

# Conceptual Framework for AI Enabled Learning and Sustainable Organizational Development

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## ABSTRACT

Artificial Intelligence (AI) offers opportunities to transform organizational learning and strengthen sustainable development. However, existing research often examines AI capability, organizational learning, digital innovation strategy, and sustainability separately. This study aims to develop an integrated conceptual framework explaining how AI-enabled organizational learning may contribute to sustainable organizational development. An integrative literature review was conducted using structured searches of Scopus, Web of Science, and ScienceDirect, supplemented by citation tracking through Google Scholar. Thirty-one scholarly sources were synthesized according to their theoretical constructs, explanatory mechanisms, and levels of analysis. The framework integrates the Resource-Based View, Dynamic Capability Theory, Technology-Organization-Environment framework, and technology acceptance theories. The study proposes an Artificial Intelligence-Enabled Learning Ecosystem (AILE) framework comprising four direct propositions linking AI Capability, AI-Enabled Learning Ecosystem, Digital Innovation Strategy, and Sustainable Organizational Development. Two additional propositions identify employee engagement and technology acceptance, alongside resource efficiency and AI governance, as moderating conditions. The framework also introduces organizational sustainability indicators, a resource cost-benefit assessment, and a four-stage implementation roadmap. The proposed framework offers a theoretical foundation for examining how AI-supported learning can contribute to organizational resilience, workforce development, and responsible digital innovation. Its potential relevance extends to SDGs 4, 8, and 9. As the framework remains conceptual, longitudinal and multilevel empirical studies are required to validate the proposed relationships and assess their practical effectiveness.

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## 1. INTRODUCTION

The rapid advancement of digital technologies has changed how organizations develop knowledge, enhance workforce capabilities, and remain competitive in dynamic environments. Among these technologies, Artificial Intelligence (AI) has emerged as a strategic enabler of intelligent decision-making, automation, personalized services, and data-driven organizational processes [1]. AI adoption is no longer limited to operational

efficiency; it increasingly extends into organizational learning through adaptive learning systems, predictive analytics, and intelligent knowledge management mechanisms [2]. As organizations face continuous technological disruption, the capacity to establish a sustainable learning ecosystem has become an important condition for continuous improvement and long-term development [3].

Conventional learning systems often struggle to address diverse employee needs, rapidly changing knowledge requirements, and evolving technological landscapes. Traditional e-learning platforms provide digital access to learning materials but offer limited personalization, real-time performance analysis, and adaptive knowledge recommendations. AI-enabled learning ecosystems offer an opportunity to transform organizational learning from static information delivery into an interactive and adaptive process supported by continuous data analysis. However, integrating AI without appropriate strategic alignment may result in technological adoption without meaningful improvements in organizational performance or sustainability [4, 5].

Previous research offers important building blocks, but each stream has a specific theoretical limitation. AI capability research grounded in the resource-based view explains how bundles of AI resources create value [4, 2], yet it treats the process through which this value emerges largely as a black box and does not specify organizational learning as that process. Organizational AI readiness models [6, 7] treat knowledge and skills as preconditions for adoption rather than as outcomes that AI-supported learning can develop. Digital transformation models [5, 8] position employee-related issues mainly as barriers rather than as a mechanism of transformation. Reviews linking learning, digitalization, and sustainability [9, 10] do not address AI-specific learning functions or the resource costs of AI, while technology acceptance theories [11, 12] operate at the individual level and are rarely connected with organization-level capability arguments.

Addressing these limitations, this study develops an Artificial Intelligence-Enabled Learning Ecosystem (AILE) framework. Its novelty lies in specifying the AI-enabled learning ecosystem as the mechanism that links AI capability with digital innovation strategy and sustainable organizational development (P1–P4), and in formulating employee engagement and technology acceptance, as well as resource efficiency and AI governance, as explicit moderating conditions (M1–M2). The study further operationalizes sustainable organizational development through assessable indicators, proposes a cost-benefit approach for evaluating resource trade-offs, and translates the framework into a staged implementation roadmap. Because the study is conceptual, all relationships are presented as propositions for future empirical testing rather than as validated findings.

The remainder of this paper is organized as follows. Section 2 reviews the literature and positions the framework against existing models. Section 3 describes the research design, search strategy, selection criteria, and theoretical integration process. Section 4 presents the framework, its propositions, its operationalization, and its resource implications. Section 5 discusses managerial implications, and Section 6 concludes the study.

## 2. LITERATURE REVIEW

### 2.1. Artificial Intelligence in Organizational Learning Transformation

AI has become one of the most influential digital technologies in transforming knowledge management and learning development. It enables organizations to use large-scale data processing, predictive analytics, natural language processing, and recommendation systems to support adaptive decision-making and personalized learning [1]. Unlike conventional digital learning approaches that mainly provide access to information resources, AI-based learning systems can analyze individual learning patterns, identify competency gaps, and recommend learning pathways aligned with organizational requirements.

Organizational learning research emphasizes that learning involves the creation, retention, and transfer of knowledge across individuals and units [3], and that new organizational knowledge emerges from continuous interaction between tacit and explicit knowledge [13]. From this perspective, AI is relevant not only because it automates tasks but because it can accelerate knowledge transfer and make learning more responsive to changing business demands. Empirical research on AI-based transformation projects indicates that the business value of AI depends on how it is embedded in organizational processes rather than on technology investment alone [2]. Similarly, AI capability research shows that tangible resources must be combined with human skills and intangible resources, such as coordination and a culture of change, to generate value [4]. Therefore, AI is treated in this study as a strategic capability that can enhance organizational learning capacity rather than merely as a technological tool.

## 2.2. AI-Enabled Learning Ecosystem and Digital Learning Capability

A learning ecosystem represents a shift from stand-alone learning management systems toward an integrated environment linking technology, people, knowledge resources, and organizational processes. Within such an ecosystem, employees, learning platforms, AI systems, and knowledge repositories interact continuously, so that learning becomes a dynamic process of knowledge creation, sharing, and application across organizational boundaries.

AI may strengthen learning ecosystems through personalized content recommendations, automated feedback, learning analytics, and competency prediction. Studies of organizational AI readiness indicate that such functions require supporting infrastructure, reliable data management, adequate skills, and governance mechanisms [6, 7]. Generative AI further expands these opportunities through intelligent assistance and content generation, but it also raises concerns regarding accuracy, accountability, and ethical use that require human oversight [14].

Evidence from educational settings illustrates design elements that organizational learning ecosystems can adopt. Digital twin technology has been applied to integrate real-time data for managing complex campus environments [15], augmented reality has been used to design immersive learning media for specialized knowledge content [16], and technopreneurship-based e-modules show how structured digital modules can support competence development [17]. Because these studies were conducted in educational rather than corporate contexts, they are used here as contextual evidence of three transferable design elements, namely real-time data integration, immersive content, and modular self-paced learning, rather than as direct evidence of organizational AI learning. Consequently, an AI-enabled learning ecosystem is conceptualized here as a socio-technical arrangement rather than a software platform.

## 2.3. Digital Innovation Strategy as an Enabler of Transformation

Digital innovation strategy refers to the strategic use of digital technologies to create new organizational capabilities, improve processes, and generate sustainable value. Digital transformation research describes transformation as a process in which digital technologies trigger strategic responses, changes in value creation paths, and structural changes, while also generating organizational barriers [5]. A systematic review by Hanelt et al. [8] further characterizes digital transformation as organizational change toward malleable designs connected to wider digital ecosystems, while Warner and Wäger [18] describe it as an ongoing process of strategic renewal that requires dynamic capabilities for digital sensing, seizing, and transforming.

Digital technologies have also changed how innovation and entrepreneurship unfold by making innovation processes more open, distributed, and ecosystem-based [19]. In addition, digital transformation can act as a springboard for product, process, and business model innovation [20]. These perspectives suggest that a digital innovation strategy is necessary to ensure that AI-enabled learning contributes to broader organizational transformation rather than remaining an isolated technology project.

## 2.4. Employee Engagement and Technology Acceptance

The success of AI-enabled learning depends on whether employees participate in it. The Technology Acceptance Model (TAM) explains that perceived usefulness and perceived ease of use shape individuals' intention to use a technology [11]. The Unified Theory of Acceptance and Use of Technology (UTAUT) extends this view by identifying performance expectancy, effort expectancy, social influence, and facilitating conditions as determinants of use [12]. Subsequent work emphasized that managerial interventions such as training, organizational support, and peer support can influence these perceptions [21]. In AI-enabled learning, employees are more likely to engage when they believe that AI recommendations are relevant to their work and careers, and when the system is easy to use.

Employee motivation is equally important. Learning participation is more sustainable when employees perceive development opportunities as meaningful rather than as mandatory compliance. Conversely, resistance to change may emerge from routine-seeking tendencies, emotional reactions to imposed change, short-term focus, and cognitive rigidity [22]. In the context of AI, resistance may be intensified by concerns about surveillance of learning data, job displacement, and reduced autonomy [1]. Leadership also shapes these responses; research on adaptive leadership in business highlights the role of leaders in guiding organizations and employees through uncertainty and change [23]. These considerations indicate that organizational AI capability does not automatically translate into employee learning participation, and that acceptance factors should be explicitly incorporated into the framework.

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## 2.5. Sustainable Organizational Development Through AI Adoption

Sustainable organizational development refers to an organization's ability to maintain continuous growth, improve capabilities, and adapt to environmental changes while balancing technological, human, and strategic factors. In the context of digital transformation, sustainability includes not only environmental aspects but also organizational resilience, knowledge sustainability, workforce development, and long-term competitiveness [9].

A cross-disciplinary review by Feeney et al. [10] indicates that organizational learning is a central mechanism through which organizations pursue sustainability goals, although the learning processes involved are often insufficiently specified. Research on digital transformation and sustainability similarly shows that digital technologies can support sustainability outcomes, but that the effect depends on integration with organizational strategy and culture [9, 5]. At the same time, AI adoption is not resource-neutral: AI systems require computational resources, energy, data infrastructure, and complementary investments whose benefits may materialize only after a delay [24, 25]. Responsible AI use also requires governance principles such as beneficence, non-maleficence, autonomy, justice, and explicability [26]. A balanced view of sustainability must therefore consider both the potential benefits and the resource and governance costs of AI-enabled learning.

## 2.6. Positioning the Proposed Framework Against Existing Models

Table 1 compares the proposed framework with selected models from previous studies. The comparison shows that existing models typically address one or two elements of the proposed framework but rarely connect AI capability, a learning mechanism, strategic alignment, sustainability outcomes, and employee acceptance within a single structure.

Table 1. Comparison of the Proposed Framework with Existing Models

| Study / Model                        | Main Focus                                               | Contribution                                                                                        | Gap Addressed by AILE                                                       |
|--------------------------------------|----------------------------------------------------------|-----------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------|
| Mikalef and Gupta [4]                | AI capability and firm performance                       | Conceptualizes and measures AI capability as a bundle of resources                                  | Learning mechanism linking AI capability to sustainability is not specified |
| Wamba-Taguimdje et al. [2]           | Business value of AI-based transformation projects       | Shows that AI value depends on process integration                                                  | Workforce learning and sustainability are not central constructs            |
| Jöhnk et al. [6]; Holmström [7]      | Organizational AI readiness                              | Identifies readiness factors and readiness stages                                                   | Readiness is not linked to learning ecosystem outcomes                      |
| Vial [5]; Hanelt et al. [8]          | Digital transformation process and organizational change | Explains strategic responses and structural change                                                  | AI-enabled learning is not treated as a specific mechanism                  |
| Guandalini [9]; Feeney et al. [10]   | Digital transformation, learning, and sustainability     | Connects learning and digitalization with sustainability                                            | AI-specific capabilities and resource trade-offs are not addressed          |
| Davis [11]; Venkatesh et al. [12]    | Individual technology acceptance                         | Explains usage intention and behavior                                                               | Not connected to organization-level capability outcomes                     |
| Proposed AILE framework (this study) | AI-enabled learning for sustainable development          | Integrates AIC, AILE, DIS, and SOD with acceptance factors, indicators, and resource considerations | Requires empirical validation                                               |

Accordingly, this study positions AI capability as a strategic resource, the AI-enabled learning ecosystem as the transformation mechanism, digital innovation strategy as the strategic enabler, and sustainable organizational development as the intended outcome, while treating employee acceptance and resource efficiency as moderating conditions.

## 2.7. Previous Evidence on the Proposed Relationships

Previous studies provide partial support for each relationship in the proposed framework. Regarding the link between AI capability and learning, Mikalef and Gupta [4] found that AI capability is associated with organizational creativity and firm performance, and Wamba-Taguimdje et al. [2] reported that the value of AI depends on how it is embedded in organizational processes. From a dynamic capability perspective, such capability enables organizations to sense changes in skill requirements and to reconfigure resources accordingly [27]. However, these studies do not specify organizational learning as the process in which AI capability is embedded.

Regarding the link between learning and strategy, Vial [5] identified organizational inertia and resistance as barriers to digital transformation, and Jöhnk et al. [6] identified knowledge and skills as key AI readiness factors. These studies treat skills mainly as preconditions, whereas the resource-based view suggests that knowledge and employee competence developed internally may become resources that are difficult to imitate [28]. Warner and Wäger [18] further describe digital transformation as an ongoing process of strategic renewal, which implies that learning and strategy may influence each other over time.

Regarding sustainability outcomes, Guandalini [9] identified digital transformation as a potential driver of sustainability, and Bresciani et al. [20] described digital transformation as a basis for product, process, and business model innovation. Feeney et al. [10] argued that organizational learning is central to sustainability, while Argote and Miron-Spektor [3] emphasized the role of knowledge retention and transfer. These studies address learning in general rather than AI-specific functions such as personalization and real-time feedback.

Regarding the conditions under which these relationships hold, technology acceptance research shows that perceived usefulness, ease of use, and facilitating conditions shape technology use [11, 12], that training and organizational and peer support can strengthen these perceptions [21], and that adaptive leadership helps organizations manage change [23]. Conversely, resistance to change [22] and concerns about surveillance and job displacement [1] may reduce participation. At the organizational level, energy-intensive AI infrastructure [24], delayed productivity returns [25], and ethical risks that require governance [26] may offset the benefits of digital initiatives, while the TOE framework explains why such technological and organizational conditions shape adoption outcomes [29].

### 3. METHODOLOGY

#### 3.1. Research Design

This study adopts a conceptual research design to develop an AI-enabled learning ecosystem framework. A conceptual design is appropriate because the objective is to integrate theoretical perspectives and previous findings into a coherent model and a set of testable propositions rather than to test hypotheses with primary data [30]. Following the logic of a model-building conceptual article, the study identifies the relevant constructs, specifies their relationships, and explains the theoretical reasoning behind each relationship. The design follows an integrative literature review approach, in which existing literature is critically reviewed and synthesized to generate a new perspective on an emerging topic [31]. The study does not claim the exhaustive coverage of a systematic literature review or the statistical aggregation of a meta-analysis. Because the framework spans individual and organizational levels, its propositions are formulated so that they can later be tested with multilevel structural equation modeling [32], which requires a sufficient number of organizations to estimate organization-level parameters accurately [33].

#### 3.2. Literature Identification and Selection Criteria

Literature searches were conducted in 2026, prior to manuscript submission, in Scopus, Web of Science Core Collection, and ScienceDirect. Google Scholar was used for backward and forward citation tracking, and Indonesian journal portals were searched to identify recent contextual applications in digital learning. Search strings combined five concept groups: AI, organizational learning, digital transformation, sustainability, and technology acceptance. For example, the Scopus query was `TITLE-ABS-KEY(("artificial intelligence" OR "AI capability" OR "AI readiness") AND ("organizational learning" OR "learning ecosystem" OR "knowledge management") AND ("digital transformation" OR "digital innovation" OR "sustainable" OR "sustainability"))`, limited to English-language articles and reviews published from 2019 onward. Equivalent topic searches were applied in Web of Science and ScienceDirect, and separate queries combining *technology acceptance*, *resistance to change*, *AI governance*, or *AI energy consumption* with *organization* were used for the moderating conditions. Seminal theoretical works were identified through backward citation tracking without a year limit, because they define the theories used for integration.

The selection criteria are summarized in Table 2. After duplicates were removed, records were screened by title and abstract against the relevance and quality criteria, and the remaining full texts were assessed against the theoretical-contribution criterion. Thirty-one sources were retained for synthesis: 11 seminal theoretical works, 7 studies on AI capability, readiness, and governance, 5 studies on digital transformation and innovation, 4 studies on learning, sustainability, and resource use, and 4 contextual studies on digital learning and leadership. Four further methodological references on conceptual, integrative, and multilevel research

Table 2. Literature Selection Criteria

| Criterion                | Description                                                                                                                                                                     |
|--------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Relevance                | The study addresses at least one construct of the framework (AIC, AILE, DIS, SOD) or one boundary condition (technology acceptance, resistance to change, resource efficiency). |
| Source quality           | Peer-reviewed journal articles, conference proceedings, or seminal scholarly books.                                                                                             |
| Theoretical contribution | The study offers a conceptual definition, a theoretical mechanism, or empirical evidence on relationships among the constructs.                                                 |
| Timeframe                | Seminal theories without restriction; AI and digital transformation studies mainly from 2019 onward.                                                                            |
| Exclusion                | Non-scholarly sources, purely technical algorithm studies without organizational implications, and studies without accessible full text.                                        |

design are cited but were not synthesized as evidence.

### 3.3. Theoretical Integration Process

Table 3. Theoretical Integration of the Proposed Framework

| Theory                                 | Core Logic                                                                      | Role in the Framework                                                                                               |
|----------------------------------------|---------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------|
| Resource-Based View [28]               | Valuable, rare, and difficult-to-imitate resources create competitive advantage | Explains AI capability and organizational knowledge as strategic resources (AIC)                                    |
| Dynamic Capability Theory [34, 35, 27] | Firms sense, seize, and reconfigure resources in changing environments          | Explains the AI-enabled learning ecosystem as a capability-building mechanism (AILE) and its link to strategy (DIS) |
| TOE Framework [29]                     | Adoption depends on technological, organizational, and environmental contexts   | Explains organizational readiness, resources, and governance as conditions for implementation                       |
| TAM / UTAUT [11, 12]                   | Perceived usefulness, ease of use, and facilitating conditions shape usage      | Explains employee engagement and participation as boundary conditions of AILE                                       |

Table 3 presents the four theories integrated in the framework, the core logic of each theory, and the role each plays in explaining the constructs and conditions of the AILE framework. Based on these theories, the theoretical integration proceeded in three steps. First, each retained source was coded by construct (AIC, AILE, DIS, SOD, or moderating condition) and by level of analysis (individual, organizational, or ecosystem). Second, recurring mechanisms across sources were grouped into theme codes: AI resource bundling, skills as a precondition for transformation, digital innovation and value creation, the learning-sustainability link, acceptance and resistance, resources and governance, and design elements of digital learning environments. Third, each theme was linked to one of the explanatory theories in Table 3 and used to derive a proposition. AI resource bundling informed P1, skills as a precondition informed P2, digital innovation and value creation informed P3, and the learning-sustainability link informed P4. Acceptance and resistance informed M1, resources and governance informed M2, and design elements of digital learning environments informed the definition of AILE.

The Resource-Based View (RBV) and dynamic capability theory explain the organization-level logic of the framework, the Technology-Organization-Environment (TOE) framework explains the contextual conditions for adoption, and TAM and UTAUT explain individual-level participation. Combining these perspectives allows the framework to connect organization-level capability arguments with the employee-level behaviors that determine whether AI-enabled learning is used in practice.

### 3.4. Construct Definitions

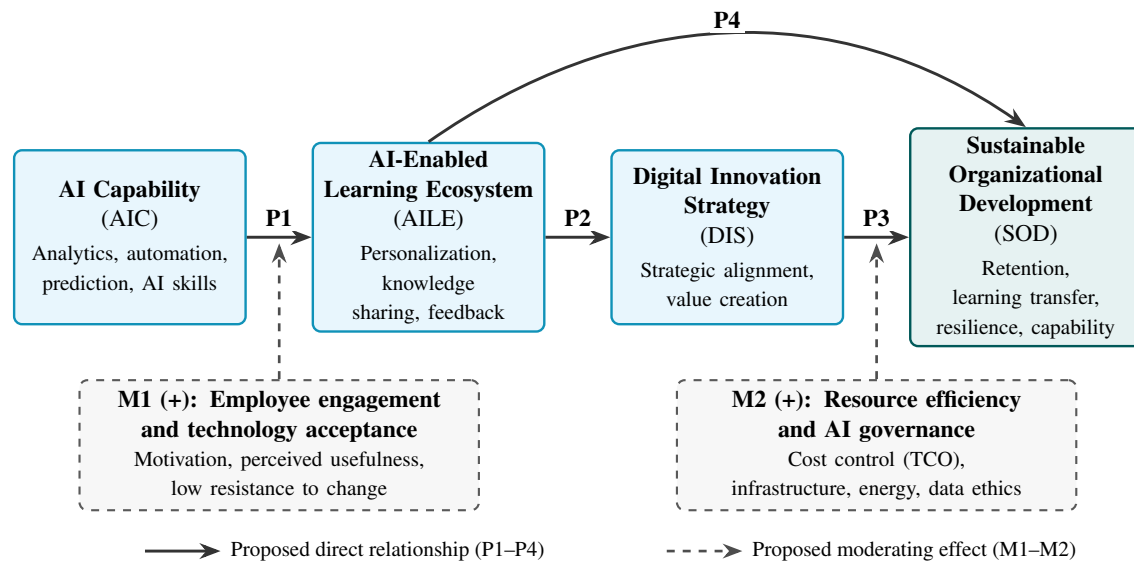
Based on the integration process, four constructs were defined, each with a distinct conceptual role. *Artificial Intelligence Capability (AIC)* is the organizational ability to deploy AI technologies, data, and AI-related skills, including analytics, automation, prediction, and decision support [4]; it represents a resource stock and excludes how AI is used for learning. *AI-Enabled Learning Ecosystem (AILE)* is an integrated learning environment that combines AI technologies, organizational knowledge resources, and adaptive learning mechanisms to support personalized learning, knowledge sharing, and continuous capability development; it

represents a process and is reflected in learning participation and process quality. *Digital Innovation Strategy (DIS)* is the organizational approach to aligning digital technologies with strategic objectives in order to create value through innovation and transformation [5, 20]; it represents a strategic orientation and excludes operational learning activities. *Sustainable Organizational Development (SOD)* is the ability of an organization to achieve continuous improvement through workforce capability, learning effectiveness, organizational resilience, and long-term capability development [10, 9]; it represents an outcome observed over time.

## 4. RESULTS AND DISCUSSION

### 4.1. Proposed Artificial Intelligence-Enabled Learning Ecosystem Framework

The outcome of the conceptual synthesis is the AILE framework illustrated in Figure 1. The framework positions AIC as the technological foundation, AILE as the mechanism that converts technological potential into organizational learning, DIS as the strategic mechanism that aligns learning with organizational objectives, and SOD as the intended outcome. Solid arrows represent four proposed direct relationships (P1–P4). Dashed arrows represent two proposed moderating effects (M1–M2); they point to a relationship rather than to a construct, indicating that the moderator changes the strength of that relationship.



Theoretical foundation: RBV • Dynamic Capability Theory • TOE framework • TAM/UTAUT

Figure 1. Proposed Artificial Intelligence-Enabled Learning Ecosystem (AILE) Framework

The framework emphasizes that AI adoption should be regarded as an organizational capability that shapes knowledge development, employee learning, and strategic transformation, rather than solely as a technological investment. The relationships in Figure 1 are theoretical propositions derived from the literature; they have not been empirically tested in this study.

### 4.2. Propositions of the Framework

**P1: AI capability positively influences the development of an AI-enabled learning ecosystem.** AI capability provides the technological basis for identifying competency gaps, recommending learning resources, and analyzing learning progress. Previous AI capability studies link AI resources to creativity and performance but leave the underlying process unspecified; the proposed framework fills this gap by specifying organizational learning as the process in which AI capability is embedded. In dynamic capability terms, AI capability allows the organization to detect emerging skill needs and to reconfigure learning resources before capability gaps widen.

**P2: An AI-enabled learning ecosystem strengthens the implementation of digital innovation strategy.** A learning ecosystem supplies the knowledge, digital literacy, and employee readiness required for transformation. Whereas readiness and transformation studies treat skills as preconditions that organizations

either possess or lack, the AILE framework proposes that AI-enabled learning can actively build these preconditions. Knowledge and competence developed in this way may become firm-specific resources that support strategy execution and are difficult for competitors to imitate.

The direction of P2 requires qualification, because digital strategy may also precede the learning ecosystem. In strategy-led organizations, a digital innovation strategy may define learning priorities and allocate the resources needed to build the ecosystem. The relationship may therefore be reciprocal over time: strategy may initiate the ecosystem, while the ecosystem determines how effectively the strategy is implemented. This study emphasizes the AILE → DIS direction because its focus is on implementation capability, while recognizing that an alternative model in which DIS precedes AILE is theoretically plausible and should be compared empirically.

**P3: Digital innovation strategy contributes to sustainable organizational development.** Digital innovation strategy aligns technological resources with long-term objectives so that transformation creates lasting value rather than isolated improvements. Beyond the general link between digital transformation and sustainability, the AILE framework proposes that this relationship depends on how efficiently resources are used and how AI is governed, which is formulated below as moderating proposition M2.

**P4: An AI-enabled learning ecosystem directly supports sustainable organizational development.** Beyond its strategic role, AI-enabled learning may contribute directly to sustainability by maintaining workforce capability and organizational knowledge. Unlike general organizational learning arguments, the AILE framework attributes this contribution to AI-specific functions such as personalization, real-time feedback, and continuous competency diagnosis.

Taken together, P1–P4 suggest that the value of AI for sustainable development may be realized mainly through learning and strategic alignment rather than through technology acquisition alone. These propositions require empirical testing, and their strength may vary across industries, organizational sizes, and levels of digital maturity.

#### 4.3. Moderating Conditions of the Framework

The relationship between AIC and AILE is not automatic, because an ecosystem exists only when employees participate in it. Employee participation in AI-enabled learning is expected to depend on perceived usefulness, motivation, and resistance to technological change. Employees are more likely to engage when AI recommendations are relevant to their roles and career development, and when learning is linked to recognition and autonomy rather than imposed as mandatory compliance. Concerns about monitoring of learning data, job displacement, or loss of autonomy may reduce participation, whereas training, organizational and peer support, and adaptive leadership may strengthen engagement.

**M1: Employee engagement and technology acceptance positively moderate the relationship between AI capability and the AI-enabled learning ecosystem.** The positive effect of AIC on AILE is expected to be stronger when perceived usefulness and motivation are high and resistance to change is low, and weaker when resistance is high. Organizations with similar AI capability may therefore develop learning ecosystems of very different quality.

The relationship between DIS and SOD is similarly conditional. A digital innovation strategy may create long-term value only if the resources it consumes remain proportionate to the benefits it produces and if AI use is governed responsibly. High implementation costs, energy-intensive infrastructure, delayed returns, or misuse of employee data may offset the capability gains of a well-designed strategy. These are technological and organizational conditions that shape the outcome of adoption.

**M2: Resource efficiency and AI governance positively moderate the relationship between digital innovation strategy and sustainable organizational development.** The positive effect of DIS on SOD is expected to be stronger when total costs are controlled relative to expected benefits and when AI governance, covering data privacy, bias control, and accountability, is mature, and weaker when costs or governance risks are high.

#### 4.4. Operationalizing Sustainable Organizational Development

In this framework, SOD refers to the human and organizational dimensions of sustainability, namely the ability to retain, develop, and redeploy capability over time. Environmental aspects, such as energy consumption and hardware footprint, are not treated as SOD outcomes; they are treated as part of the resource-efficiency condition (M2) and are monitored through the cost-benefit assessment. To improve the practical applicability of the framework, SOD is operationalized through four dimensions with proposed indicators, as

shown in Table 4. Data for these indicators are expected to come mainly from human resource (HR) information systems, learning analytics, and workforce planning records.

Table 4. Proposed Indicators for Assessing Sustainable Organizational Development

| SOD Dimension                    | Proposed Indicators                                                                                                                                 | Possible Data Sources                                             |
|----------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------|
| Employee retention               | Voluntary turnover rate; retention of high-potential and critical-skill employees; internal mobility rate                                           | HR information systems, exit interviews                           |
| Learning effectiveness           | Course completion and active participation rates; post-training assessment scores; transfer of learning to job performance; time-to-competency      | Learning management and analytics systems, performance appraisals |
| Organizational resilience        | Time required to redeploy employees after disruption; proportion of roles with trained successors; speed of adopting new processes or technologies  | Business continuity reports, workforce planning records           |
| Long-term capability development | Closure rate of identified competency gaps; share of workforce with digital and AI skills; number of employee-generated improvements or innovations | Competency frameworks, skills inventories, innovation records     |

Each indicator should be specified with an operational definition, unit, observation period, baseline, and verification source. For example, the voluntary turnover rate can be defined as voluntary separations divided by average headcount, expressed as a percentage over a rolling twelve-month period and compared with the twelve months before implementation using HR records. Similarly, time-to-competency can be measured in days from role assignment until a defined competency standard is met, compared with a previous cohort that did not use AI-enabled learning. Within the learning effectiveness dimension, course completion and participation rates function as process indicators that reflect AILE, whereas assessment scores, learning transfer, and time-to-competency capture SOD outcomes; distinguishing these two types prevents overlap between the constructs. The indicators are proposed as a starting point and are not validated measurement scales.

#### 4.5. Resource Efficiency and Sustainability Trade-offs

The relationship between AI-enabled learning and sustainability involves trade-offs. On the one hand, AI-enabled learning can improve long-term efficiency by reducing redundant training, shortening time-to-competency, and targeting learning investments to actual skill gaps. On the other hand, it requires substantial investment in infrastructure, data management, licensing, and specialized personnel. Training and operating AI models also consume considerable computational energy. In addition, organizations often need complementary investments in process redesign and skills before productivity gains become visible, which may produce an initial period of lower measured returns. Table 5 summarizes these considerations.

Table 5. Resource Considerations and Trade-offs of AI-Enabled Learning

| Aspect                  | Resource Requirement                                          | Potential Benefit                                                 | Trade-off / Risk                                                   |
|-------------------------|---------------------------------------------------------------|-------------------------------------------------------------------|--------------------------------------------------------------------|
| Implementation cost     | Platform licensing, integration, content development          | Scalable learning delivery and reduced per-learner cost over time | High initial investment and delayed returns                        |
| Technological resources | Computing infrastructure, data storage, cloud services        | Real-time analytics and personalization                           | Energy consumption and dependence on vendors                       |
| Data and governance     | Data quality management, privacy protection, ethics oversight | More accurate competency diagnosis                                | Compliance costs and risks of bias or misuse of employee data      |
| Human resources         | AI-literate trainers, data specialists, change agents         | Stronger internal capability and knowledge retention              | Skill shortages and additional workload during transition          |
| Long-term efficiency    | Continuous maintenance and model updating                     | Reduced redundant training and faster redeployment                | Benefits depend on sustained participation and strategic alignment |

To compare these benefits and costs systematically, a total cost of ownership (TCO) perspective is recommended. Total costs  $C_t$  include acquisition and implementation, operation and infrastructure including energy use, governance and compliance, and human and change-management costs, while benefits  $B_t$  include avoided external training costs, avoided turnover costs, and the productivity value of shorter time-to-competency. The net value over an evaluation horizon  $T$  can be estimated as a net present value (NPV):

$$\text{NPV} = \sum_{t=0}^T \frac{B_t - C_t}{(1 + r)^t}, \quad (1)$$

where  $r$  is the organization's discount rate. Because benefits are likely to appear after a delay, an evaluation horizon of three to five years is more appropriate than a single-year assessment. Smaller organizations may reduce fixed costs through modular or shared solutions, such as cloud-based platforms or consortium arrangements.

#### 4.6. Theoretical Contributions

The framework contributes to theory in three ways. First, it extends AI capability research by proposing an organizational learning mechanism through which AI capability may contribute to sustainability outcomes. Second, it extends dynamic capability theory by conceptualizing the AI-enabled learning ecosystem as a capability-building mechanism whose effectiveness is conditioned by employee acceptance (M1) and by resource efficiency and governance (M2). Third, it connects individual-level acceptance theories with organization-level capability theories, offering a cross-level structure that can be examined with multilevel structural equation modeling. These contributions are conceptual and should be evaluated empirically.

### 5. MANAGERIAL IMPLICATIONS

The proposed framework suggests that managers should implement AI-enabled learning through four stages rather than treating it as a one-time technology investment. The first stage involves assessing organizational readiness, including AI infrastructure, digital competencies, and employee attitudes, under the responsibility of senior management together with HR and IT units, and ends with an approved business case and recorded baselines for the SOD indicators. The second stage focuses on pilot implementation in at least one unit, led by the learning and development team, to evaluate participation, perceived usefulness, and learning transfer. The third stage emphasizes workforce training and gradual expansion across organizational units, with AI literacy coverage and time-to-competency as key performance indicators. Finally, continuous improvement requires an annual review of SOD indicators, net benefits, and governance audit results, coordinated by an AI governance committee.

From a managerial perspective, successful implementation requires employee engagement, transparent governance, and sustainable investment planning. Managers should encourage participation by connecting AI-enabled learning with career development opportunities while addressing data privacy, algorithmic bias, and ethical concerns. Investment decisions should be based on multi-year costs and expected organizational benefits rather than on first-year results. Furthermore, organizations should adapt the implementation roadmap to their size, industry characteristics, and digital maturity to ensure sustainable workforce development and organizational performance.

### 6. CONCLUSION

This study developed an Artificial Intelligence-Enabled Learning Ecosystem framework that links AI capability, AI-enabled learning, digital innovation strategy, and sustainable organizational development through four direct propositions and two moderating propositions. Its main contribution is to specify organizational learning as the mechanism through which AI capability may generate sustainable value, and to connect organization-level capability theories with individual-level technology acceptance theories. In addition, the study operationalizes sustainable organizational development through indicators of employee retention, learning effectiveness, organizational resilience, and long-term capability development, and proposes a cost-benefit approach for evaluating the resource and governance trade-offs associated with AI adoption.

This study has several limitations. Because it is conceptual, the propositions, indicators, and roadmap have not been empirically validated, and the integrative review did not follow a systematic review protocol.

The scope of sustainability is also limited to its human and organizational dimensions. Future research should test the framework with a multilevel design in which employees are nested within organizations. Organization-level constructs, namely AI capability, digital innovation strategy, and resource efficiency and governance, can be measured through multiple key informants, while employee acceptance and learning participation can be measured at the employee level, and sustainable organizational development can be assessed using archival HR records. Organizations can be selected through stratified sampling by sector and size, with employees randomly sampled within each organization. Multilevel structural equation modeling is suitable for testing the cross-level relationships, whereas longitudinal designs are needed to examine the potentially reciprocal relationship between the learning ecosystem and digital innovation strategy.

## 7. DECLARATIONS

### 7.1. About Authors

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### 7.2. Author Contributions

Conceptualization: AA and IN; Methodology: AA and ZA; Validation: AA and IN; Formal Analysis: IN and ZA; Investigation: IN and ZA; Writing Original Draft Preparation: AA and IN; Writing Review and Editing: AA, IN, and ZA; Visualization: ZA; All authors (AA, IN, and ZA) have read and agreed to the published version of the manuscript.

### 7.3. Data Availability Statement

No primary dataset was generated in this study. The study analyzed previously published literature, all of which is cited in the reference list. The literature coding matrix supporting the synthesis is available from the corresponding author upon reasonable request.

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### 7.5. Declaration of Conflicting Interest

The authors declare that there are no financial or personal conflicts of interest that could have influenced the findings or conclusions presented in this study.

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