A Multilevel Analysis of Large Language Model Adoption in Distance Education

Integration Patterns and Governance Implications

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***Abstract*— The rapid adoption of large language models (LLMs) has significantly influenced distance education practices, yet existing research remains unevenly distributed across system levels. This study presents a PRISMA 2020-compliant systematic review to examine integration patterns and governance implications of LLM adoption in distance education. Data were collected from Scopus and Web of Science databases, yielding 250 records, of which 170 unique studies were screened and 94 full-text articles were included. Empirical studies were assessed using the Mixed Methods Appraisal Tool (MMAT, 2018), indicating predominantly moderate methodological quality.**

The findings show that LLM adoption is primarily concentrated at the micro level, where models are used as tools or pedagogical assistants, while meso-level integration—particularly through learning management systems and institutional workflows—has increased notably after 2024. In contrast, macro-level governance considerations remain limited. Chi-square analysis revealed a significant association between publication year and system-level distribution ($\chi^2 = 14.53$, $p < .05$, Cramer's V = .28), suggesting a structural shift toward institutional embedding over time.

The study contributes to the literature by providing a multilevel analysis of LLM adoption and highlighting emerging governance implications. The results indicate that while integration is expanding across system levels, governance-related considerations are developing more gradually, pointing to an area requiring further empirical and conceptual attention.

***Index Terms*—LLM, AI, Large Language Model, Artificial Intelligence, Distance Education, Educational Technologies.**

I. INTRODUCTION

The rapid proliferation of large language models (LLMs) has significantly transformed distance education practices within a remarkably short period. Since the public diffusion of generative artificial intelligence tools such as ChatGPT, research has expanded rapidly across a wide range of educational applications, including content generation, formative feedback, tutoring support, and assessment processes [1] [2]. These developments have been widely associated with increased accessibility, efficiency, and personalization in learning environments. However, alongside these opportunities, the literature has also identified critical concerns related to academic integrity, overreliance on AI-generated outputs, and the potential erosion of deep learning processes [3] [4].

Despite the growing body of research, existing studies remain uneven in their analytical focus. A substantial portion of the literature concentrates on micro-level adoption, particularly on how learners and instructors interact with LLMs in instructional contexts. In these studies, LLMs are primarily conceptualized as cognitive tools or pedagogical assistants that support individual learning tasks. While such work provides valuable insights into instructional affordances, it offers a limited understanding of how LLMs are embedded within broader educational systems [5] [6].

More recently, a smaller but growing body of research has begun to explore meso-level integration, focusing on how LLMs are embedded within institutional infrastructures such as learning management systems (LMS), student support services, and administrative workflows. This shift reflects a transition from isolated tool usage toward system-level embedding, where LLMs influence not only learning processes but also organizational operations [7]. However, this emerging institutional integration has not been accompanied by an equivalent expansion in research addressing governance structures.

At the macro level, which includes policy frameworks, regulatory mechanisms, and institutional governance, the literature remains comparatively limited. International organizations have emphasized the importance of developing governance frameworks for the responsible use of generative AI in education. For instance, UNESCO (2026) highlights the need for human-centered design, ethical guidelines, and institutional capacity-building [8], while the OECD (2023) underscores the importance of regulatory readiness and accountability mechanisms in the deployment of generative AI technologies [9]. Nevertheless, empirical research examining how these governance considerations are operationalized within distance education systems remains scarce.

This imbalance suggests that LLM adoption in distance education may be progressing unevenly across system layers. From a sociotechnical perspective, such uneven development can lead to structural tensions within complex systems, particularly when technological capabilities advance more rapidly than organizational and regulatory frameworks [10] [11]. In the context of education, this imbalance may manifest as discrepancies between what technologies can do and what institutions are prepared to govern.

Furthermore, from a distributed cognition perspective [12]. LLMs can be understood as cognitive agents that extend and redistribute human thinking processes. While this redistribution has the potential to enhance learning efficiency, it also raises

important questions about epistemic responsibility, authorship, and control. When cognitive processes are increasingly mediated by AI systems without corresponding governance structures, the distribution of responsibility may become ambiguous.

Given these dynamics, there is a need for a systematic analysis that examines LLM adoption in distance education across multiple system levels. Rather than focusing solely on pedagogical applications, such an analysis should consider how LLM integration is distributed across micro, meso, and macro layers, and what this distribution implies for governance.

Accordingly, this study addresses the following research questions:

- How are LLMs positioned in distance education research in terms of ontological role?
- At which system layers is LLM adoption concentrated?
- How has this distribution evolved over time (2023–2026)?
- What governance implications emerge from these integration patterns?

By addressing these questions, this study contributes to the literature in three ways. First, it provides a systematic multilevel analysis of LLM adoption in distance education. Second, it identifies emerging patterns of integration across system layers. Third, it highlights governance implications associated with these patterns, offering a basis for future research and policy development.

II. METHOD

Research Design and Reporting Framework

This study employed a systematic review design to examine patterns of LLM adoption in distance education across different system levels. The review was conducted in accordance with the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, which provide a standardized framework for transparent and reproducible reporting of systematic reviews [13].

Given the heterogeneity of the literature—including empirical, conceptual, and technical/system-oriented studies—a mixed evidence synthesis approach was adopted. This approach enabled both quantitative mapping of integration patterns and qualitative interpretation of governance implications.

Data Sources and Search Strategy

The literature search was conducted in two major databases widely used in educational and interdisciplinary research:

- Scopus
- Web of Science (WoS)

The search strategy was designed to capture studies related to LLM adoption in distance education by combining three groups of keywords:

1. LLM-related terms:
   "large language model*", "generative AI", "ChatGPT", "foundation model*"
2. Educational context terms:
   "distance education", "online learning", "open education", "higher education", "learning management system", "LMS"
3. Integration-related terms:
   "integration", "implementation", "adoption", "governance", "policy", "pedagogy", "assessment"

The search was limited to:

- Publication years: 2020–2026
- Document types: Article or Review
- Language: English

This timeframe was selected to capture the rapid emergence and diffusion of LLM technologies in education, particularly following the release of ChatGPT in late 2022.

Screening and Selection Process

The initial search yielded 250 records (Scopus = 143; WoS = 107). After removing 80 duplicate records, a total of 170 unique studies remained for screening.

The screening process was conducted in two stages:

Title and Abstract Screening

Studies were included if they:

- Explicitly addressed LLMs or generative AI technologies
- Were situated within distance, online, or LMS-based education contexts
- Examined integration, adoption, pedagogical use, or governance

Studies were excluded if they:

- Focused solely on technical model development
- Lacked an educational context
- Mentioned LLMs only tangentially

Full-Text Screening

Following title and abstract screening, full-text versions of the remaining studies were assessed against the inclusion criteria. A total of 94 studies met all criteria and were included in the final analysis.

To enhance reliability, screening decisions were conducted by multiple coders, and disagreements were resolved through discussion and consensus.

Data Extraction and Coding Scheme

A structured data extraction and coding framework was developed to systematically analyze the included studies. Each study was coded across three primary dimensions:

Ontological Role of LLMs

Studies were categorized based on how LLMs were conceptually positioned:

- Tool (instrumental use)
- Assistant (pedagogical support)
- Embedded Service (institutional integration)
- Orchestrator (multi-process coordination)

System Layer

Each study was classified according to the level at which LLM integration occurred:

- Micro level: learner–LLM or instructor–LLM interaction
- Meso level: institutional systems (e.g., LMS, workflows)
- Macro level: governance, policy, and regulation

Integration Depth

Integration was further categorized based on its level of complexity:

- Surface use (isolated interaction)
- Pedagogical embedding
- System integration (e.g., LMS/API integration)
- Workflow coordination

This multidimensional coding scheme enabled a comprehensive analysis of how LLM adoption is distributed across educational systems.

Quality Appraisal

The methodological quality of empirical studies was assessed using the Mixed Methods Appraisal Tool (MMAT) 2018 [14]. The MMAT is widely used in systematic reviews involving heterogeneous study designs and evaluates criteria such as:

- Clarity of research questions
- Appropriateness of data collection
- Sampling strategy
- Measurement validity
- Analytical rigor

Based on these criteria, studies were categorized as:

- Moderate quality
- Low–moderate quality

Conceptual, review, and technical/system-oriented studies were not subjected to MMAT appraisal, as the tool is specifically designed for empirical research.

Data Analysis

Data analysis was conducted in two stages:

Descriptive Analysis

Descriptive statistics were used to identify patterns in:

- Ontological role distribution
- System layer distribution
- Study types
- Temporal trends

Cross-tabulations were performed to examine relationships between variables, including:

- Role × System Layer
- Year × System Layer
- Year × Ontological Role

Inferential Analysis

To examine structural changes over time, chi-square tests of independence were conducted:

- Year × System Layer
- Year × Ontological Role

Effect sizes were calculated using Cramer's V, providing insight into the strength of associations [15] [16]. This combination of descriptive and inferential analysis enabled both pattern identification and statistical validation of observed trends in LLM adoption.

III. FINDINGS

Study Characteristics and Methodological Distribution

The final dataset consisted of 94 studies that met all inclusion criteria. The distribution of study types indicates that the literature is predominantly empirical, with a strong emphasis on quantitative approaches. Table 1 presents data on the research methods used in the studies.

Table 1. Research methods used in the studies.

Study Type	n	%
Quantitative	45	47.9
Qualitative	20	21.3
Mixed Methods	15	16.0
Technical/System	14	14.9

This distribution suggests that research on LLM adoption in distance education has moved beyond purely conceptual discussions and increasingly focuses on applied contexts. However, the relatively limited number of mixed-method and design-based studies indicates that integrative and system-level investigations remain underdeveloped.

Quality appraisal using MMAT revealed that the majority of empirical studies were of moderate quality. This pattern reflects an emerging field in which research is methodologically stable but not yet mature in terms of longitudinal or experimental rigor.

The final dataset consisted of 94 studies that met all inclusion criteria. The methodological composition of the corpus indicates a predominantly empirical research landscape, with quantitative studies forming the largest proportion (n = 45), followed by qualitative (n = 20) and mixed-method designs (n = 15), alongside a smaller number of technical/system-oriented contributions (n = 14).

This distribution suggests that research on LLM adoption in distance education has progressed beyond purely conceptual discussions and is increasingly grounded in applied contexts. However, the relatively limited presence of mixed-method and integrative designs indicates that the field is still developing in terms of methodological depth, particularly with respect to system-level and longitudinal analyses. This pattern aligns with broader observations in emerging AI-in-education research, where rapid technological adoption often precedes methodological maturity [9].

Quality appraisal using the MMAT further supports this interpretation. The majority of empirical studies were categorized as moderate in methodological quality, indicating that while the evidence base is stable and consistent, it has not yet reached the level of rigor typically associated with mature research fields, such as large-scale experimental or longitudinal studies [14].

Quantitative studies largely focused on:

- perception surveys
- technology acceptance
- usage patterns

Qualitative studies explored:

- user experiences
- perceptions
- instructional integration

Mixed-method studies were relatively limited, indicating that deep, integrative analyses of LLM adoption remain underdeveloped.

A cross-analysis of research methods and system layers reveals a notable alignment between methodological choices and system focus. Micro-level studies are predominantly quantitative, often employing survey-based approaches to measure perceptions, acceptance, and usage patterns. Meso-level studies are more likely to adopt mixed-method or system-design approaches, reflecting the complexity of institutional integration.

Macro-level studies, although limited in number, are primarily conceptual, focusing on policy and governance issues. This pattern suggests that as research moves toward higher system levels, it becomes more interpretive and less empirically grounded.

This methodological gradient indicates that while micro-level phenomena are relatively well-measured, meso-level processes are still being explored, and macro-level dynamics remain largely conceptual.

Ontological Positioning of LLMs

The analysis of ontological roles shows that LLMs are primarily conceptualized as tools within distance education research. Table 2 shows the distribution of ontological roles.

Table 2 Ontological Role Distributions

Role	n	%
Tool	59	62.8
Assistant	19	20.2
Embedded Service	14	14.9
Orchestrator	2	2.1

The dominance of the tool category indicates that LLM adoption is still largely framed in terms of productivity and support functions. Assistant-level roles, which involve structured pedagogical interaction such as feedback and tutoring, represent a secondary layer of development.

More advanced roles, such as embedded services and orchestrators, appear less frequently but indicate a shift toward institutional and system-level integration. Notably, orchestrator-level studies remain extremely limited, suggesting that fully coordinated AI-driven educational processes are still at an early stage.

The analysis of ontological roles reveals that LLMs are predominantly conceptualized as tools within the current literature. Out of the 94 studies, 59 positioned LLMs as instrumental tools, while 19 framed them as pedagogical assistants, 14 as embedded institutional services, and only 2 as orchestrators.

This distribution indicates that LLM adoption is still largely interpreted through a functional and task-oriented lens. Tool-based usage, which includes content generation, summarization, and prompt-based interaction, represents the dominant mode of engagement. Assistant-level roles, which involve structured pedagogical mediation such as feedback generation and tutoring, represent a secondary layer of development.

More advanced conceptualizations—particularly embedded services and orchestrators—appear less frequently but signal an emerging shift toward system-level integration. Notably, the scarcity of orchestrator-level studies suggests that coordinated, multi-process AI integration remains in its early stages. This finding is consistent with recent literature indicating that while generative AI is widely adopted in instructional contexts, its role as a coordinating or decision-making entity within educational systems is still underexplored [3].

System Layer Distribution

The distribution of studies across system layers reveals a strong concentration at the micro level. Table 3 shows the distribution of studies across system layers.

Table 3. System levels of studies

System Layer	n	%
Micro	72	76.6
Meso	20	21.3
Macro	2	2.1

Micro-level studies focus primarily on learner–LLM and instructor–LLM interactions. These include applications such as content generation, feedback provision, and instructional support.

Meso-level studies, although fewer in number, represent an important shift toward institutional embedding. These studies examine how LLMs are integrated into LMS platforms, student services, and administrative workflows.

Macro-level studies are extremely limited, indicating that governance, policy, and regulatory aspects of LLM adoption remain largely unexplored in the empirical literature.

The distribution of studies across system layers demonstrates a clear concentration at the micro level (n = 72), followed by meso-level studies (n = 20), and a very limited number of macro-level investigations (n = 2).

Micro-level studies primarily focus on learner–LLM and instructor–LLM interactions, including applications such as automated feedback, content generation, and instructional support. This dominance reflects the initial phase of technological adoption, where innovations are first explored at the level of individual use.

However, the presence of meso-level studies, although smaller in number, represents a significant shift. These studies examine the integration of LLMs into institutional systems such as LMS platforms, student support infrastructures, and administrative workflows. This transition suggests that LLM adoption is moving beyond isolated use cases toward organizational embedding.

In contrast, macro-level studies—those addressing governance, policy, and regulatory frameworks—remain extremely limited. This imbalance reflects a broader pattern identified in international reports, which emphasize that governance structures for generative AI are still developing and lag behind technological implementation [8] [9].

Temporal Patterns of Adoption

The temporal distribution of studies indicates a clear evolution between 2023 and 2025.

- 2023: Predominantly tool-based, micro-level usage
- 2024: Emergence of embedded services and institutional integration
- 2025: Expansion of assistant roles and increased meso-level adoption

This progression suggests that LLM adoption is moving from individual experimentation toward institutional integration. However, this transition is uneven, as macro-level governance considerations do not show a comparable increase.

A temporal analysis of the dataset reveals a clear progression in LLM adoption between 2023 and 2025. Early studies (2023) are overwhelmingly concentrated in tool-based, micro-level applications. By 2024, there is a noticeable increase in studies examining embedded services and institutional integration. This trend becomes more pronounced in 2025, with a significant rise in assistant roles and meso-level implementations.

This progression suggests a shift from experimental and exploratory use toward more structured and institutionalized forms of integration. However, this evolution is not uniform across system layers. While micro and meso levels show clear expansion, macro-level governance considerations do not exhibit a comparable increase. This divergence indicates that technological integration is advancing more rapidly than governance development.

Role × System Layer Interaction

A cross-analysis of ontological roles and system layers reveals a structured clustering pattern:

- Tool → primarily micro-level
- Assistant → almost exclusively micro-level
- Embedded Service → predominantly meso-level
- Orchestrator → limited to meso-level

This clustering indicates that as LLM roles become more complex, they shift toward higher system layers. However, the absence of orchestrator roles at the macro level suggests that full system-wide coordination has not yet been realized.

A cross-analysis of ontological roles and system layers reveals a structured clustering pattern. Tool and assistant roles are predominantly associated with the micro level, reflecting their focus on individual learning and teaching processes. In contrast, embedded service roles are primarily associated with the meso level, indicating their integration into institutional systems.

Orchestrator roles, although rare, are exclusively observed at the meso level. This suggests that higher levels of coordination and integration are beginning to emerge within institutional contexts but have not yet extended to broader system-level or governance-level applications.

This clustering pattern highlights a layered progression in LLM adoption: as the complexity of the role increases, so does its position within the system. However, the absence of orchestrator roles at the macro level indicates that full system-wide coordination has not yet been realized.

Emerging Governance Patterns

Although governance-related discussions appear in some studies, they are generally limited in scope and tend to be conceptual rather than operational.

Most studies addressing governance focus on:

- Ethical concerns
- Academic integrity
- Data privacy

However, very few studies examine:

- Institutional governance mechanisms
- Policy implementation
- System-level accountability

This pattern suggests that governance considerations are emerging but not yet systematically integrated into the literature.

The analysis of author keywords reveals a strong concentration around pedagogical and instructional themes. Frequently occurring keywords include ChatGPT, generative AI, online learning, higher education, assessment, and academic integrity.

This thematic focus indicates that current research is primarily concerned with immediate instructional applications and challenges, particularly those related to assessment and academic honesty. While these concerns are important, the relative absence of keywords related to governance, policy, and institutional strategy suggests that system-level and regulatory dimensions remain underrepresented.

This imbalance reinforces earlier findings regarding system layer distribution, indicating that the literature is heavily oriented toward micro-level concerns while macro-level considerations are still emerging.

Keyword Co-occurrence and Thematic Orientation

An analysis of author keywords revealed that the literature is strongly centered around a limited set of recurring themes. The most frequently observed keywords included:

- ChatGPT
- Generative AI
- Artificial Intelligence in Education
- Online Learning
- Higher Education
- Assessment
- Academic Integrity

This distribution indicates that current research is primarily focused on immediate pedagogical applications and concerns, particularly assessment and academic integrity.

Notably, keywords related to:

- governance
- policy
- institutional strategy
- AI regulation

were significantly underrepresented. Figure 1 is a word cloud of frequently used keywords.

Figure 1. Keyword Distribution in LLM Research in Distance Education

The word cloud illustrates the relative prominence of keywords in the analyzed dataset. Terms such as ChatGPT, Generative AI, and Online Learning dominate the literature, indicating a strong focus on pedagogical applications. In contrast, governance-related terms such as policy, regulation, and institutional strategy appear less frequently, suggesting that system-level and governance-oriented research remains comparatively underdeveloped.

The analysis of participant groups further supports this interpretation. The majority of studies focus on university students, followed by pre-service teachers. In contrast, studies involving institutional actors, such as administrators or policymakers, are limited, and those addressing governance-level stakeholders are nearly absent.

This distribution suggests that LLM adoption is primarily examined from the perspective of end users rather than institutional or regulatory actors. As a result, the literature provides detailed insights into how LLMs are used but offers less understanding of how their use is governed or managed at higher system levels.

Research Methods Distribution

The analysis of participant groups revealed that the literature is heavily concentrated on student populations. Table 4 contains the analysis of participant groups.

Table 4. The analysis of participant groups

Participant Group	Dominant Presence
University students	High
Pre-service teachers	Moderate
In-service teachers	Limited
Administrators	Very limited
Policy-level actors	Nearly absent

This distribution indicates that:

- Research is learner-centric
- Institutional actors are underrepresented
- Governance-level stakeholders are almost absent

LLM adoption is being studied primarily from the user perspective, rather than from an institutional or governance perspective.

3.10. Alignment Between Methods and System Layers

A cross-analysis of research methods and system layers revealed a notable alignment:

- Micro-level studies → predominantly quantitative
- Meso-level studies → mixed methods / system design
- Macro-level → mostly conceptual

IV. RESULTS

The analytical results of this study provide a comprehensive understanding of how large language model (LLM) adoption in distance education is distributed across system layers and conceptual roles, and how these patterns have evolved over time. Building on the descriptive findings, inferential analyses were conducted to examine structural shifts and relationships within the dataset.

Structural Shifts Across System Layers

To examine whether LLM adoption patterns vary across time, a chi-square test of independence was conducted between publication year and system layer (micro, meso, macro). The analysis revealed a statistically significant association:

$\chi^2(6) = 14.53$, $p = .024$, Cramer's $V = .28$

The effect size indicates a moderate association, suggesting that the distribution of studies across system layers has changed meaningfully over time.

A closer inspection of the contingency table indicates that micro-level studies remain dominant across all years; however, a notable increase in meso-level studies emerges after 2024. This pattern suggests a transition from individual-level usage toward institutional embedding, where LLMs are increasingly integrated into learning management systems (LMS), student support infrastructures, and organizational workflows. Importantly, this shift reflects not only a growth in the number of studies but also a structural change in how LLMs are positioned within educational systems.

Despite this progression toward meso-level integration, macro-level studies remain extremely limited across all years. This persistent scarcity indicates that while institutions are increasingly embedding LLMs into their operational structures, research addressing governance, policy, and system-level regulation has not expanded at a comparable rate.

4.2. Ontological Role Stability and Emerging Complexity

A second chi-square analysis was conducted to examine the relationship between publication year and ontological role (tool, assistant, embedded service, orchestrator). The results indicated that the association was not statistically significant:

$\chi^2 = 10.98$, $p = .277$, Cramer's $V = .20$

Although the effect size suggests some variation, the lack of statistical significance indicates that ontological role distributions have not yet undergone a stable structural transformation over time. In practical terms, LLMs continue to be predominantly framed as tools, even as they are increasingly embedded within institutional systems. This finding suggests that system-layer integration is evolving more rapidly than the conceptual language used to describe LLM roles in the literature.

4.3. Divergence Between Integration Depth and Governance Development

Further analysis of the relationship between ontological roles and system layers revealed a structured clustering pattern. Tool and assistant roles were predominantly associated with micro-level contexts, reflecting their focus on individual learning and instructional processes. In contrast, embedded service roles were primarily associated with the meso level, indicating their integration into institutional systems. Orchestrator roles, although limited in number, appeared exclusively at the meso level, suggesting that higher levels of coordination are beginning to emerge within institutional contexts but have not yet extended to broader governance-level applications.

When these patterns were considered alongside governance-related themes, a clear discrepancy became visible. While micro- and meso-level studies showed evident growth, governance-related studies remained sparse and largely conceptual. Macro-level empirical evidence was almost absent. Although some studies addressed governance issues such as ethics, academic integrity, and data privacy, these discussions were generally limited in scope and often remained conceptual rather than operational. Empirical studies explicitly examining governance structures, policy implementation, or system-level accountability were rare.

Overall these findings suggest that LLM adoption is characterized by asymmetrical development across system layers. Integration is expanding, particularly at the institutional level, but governance structures are not developing at the same pace. This creates a visible gap between what educational systems are doing in practice and how these processes are being governed.

4.4. Evidence of Uneven Development

When the findings are examined collectively, a consistent pattern becomes apparent. First, the system-layer distribution shifts significantly over time, indicating that LLM adoption is moving beyond user-level experimentation toward institutional embedding. Second, ontological role distributions do not exhibit a comparable level of change, suggesting that conceptual understandings of LLMs remain relatively stable despite increasing integration complexity. Third, macro-level governance studies remain scarce, even as meso-level embedding expands. Finally, the literature continues to concentrate heavily on learner-facing and instructional applications.

These patterns indicate that LLM adoption in distance education is developing unevenly across system layers. More specifically, integration processes are advancing toward institutional embedding, while governance-related research and conceptual development remain comparatively limited. This uneven development does not necessarily imply the absence of governance; rather, it suggests that governance considerations are evolving more gradually than technological integration.

4.5. Synthesis of Analytical Results

The combined descriptive and inferential analyses point to a coherent structural pattern. LLM adoption is expanding beyond individual use, institutional integration is increasing, and governance-related research is present but not proportionally developed. Overall, the results demonstrate that LLM adoption in distance education is evolving into a more complex and multilayered phenomenon; however, this evolution is not occurring uniformly across system levels. This highlights an important area for further research and development, particularly in relation to governance, accountability, and system-level coordination.

V. DISCUSSION

The findings of this study provide a nuanced understanding of how large language model (LLM) adoption in distance education is evolving across system levels and conceptual roles. Rather than indicating a uniform progression, the results suggest a differentiated trajectory in which integration expands at varying speeds across micro, meso, and macro layers.

At the micro level, the dominance of tool- and assistant-based roles reflects the initial phase of technological adoption, where LLMs are primarily used to support instructional tasks and individual learning processes. This pattern aligns with previous research emphasizing the pedagogical affordances of generative AI, particularly in relation to feedback generation, content creation, and personalized learning support [17] [3] [18]. The strong presence of micro-level studies also indicates that LLM adoption is currently most visible and measurable at the level of user interaction.

However, the statistically significant shift toward meso-level integration indicates that LLMs are increasingly embedded within institutional systems. This transition suggests that LLM adoption is moving beyond individual experimentation toward organizational implementation, where technologies are integrated into learning management systems, student support infrastructures, and administrative workflows. From a sociotechnical perspective, this shift can be interpreted as a transition from peripheral tool use to infrastructural embedding, where technology becomes part of the core operational logic of the system.

Despite this progression, the results indicate that macro-level governance considerations remain limited. While some studies address issues such as ethics, academic integrity, and data privacy, these discussions are often conceptual and do not extend to the design or evaluation of governance mechanisms. This pattern is consistent with broader observations in the literature, which suggest that governance frameworks for generative AI are still emerging and have not yet been fully operationalized in educational contexts [8][9].

The divergence between increasing institutional integration and limited governance development can be interpreted as a form of sociotechnical imbalance. Sociotechnical systems theory emphasizes that technological systems and social structures must co-evolve to maintain stability and effectiveness. When technological capabilities expand more rapidly than institutional and regulatory frameworks, systems may experience misalignment, ambiguity in responsibility, and potential risks in implementation. In the context of LLM adoption, this imbalance is reflected in the growing complexity of integration at the meso level without a corresponding expansion of governance at the macro level.

This imbalance can also be examined through the lens of distributed cognition [12]. As LLMs become more integrated into educational systems, cognitive processes are increasingly distributed across human and artificial agents. While this distribution can enhance efficiency and scalability, it also raises important questions regarding epistemic responsibility and control. When tasks such as feedback generation, content production, and even elements of decision-making are partially delegated to AI systems, the boundaries of authorship, accountability, and expertise become less clearly defined.

Importantly, the findings suggest that this redistribution of cognitive processes is occurring primarily at the micro and meso levels, while governance structures that could regulate or guide this redistribution remain underdeveloped. This creates a situation in which cognitive authority is increasingly shared with AI systems, yet the institutional mechanisms for managing this shift are still evolving. As a result, questions related to transparency, accountability, and decision-making authority become more complex.

The stability of ontological role distributions further reinforces this interpretation. Although LLMs are increasingly embedded within institutional systems, they continue to be predominantly conceptualized as tools. This suggests that conceptual frameworks have not yet fully adapted to reflect the changing role of LLMs within educational systems. In other words, there is a lag between how LLMs are used in practice and how they are understood theoretically.

This conceptual lag has important implications. If LLMs are treated primarily as tools, their integration may be managed at the level of individual use rather than as part of a broader system transformation. However, as the findings indicate, LLMs are increasingly functioning as components of institutional infrastructure. This shift requires a corresponding expansion in conceptual and governance frameworks to adequately address their role within the system.

Overall, the findings suggest that LLM adoption in distance education is transitioning toward a more complex and multilayered structure, but this transition is not occurring uniformly across system levels. The increasing prominence of meso-level integration, combined with the limited development of macro-level governance, highlights an emerging area of concern for both research and

practice. Addressing this imbalance will require not only further empirical investigation but also the development of conceptual and policy-oriented frameworks that can support the responsible and sustainable integration of LLMs in educational systems.

VI. IMPLICATIONS

The findings of this study have several implications for policy development, institutional practice, and pedagogical design in distance education. By revealing how LLM adoption is unevenly distributed across system levels, the results highlight the need for more coordinated and forward-looking approaches to integration and governance.

6.1. Implications for Policy and Governance

At the policy level, the findings indicate a growing need to move beyond general ethical guidelines toward more operational governance frameworks. While existing international reports emphasize principles such as transparency, accountability, and human-centered AI [8][9], the limited presence of macro-level studies suggests that these principles are not yet systematically translated into institutional practices.

This points to the need for policy frameworks that are not only normative but also implementable. Such frameworks should address issues such as:

- accountability for AI-assisted outputs
- transparency in AI-mediated decision-making
- data governance and privacy in LLM-integrated systems
- clear delineation of responsibility between human actors and AI systems

Importantly, governance should not be treated as a reactive response to technological risks but as an integral component of system design. As LLMs become more embedded within educational infrastructures, policy development needs to anticipate rather than follow technological integration.

6.2. Implications for Institutions

At the institutional level, the shift toward meso-level integration suggests that LLM adoption is increasingly becoming an organizational issue rather than an individual one. Universities and distance education providers are beginning to incorporate LLMs into LMS platforms, student support services, and administrative workflows. This transition requires institutions to rethink their operational structures and capacities.

Institutions need to develop:

- AI integration strategies aligned with educational goals
- staff training programs that go beyond basic tool use
- institutional guidelines for responsible and consistent AI use
- monitoring and evaluation mechanisms for AI-supported processes

The findings also suggest that institutional adoption is currently outpacing governance development. Therefore, institutions may need to establish internal governance mechanisms—such as AI oversight committees or policy frameworks—before external regulations become fully established.

6.3. Implications for Educators

For educators, the dominance of micro-level adoption indicates that LLMs are already deeply embedded in teaching and learning practices. However, the evolving nature of these technologies requires a shift from viewing LLMs as optional tools toward understanding them as components of the learning environment.

Educators need to reconsider:

- how learning tasks are designed in AI-mediated environments
- how assessment practices account for AI-assisted work
- how to support students in critically engaging with AI-generated content

In particular, the increasing distribution of cognitive processes between human learners and AI systems suggests that instructional design should focus not only on knowledge acquisition but also on:

- critical evaluation of AI outputs
- epistemic awareness
- responsible use of AI tools

This shift aligns with emerging perspectives that emphasize the importance of AI literacy as a core component of digital competence in education.

6.4. Implications for Future Research

The findings also highlight several directions for future research. First, there is a clear need for more empirical studies at the macro level, particularly those examining governance mechanisms, policy implementation, and institutional accountability. Second, longitudinal and design-based studies are needed to better understand how LLM integration evolves over time within educational systems.

Third, future research should explore the relationship between system layers more explicitly, examining how micro-level practices interact with meso-level structures and macro-level governance. Finally, interdisciplinary approaches that combine educational research with perspectives from information systems, policy studies, and human–computer interaction may provide a more comprehensive understanding of LLM integration.

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