 1. Boolean Search Query Structure
8	Selection process	Figure 1. PRISMA process diagram
9	Data collection process	Data collection process
10a	Data items (Outcomes)	
10b	Data items (Other variables)	
11	Risk of bias assessment	Not applicable
12	Effect measures	
13a	Synthesis eligibility	Methods-Inclusion/Exclusion Criteria
13b	Data preparation	
13c	Presentation methods/graphical	
13d	Synthesis methods/statistical	
13e	Heterogeneity exploration	
13f	Sensitivity analyses	
14	Reporting bias assessment	
15	Certainty assessment	
16a	Results/Study selection	Results
16b	Excluded studies	
17	Study characteristics	Table 2. Summary of background characteristics of analyzed studies
18	Risk of bias in studies	Not applicable

19	Results of individual studies	
20a	Synthesis summaries	
20b	Synthesis results/statistical	
20c	Heterogeneity causes	
20d	Sensitivity analyses	
21	Reporting biases	
22	Certainty of evidence	
23a	Discussion/Interpretation	Discussion
23b	Evidence limitations	Discussion-Limitations
23c	Review process limitations	
23d	Implications	Discussion-Implications
24a	Other information/Registration	
24b	Protocol	
24c	Amendments	
25	Support	
26	Competing interests	
27	Availability of data	

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