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# Strategic Stakeholder Integration in the AI Era: A Bibliometric Mapping of the Shift from Intelligent Tutoring to Generative Educational Systems

**Ramzi Talmoudi [1*] and Jamel Choukir [1]**

[1] Department of Business Administration, College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh 13318, Kingdom of Saudi Arabia.

* **Corresponding author:** rtalmoudi@imamu.edu.sa .

**ABSTRACT:** Higher education faces social and technological challenges driven by the democratization of the generative artificial intelligence (GenAI). The generative shockwave has marked a major shift in traditional learning from centralized and controlled Intelligent Tutoring Systems (ITS) to decentralized and unmanaged Shadow IT. To rigorously map higher education institution transition during the generative shockwave, the current study used a pre-defined protocol for an exploratory PRISMA-based bibliometric analysis of 459 academic documents retrieved from the Web of Science Core Collection. Its main findings highlight the magnitude of this shift, as 82% of the considered articles were published in 2024 and 2025, confirming the generative AI shockwave. Thematic mapping shows that while the key problems with artificial intelligence in education are universally recognized, higher education institutions lack adequately adapted policies to manage them. Furthermore, important psychological factors that influence technology acceptance, such as students' self-efficacy and mental strain, require special academic interest. By considering the dual theoretical lenses, using a scalar analysis approach, of the micro-level Technology Acceptance Model (TAM) and the macro-level Institutional Theory, the current study highlights the relationship between AI-based learning evolution and the inefficient management of AI risks through top-down IT systems. Instead, a collaborative approach that integrates stakeholders must be built. By working with localized institutional entrepreneurs and providing appropriate socio-technical support, universities can bridge gaps, meet the expectations of modern students, sustain their legitimacy, and adapt to the inevitable challenges posed by artificial intelligence, especially in an adaptive personalized learning ecosystem.

**Keywords:** Generative AI disruption, Intelligent tutoring systems, Strategic stakeholder integration, Technology acceptance model, Adaptive educational ecosystems.

## I. INTRODUCTION

Higher education institutions are currently navigating the most profound socio-technical challenges of the 21st century. Within the educational sector, the system is facing a major crisis that has disrupted traditional service delivery systems, changed students' expectations, and led to a critical reevaluation of institutional resilience [1-4]. Historically, rapid transitions in technology, particularly those driven by crises or shifting economic variables, have been shown to cause significant professional vulnerability among educators. Such vulnerability is driven by a lack of administrative support and an excessive focus on the technology itself [5-7]. Today, university administrators are confronting a severe catalyst for disruption.

Indeed, the current generative shockwave requires an urgent strategic response to ensure institutional resilience and prevent paralysis [8-10].

To understand the nature of this crisis, we need to examine the development of assistive technologies. Artificial intelligence (AI) has been part of educational research for decades, initially focusing on developing adaptive learning and Intelligent Tutoring Systems (ITS) for computer science departments. In its early stages, it was considered a foundational experimental environment [11-13]. These outdated systems, including the pervasive distance-learning adaptations, were highly centralized, predictive, and restricted by institutional IT infrastructure [14-16]. However, the abrupt deployment of generative AI (GenAI) tools, such as ChatGPT, has triggered a sudden rupture across the education sector worldwide [17-20]. The adaptive learning paradigm suddenly shifted from centralized tutoring to dynamic, user-driven generative models and became available in the hands of the students [21]. Although these technologies have immense potential for personalized learning development, it increasingly raises serious ethical, pedagogical, and strategic concerns regarding academic integrity [22-23].

This technological breach has led to a serious governance problem. With the advancement of AI, which has evolved from centralized to decentralized generative models [24-27], a transition from IT deployment to bottom-up stakeholder integration is necessary. As generative AI creates shadow IT for learning environments [28-30], traditional rules are losing their significance. However, institutional theory suggests that universities shall rely on institutional entrepreneurs, such as, lecturers and staff in innovation pockets who are actively involved in thoroughly building capacity for new adaptive frameworks [31-33] Furthermore, understanding, connecting with, and managing bottom-up stakeholder integration and psychological susceptibilities can be difficult, complex, and often exhausting. The empirically supported Technology Acceptance Model (TAM) suggests that AI's successful endorsement relies on strong university support to improve self-efficacy [34]. At the same time, institutions must focus on education and the need for multimodal AI literacy to reduce students' cognitive load and anxiety, which may arise from unclear integrity policies [35, 36]. Hence, the participative creation of ethical governance and the satisfaction of students' adaptive expectations" through the effective implementation of the strategic stakeholder integration will maintain institutional legitimacy during the shockwave [1].

Although the recent excessive expansion of literature confirming the generative shockwave, a critical gap remains in the academic discourse. Indeed, research in this area is still fragmented and highly sensitive to specialization. Consequently, computer science literature focuses on the potential of AI, while management and psychological studies prioritize faculty vulnerability and ethical governance topics. There is still no thorough bibliometric analysis that exposes the AI evolutionary shift using the dual theoretical lens of institutional theory and the technology acceptance model. The current study attempts to reach an understanding of how higher education institutions are managing this socio-technical transition. To address this gap, a quantitative bibliometric analysis is implemented using the PRISMA protocol to reach answers to the following research questions:

- RQ1: How has the intellectual structure and foundational knowledge of personalized and adaptive learning evolved in response to the Generative AI shockwave?
- RQ2: What is the core conceptual themes (Motor, Niche, Basic, and Emerging) currently driving the integration of AI in higher education?
- RQ3: How does the current publication trend reflect the necessary institutional management evolution to strategic stakeholder integration?

This study is capturing the 2024-2025 generative shockwave as unique thematic rupture. The phenomenon is too recent to be captured by earlier longitudinal reviews. Furthermore, the current study employs the Shadow IT framework to conceptualize the evolution from institutionally controlled to uncontrolled tools. Finally, the thematic map clusters are considered using the double lens of TAM and Institutional Theory.

## II. THEORETICAL FRAMEWORK

To systematically map the digital transformation occurring within higher education, this study constructs a dual-lens theoretical framework. This framework first establishes the technological baseline of the disruption, and then utilizes macro-level institutional theory alongside micro-level technology acceptance models to explain why strategic stakeholder integration the only viable management response is.

### 1. THE TECHNOLOGICAL BASELINE AND CATALYST: FROM INTELLIGENT TUTORING TO GENERATIVE DISRUPTION

To rigorously interpret the bibliometric overview, we must first outline the dimensions of the technology under investigation. In other words, before we can explain how academic research changes, we must explain how educational tools are transforming from inflexible software to open-ended digital tools [37]. Historically, the implementation of artificial intelligence (AI) in higher education has been characterized by high computational complexity and predictability [13, 38]. In practice, this means that the initial AI is narrow and rigid; a smart and sophisticated flowchart in which incorrect answers from students trigger specific hints. For decades, academic research was influenced by the development of intelligent tutoring systems (ITS) and adaptive learning systems. These systems are designed to provide a personalized learning experience and to personalize information about academic performance. These outdated systems can be thought of as being like a train: The program can be accelerated as needed by the student, and the student never deviates from the path specified in the original program [39]. It is important to note that these old technologies were highly centralized. They were coded by computer scientists, purchased by universities administrators, and finally deployed top-down through the IT departments. This creates a closed ecosystem for learning [40] as technological hardware belongs to the institutions not to learners. Universities have complete control over the algorithms, data, and learning resources. If a student wants to explore a different topic or asks a question not covered in the curriculum, the system does not respond.

The rapid development of generative artificial intelligence (GenAI), such as ChatGPT, is extremely effective and is disrupting existing working methods [19]. Suddenly advanced technology was pulled out of the universities and became accessible to anyone having a smartphone and internet connection [18]. Students are no longer passengers in a train, instead, they are driving the car as they are managing their own learning without institutional oversight. GenAI fundamentally changes the adaptive learning paradigm: it allows students to bypass university IT infrastructure and to transform Large Language Model (LLM) into a personalized learning system through natural language processing [41]. The major technological shift driving this bibliometric analysis is the abrupt shift from centralized, predictive-based learning systems to decentralized, user-driven learning systems that promote autonomy. Ultimately, this study captures a pivotal moment when the educational literature recognized that the control of educational technology has shifted from institutions to learners.

It is essential to clarify that the transition from Intelligent Tutoring Systems (ITS) to Generative AI does not represent a deterministic erasure of previous technologies, but rather a punctuated equilibrium in educational evolution. The rupture is therefore not technological in its origin, but societal and bibliometric in its impact. The current study operationalizes the dual-lens framework by utilizing a scalar analysis approach. The Technology Acceptance Model (TAM) is operationalized at the micro-level to categorize bibliometric clusters related to individual psychometric variables, including user self-efficacy, perceived ease of use, and technostress. Conversely, Institutional Theory is operationalized at the macro-level to analyze clusters pertaining to organizational governance, regulatory isomorphism, and the Shadow IT gap. This operationalization allows for a multidimensional interpretation of the generative shockwave, wherein individual adoption (TAM) is contrasted against institutional inertia and structural policy responses (Institutional Theory).

### 2. MACRO-LEVEL DYNAMICS: INSTITUTIONAL THEORY AND ADAPTIVE EXPECTATIONS

As the infrastructures providing personalized learning shifted from centralized IT systems to decentralized, uncontrolled infrastructure, so-called shadow IT, it triggered an organizational crisis.

Specifically, shadow IT means that students and staff have begun using powerful digital tools on their personal devices instead of using university's approved software and firewalls [42]. This unsettles administrators, as suddenly, necessary equipment for students learning were concealed and completely outside the institutional control. Let's consider this institutional revolution from the perspective of Institutional Theory. This theory helps us understand that organizations do not always seek logical efficient solutions when faced with unexpected and abrupt threats; instead, they prioritize solutions that maintain their reputation and identity and make them look competent to the outside world [43].

Traditional universities operate within a rigid, hierarchical structure geared toward accreditation and risk aversion. They are structured like a large merchant ship; Traditional higher education institutions are designed for long term stability and slow movements. They are clearly structured into committees, departmental teams, review boards, and multi-year planning processes to prevent risky sudden changes [44]. Therefore, their policies are not appropriate to manage the rapid evolution of generative models. When a new AI model updates its capabilities weekly, the university governance board that meet once per semester is not capable to keep up. The bureaucratic machinery is considerably surpassed by the speed Silicon Valley. To survive this digital disruption, Institutional Theory suggests that universities should rely on institutional entrepreneurs operating into departmental pockets of innovation [32]. Hence, instead of waiting years for a university AI policy, a professor could, for example, might test ChatGPT assignment, or an instructional designer could develop an engineering guide for a given department [45, 46]. These entrepreneurs are figuring out what works on the ground before the university commits to a strategy.

The goal of institutional entrepreneurs and the overall management of university issues is to maintain the university's legitimacy. Trust and acceptance are the currency of higher education. If a university loses its academic reputation, its programs become irrelevant. According to [1], the university's reputation is maintained if it completely succeeds in meeting the expectations of its students, even during technological disruption. Students expect an education that prepares them for the real world. If the modern job market is heavily reliant on AI and scared administrators ban it, students will perceive the university as outdated and irrelevant. Conversely, if universities demonstrate the ability to adapt their services to technological disruptions, student satisfaction will not decline. Students do not expect the university to answer all their questions on the first day, but they do expect it to proactively rethink the curriculum, advance the debate on artificial intelligence, and improve teaching methods before thinking of establishing more obstacles [47]. By safely implementing the use of basic GenAI as an adaptive learning tool, universities can meet these adaptive expectations and turn the threat into an institutional asset. By moving AI out of the shadows and formally integrating it into the classroom, universities are regaining control. They show their stakeholders that they are not afraid of the future, thus guaranteeing their popularity and relevance for the next generation. The goal is to sustain organizational legitimacy by meeting key stakeholders' expectations about learning during systemic disruptions [9, 43, 48].

### *3. MICRO-LEVEL DYNAMICS: DIFFERENTIATED TECHNOLOGY ACCEPTANCE (TAM)*

Although Institutional theory addresses various management objectives at the macro level, the practical implementation of digital transformation depends solely on user acceptance at that level. Indeed, any technological innovation is only successful if stakeholders feel confident and competent in using the new tools [49]. This is supported by the Technology Acceptance Model (TAM). Traditionally, this model assumes that people adopt a technology when they experience benefits and ease of use [50]. However, since GenAI is a decentralized technology that affects users in diverse ways, TAM cannot be applied universally; the psychological changes that lead to acceptance vary depending on the stakeholder. You cannot evaluate a professor's reaction to ChatGPT on the same psychological metrics as those of a 19-year-old student. They are playing different games with different interests [51].

- Faculty Vulnerability: The sudden deployment of AI tools without guidance poses significant professional vulnerability for teachers, including fear of pedagogical obsolescence and the burden of redesigning assessments [6]. Imagine spending two decades perfecting a curriculum only to find a free chatbot dismantling its assessments instantly. This presents a serious professional identity threat and so-called technostress, which is defined as a significant psychological strain that arises when technology evolves faster than humans can adapt to it [52]. If institutions mandate the integration of AI without support, teachers will resist [53]. A recent TAM study found that teachers' willingness to use AI depends on strong institutional support, which influences their competence in using modern technology and their self-efficacy [34]. Professors do not want to be replaced by algorithms, nor do they want to be mere facilitators of technological support. Therefore, their desire to integrate humanistic psychology into teaching is rooted in the fact that the environment offers a safe and collaborative space where they can regain their confidence in learning without the immediate pressure of perfection [54].

- Student Cognitive Load: In the past, some students used AI as an adaptive learning system but were discouraged by over-reliance on the algorithm, cognitive load, cognitive laziness [55] and pervasive anxiety of transgressing integrity policy [22, 56, 57]. For today's students, dealing with AI is comparable to walking a tightrope without a net. The market constantly suggests that students must learn AI to succeed in the future job market. However, they soon face the reality that even the accidental misuse of AI can lead to plagiarism suspicions and expulsion from university. This contradiction has significant psychological repercussions due to "AI shame," as its use, while widespread, is masked in secrecy [58]. Introducing this technology to students requires clear codes of conduct and concrete guidelines that reduce the fear of plagiarism. Instead of rigid and unprecedented restrictions, modern and consistent guidelines are needed. Integrating the next generation of AI as a personalized learning partner will only be possible if universities stop treating it as a potential suspect and instead recognize it as an equal partner in the new digital reality [59].

## *4. THE IMPERATIVE OF STRATEGIC STAKEHOLDER INTEGRATION*

As generative Intelligent Tutoring Systems are decentralized and user-driven, the management strategy must reflect this decentralization. Universities can no longer rely on top-down IT implementation. Instead, they should pursue a bottom-up integration strategy [60]. Previously, the university could purchase a software license, install it on campus computers, and mandate its use. Generative AI is revolutionizing this model. Today, technology is available on every student's smartphone and every professor's browser, and it's evolving so rapidly that no IT department can keep up. While the use of AI is inherently decentralized, the rules governing it must also be decentralized. Instead of implementing rigid top-down policies, leaders should develop flexible systems from the ground up and empower users to actively participate in shaping business solutions.

Stakeholder engagement requires the direct involvement of institutional entrepreneurs (innovative faculty) and the end-users (students) in policy and government [61]. This collaboration solves two theoretical problems: First, it involves attracting isolated, subject-matter experts from their respective fields and enabling them to assume leadership roles. Second, it invites students, especially those most at stake, into the governance committees. When users are considered co-designers, not just consumers, universities can create an inclusive design culture that reflects classroom reality.

- At the micro-level (TAM): Stakeholder collaboration ensures culturally relevant professional development that directly addresses instructors' weaknesses and establishes clear standards for AI literacy, enabling students to feel psychologically safe. Given the individual psychology of AI adoption, this approach proves helpful. When professors participate in AI training design, it will help them to overcome their unspoken and specific fears of becoming obsolete. Similarly, guidelines become clear, specific, and student-centered when students are involved in developing academic standards rather than relying on disciplinary action. This reduces the anxiety of unintentional plagiarism.
- At the macro-level (Institutional Theory): This approach eliminates complex bureaucracy and enables the university to operate with agile and disciplined governance that can keep pace with the speed of AI development and thus meet evolving user expectations. A top-down approach to AI is needed, as bureaucratic committees are unable to keep up with weekly technological updates. Universities must first understand technological trends to adapt their strategies accordingly.

This theoretical framework suggests that higher education institutions cannot rely only on technical solutions to keep up with the generative shockwave. It is, in fact, also a social issue that requires human involvement [62]. Consequently, to alleviate people's anxieties, education should smoothly integrate technology with human needs. In what follows, different components of the theoretical framework are identified in the outputs of the next bibliometric analysis. The purpose is to establish a bibliometric mapping of the shift from ITS to Generative educational systems.

## III. METHODOLOGY

To systematically map the trajectory of AI integration in higher education and uncover the strategic imperatives driving this digital transformation, this study employs a quantitative bibliometric analysis. Bibliometrics allows for the macroscopic evaluation of large volumes of literature, objectively mapping the conceptual, intellectual, and social structures of a research domain. To ensure absolute methodological rigor, transparency, and reproducibility, the data collection, extraction, and refinement processes were executed in strict adherence to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines.

### *1. RESEARCH DESIGN AND DATA EXTRACTION*

Because the technological intersection of artificial intelligence and higher education is highly multidisciplinary spanning computer science, pedagogy, and strategic management a rigorous extraction protocol was essential during the first identification phase to prevent selection bias. Data extraction was conducted on March 15, 2026, utilizing the Web of Science (WoS) Core Collection, recognized as the premier database for high-impact, peer-reviewed academic literature. The search was limited to the following indexes: Social Sciences Citation Index (SSCI), Arts & Humanities Citation Index (AHCI), and the Emerging Sources Citation Index (ESCI). To capture the full evolutionary spectrum of the research from foundational predictive architectures to modern generative ecosystems the following Boolean search string was applied to the Topic (TS) field (encompassing titles, abstracts, and keywords): TS= ("Artificial Intelligence" OR "AI") AND TS=("Higher Education" OR "Universit*" OR "College*") AND TS= ("Adaptive Learning" OR "Adaptive Educational System*" OR "Personalized Learning" OR "Intelligent Tutoring System*"). This initial systematic query yielded a primary raw corpus of 803 records.

In this study the generative shockwave is defined using two dimensions: temporal density, and paradigm shift. Temporal density means that the generative shockwave is confirmed if there is a recent literature concentration in a relatively short period of time. The second dimension means that there is a rapid transition in intellectual structure marked by the rapid obsolescence of the institutionally controlled tools in favor of uncontrolled Shadow IT. The generative shockwave is the high-intensity thematic rupture. To eliminate individual subjectivity, a blinded reviewer agreement is conducted leading to consensus-based deliberation session. The process included two independent researchers who checked any inclusion issues regarding the identified records.

The terms generative artificial intelligence, ChatGPT, and Large Language Model were intentionally discarded from the Boolean search string to avoid recency bias. Hence, the used terms preserve the longitudinal integrity of the evolutionary mapping. Using these terms in the search string creates an artificially skewed search toward post 2022 era and probably fails into capturing Intelligent Tutoring Systems and Adaptive Learning literature. The generative shockwave is objectively demonstrated using the umbrella category "Artificial Intelligent" rather than pre-supposing.

### *2. PRISMA SCREENING AND ELIGIBILITY*

During the primary Screening Phase, strict automated inclusion and exclusion criteria were applied within the WoS database to ensure the dataset reflected only finalized, high-quality academic literature within the study's defined temporal boundaries (1992–2025). The screening phase followed three-stage PRISMA 2020 workflow: i) identification of records using database search, ii) screening the titles and abstract for relevance, and, iii) Assessment of full-text eligibility. First, 40 documents (comprising early-access records and 1 publisher-invited review) were excluded, resulting in 763 records. Subsequently, 95 documents indexed prematurely under the year 2026 were removed to maintain strict chronological integrity, leaving 668 records. Finally, to guarantee scientific rigor, the dataset was limited strictly to peer-reviewed Articles and Review Articles. This resulted in the exclusion of 167 non-standard academic documents (160 proceeding papers, 4 retracted publications, 1 data paper, 1 meeting abstract, and 1 editorial material), reducing the corpus to a validated pool of 501 documents.

In the Eligibility Phase, the metadata of these 501 documents were evaluated to eliminate remaining false positives and anomalies. An automated language filter was applied to guarantee linguistic consistency, resulting in the exclusion of 21 non-English documents (11 Spanish, 6 Russian, 1 French, 1 German, 1 Portuguese, and 1 Ukrainian), refining the pool to 480 records. Finally, the authors conducted a manual review of titles, abstracts, and persistent metadata anomalies to confirm thematic relevance. During this verification, 21 lingering early-access 2026 anomalies were detected and purged. This rigorous sequential filtration culminated in a final, highly relevant dataset of 459 documents (Phase 4: Inclusion), comprising 393 articles and 66 reviews.

## *3. DATA HARMONIZATION AND NORMALIZATION*

The finalized corpus of 459 documents was exported in plaintext format and imported into the bibliometrix R-package (Version 4.5.3) via its web-based interface, Biblioshiny [63]. This specialized software was utilized exclusively to execute the final data cleaning and bibliometric mapping. The harmonized dataset revealed an extreme chronological concentration, with 378 documents (82%) published exclusively in the 2024–2025 period, empirically validating the "generative shockwave" currently disrupting higher education across 210 diverse sources and 1,591 distinct authors. To prevent the fragmentation of the bibliometric networks prior to map generation, two critical normalization procedures were executed within Biblioshiny: Reference Matching and Thesaurus and Synonym Cleaning.

### *3.1 Reference Matching*

An algorithmic matching process was applied to the cited references to clean the intellectual structure (co-citation) networks. An initial pool of 20,438 raw citations was parsed, and 393 duplicated or miswritten variants were merged, resulting in a harmonized foundation of 20,105 unique citations.

### *3.2 Thesaurus and Synonym Cleaning*

To ensure thematic coherence and eliminate redundant concept splitting in the conceptual structure (co-word) networks, a custom dictionary was deployed. This normalized diverse technological variants into unified master terms across three overarching categories:

- Core Technology: Variations such as artificial intelligence, artificial intelligence (ai), and artificial-intelligence were merged under the master term AI.
- Generative Paradigms: Proprietary models and broad descriptors, specifically chatgpt and "generative artificial intelligence, were generalized under the master term Generative AI to capture the overarching technological paradigm rather than isolated commercial tools.
- System Pluralization: Grammatical anomalies (for example, intelligent tutoring system) were normalized to the plural master term Intelligent Tutoring Systems.

Through this meticulous extraction and harmonization process, the data was perfectly optimized to map the true intellectual and thematic structure of AI's integration into higher education. Data normalization was executed within the bibliometrix environment using the Association Strength. It is implemented to account for keyword frequency variations and to prevent the over-generalization of thematic clusters.

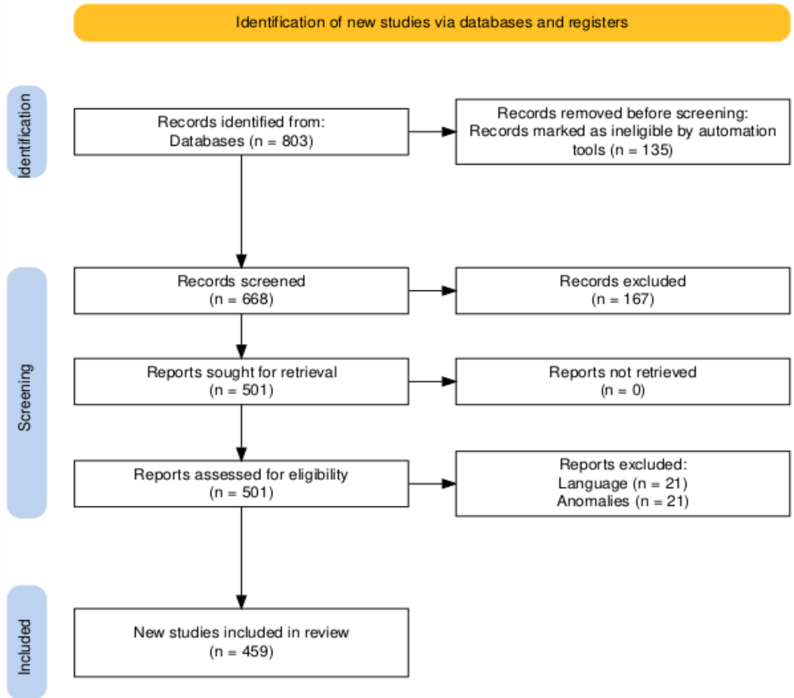


FIGURE 1. PRISMA protocol.

## IV. RESULTS: THE BIBLIOMETRIC LANDSCAPE OF THE GENERATIVE SHOCKWAVE

In what follows a bibliometric analysis is implemented based on 459 collected academic documents during the period from 1992 to 2025. The purpose is to answer the research questions and to examine the analysis results using a dual theoretical lens of macro- level institutional theory and micro-level (TAM). The dual lens focuses specifically on co-citation analysis, and Thematic mapping to understand the challenges of the technological transition. It must be acknowledged first that although the study the transition from centralized ITS to decentralized educational systems, the terms generative AI or ChatGPT were included into the search string as the first opinion was that these terms do not necessarily cover the entire period of the study. However, these terms dominated keywords usage in that period, leading to 82% of the published academic articles during only the two years 2024 and 2025. This information, together with the annual scientific production in figure 1 confirm the disruption. Hence, the generative shockwave did not only expand the literature but also completely transformed ITS, and adaptive learning.

**Table1.** Keywords occurrences.

| Words | Occurrences |
|---|---|
| AI | 274 |
| Higher education | 114 |
| Generative artificial intelligence | 109 |
| Education | 72 |
| Personalized learning | 66 |
| Intelligent tutoring system | 45 |
| Adaptive learning | 38 |

*1. THE GENERATIVE SHOCKWAVE AND THE EVOLUTION OF ADAPTIVE LEARNING*

This subsection answers the first research question by illustrating the institutional disruption at the macro level through the evolution of the research field.

- The Historical Baseline (1992–2022): It should first be noted that the literature addressing adaptive learning, and ITS, experienced slow growth and gradual expansion from its initial publication in 1992 until the emergence of the ChatGPT in 2022. This period marks part of the artificial intelligence era. These articles incorporate computer science paradigms that focus on robust algorithmic approaches rather than institutional management [13].
- The 2024–2025 Institutional Rupture: A look at the evolution of the annual scientific production is remarkable: 90 of the 459 publications appeared in 2024, while unprecedented 288 articles were published in 2025. This means that 82.3% of the scientific academic production of 33 years was published only in the recent two years. Hence the theory of the generative shockwave" is confirmed [19, 48]. Indeed, the abrupt emergence of tools based on AI and LLMs decentralized suddenly the educational system and forced universities to struggle to preserve their institutional legitimacy.

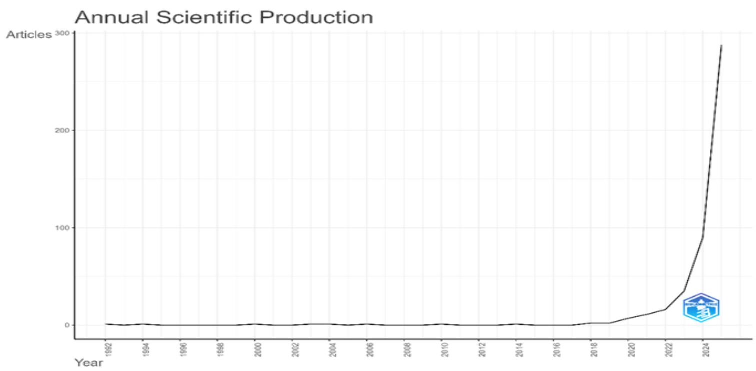


FIGURE 2. Annual scientific production and growth trajectory.

*2. INTELLECTUAL STRUCTURE: THE PIVOT TOWARD SOCIO-TECHNICAL GOVERNANCE*

Using co-citation network, the current study shows that foundational knowledge of "adaptive learning" is abandoning algorithmic research in favor of policy and management research.

- The Predictive Anchors (The Core Cluster): By analyzing the intellectual network a core cluster is noticed with a foundational node [13] which represents the pinnacle of the ITS era. Literature was starting to question missing topics as main attractive topics were ITS, profiling and prediction, and assessment and evaluation with lack of ethical and pedagogical reflection. It was also noticed that most publications were being conducted by computer science and STEM departments with absence of significant input from researchers in education, pedagogy, psychology, and the social sciences.
- The Rapid Pivot to Decentralized Governance: Peripheral clusters around central nodes represent a structural rupture. Intellectual lineage shifted toward regulatory and ethical gaps established by GenAI. Modern scholars are citing pre-GenAI literature to explain the unstructured and decentralized reality of modern LLMs. The high co-citation of articles related to academic integrity, data privacy, and ethical guidelines [22, 23, 64] suggests that academic focus has shifted toward managing the unmanaged "Shadow IT" instead of how to build an adaptive system.

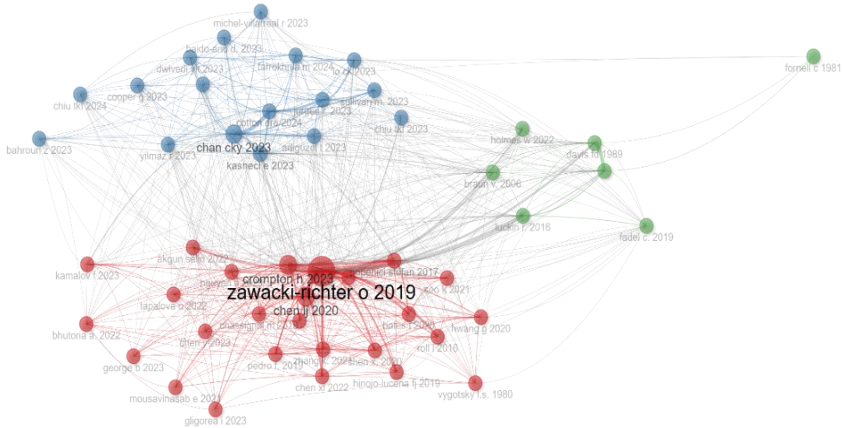


FIGURE 3. Co-citation network of foundational knowledge.

### *3. CONCEPTUAL STRUCTURE: MAPPING THE UNMANAGED SHADOW-IT*

Conceptual structural analysis using thematic four-quadrant analysis yielded a precise conceptual mapping of the search terms.

- Motor Themes (High Centrality, High Density): The upper right quadrant of the Thematic Mapping, representing motor themes with high centrality and density, exhibits a robust cluster characterized by the terms: education, challenges, and knowledge. This means that main drivers in this research field are not algorithmic but completely connected with pedagogical strategies. Furthermore, the academic community is recognizing the educational challenges caused by the generative shockwave. These challenges are currently well documented and theoretically based. However, this quadrant does include neither the solutions to these challenges nor governance frameworks which remain dispersed in other areas of the thematic mapping.
- Basic and Transversal Themes (High Centrality, Low Density): Uncontrolled shadow IT lower right quadrant encompasses basic themes, highlighting serious structural deficiencies in the current institutional response. It is striking that the main categories of bibliometric search queries: AI (274 hits), higher education (114), generative artificial intelligence (109), intelligent learning systems (45), and machine learning (26), are all related to this structurally underdeveloped area. Themes in this quadrant have high centrality as they are universally recognized, however, they have low density which means that they lack theoretical cohesion. This placement is empirically revealing what was presented in the theoretical framework. Used technologies at universities worldwide are decentralizing educational systems and they are creating an unmanaged Shadow IT. However, the necessary governance framework and codes of ethics for managing them are still underdeveloped [65].
- Niche Themes (Low Centrality, High Density): In contrast, the upper left quadrant contains niche topics specific research areas that, due to their high internal density, play a less prominent role in the broader discourse on institutional governance. This quadrant reveals the nodes associated with micro-concepts such as skills, cognitive load, self-efficacy, and impact. The concept of these terms is directly linked to the micro-dynamics of the Technology Acceptance Model (TAM). Academic research is focusing on psychological vulnerabilities endured by faculty and students during the transition. Indeed, the literature is keeping up faculty high psychological burden [6] as well as students high cognitive load caused by the interaction with uncontrollable AI [35, 66]. However, this research is still siloed in specific psychological disciplines. They are considered as isolated trends rather than integrated into macro level institutional policy.

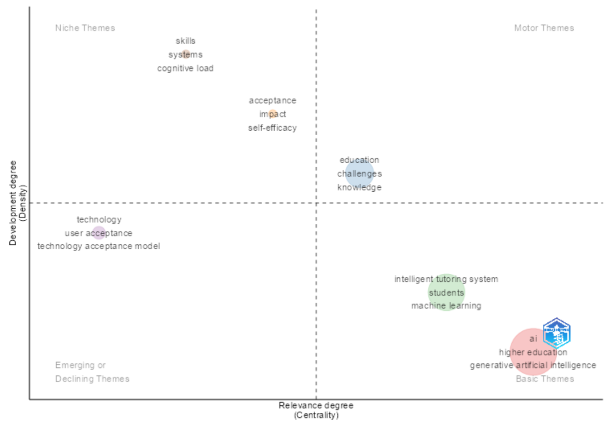


FIGURE 4. Thematic map of the conceptual structure.

*4. EMERGING TRAJECTORIES: THE EMPIRICAL NEED FOR STRATEGIC STAKEHOLDER INTEGRATION*

The lower left quadrant of the thematic map: a centralized, low-density area reflecting recent advances in the literature, contains the keywords: technology acceptance model, user acceptance, and overarching educational technology. This bibliometric positioning provides compelling evidence of fundamental shifts in academic discourse. The data suggest that universities can no longer rely on traditional, top-down IT implementation strategies to address educational challenges (situated in the Motor themes) and to manage shadow IT (Basic themes). Bibliometric trends thus indicate an urgent need to evolve generic corporate governance strategies that incorporate new acceptance models at the micro level. Understanding how end users process, adopt, and utilize these technologies is increasingly becoming a key prerequisite for effective governance at the macro level.

The conceptual structure of the current literature empirically mandates on definitive pivot for strategic stakeholder integration. As previously mentioned, psychological and cognitive variables are categorized into niche quadrant. To successfully integrated these fragmented variables into institutional policies, university leaders need to actively support institutional entrepreneurs who are experienced in building and developing digital competencies [32].

This structural support should also be complemented by targeted measures. Organizational support for self-efficacy in education and the use of various AI technologies is often highlighted [34]. By supporting institutional entrepreneurs and promoting user acceptance, universities have successfully established necessary robust socio-economic management to ensure successful technological transition. Strategic stakeholder integration is an effective step toward addressing the generative shockwave institutional policy gap. This is a critical approach for universities to succeed the technological transition, meet modern students expectation, and ensure legitimacy [1].

**Table 2.** Operationalization table.

| Bibliometric themes | Dominant Clusters | Theoretical Construct | Operational Level |
|---|---|---|---|
| Niche | skills, cognitive load, self-efficacy | TAM | Micro (individual) |
| Emerging | technology acceptance model, user acceptance, educational technology | TAM | Micro (individual |
| Basic | AI, higher education, generative artificial intelligence, intelligent learning systems, and machine learning | Institutional Theory | Macro (Structural) |
| Motor | education, challenges, and knowledge | Institutional Theory | Macro (Structural) |

## V. DISCUSSION: GOVERNING THE DECENTRALIZED ADAPTIVE ECOSYSTEM

The bibliometric mapping of 459 foundational and contemporary documents explicitly answers the research questions posed in this study. The data confirms that Higher Education is currently operating within a prolonged state of macro-level disruption, driven by the unprecedented democratization of AI. However, beyond simply proving that an institutional shockwave occurred in the 2024-2025 window, the conceptual and intellectual structures of the literature reveal a profound socio-technical paradigm shift. The following discussion synthesizes these empirical results to explain how the legacy concepts of adaptive education have dissolved, and why strategic stakeholder integration has emerged as the mandatory institutional response.

### 1. THE DISSOLUTION OF TRADITIONAL INTELLIGENT TUTORING SYSTEMS

To understand the current institutional crisis, we must trace the development of the innovative technologies identified in our search string. Historically, the literature on (ITS) and adaptive learning has been centralized. These systems are theoretically anchored and validated at the central node of the co-citation [13]. Moreover, they are based on closed-loop predictive algorithms and strictly controlled and implemented by university IT departments. Consequently, the resulting management strategy was top-down. The organization controls the algorithm and stakeholders just interact with it.

The results of the thematic map and as shown in Table 2, particularly the placement of AI and generative AI in the underdeveloped "Basic" quadrant, confirm that this centralized paradigm has failed. Generative AI has democratized ITS. Today, every student with a smartphone has access to a sophisticated, unsupervised learning systems that act as a personal tutor [18, 19]. Current adaptive learning infrastructure has shifted from secure university servers to private, unsupervised learning environments, the so-called shadow IT [65]. This explains why bibliometric data on citations are undergoing rapid change: the focus is shifting from algorithmic design to academic integrity and data security [22, 67]. The university no longer controls the learning algorithm, but rather the individuals who use it.

### 2. STRATEGIC STAKEHOLDER INTEGRATION AS THE NEW INSTITUTIONAL LOGIC

This technological decentralization mandates a complete inversion of traditional management strategies. The bibliometric emergence of technology acceptance as a key future trajectory (situated in the Emerging Themes quadrant) proves that top-down bureaucratic mandates are no longer viable. Governing a decentralized AI ecosystem requires a decentralized, bottom-up management approach. This is where Strategic Stakeholder Integration becomes the paramount institutional logic.

Viewed through the lens of Institutional Theory, rigid academic bureaucracies are structurally incapable of keeping pace with generative AI updates. To survive, universities must integrate frontline stakeholders into the core governance process. By elevating institutional entrepreneurs, the agile faculty, instructional designers, and students actively experimenting within departmental pockets of innovation universities can co-create agile, culturally responsive policies [32, 33]. Strategic integration ensures that policy formulation is not an abstract administrative exercise, but a highly localized, socio-technical collaboration that actively bridges the regulatory gap.

### 3. DIFFERENTIATED TECHNOLOGY ACCEPTANCE AND THE RESCUE OF PERSONALIZED LEARNING

The main goal of strategic stakeholder integration is not only to establish a code of conduct but also to specifically undo the benefits of self-directed learning. However, the thematic map and in Table 2 shows that the key elements required for this: cognitive load, self-efficacy, and acceptance, are siloed into niche disciplines. However, universities shall consider these variables in their policies. Furthermore, TAM must be implemented within specific frameworks as it operates differently across the academic spectrum. Consequently, strategic stakeholder integration shall address different vulnerabilities:

- Mitigating Faculty Vulnerability: Because of the generative shockwave, instructors fear pedagogical obsolescence [6]. Addressing this vulnerability successfully involves the continuous professional development of instructors, which is managed by the university beyond the classroom. [34] argue that strong university support for the adoption of AI in higher education is crucial. By actively building instructors' self-efficacy, higher education institutions can transform AI from an institutional threat into a powerful educational tool.

- Safeguarding Student Cognitive Load: The unmanaged GenAI creates a cognitive overload for students and a fear of transgressing academic integrity [22, 56]. By involving students in the management process, higher education institutions can create a clear and consistent system for AI literacy [36]. Clear disciplinary boundaries eliminate doubts about the use of AI and allow students to build relevant skills safely, benefiting from personalized learning platforms. When universities successfully integrate these stakeholders, they will successfully manage the crisis and succeed to keep up the technological transition. Therefore, universities must formally adopt the GenAI and manage it as an authorized learning system.

## VI. CONCLUSION

### *1. THEORETICAL AND EMPIRICAL SYNTHESIS*

This study employed a rigorous bibliometric approach based on the PRISMA framework to map the evolutionary integration of AI into higher education. Analyzing 459 relevant articles, the study empirically demonstrates a significant socio-technical shift: the adaptive learning paradigm has abruptly shifted from a centralized and predictable system of vocational training to a decentralized and generative AI wave. The data confirm a striking temporal concentration: 82% of the modern knowledge base will be generated by 2024-2025. More importantly, the thematic analysis and the analysis of intellectual networks reveal that while key AI technologies are ubiquitous in higher education, the structural guidelines for their management are still insufficiently developed. Further development of bibliometrics requires a paradigm shift from pure computer science to the micro-level technology acceptance and socio-technical management at the macro level.

By operationalizing both TAM and Institutional Theory, this study unquestionably demonstrates that the generative shockwave is not merely a technological trend, but a structural conflict between individual cognitive acceptance and organizational regulatory capacity. This dual-lens approach provides a reliable roadmap for future stakeholder integration that addresses both the psychological needs of the user and the governance requirements of the institution.

### *2. MANAGERIAL IMPLICATIONS*

The interrelationships mapped in this study provide a definitive roadmap for university administrators. Modern AI is a decentralized, user-driven technology that cannot be controlled by centralized IT applications or rigid bureaucratic hurdles. Organizations must immediately support strategic stakeholders. Leaders must empower competent institutional entrepreneurs to circumvent complex bureaucratic processes and develop ethical, student-centric AI policies. Furthermore, organizations must implement differentiated acceptance models to address the various vulnerabilities of users: self-efficacy to reduce obsolescence anxiety in the teaching profession and the creation of a readily available AI literacy frameworks to avoid students' cognitive load. Only through this strategic, human-centric integration can universities transform the disruptive threat of Generative AI into a sustainable, Personalized Learning ecosystem that satisfies the adaptative expectations of modern learners.

### *3. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS*

While this study provides a robust mapping of the disruptions caused by AI, it also has limitations. The data analysis is limited to a single database (Web of Science (WoS) Core Collection). While this ensures high scientific accuracy, it excludes other databases such as Scopus or Google scholar. In addition, the bibliometric landscape for new technologies is evolving rapidly due to changes in (LLM) and institutional responses. Furthermore, the implement PRISMA 2020 protocol emphasizes on structural patterns and may marginalize individual study quality assessment.

This limitation opens an important area of research. Theoretically, the area has great potential for development if the macroscopic bibliometric mapping is complemented by more in-depth qualitative empirical validation. Researchers should carry on longitudinal studies on institutional entrepreneurs identified in the study. Moreover, the way academic departments execute strategic stakeholder integration should be explored. Given the importance of technology acceptance and self-efficacy, researchers, should conduct comprehensive studies using PLS-SEM. These quantitative models are crucial for determining how professional support and AI literacy activities can be strategically used to reduce cognitive load and improve the long-term academic performance of teachers and students. Finally, future studies should expand the search string to include specific architectural terms and validate the identified clusters longevity.

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## Author Contributions

Conceptualization, Ramzi Talmoudi; methodology, Ramzi Talmoudi; software, Ramzi Talmoudi; validation, Ramzi Talmoudi.; formal analysis, Jamel Choukir; writing—original draft preparation, Ramzi Talmoudi; writing—review and editing, Ramzi Talmoudi.; visualization, Jamel Choukir; supervision, Jamel Choukir.; All authors have read and agreed to the published version of the manuscript.

## Conflicts of Interest

The authors declare no conflicts of interest.

## Data Availability Statement

Data are available from the authors upon request.

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