KMAN PUBLISHING INSTITUTE

**Article history:**
**Received 11 August 2026**
**Revised 28 September 2026**
**Accepted 16 November 2026**
**Initial Publish 28 November 2026**
**Published online 01 May 2027**

**Journal of Resource Management and Decision Engineering**

**Volume 6, Issue 3, pp 1-21**




# Interpretive Structural Analysis of the Factors Influencing Employees' Digital Adaptive Learning Using an Integrated Thematic Analysis and ISM Approach: A Case Study of Golestan Province Water and Wastewater Company

Valiollah. Farrokhi-Manesh[1], Alireza. Mazidi[1*], Samereh. Shojaei[1]

[1] Department of Management, AK.C., Islamic Azad University, Aliabad Katoul, Iran

*** Corresponding author email address**: a.mazidi@iau.ac.ir

A r t i c l e  I n f o

**Article type:**
*Original Research*

**How to cite this article:**
Farrokhi-Manesh, V., Mazidi, A., & Shojaei, S. (2027). Interpretive Structural Analysis of the Factors Influencing Employees' Digital Adaptive Learning Using an Integrated Thematic Analysis and ISM Approach: A Case Study of Golestan Province Water and Wastewater Company. *Journal of Resource Management and Decision Engineering*, *6*(3), 1-21.
https://doi.org/10.61838/kman.jrmde.488

© 2027 the authors. Published by KMAN Publication Inc. (KMANPUB). This is an open access article under the terms of the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) License.

A B S T R A C T

The present study aimed to conduct an interpretive structural analysis of the factors influencing employees' digital adaptive learning in Golestan Province Water and Wastewater Company. In terms of purpose, this study is applied, and in terms of methodology, it is descriptive–exploratory. The research was conducted using a qualitative approach through the integration of thematic analysis and Interpretive Structural Modeling (ISM). In the first stage, data were collected through semi-structured interviews with academic and executive experts. Purposive sampling was employed, and after theoretical saturation was achieved in 20 interviews, two additional interviews were conducted to ensure greater confidence in data adequacy. Accordingly, a total of 22 interviews were conducted, with the first 20 interviews serving as the basis for analysis. The qualitative data were analyzed using thematic analysis and classified into 14 organizing themes and five overarching themes. In the second stage, Interpretive Structural Modeling was conducted with the participation of 20 experts to explain the interrelationships among and determine the hierarchical levels of the 14 components (organizing themes). Data for this stage were collected using a pairwise-comparison questionnaire and a Structural Self-Interaction Matrix and were aggregated based on a minimum agreement criterion of 75%. The findings indicated that the relevant components were positioned across six hierarchical levels. Digital transformation adoption and institutionalization within the organization, together with ethical and accountable digital governance, were located at Level 6 as foundational components, whereas organizational performance sustainability and competitiveness were positioned at Level 1 as the final outcome of the model. The findings further indicate that achieving digital adaptive learning requires simultaneous attention to institutional and governance foundations, technological infrastructure, employee empowerment, and the alignment of learning with organizational objectives. Therefore, the findings of this study can provide a basis for prioritizing managerial initiatives and planning for the development of digital learning in Golestan Province Water and Wastewater Company.

***Keywords:*** *digital adaptive learning, thematic analysis, Interpretive Structural Modeling, digital transformation, organizational learning.*

## 1. Introduction

Digital transformation has become one of the most consequential forces reshaping contemporary organizations, changing not only technologies and operational processes but also organizational structures, governance arrangements, employee competencies, decision-making mechanisms, and patterns of learning. The increasing diffusion of artificial intelligence, data analytics, digital platforms, automation, and integrated information systems has made organizational adaptation increasingly dependent on the capacity of employees to continuously learn, update their competencies, and respond effectively to technological change. Recent studies have emphasized that digital transformation should not be viewed merely as the adoption of new technologies, but rather as a multidimensional organizational process in which technological capability, human capital, governance, innovation, agility, and sustainability interact to determine organizational outcomes (Fülöp, 2025; Yadav et al., 2026; Zhao et al., 2024). This perspective is particularly relevant in public utility organizations, where digitalization affects service delivery, resource management, customer interaction, infrastructure monitoring, and organizational responsiveness. Under such conditions, employees' ability to engage in adaptive digital learning becomes a critical organizational capability because the effectiveness of technological investments ultimately depends on whether personnel can understand, accept, use, and continuously adapt to new digital systems.

The growing emphasis on environmental, social, and governance considerations has further strengthened the connection between digital transformation and organizational capability development. ESG-oriented research increasingly demonstrates that sustainable organizational performance depends on the alignment of governance systems, technological infrastructure, stakeholder expectations, human resources, and innovation capabilities (F.-R. Chen et al., 2025; Garefalakis, 2026; Teixeira et al., 2024). Although ESG research has traditionally focused on sustainability disclosure, financial outcomes, governance quality, and environmental responsibility, its broader organizational implications are highly relevant to digital adaptive learning. For example, governance arrangements influence the transparency, accountability, ethical use, and institutional legitimacy of digital technologies, while social dimensions influence employee participation, justice, engagement, identification, and willingness to adopt new organizational practices. Sustainable organizational transformation therefore requires not only technological modernization but also governance mechanisms capable of directing learning, protecting organizational data, supporting fairness, and ensuring that digital change is aligned with organizational objectives. Studies examining sustainable disclosure, governance structures, and organizational sustainability suggest that formal systems of accountability and institutional governance can shape organizational performance and stakeholder confidence (Abdulrahman, 2025; Monteiro et al., 2024; Tahat et al., 2026).

From a strategic management perspective, digital adaptive learning can be understood as an organizational mechanism through which employees continually adjust their knowledge, skills, cognitive frameworks, and work behaviors in response to emerging technologies and changing organizational requirements. Such learning differs from conventional periodic training because it requires continuous capability renewal, personalization, responsiveness, and integration with ongoing work processes. This interpretation is consistent with the dynamic capabilities perspective, which emphasizes the importance of sensing changes, seizing emerging opportunities, and reconfiguring organizational resources in response to environmental turbulence. The relationship between resilience, dynamic capabilities, and ESG performance indicates that organizations operating in uncertain and complex environments need flexible capabilities that allow them to adapt both strategically and operationally (Khurshid et al., 2026). Similarly, research on green economic growth and organizational green capability suggests that organizational outcomes are often mediated by internally developed capabilities that translate strategic orientations into concrete performance improvements (Gupta et al., 2026). Digital adaptive learning can therefore be considered a human-capital-oriented dynamic capability that enables employees and organizations to respond more rapidly and effectively to technological, operational, and institutional changes.

The development of such capability requires a supportive organizational context. Employees are unlikely to engage effectively in digital learning if technological transformation is introduced without adequate trust, governance, institutional support, strategic alignment, or perceived fairness. Research on ESG activities and employee outcomes has shown that employees' perceptions of organizational practices can significantly influence organizational

commitment, citizenship behavior, psychological well-being, identification, and workplace attitudes (Choi & Park, 2024; Choi et al., 2024; Jeong & Dong-Seop, 2025). Moreover, employee perceptions of sustainability-related practices can shape green behavior and broader pro-organizational conduct, indicating that organizational initiatives become effective when employees recognize them as credible, meaningful, and aligned with organizational values (K.-S. Chen et al., 2025; Hu, 2025). These findings have implications for digital learning because the adoption of intelligent learning systems, artificial intelligence, and digital training platforms is similarly dependent on employee acceptance, perceived legitimacy, organizational identification, and confidence in institutional processes. Accordingly, digital adaptive learning should be examined not only as a technological phenomenon but also as a behavioral and organizational process embedded in broader governance and cultural conditions.

One important requirement of digital adaptive learning is the institutionalization of digital transformation itself. Organizations may acquire advanced technologies without achieving meaningful digital transformation if those technologies remain detached from organizational culture, workflows, decision processes, and employee development systems. Research increasingly indicates that digitalization can improve organizational sustainability and performance when it is integrated with organizational strategy, innovation, and capability development (Xi, 2024; Yadav et al., 2026). Digital transformation has also been associated with sustainability performance in small and medium-sized enterprises, particularly when technological modernization supports organizational adaptability and strategic renewal (Fülöp, 2025). In addition, evidence regarding the relationship between digitalization of human resource management, green strategy, and ESG performance highlights the role of digitally enabled HR practices in strengthening organizational capability and environmental management (Honglei et al., 2025). Therefore, the institutionalization of digital learning requires more than providing digital tools; it requires embedding learning into human resource systems, organizational routines, performance expectations, and managerial decision-making.

Technological infrastructure represents another fundamental condition. Adaptive digital learning depends on access to reliable platforms, integrated information systems, analytical tools, digital content, and secure data environments. The increasing application of artificial intelligence in organizational and sustainability contexts illustrates the growing importance of technology-enabled decision-making and organizational intelligence (Wu et al., 2025). AI-based systems can facilitate personalization, prediction, resource optimization, and real-time adaptation, yet their effectiveness depends on technological readiness, organizational support, and governance. Research using technology–organization–environment perspectives has demonstrated that adoption of AI-driven systems is influenced by the interaction between technological capacity, organizational conditions, and external pressures (Abdalla et al., 2026). Consequently, digital learning systems should be designed within a broader institutional and technological architecture that supports standardization, interoperability, security, privacy, and responsible data use. Without these conditions, employees may face fragmented learning experiences, limited trust in digital platforms, or uncertainty concerning the ethical use of organizational data.

Data protection and ethical digital governance are especially important in organizations increasingly dependent on artificial intelligence and data-intensive systems. As digital infrastructures collect and process growing volumes of employee and organizational information, issues of transparency, accountability, privacy, cybersecurity, and responsible algorithmic decision-making become central managerial concerns. The governance dimension of ESG emphasizes organizational responsibility, accountability structures, oversight, and transparency, all of which are directly relevant to the management of digital learning ecosystems (Garefalakis, 2026; Teixeira et al., 2024). Research has also shown that legal and institutional contexts can moderate the effects of ESG controversies on economic and governance outcomes, suggesting that organizational practices cannot be separated from broader regulatory environments (Falco et al., 2025). Similarly, the relationship between governance, executive characteristics, and organizational performance indicates that leadership structures can influence the translation of sustainability-oriented practices into organizational outcomes (Ndione et al., 2026). Ethical and accountable digital governance can therefore be expected to function as a foundational condition for employee trust, technology acceptance, responsible data use, and sustainable implementation of adaptive learning systems.

Human empowerment is equally central to the digital learning process. The rapid evolution of digital technologies continually changes the competencies required for effective performance, making traditional static skill sets increasingly insufficient. Employees need not only technical proficiency

but also critical thinking, data literacy, problem-solving, judgment, adaptability, and the ability to interact productively with intelligent systems. The strategic importance of employees in sustainability-oriented transformation is reflected in research demonstrating links among workforce characteristics, organizational practices, and sustainability outcomes (Monteiro et al., 2024). Studies of organizational citizenship, commitment, and ESG performance likewise show that employee attitudes and discretionary behaviors constitute important mechanisms through which organizational strategies generate outcomes (Camacho, 2025; Jeong & Dong-Seop, 2025). In addition, evidence that ESG-related organizational practices affect employee green behaviors suggests that institutional priorities can become embedded in everyday employee conduct when supported by appropriate organizational systems (Hu, 2025). Accordingly, adaptive digital learning should be designed to strengthen employees' professional and cognitive competencies while enabling them to continuously respond to new technological demands.

The personalization of learning pathways is another increasingly important dimension. Conventional standardized training programs often assume relatively homogeneous employee needs, whereas digital workforces differ substantially in prior knowledge, digital proficiency, learning pace, occupational requirements, and readiness for technological change. Intelligent technologies can support personalized competency development by analyzing skill gaps, tailoring content, recommending learning pathways, and providing adaptive feedback. The wider organizational literature indicates that innovation and technology generate stronger performance outcomes when they are effectively integrated with organizational capability-building mechanisms (Duan et al., 2026; Tripopsakul, 2025). Innovation has also been identified as an important mediating mechanism linking ESG-related organizational performance to financial and sustainability outcomes, suggesting that strategic objectives are frequently realized through intermediate organizational capabilities rather than direct effects alone (Duan et al., 2026; Zhou et al., 2023). In the context of digital learning, personalized and continuous competency development may play a similar intermediary role by translating technological investment into employee capability and, ultimately, organizational performance.

Continuous learning also requires effective resource allocation. Organizations must decide how to distribute time, budgets, digital tools, learning opportunities, and managerial attention across different groups of employees. Resource optimization is particularly important in public service organizations, where operational continuity, financial constraints, and accountability requirements may limit the feasibility of extensive training interventions. Research on sustainability and financial performance has increasingly highlighted the importance of mediating mechanisms that explain how organizational practices generate performance outcomes (Choi et al., 2025; Salem et al., 2024). Similarly, research on carbon performance and sustainable organizational practices demonstrates that intermediate performance mechanisms can influence the relationship between broader strategic orientations and economic behavior (Mansour et al., 2026). These findings underscore the need to understand not simply whether digital learning influences organizational outcomes, but how specific supporting mechanisms such as resource allocation, assessment, technological infrastructure, and employee capability operate within a structured system.

Assessment and continuous improvement are also essential components of digital adaptive learning. Organizations need mechanisms for evaluating learning effectiveness, monitoring digital competency development, identifying gaps, and adjusting training strategies based on evidence. Sustainable organizational performance increasingly depends on the capacity to measure and interpret multidimensional performance indicators rather than relying on narrow financial metrics. ESG research illustrates this shift toward integrated performance evaluation and demonstrates the importance of combining environmental, social, governance, and economic indicators (Abdulrahman, 2025; F.-R. Chen et al., 2025). Research on substantive green innovation also indicates that organizational performance can be influenced by the extent to which strategic commitments are translated into actual operational practices rather than remaining symbolic (Hui-rong, 2025). For digital learning systems, this implies that organizations should evaluate not only participation in training but also actual competency development, behavioral change, technology use, decision quality, service improvement, and organizational adaptability.

Strategic alignment is particularly important because learning initiatives produce limited value when they are disconnected from organizational priorities. Digital learning should support the organization's mission, operational requirements, technological strategy, service objectives, and long-term sustainability agenda. Research on green transformation and sustainable competitive advantage indicates that organizational transformation can generate

stronger competitive outcomes when sustainability management is integrated with strategic change (Xi, 2024). Likewise, ESG strategies have been associated with sustainable organizational performance in multinational enterprises, emphasizing the role of strategic integration rather than isolated initiatives (F.-R. Chen et al., 2025). Evidence from ASEAN firms also indicates that green innovation can connect ESG practices with financial performance, demonstrating the importance of mechanisms that link strategic orientations to concrete organizational results (Tripopsakul, 2025). In the domain of digital adaptive learning, strategic alignment means that learning content, digital technologies, competency development, and performance evaluation should collectively contribute to organizational objectives rather than functioning as independent administrative activities.

The consequences of such alignment may extend to organizational agility, service quality, decision-making, sustainability, and competitiveness. Digital technologies can improve decision quality by enabling more rapid access to information, predictive analysis, and evidence-based management. At the same time, adaptive learning enhances employees' ability to interpret and use those technologies effectively. Organizational agility is especially important in environments characterized by rapid technological and regulatory change, and recent studies have shown that agility can act as a mechanism through which digital transformation contributes to broader sustainability outcomes (Yadav et al., 2026). Similarly, resilience and dynamic capabilities strengthen organizations' ability to maintain performance under changing conditions (Khurshid et al., 2026). Research on climate-risk perception and green innovation further indicates that cognitive awareness can shape organizational behavioral responses, demonstrating the importance of moving from perception and knowledge toward action (Bao & Zhang, 2026). Thus, employee learning, organizational cognition, technological capability, and adaptive action should be viewed as interconnected rather than independent processes.

Organizational justice and meritocracy may further influence whether employees engage positively with digital transformation and learning initiatives. New technologies can alter job responsibilities, evaluation methods, promotion opportunities, access to training, and organizational power relations. If employees perceive such changes as unfair or inconsistently implemented, resistance may increase and learning motivation may decline. Studies concerning ESG practices and employee outcomes suggest that organizational perceptions can influence commitment, psychological well-being, identification, citizenship behavior, and perceived meaningfulness of work (Choi & Park, 2024; Choi et al., 2024; Jeong & Dong-Seop, 2025). Research on internal pay gaps likewise demonstrates the relevance of internal organizational distribution and fairness mechanisms to ESG-related organizational behavior (Liu & Yan, 2025). At the governance level, diversity and inclusion in organizational leadership have also been linked to ESG performance and firm value, highlighting the broader strategic implications of representation, equity, and governance quality (Federo & Aguilera, 2025; Tahat et al., 2026). Therefore, a robust digital adaptive learning framework should incorporate fairness and meritocracy in access to learning opportunities, competency assessment, promotion, reward, and employee development.

The importance of these relationships becomes even more pronounced when organizations pursue long-term performance sustainability and competitiveness. Contemporary performance cannot be sustained solely through technological acquisition because technologies rapidly diffuse across organizations and become obsolete. Sustainable advantage increasingly depends on the ability to continually renew capabilities, convert knowledge into innovation, and integrate employee learning with strategic change. Empirical work suggests that innovation can mediate the relationship between ESG and firm performance, reinforcing the importance of internal organizational processes in converting strategic commitments into measurable results (Duan et al., 2026; Zhou et al., 2023). Research on corporate green capability similarly demonstrates that capability development can serve as an important pathway toward sustainable economic performance (Gupta et al., 2026). Furthermore, studies of organizational and corporate citizenship suggest that employee-level behaviors can contribute to effective sustainability performance when organizational systems successfully translate strategic priorities into shared behavioral norms (Camacho, 2025). Digital adaptive learning can therefore be expected to contribute indirectly to organizational sustainability by strengthening the human and cognitive foundations required for innovation, agility, service quality, and evidence-based decision-making.

Despite the increasing recognition of digital transformation, organizational sustainability, artificial intelligence, and capability development, the existing literature remains fragmented regarding the structural relationships among the organizational conditions that

enable employees' digital adaptive learning. Many studies have examined individual relationships between digitalization and sustainability performance (Fülöp, 2025; Zhao et al., 2024), between ESG practices and employee outcomes (K.-S. Chen et al., 2025; Choi et al., 2024), between innovation and organizational performance (Hui-rong, 2025; Tripopsakul, 2025), or between governance characteristics and sustainability-related outcomes (Falco et al., 2025; Ndione et al., 2026). Other studies have highlighted the growing intersection of artificial intelligence, organizational transformation, and sustainability management (Abdalla et al., 2026; Wu et al., 2025). However, less attention has been devoted to identifying how institutional, governance, technological, human, learning, and strategic factors interact hierarchically to form a coherent system of digital adaptive learning. This gap is especially significant in public utility organizations, where technological modernization must coexist with service continuity, public accountability, cybersecurity requirements, employee capability constraints, and increasing expectations for efficient and digitally enabled service provision.

Accordingly, there is a need for an integrative analytical framework capable of identifying the relevant components of employees' digital adaptive learning and clarifying the direction and hierarchical structure of relationships among them. Thematic analysis can provide a grounded understanding of the components that emerge from expert experience, while Interpretive Structural Modeling can reveal how these components influence one another and distinguish foundational drivers from intermediate enabling factors and ultimate outcomes. Such an integrated approach can help managers move beyond fragmented digital-training initiatives toward a systemic understanding of how governance, infrastructure, continuous learning, competency development, resource optimization, assessment, strategic alignment, decision intelligence, justice, agility, and performance sustainability interact. This perspective is especially useful for organizations seeking to prioritize interventions because it identifies not only which factors matter but also which factors should logically receive earlier managerial attention due to their broader driving influence within the system.

The present study aims to identify, classify, and interpretively structure the factors influencing employees' digital adaptive learning in Golestan Province Water and Wastewater Company through an integrated thematic analysis and Interpretive Structural Modeling approach.

## 2. Methods and Materials

In terms of purpose, the present study is applied, and in terms of methodology, it is descriptive–exploratory. It was conducted using a qualitative approach and an integration of thematic analysis and Interpretive Structural Modeling. In the first stage, semi-structured interviews with theoretical and practical experts were used to identify the factors and components influencing employees' digital adaptive learning. Participants at this stage included faculty members and specialists in human resource management, organizational learning, and information technology, as well as managers and experts from Golestan Province Water and Wastewater Company. Purposive sampling continued until theoretical saturation was achieved. Theoretical saturation was reached after 20 interviews; however, to ensure data adequacy and stabilize the identified themes, two additional interviews were conducted. Thus, a total of 22 interviews were included in the analysis. To evaluate the credibility and reliability of the qualitative findings, the criteria of credibility, transferability, confirmability, and dependability were employed. Credibility was assessed by having participants and several experts familiar with the research topic review the extracted codes and themes. Transferability was addressed by providing a clear description of the research context, participant characteristics, and data collection process. Moreover, to strengthen confirmability and dependability, the coding procedures, analytical decisions, and modifications made to the thematic classifications were systematically documented to enable the analytical process to be traced and reviewed.

**Table 1**

*Characteristics of the Experts*

| No. | Educational Level | Field of Specialization | Position/Occupation | Province of Employment | Work Experience (Years) |
|---|---|---|---|---|---|
| 1 | Master's degree | Civil Engineering–Hydraulic Structures | Director of Management Development and Research Office | Golestan | 28 |
| 2 | Master's degree | Public Administration (Human Resource Management) | Director of Security and Confidential Affairs Office | Golestan | 18 |
| 3 | Master's degree | Industrial Management (Production and Operations) | Complaints Investigation Expert | Golestan | 14 |
| 4 | Master's degree | Civil Engineering–Infrastructure Engineering and Management | Deputy for Human Resources and Research | Golestan | 18 |
| 5 | Bachelor's degree | Civil Engineering–Water and Wastewater | Consultant | Golestan | 24 |
| 6 | Master's degree | ---- | Deputy for Customer Services and Revenue | Golestan | 20 |
| 7 | PhD | Industrial Engineering | Assistant Professor | Golestan | 8 |
| 8 | PhD | Public Administration | Deputy for Research | Golestan | 11 |
| 9 | PhD | Industrial Management | Assistant Professor | Golestan | 10 |
| 10 | PhD | Industrial Management | Assistant Professor | Golestan | 15 |
| 11 | PhD | Industrial Engineering | Assistant Professor | Golestan | 9 |
| 12 | PhD | Industrial Engineering | Assistant Professor | Golestan | 8 |
| 13 | PhD | Management | Assistant Professor | Golestan | 11 |
| 14 | PhD | Management | Assistant Professor | Golestan | 7 |
| 15 | PhD | Management | Assistant Professor | Babol | 27 |
| 16 | PhD | Management | Associate Professor | Qaem Shahr | 27 |
| 17 | PhD | Educational Management | Associate Professor and Director of the Artificial Intelligence Academy Institute | Golestan | 25 |
| 18 | PhD | Public Administration | Assistant Professor and Artificial Intelligence Workshop Instructor | Golestan | 30 |
| 19 | PhD | Statistics and Information Technology Management | Assistant Professor and Secretary of the Artificial Intelligence Committee | Mazandaran | 22 |
| 20 | PhD | Environmental Planning and Management | Assistant Professor and Secretary of the Artificial Intelligence Committee | Golestan | 15 |

In the second stage, Interpretive Structural Modeling, as proposed by Warfield (1974), was employed to determine the hierarchical levels of the extracted components. The expert population at this stage consisted of managers, specialist professionals, and academic experts relevant to the research topic, of whom 20 were selected through purposive sampling. Data were collected using a pairwise-comparison questionnaire based on the Structural Self-Interaction Matrix (SSIM), in which the experts specified relationships among the components using the four standard symbols V, A, X, and O. To aggregate expert opinions, a minimum agreement threshold of 75%, equivalent to 15 of the 20 experts, was established as the criterion for accepting a relationship. Where the required level of agreement was not achieved, the issue was referred back to the experts for review and reassessment.

## 3. Findings and Results

In the first stage of data analysis, the systematic approach proposed by Braun and Clarke (2006) was employed to conduct the thematic analysis. At this stage, to develop a comprehensive and in-depth familiarity with the data, all interviews conducted with the experts were fully transcribed, and the transcripts were carefully read several times. Although a total of 22 interviews were conducted with experts, the concurrent analysis of the data indicated that after Interview 20, no new information containing new concepts, codes, or themes emerged, suggesting that theoretical saturation had been achieved. Nevertheless, to increase confidence and ensure data adequacy, the interviews continued through Participant 22. Throughout this process, complete immersion in the qualitative data enabled the identification of key concepts, preliminary patterns, and salient points raised by participants. Analytical notes were simultaneously recorded during the review of the

transcripts to provide an appropriate basis for proceeding to the subsequent stages of analysis. An excerpt from one interview and the corresponding codes is presented below as an example.

**Table 2**

*Example of an Interview Excerpt and Its Corresponding Codes*

| Interview Text | Key Codes |
|---|---|
| From my perspective, within the organization's operational environment, implementing a digital adaptive learning model represents a profound cultural and cognitive transformation rather than merely an instrumental change. The introduction of artificial intelligence is no longer an optional proposition; rather, it is a pervasive development affecting all dimensions of the company. However, employees do not possess the same level of familiarity with or mastery of emerging technologies, and for many colleagues, the greatest defensive barrier against technology is "lack of trust in the digital system." Our experience of transitioning from traditional methods, such as paper bills, to online systems demonstrated that, despite the facilitation of work processes, many employees resisted the change because of this skepticism. I initially felt the same way; however, when I observed how artificial intelligence could provide practical solutions in real organizational scenarios, such as analyzing receivables collection and costs, my perspective changed. Therefore, the first and most important step in this model is to gradually build trust and overcome cognitive resistance by demonstrating objective and tangible results. | Resistance to technology; Distrust of the digital system |

After achieving full familiarity with the interview data, the transcripts were examined carefully, repeatedly, and systematically, and segments of the data associated with the research objective and the various dimensions of employees' digital adaptive learning were identified and extracted. At this stage, efforts were made to consider all participant statements without restricting the analysis to predetermined concepts so that the various dimensions of the phenomenon could emerge from the interviewees' perspectives. Subsequently, meaningful concepts, expressions, and propositions extracted from the interview transcripts were recorded and classified as initial codes. During the coding process, while preserving the original meaning of participant statements, each code was formulated to represent a specific, independent concept relevant to the research topic. Codes with similar content were also compared to prevent unnecessary duplication and conceptual fragmentation while preserving meaningful differences among participant perspectives. The extracted initial codes were subsequently compared in terms of their conceptual and substantive content to identify similarities, differences, and relationships among them. This comparison aimed to identify common patterns in participants' statements and uncover concepts associated with the different dimensions of employees' digital adaptive learning. Codes that were similar in meaning, content, and conceptual implication were grouped together, and preliminary themes were identified based on the emerging semantic patterns. In this process, relationships among codes were not determined solely on the basis of lexical similarity; rather, the conceptual content and role of each code in explaining the research phenomenon were also taken into consideration. The groups were then reviewed and reorganized, and the basic themes were classified within broader conceptual categories, leading to the formation of organizing and overarching themes. The purpose of this stage was to move from fragmented and specific concepts toward a set of related and meaningful themes in order to develop a coherent structure of the factors influencing employees' digital adaptive learning. Following the identification and development of the themes, they were reviewed to ensure internal coherence, conceptual distinctiveness, and consistency with the original data. At this stage, the codes assigned to each theme were first examined separately to determine whether all codes within each group were substantively and conceptually consistent with the corresponding theme. The relationship of each theme with the other themes and its position within the overall structure of the findings were also evaluated. Subsequently, the identified themes were compared again with the interview dataset to ensure that the final structure reflected the substantive content of participants' statements and that no important dimension of the research phenomenon had been overlooked during coding and classification. This review considered possible overlap among themes, conceptual redundancy, excessive breadth of certain categories, and inappropriate separation of concepts. Accordingly, where necessary, certain themes were conceptually revised, merged, or separated to improve the clarity, coherence, and explanatory capacity of the resulting structure. In the next stage, the final themes were conceptually defined and labeled. For each theme, its principal content and conceptual domain were specified so that its boundaries and characteristics could be clearly distinguished from those of other themes. Accordingly, the title of each theme was selected to be concise and clear while accurately representing the relevant codes and concepts and reflecting the most important common feature of the data included in that group. On this basis, the final results of the

thematic analysis, including the basic, organizing, and overarching themes and their conceptual classification, are presented in Table 3.

**Table 3**

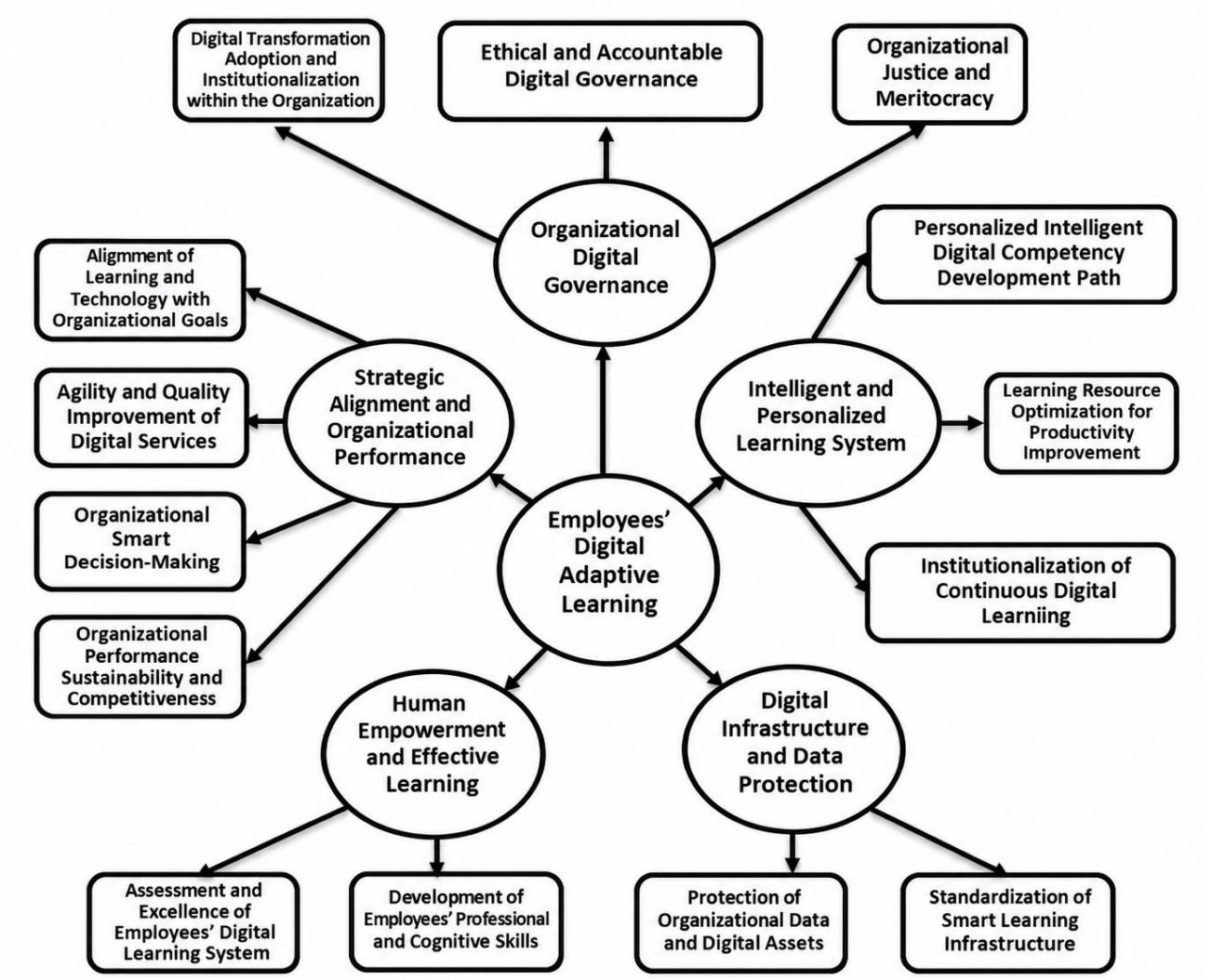
*Final Output of the Thematic Analysis*

| No. | Overarching Theme | Organizing Theme | Definition of the Organizing Theme |
|---|---|---|---|
| 1 | Organizational Digital Governance | Digital Transformation Adoption and Institutionalization within the Organization | The process of developing organizational readiness, building a supportive culture, and aligning employee mindsets and organizational structures with emerging technologies so that digital tools and digital thinking become an integral part of organizational culture and everyday organizational activities. |
| 2 | Organizational Digital Governance | Organizational Justice and Meritocracy | Establishing fair systems for employee evaluation, appointment, reward, and development based on competencies, capabilities, and actual value creation, free from subjective bias. |
| 3 | Organizational Digital Governance | Ethical and Accountable Digital Governance | Adherence to ethical principles, regulations, and transparency in the use of technologies and data, together with accountability for the consequences of digital decisions affecting employees, customers, and society. |
| 4 | Intelligent and Personalized Learning System | Personalization of the Intelligent Digital Competency Development Path | Providing individualized learning and development pathways tailored to each employee's needs, strengths, skill gaps, and learning pace through artificial intelligence tools and data analytics. |
| 5 | Intelligent and Personalized Learning System | Institutionalization of Continuous Digital Learning | Embedding a culture of ongoing and continuous learning through digital tools so that learning becomes an ongoing, dynamic, and continuous process integrated with routine work activities. |
| 6 | Intelligent and Personalized Learning System | Learning Resource Optimization for Productivity Improvement | Intelligent management, effective allocation, and monitoring of learning resources, including time, budget, and tools, to enhance the effectiveness of organizational learning processes. |
| 7 | Digital Infrastructure and Data Protection | Standardization of Smart Learning Infrastructure | Establishing frameworks, protocols, and technical and operational standards for deploying and integrating platforms, tools, and emerging educational technologies within the organization. |
| 8 | Digital Infrastructure and Data Protection | Protection of Organizational Data and Digital Assets | Establishing comprehensive security and privacy measures to protect sensitive information, employee data, and the organization's intangible digital assets against cyber risks and information leakage. |
| 9 | Human Empowerment and Effective Learning | Development of Employees' Professional and Cognitive Skills | Planning for the enhancement of employees' intellectual capabilities, problem-solving skills, critical thinking, data analysis capabilities, and specialized occupational skills in accordance with the requirements of the digital era. |
| 10 | Human Empowerment and Effective Learning | Assessment and Excellence of Employees' Digital Learning System | Continuous assessment of course quality, training effectiveness, and learner performance in digital environments with the aim of improving the organization's learning system. |
| 11 | Strategic Alignment and Organizational Performance | Alignment of Learning and Technology with Organizational Goals | Aligning skill-development programs, educational technologies, and digital strategies with the organization's overarching objectives, vision, and mission. |
| 12 | Strategic Alignment and Organizational Performance | Agility and Quality Improvement of Digital Services | Enhancing the speed, flexibility, and quality of products and services and improving responsiveness to stakeholders through agile capabilities and emerging digital tools. |
| 13 | Strategic Alignment and Organizational Performance | Organizational Smart Decision-Making | Applying data analytics, predictive models, and intelligent tools to reduce human error and support strategic and operational decision-making based on accurate evidence. |
| 14 | Strategic Alignment and Organizational Performance | Organizational Performance Sustainability and Competitiveness | The organization's ability to maintain long-term growth and productivity through continuous innovation, agility, and adaptability to environmental changes. |

Based on the findings of the thematic analysis, the initial conceptual model of the study was developed. This model resulted from organizing 14 organizing themes within five overarching themes. Within this framework, the overarching themes were considered the principal dimensions of the model, while the organizing themes represented the components constituting each dimension. The model derived from the thematic analysis is presented in Figure 1.

**Figure 1**

*Model Extracted from the Thematic Analysis*




In the second stage of the study, Interpretive Structural Modeling was employed to examine the interrelationships among the components identified during the thematic analysis stage and to explain their relational structure.

**Step 1: Identification and Finalization of the Key Components**

At this stage, the 14 organizing themes extracted during the qualitative phase of the study were considered the principal components of the model and served as the basis for analyzing structural relationships. The purpose of applying this method was to identify and explain the influence and dependence relationships among the components and to determine the structural position of each component within the final model.

**Table 4**

*Coding of the Components*

| No. | Expression | Abbreviation |
|---|---|---|
| 1 | Digital Transformation Adoption & Institutionalization | DTAI |
| 2 | Personalized Digital Competency Development Path | PDCP |
| 3 | Continuous Digital Learning Institutionalization | CDLI |
| 4 | Learning Resource Optimization for Productivity | LROP |
| 5 | Standardization of Smart Learning Infrastructure | SLSI |

| | | |
|---|---|---|
| 6 | Protection of Organizational Data & Digital Assets | PDDA |
| 7 | Development of Professional & Cognitive Skills | DPCS |
| 8 | Assessment & Excellence of Digital Workforce Learning | AEDL |
| 9 | Alignment of Learning & Technology with Goals | ALTG |
| 10 | Agility & Quality Improvement of Digital Services | AQID |
| 11 | Organizational Smart Decision-Making | OSDM |
| 12 | Performance Sustainability & Competitiveness | PSC |
| 13 | Organizational Justice & Meritocracy | OJM |
| 14 | Ethical & Accountable Digital Governance | EADG |

**Step 2: Formation of the Structural Self-Interaction Matrix (SSIM)**

To implement this stage, the opinions of 20 academic and executive experts familiar with the fields of human resource management, organizational learning, digital transformation, and information technology were utilized. Experts were selected purposively based on their specialized knowledge, academic backgrounds, and executive experience relevant to the research topic. The required data were collected using a pairwise-comparison questionnaire in which the 14 organizing themes were compared in pairs so that the experts could judge the existence and direction of the relationships among them. After the questionnaires were completed, expert responses for each pair of components were separately examined and aggregated. For this purpose, the frequency of judgments regarding each relationship was calculated, and the predominant expert judgment was determined based on the degree of agreement. A 75% agreement threshold was adopted as the criterion for accepting relationships. Thus, whenever at least 75% of the experts agreed on the existence and direction of a relationship, that relationship was entered into the final Structural Self-Interaction Matrix. Where the degree of agreement did not reach the specified threshold, the corresponding relationship was not incorporated into the final matrix on the basis of collective expert judgment. In this manner, the Structural Self-Interaction Matrix was developed through the systematic aggregation of the views of 20 experts in accordance with the predefined agreement criterion and served as the basis for the subsequent stages of Interpretive Structural Modeling. For each cell of the matrix, the frequencies of the four symbols (V, A, X, and O) were examined, and the symbol with the highest frequency across expert opinions was selected as the final symbol for that cell in the consensus matrix. This approach preserved collective expert judgment while enabling the dominant opinions to be systematically monitored.

**Table 5**

*Structural Self-Interaction Matrix*

| Factor | DTAI | PDCP | CDLI | LROP | SLSI | PDDA | DPCS | AEDL | ALTG | AQID | OSDM | PSC | OJM | EADG |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DTAI | — | V | V | O | V | O | O | O | V | O | O | O | O | O |
| PDCP | | — | O | V | O | V | V | O | O | O | O | O | O | A |
| CDLI | | | — | V | O | V | V | O | O | O | V | O | O | A |
| LROP | | | | — | A | O | O | V | A | O | V | O | O | O |
| SLSI | | | | | — | V | V | V | O | O | O | O | O | A |
| PDDA | | | | | | — | O | V | A | O | V | O | O | A |
| DPCS | | | | | | | — | V | A | V | V | O | O | O |
| AEDL | | | | | | | | — | O | V | O | V | V | O |
| ALTG | | | | | | | | | — | O | V | O | O | A |
| AQID | | | | | | | | | | — | A | V | O | O |
| OSDM | | | | | | | | | | | — | V | V | O |
| PSC | | | | | | | | | | | | — | A | O |
| OJM | | | | | | | | | | | | | — | A |
| EADG | | | | | | | | | | | | | | |

**Step 3: Conversion of the SSIM into the Initial Reachability Matrix**

After completing the Structural Self-Interaction Matrix (SSIM) and specifying the relationships among the key research components, the next step in Interpretive Structural

Modeling was to convert this matrix into the initial reachability matrix. At this stage, the qualitative relationships among the components were converted into numerical values to enable quantitative analysis and the calculation of indirect relationships. Accordingly, the symbols V, A, and X, representing the influence of one factor on another or a bidirectional relationship, were converted to 1, whereas the symbol O, indicating the absence of a relationship, was converted to 0.

**Table 6**

*Conversion of Symbols into Numerical Values*

| Symbol | Interpretation | Numerical Value |
|---|---|---|
| V | The row influences the column | 1 |
| A | The column influences the row | 1 |
| X | Bidirectional; both exert influence | 1 |
| O | No relationship exists | 0 |

**Table 7**

*Initial Reachability Matrix*

| Factor | DTAI | PDCP | CDLI | LROP | SLSI | PDDA | DPCS | AEDL | ALTG | AQID | OSDM | PSC | OJM | EADG | Row Sum |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DTAI | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 5 |
| PDCP | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4 |
| CDLI | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 5 |
| LROP | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 3 |
| SLSI | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 5 |
| PDDA | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 3 |
| DPCS | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 4 |
| AEDL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 4 |
| ALTG | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 5 |
| AQID | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 2 |
| OSDM | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 4 |
| PSC | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| OJM | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 2 |
| EADG | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 7 |
| Column Sum | 1 | 3 | 3 | 5 | 3 | 6 | 5 | 5 | 3 | 4 | 6 | 5 | 4 | | |

**Step 4: Final Reachability Matrix**

After the formation of the initial reachability matrix in Interpretive Structural Modeling (ISM), the principle of transitivity was applied to the matrix, resulting in the final reachability matrix. At this stage, indirect relationships were identified and incorporated into the matrix in addition to the direct relationships among the components. In other words, if one factor influences a second factor and that second factor influences a third factor, a relationship between the first and third factors is also incorporated into the final matrix.

**Table 8**

*Final Reachability Matrix*

| Factor | DTAI | PDCP | CDLI | LROP | SLSI | PDDA | DPCS | AEDL | ALTG | AQID | OSDM | PSC | OJM | EADG | Row Sum |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DTAI | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 13 |
| PDCP | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 9 |
| CDLI | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 9 |
| LROP | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 6 |
| SLSI | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 9 |
| PDDA | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 6 |
| DPCS | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 6 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AEDL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 4 |
| ALTG | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 9 |
| AQID | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 2 |
| OSDM | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 4 |
| PSC | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| OJM | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 2 |
| EADG | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 13 |
| Column Sum | 1 | 3 | 3 | 7 | 3 | 7 | 7 | 10 | 3 | 12 | 10 | 14 | 12 | | |

**Step 5: Level Partitioning of the Components**

To develop the hierarchical structure and determine the influence priorities of the components, level partitioning was performed using the final reachability matrix. In this process, for each component, the reachability or output set—comprising the factor itself and all factors that it can influence directly or indirectly—and the antecedent or input set—comprising the factor itself and all factors that influence it—were extracted from the final reachability matrix. The mathematical intersection of these two sets was then calculated for each component to assess the conditions for its placement and differentiation across the various levels of the structural hierarchy.

In Interpretive Structural Modeling, the research components are classified into different levels from the base to the apex of the model according to the intersection of their reachability and antecedent sets. Within this structure, the components were positioned across six levels as follows:

At Level 1, only one factor is positioned and is regarded as the most dependent component. At Level 2, two additional factors are positioned one step higher in the chain of dependence. Level 3 includes two factors that establish direct relationships with the lower levels. Moving upward, three factors are positioned at Level 4. At Level 5, four additional factors are located whose antecedent domains are broader. Finally, at Level 6, which represents the most fundamental, foundational, and influential part of the overall system, two factors are positioned that play the strongest role in directing the structure.

**Table 9**

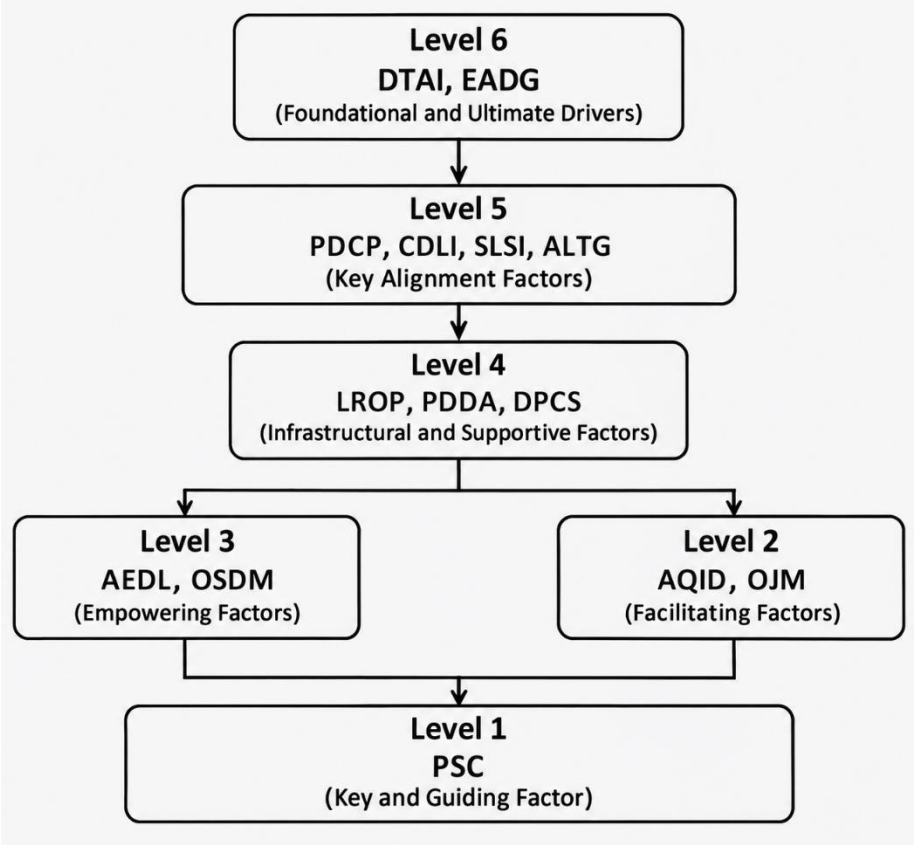
*Level Partitioning of the Components*

| Level | Factor Code | Abbreviation | Reachability Set R(s) | Antecedent Set A(s) | Intersection R∩A |
|---|---|---|---|---|---|
| 1 | PSC | PSC | {PSC} | {All 14 factors} | {PSC} |
| 2 | AQID | AQID | {AQID, PSC} | {DTAI, PDCP, CDLI, LROP, SLSI, PDDA, DPCS, AEDL, ALTG, AQID, OSDM, EADG} | {AQID} |
| 2 | OJM | OJM | {OJM, PSC} | {DTAI, PDCP, CDLI, LROP, SLSI, PDDA, DPCS, AEDL, ALTG, OSDM, OJM, EADG} | {OJM} |
| 3 | AEDL | AEDL | {AEDL, AQID, PSC, OJM} | {DTAI, PDCP, CDLI, LROP, SLSI, PDDA, DPCS, AEDL, ALTG, EADG} | {AEDL} |
| 3 | OSDM | OSDM | {OSDM, AQID, PSC, OJM} | {DTAI, PDCP, CDLI, LROP, SLSI, PDDA, DPCS, ALTG, OSDM, EADG} | {OSDM} |
| 4 | LROP | LROP | {LROP, AEDL, AQID, OSDM, PSC, OJM} | {DTAI, PDCP, CDLI, LROP, SLSI, ALTG, EADG} | {LROP} |
| 4 | PDDA | PDDA | {PDDA, AEDL, AQID, OSDM, PSC, OJM} | {DTAI, PDCP, CDLI, SLSI, PDDA, ALTG, EADG} | {PDDA} |
| 4 | DPCS | DPCS | {DPCS, AEDL, AQID, OSDM, PSC, OJM} | {DTAI, PDCP, CDLI, SLSI, DPCS, ALTG, EADG} | {DPCS} |
| 5 | PDCP | PDCP | {PDCP, LROP, PDDA, DPCS, AEDL, AQID, OSDM, PSC, OJM} | {DTAI, PDCP, EADG} | {PDCP} |
| 5 | CDLI | CDLI | {CDLI, LROP, PDDA, DPCS, AEDL, AQID, OSDM, PSC, OJM} | {DTAI, CDLI, EADG} | {CDLI} |
| 5 | SLSI | SLSI | {SLSI, LROP, PDDA, DPCS, AEDL, AQID, OSDM, PSC, OJM} | {DTAI, SLSI, EADG} | {SLSI} |
| 5 | ALTG | ALTG | {ALTG, LROP, PDDA, DPCS, AEDL, AQID, OSDM, PSC, OJM} | {DTAI, ALTG, EADG} | {ALTG} |
| 6 | DTAI | DTAI | {DTAI, PDCP, CDLI, LROP, SLSI, PDDA, DPCS, AEDL, ALTG, AQID, OSDM, PSC, OJM} | {DTAI, EADG} | {DTAI} |
| 6 | EADG | EADG | {All 15 factors / including all} | {EADG} | {EADG} |

In Interpretive Structural Modeling, after the hierarchical levels of the components and the relationships among them have been determined, the hierarchical research model is depicted as a more coherent structural configuration. In this diagram, the components are arranged across six levels, ranging from the most fundamental drivers to the most outcome-oriented objective of the system. Accordingly, the root and ultimately influential components are positioned at the highest logical layer and, through their influence on the intermediate levels—including aligned, infrastructural, empowering, and facilitating components—ultimately affect the key strategic factor at Level 1. The direction of the arrows within this structure represents the flow of influence from the foundational factors toward the final outcome of the system.

**Figure 2**

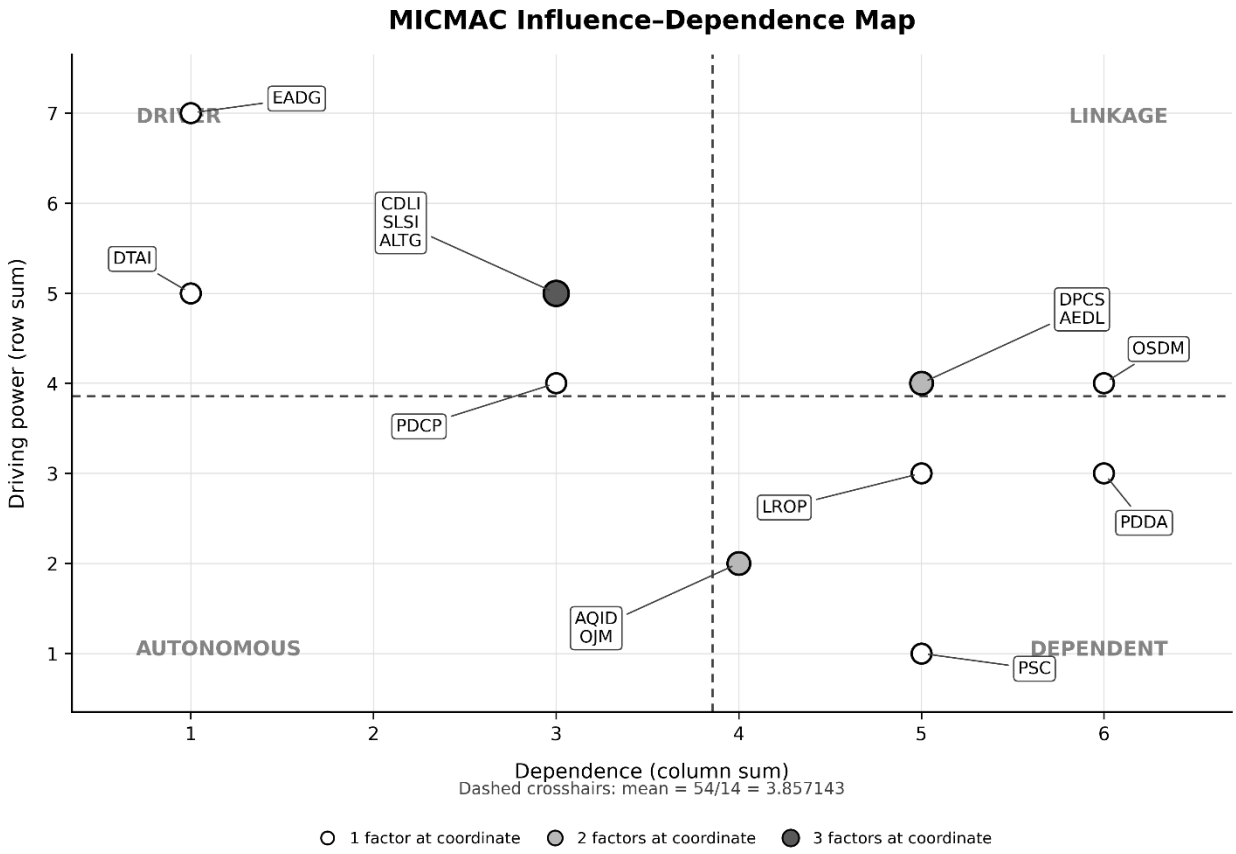
*Hierarchical Model Based on the Final Reachability Matrix*




Based on the Interpretive Structural Modeling (ISM) analysis and the MICMAC assessment of driving power and dependence across the 14 key factors of the system, the system structure was formed across seven hierarchical levels, extending from the foundational factor EADG at Level 7 as the primary initiating factor to PSC at Level 1 as the ultimate objective. The MICMAC classification results indicate that EADG, DTAI, SLSI, CDLI, ALTG, and PDCP constitute the principal driving factors of the system, characterized by high driving power and low dependence, whereas LROP, PDDA, PSC, and AQID are categorized as dependent factors. Furthermore, DPCS, AEDL, and OSDM operate as linkage factors, forming a bridge between the system's foundational elements and its outcomes.

**Figure 3**

*Driving Power–Dependence Diagram*




"Based on the Interpretive Structural Modeling (ISM) analysis and the MICMAC assessment of driving power and dependence across the 14 key factors of the system, the system structure was formed across seven hierarchical levels, extending from 'Ethical and Accountable Digital Governance' (EADG) at Level 7 as the principal initiating factor to 'Organizational Performance Sustainability and Competitiveness' (PSC) at Level 1 as the ultimate objective. The MICMAC classification results indicate that 'Ethical and Accountable Digital Governance' (EADG), 'Digital Transformation Adoption and Institutionalization within the Organization' (DTAI), 'Standardization of Smart Learning Infrastructure' (SLSI), 'Institutionalization of Continuous Digital Learning' (CDLI), 'Alignment of Learning and Technology with Organizational Goals' (ALTG), 'Personalization of the Intelligent Digital Competency Development Path' (PDCP), and 'Organizational Justice and Meritocracy' (OJM) constitute the principal driving variables of the system, characterized by high driving power and low dependence. In contrast, 'Learning Resource Optimization for Productivity Improvement' (LROP), 'Protection of Organizational Data and Digital Assets' (PDDA), 'Organizational Performance Sustainability and Competitiveness' (PSC), and 'Agility and Quality Improvement of Digital Services' (AQID) are categorized as dependent variables. Furthermore, 'Development of Employees' Professional and Cognitive Skills' (DPCS), 'Assessment and Excellence of Employees' Digital Learning System' (AEDL), and 'Organizational Smart Decision-Making' (OSDM) function as linkage variables, forming a bridge between the system's foundational dimensions and its outcomes."

## 4. Discussion and Conclusion

The findings of the present study provide a structured explanation of the factors influencing employees' digital adaptive learning and demonstrate that this phenomenon should be understood as a multilevel organizational system rather than as an isolated training or technology-adoption issue. The thematic analysis identified 14 organizing themes grouped into five overarching dimensions: organizational digital governance, intelligent and personalized learning

systems, digital infrastructure and data protection, human empowerment and effective learning, and strategic alignment and organizational performance. The subsequent Interpretive Structural Modeling analysis showed that these components are hierarchically interdependent, with Digital Transformation Adoption and Institutionalization within the Organization (DTAI) and Ethical and Accountable Digital Governance (EADG) positioned at the deepest structural level and Organizational Performance Sustainability and Competitiveness (PSC) positioned as the most dependent outcome. This configuration indicates that sustainable digital learning outcomes emerge from institutional and governance foundations that progressively shape technological infrastructure, learning processes, employee capabilities, decision quality, service agility, and ultimately organizational sustainability and competitiveness. Such a systemic interpretation is consistent with research emphasizing that digital transformation produces organizational value only when technological change is embedded within organizational routines, governance systems, dynamic capabilities, and strategic priorities (Fülöp, 2025; Yadav et al., 2026; Zhao et al., 2024).

The positioning of EADG and DTAI as the most fundamental driving components is one of the most important findings of the study. Ethical and accountable digital governance creates the institutional conditions through which organizations can implement digital technologies in a transparent, legitimate, and responsible manner, while digital transformation adoption and institutionalization ensures that technological change becomes embedded in organizational culture, structures, routines, and employee mindsets. These factors therefore operate as antecedent conditions for the remaining components of digital adaptive learning. This result is compatible with the broader governance and sustainability literature, which highlights the importance of accountability, transparency, leadership structures, institutional credibility, and organizational governance in shaping sustainable organizational outcomes (Garefalakis, 2026; Tahat et al., 2026; Teixeira et al., 2024). It also supports findings indicating that governance mechanisms and organizational contexts can influence how sustainability-related strategies affect economic and non-economic performance (Falco et al., 2025; Ndione et al., 2026). In the context of digital learning, these findings suggest that employees are more likely to accept and engage with digital systems when they perceive that technologies are introduced through legitimate, transparent, and accountable organizational processes.

The high driving role of digital transformation institutionalization also confirms that technology itself cannot create adaptive learning unless it becomes integrated with organizational strategy and daily work practices. Previous research has shown that digital transformation can strengthen organizational sustainability and performance when it is combined with organizational agility, green innovation, and strategic capability development (Xi, 2024; Yadav et al., 2026). Similarly, digitalization has been identified as a pathway through which organizations can improve ESG-related and sustainable performance outcomes (Zhao et al., 2024). The findings of Fülöp further indicate that the impact of digital transformation is strongly related to the organization's ability to combine technological change with broader organizational adaptation (Fülöp, 2025). Accordingly, the present results imply that digital adaptive learning requires digital transformation to be normalized and institutionalized across organizational systems rather than being treated as a temporary project or a set of standalone technological interventions.

The placement of Personalized Digital Competency Development Path (PDCP), Continuous Digital Learning Institutionalization (CDLI), Standardization of Smart Learning Infrastructure (SLSI), and Alignment of Learning and Technology with Organizational Goals (ALTG) at the next major hierarchical level indicates that these factors function as key translation mechanisms between foundational governance conditions and operational outcomes. Once the organization establishes a legitimate digital governance framework and institutionalizes digital transformation, it must create structures through which employees can continuously acquire relevant competencies. Personalized competency pathways are particularly important because employee learning needs, digital readiness, job responsibilities, and prior technological experience are heterogeneous. Artificial intelligence and data-enabled learning systems can address such heterogeneity by customizing training content and developmental pathways. The growing integration of artificial intelligence into organizational and sustainability systems supports the importance of this finding (Abdalla et al., 2026; Wu et al., 2025). AI-driven organizational systems can enhance personalization, predictive analysis, and decision support, but their effective utilization requires organizational readiness, governance, and alignment with broader strategic objectives.

The identification of continuous digital learning as a high-level driver also emphasizes the need to move beyond

episodic training models. In rapidly changing digital environments, employees require continuous competence renewal because technological knowledge can become obsolete quickly. This result can be interpreted through the lens of dynamic capabilities, according to which organizations must continuously renew and reconfigure internal capabilities in response to environmental change. Research connecting resilience, dynamic capabilities, and ESG performance similarly emphasizes that adaptive capability is necessary for organizations to maintain performance under conditions of uncertainty and transformation (Khurshid et al., 2026). The finding is also consistent with studies showing that organizational capability can act as a mediating mechanism through which broader strategic initiatives generate sustainable outcomes (Gupta et al., 2026). In this sense, continuous digital learning can be regarded as an internal capability-building process that allows organizations to translate technological investment into sustained employee adaptability.

The position of SLSI confirms that technological standardization is not merely a technical concern but a structural prerequisite for effective digital learning. Standardized platforms, interoperable systems, common protocols, stable access, and reliable digital tools reduce fragmentation and enable learning processes to operate consistently across organizational units. The importance of technological infrastructure can also be inferred from studies of AI adoption, digital transformation, and sustainable organizational performance, which show that technology-oriented outcomes depend on the interaction between technological readiness and organizational capability (Abdalla et al., 2026; Zhao et al., 2024). The present findings suggest that smart learning environments require an infrastructural architecture that is stable enough to support continuous learning while remaining sufficiently flexible to accommodate personalization, analytics, automation, and changing competency requirements.

The hierarchical importance of ALTG further shows that digital learning cannot be effective when disconnected from organizational mission and performance objectives. Learning initiatives must contribute to operational priorities, service quality, workforce capability, and strategic transformation. This result is consistent with research showing that strategic integration plays a decisive role in converting sustainability initiatives into organizational performance (F.-R. Chen et al., 2025). Similar evidence indicates that green transformation and ESG-related strategies can contribute to competitive advantage when they are integrated into organizational management systems rather than treated as isolated initiatives (Xi, 2024). Furthermore, the relationship between ESG practices, green innovation, and financial performance demonstrates the importance of mediating processes that connect strategy to measurable outcomes (Tripopsakul, 2025). In the present study, alignment between learning and organizational goals plays a similar mediating role by ensuring that digital learning contributes directly to organizational priorities.

The fourth hierarchical level, consisting of Learning Resource Optimization for Productivity (LROP), Protection of Organizational Data and Digital Assets (PDDA), and Development of Professional and Cognitive Skills (DPCS), represents an important operational bridge between strategic learning architecture and downstream performance outcomes. LROP indicates that digital adaptive learning requires efficient allocation of time, budgets, platforms, and educational resources. Organizations cannot assume that learning automatically produces value; rather, resources must be strategically directed toward competencies that generate meaningful operational returns. This interpretation is consistent with research emphasizing that organizational performance outcomes often emerge through mediating pathways and resource-allocation mechanisms rather than through direct strategic effects (Mansour et al., 2026; Salem et al., 2024). The present results therefore suggest that effective digital learning requires both adequate investment and disciplined resource management.

PDDA emerged as another significant infrastructural factor. This finding is especially important because adaptive digital learning systems increasingly rely on employee data, learning analytics, performance information, artificial intelligence, and interconnected digital platforms. Without appropriate data protection, cybersecurity, and privacy safeguards, employees may be reluctant to trust digital learning systems or may perceive them as intrusive. Ethical digital governance and data protection are therefore mutually reinforcing. Research on ESG governance, legal context, and organizational accountability similarly indicates that institutional legitimacy and regulatory conditions shape the consequences of organizational practices (Falco et al., 2025; Tahat et al., 2026). Moreover, the increasing role of artificial intelligence in organizational decision-making further elevates the importance of responsible data governance (Wu et al., 2025). Thus, the location of PDDA within the middle structure of the model reflects its role as an enabling condition that translates high-

level governance principles into practical organizational safeguards.

DPCS also occupies a central structural position because digital adaptive learning ultimately depends on employees' ability to transform learning opportunities into usable cognitive and professional capabilities. Employees require more than basic technical skills; they increasingly need problem-solving ability, critical thinking, analytical competence, data literacy, and the capacity to work with intelligent systems. The importance of employee-level capabilities is supported by research showing that organizational sustainability strategies can influence employee attitudes, behaviors, and organizational citizenship through psychological and relational processes (Choi et al., 2024; Jeong & Dong-Seop, 2025). Studies have also shown that perceptions of ESG practices can influence psychological well-being and meaningfulness of work (Choi & Park, 2024), while sustainability performance can shape employee green behavior (Hu, 2025). These findings support the interpretation that organizational strategies are realized through employee-level cognitive and behavioral mechanisms. Accordingly, developing professional and cognitive skills is a critical link between organizational digital strategy and performance.

At the third level, Assessment and Excellence of Digital Workforce Learning (AEDL) and Organizational Smart Decision-Making (OSDM) emerged as empowering and linkage components. The position of AEDL suggests that organizations must continuously evaluate the quality, effectiveness, and outcomes of digital learning. Without assessment, learning systems may become administratively active but strategically ineffective. This finding parallels the broader sustainability literature, where multidimensional evaluation and performance measurement are increasingly emphasized (Abdulrahman, 2025). Research has also shown that substantive organizational practices are more consequential than symbolic commitments, reinforcing the importance of evaluating whether strategic initiatives generate actual operational change (Hui-rong, 2025). Accordingly, digital learning systems should be assessed not only through participation rates but also through competency development, performance improvement, technology adoption, and behavioral change.

OSDM reflects the expected consequence of integrating learning, data, and technology. Employees who possess stronger digital and cognitive capabilities are better able to interpret data, use analytical tools, and contribute to evidence-based organizational decisions. This finding is consistent with the increasing emphasis on artificial intelligence and digital analytics in organizational management (Wu et al., 2025). It also aligns with evidence showing that innovation functions as an important mechanism through which organizational strategies are converted into financial and sustainability outcomes (Duan et al., 2026; Zhou et al., 2023). Smart decision-making can similarly be interpreted as a capability through which digital learning is transformed into improved organizational action.

The emergence of AQID and OJM at Level 2 indicates that digital adaptive learning ultimately contributes to organizational agility and service quality while also operating within a system of perceived justice and meritocracy. The position of AQID is consistent with research showing that agility can mediate the relationship between digital transformation and sustainable performance (Yadav et al., 2026). Adaptive employees can respond more rapidly to technological changes, customer needs, and operational disruptions, which in turn can increase service flexibility and quality. OJM, meanwhile, indicates that justice and meritocracy are not merely background cultural values but important organizational outcomes and facilitative mechanisms. Evidence from prior studies shows that employee perceptions of organizational practices influence commitment, identification, citizenship behavior, and well-being (Choi & Park, 2024; Choi et al., 2024; Jeong & Dong-Seop, 2025). Internal organizational fairness is also relevant to sustainability-oriented governance and compensation structures (Liu & Yan, 2025). In addition, leadership diversity and inclusive governance have been associated with ESG performance and firm value, highlighting the strategic importance of fairness and representation (Federo & Aguilera, 2025). Therefore, employees are more likely to engage positively with digital transformation when access to learning, development, rewards, and advancement is perceived as fair and competency-based.

PSC was identified as the final and most dependent outcome in the model. This finding indicates that organizational performance sustainability and competitiveness result from the cumulative effects of governance, learning, infrastructure, employee development, assessment, smart decision-making, service agility, and institutional fairness. The finding is consistent with studies demonstrating that sustainability and financial performance frequently depend on intermediate capabilities such as innovation, agility, and organizational capability (Duan et al., 2026; Gupta et al., 2026; Tripopsakul, 2025).

Research has also shown that green innovation mediates relationships between ESG practices and broader performance outcomes (Zhou et al., 2023), while strategic transformation can contribute to sustainable competitive advantage (Xi, 2024). Moreover, organizational citizenship and employee engagement mechanisms have been linked to effective ESG performance (Camacho, 2025). These studies support the present conclusion that sustainable performance is unlikely to emerge directly from digital technology alone; rather, it develops through a chain of organizational capabilities and employee-centered mechanisms.

The MICMAC findings further reinforce this interpretation by classifying EADG, DTAI, SLSI, CDLI, ALTG, PDCP, and OJM as major driving variables, while LROP, PDDA, AQID, and PSC were more dependent. DPCS, AEDL, and OSDM operated as linkage variables that connect foundational conditions to organizational outcomes. This configuration suggests that managerial intervention should begin with governance, institutionalization, strategic alignment, learning architecture, and infrastructure rather than focusing exclusively on visible outcomes such as service quality or competitiveness. This interpretation is consistent with the broader evidence that organizational outcomes depend on underlying mechanisms and mediating capabilities (Choi et al., 2025; Duan et al., 2026; Salem et al., 2024). Stakeholder pressures have also been shown to mediate relationships between ESG mechanisms and financial performance, further supporting the importance of understanding indirect organizational pathways (Choi et al., 2025). Similarly, sustainability-related organizational strategies can affect employee and organizational outcomes through multiple intermediate mechanisms rather than through a single direct path (Bao & Zhang, 2026; K.-S. Chen et al., 2025). Overall, the results confirm that employees' digital adaptive learning is a system-level organizational capability in which governance, technology, learning, human capital, and strategy interact recursively to produce sustainable performance.

The present study has several limitations that should be considered when interpreting the findings. First, the qualitative stage relied on purposive sampling and expert interviews within a specific organizational and sectoral context, which may limit the transferability of the identified themes to organizations operating under different regulatory, technological, or cultural conditions. Second, the ISM model reflects expert judgments regarding the existence and direction of relationships among components; therefore, although the model provides a structured representation of perceived causal ordering, it does not constitute statistical proof of causal effects. Third, the study focused on one provincial water and wastewater organization, and organizational characteristics such as public-sector governance, service obligations, technological maturity, and workforce composition may have influenced the prioritization of specific factors. Fourth, the cross-sectional nature of the expert judgments does not capture how relationships among the components may change over time as digital technologies mature and employee competencies develop. Finally, the model emphasizes organizational-level structures and may not fully capture individual differences in digital readiness, learning motivation, technology anxiety, age, occupational background, or prior digital experience.

Future research can extend the present findings in several directions. Quantitative studies should test the proposed hierarchical relationships using larger samples and techniques such as structural equation modeling, partial least squares structural equation modeling, or longitudinal path analysis. Comparative studies across public utilities, private-sector organizations, and different geographical regions could assess the stability of the identified dimensions and clarify the role of organizational context. Longitudinal research could examine how digital adaptive learning capabilities evolve over time and whether the importance of specific drivers changes as organizations progress through different stages of digital maturity. Future studies may also investigate moderating variables such as organizational culture, leadership style, employee digital readiness, technology acceptance, psychological safety, and generational differences. Combining ISM with methods such as DEMATEL, fuzzy MICMAC, analytic network process, or system dynamics may also provide more detailed evidence concerning the strength, feedback effects, and temporal behavior of relationships among components.

From a managerial perspective, organizations should prioritize the establishment of ethical and accountable digital governance and the institutionalization of digital transformation before investing heavily in isolated digital training programs. Managers should develop clear governance policies for artificial intelligence, employee data, cybersecurity, transparency, and accountability while simultaneously promoting trust in digital systems. Learning systems should be personalized according to employees' competency gaps and job requirements and should support continuous rather than episodic development. Organizations should standardize learning infrastructure, protect digital assets, and integrate learning objectives with strategic and

operational goals. Employee development should include technical skills as well as critical thinking, problem-solving, data literacy, and intelligent decision-making capabilities. Continuous evaluation mechanisms should be established to assess the actual effectiveness of digital learning and to revise programs accordingly. Finally, access to learning opportunities, competency evaluation, promotion, and rewards should be governed by transparent and merit-based procedures so that digital transformation strengthens employee trust, organizational agility, service quality, and long-term competitiveness.

## Authors' Contributions

Authors contributed equally to this article.

## Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

## Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

## Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

## Declaration of Interest

The authors report no conflict of interest.

## Funding

According to the authors, this article has no financial support.

## Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

## References

Abdalla, R. A., Hidaytalla, L. A., & Mulla, G. S. (2026). Mediating Pathways to Sustainable Investment: A TOE Framework for AI-Driven Green Fintech Adoption in Banking. *Journal of Risk and Financial Management*, *19*(7), 496. https://doi.org/10.3390/jrfm19070496

Abdulrahman, A. A. J. (2025). Integrating ESG Framework With Social Sustainability Metrics: A Dual SEM-PLS Formative–Reflective Model Perspective. *Sustainability*, *17*(6), 2566. https://doi.org/10.3390/su17062566

Bao, X., & Zhang, X. (2026). Climate Risk Perception and Corporate Green Innovation: From Cognitive Awareness to Behavioral Response. *Sustainability*, *18*(2), 752. https://doi.org/10.3390/su18020752

Camacho, L. J. (2025). Bridging Organizational Citizenship Behavior and Corporate Citizenship as a Pathway to Effective ESG Performance. *Businesses*, *5*(3), 38. https://doi.org/10.3390/businesses5030038

Chen, F.-R., Ko, W. H., & Lu, M.-Y. (2025). Linking Sustainability and Brand Love Through Employees' Insights on ESG Practices in the Airline Industry. *Sustainability*, *17*(22), 10408. https://doi.org/10.3390/su172210408

Chen, K.-S., Lin, S.-T., & Chuang, C.-J. (2025). ESG Strategies and Sustainable Performance in Multinational Enterprises. *Sustainability*, *17*(2), 751. https://doi.org/10.3390/su17020751

Choi, A. Y., Kim, D., & Na, J. (2025). Disaggregating ESG Mechanisms: The Mediating Role of Stakeholder Pressure in the Financial Performance of Logistics Firms. *Sustainability*, *17*(19), 8840. https://doi.org/10.3390/su17198840

Choi, S., & Park, S. R. (2024). ESG Activity Recognition Enhances Organizational Commitment and Service-Oriented Organizational Citizenship Behavior Among Insurance Call Center Staff. *Heliyon*, *10*(11), e31999. https://doi.org/10.1016/j.heliyon.2024.e31999

Choi, W., Wang, W., Kim, H. J., Lee, J.-M., & Kang, S. W. (2024). Unraveling the Link Between Perceived ESG and Psychological Well-Being: The Moderated Mediating Roles of Job Meaningfulness and Pay Satisfaction. *Behavioral Sciences*, *14*(7), 606. https://doi.org/10.3390/bs14070606

Duan, J., Hrouda, M., Ameir, O., & Grycz, O. (2026). Innovation as a Mediating Mechanism Between ESG Performance and Financial Performance. *Sustainability*, *18*(13), 6685. https://doi.org/10.3390/su18136685

Falco, S. E. D., Coniglio, G., & Dalipi, E. (2025). The Moderating Role of the Legal Context Between <scp>ESG</Scp> Controversies, Economic Performance and Board of Directors. *Corporate Social Responsibility and Environmental Management*, *33*(3), 3208-3224. https://doi.org/10.1002/csr.70316

Federo, R., & Aguilera, R. V. (2025). How Does the Visibility of <scp>LGBTQ</Scp>+ Directors Influence Firm Value? The Mediating Role of Environmental, Social, and Governance Performance. *Human Resource Management*, *64*(3), 731-752. https://doi.org/10.1002/hrm.22283

Fülöp, M. T. (2025). Balancing Technology and Sustainability: The Role of Digital Transformation on Romanian <scp>SMEs</Scp>. *Business Strategy & Development*, *8*(4). https://doi.org/10.1002/bsd2.70239

Garefalakis, A. (2026). Green Accounting and ESG Research in Dynamic Organizational Environments. *Administrative Sciences*, *16*(9), 430. https://doi.org/10.3390/admsci16090430

Gupta, A. S., Sayem, S. M., Sultana, N., Akter, M. S., & Islam, K. M. (2026). Transition Toward Green Economic Growth: The Mediating Role of Organizational Green Capability. *Business Strategy & Development*, *9*(3). https://doi.org/10.1002/bsd2.70377

Honglei, H., Mehmood, A., Frooghi, R., Usman, M., & Rashid, M. (2025). Advancing Environmental Management in Manufacturing Firms: The Role of Carbon Footprint Awareness, Digitalization Of <scp>HRM</Scp> , and Green

Business Strategy in Driving Firm <scp>ESG</Scp> Performance. *Corporate Social Responsibility and Environmental Management*, *33*(2), 2616-2633. https://doi.org/10.1002/csr.70299

Hu, Y. (2025). Green Behaviors Among Employees in Chinese E-Commerce Companies: Impact of Environmental, Social, and Governance (ESG) Performance. *Sustainability*, *17*(3), 940. https://doi.org/10.3390/su17030940

Hui-rong, L. I. (2025). Corporate Dual-Organizational Performance and Substantive Green Innovation Practices: A Quasi-Natural Experiment Analysis Based on ESG Rating Events. *Sustainability*, *17*(19), 8897. https://doi.org/10.3390/su17198897

Jeong, S.-C., & Dong-Seop, C. (2025). Exploring the Influence of ESG Activities on Organizational Citizenship Behavior in IT Manufacturing Companies: Mediating Effects of Organizational Commitment and Identification. *Sustainability*, *17*(18), 8441. https://doi.org/10.3390/su17188441

Khurshid, A., Xu, S., Khan, K. B., & Cifuentes-Faura, J. (2026). Resilience, Dynamic Capabilities, and ESG: The Strategic Connection. *Business Strategy and the Environment*, *35*(6), 8365-8379. https://doi.org/10.1002/bse.70627

Liu, C., & Yan, J. (2025). ESG Performance, Donations and Internal Pay Gap—Empirical Evidence Based on Chinese a-Share Listed Companies. *Administrative Sciences*, *15*(12), 483. https://doi.org/10.3390/admsci15120483

Mansour, M., Zureigat, B. N., Alharasis, E. E., Hady, O. T. A. A., Alomair, A., & Saleh, M. W. (2026). Does Carbon Performance Mediate the Link Between ESG Performance and Corporate Tax Avoidance? *Sustainability*, *18*(14), 6978. https://doi.org/10.3390/su18146978

Monteiro, A. P., Cepêda, C., & Silva, A. F. d. (2024). Does the Workforce and Sustainability Reports Strengthen the Relationship Between Gender Diversity and Sustainability Performance Reporting? *Administrative Sciences*, *14*(6), 105. https://doi.org/10.3390/admsci14060105

Ndione, M., Bauweraerts, J., Afolabi, E., & Kaboré, R. E. (2026). Executive Succession and Performance of European Listed Companies: The Mediating Role Of <scp>ESG</Scp> Performance. *Corporate Social Responsibility and Environmental Management*, *33*(5), 7386-7400. https://doi.org/10.1002/csr.70546

Salem, M. R. M., Shahimi, S., & Alma'amun, S. (2024). Does Mediation Matter in Explaining the Relationship Between ESG and Bank Financial Performance? A Scoping Review. *Journal of Risk and Financial Management*, *17*(8), 350. https://doi.org/10.3390/jrfm17080350

Tahat, Y., Al-Shattarat, W., Hassanein, A., Allusi, R., Hossain, M. M., & Ahmed, A. H. (2026). Sustainable Disclosure and Market Valuation: The Interplay Between ESG Reporting and Board Gender Diversity. *Journal of Risk and Financial Management*, *19*(7), 499. https://doi.org/10.3390/jrfm19070499

Teixeira, F. S. R., Carvalho, L., & Rosa, A. A. S. (2024). Environmental, Social and Corporate Governance (ESG). *Revista Catarinense Da Ciência Contábil*, *23*, e3510. https://doi.org/10.16930/2237-7662202435102

Tripopsakul, S. (2025). ESG Practices, Green Innovation, and Financial Performance: Panel Evidence From ASEAN Firms. *Journal of Risk and Financial Management*, *18*(8), 467. https://doi.org/10.3390/jrfm18080467

Wu, Q., Khattak, M. S., Anwar, M., & Nevries, P. (2025). Artificial Intelligence and Environmental, Social, and Governance: A Hybrid Bibliometric Approach. *Business Strategy and the Environment*, *35*(4), 5749-5775. https://doi.org/10.1002/bse.70430

Xi, L. (2024). The Influence of Green Transformation on ESG Management and Sustainable Competitive Advantage: An Empirical Comparison of Companies in the Pearl River Delta and Yangtze River Delta. *Sustainability*, *16*(18), 7911. https://doi.org/10.3390/su16187911

Yadav, P. S., Yadav, P. B., & Kumari, P. (2026). Digital Transformation and ESG Performance in Sustainable Food Production: The Mediating Role of Green Innovation and Organizational Agility. https://doi.org/10.21203/rs.3.rs-10249785/v1

Zhao, F., Han, Z., & Wang, L. (2024). Digitization Path to Improve ESG Performance: A Study on Organizational Perspectives. *PLoS One*, *19*(12), e0313686. https://doi.org/10.1371/journal.pone.0313686

Zhou, S., Rashid, M. H. U., Zobair, S. A. M., Sobhani, F. A., & Siddik, A. B. (2023). Does ESG Impact a Firm's Sustainability Performance? The Mediating Effect of Firm Innovation Performance. https://doi.org/10.20944/preprints202303.0058.v1