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Navigating the Tech Turn: A Bibliometric Analysis of Decision-Making Trends in 21st Century Education

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Abstract. This bibliometric analysis illustrates how, between 2020 and 2024, technology has impacted educational decisions. Using the Web of Science Core Collection, 371 English-language publications in the field of education and educational research were analysed. In VOSviewer, assessments of performance, co-citation, and keyword co-occurrence were carried out. Six thematic clusters emerged: (1) qualitative research and pedagogical frameworks; (2) technology acceptance and behavioral theories; (3) e-learning, learning analytics, and pandemic adaptation; (4) artificial intelligence, ethics, and mixed-method evaluation; (5) active learning, diffusion of innovations, and learning efficacy; and (6) social cognitive and motivational perspectives on STEM pathways. The corpus is worldwide in scope and has strong ties to analytics-informed leadership, policy responsiveness, and teacher practice. The findings demonstrate a growing interest in evidence-based education, data-driven leadership, and AI governance – all of which are consistent with Sustainable Development Goal 4 (Quality Education). This study's thorough intellectual map connects adoption, pedagogy, analytics, and

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governance while offering helpful recommendations for institutional and policy decision-making on curriculum, funding, and capacity building. The bibliometric analysis updates to track this rapidly evolving topic and spot a clear research gap: the requirement for multi-theoretical, equity-sensitive models that integrate analytics and artificial intelligence with institutional decision-making processes.

Keywords: educational technology; inclusive education; technology adoption; AI in education; digital transformation

1. Introduction

The rapid rate of technological development in recent decades has had a significant impact on educational institutions all around the world. Education systems are constantly adjusting to the changing digital landscape, from data-driven learning environments to AI-assisted administration (Jin et al., 2025). At several educational levels, the incorporation of cutting-edge technologies has transformed decision-making procedures in addition to teaching and learning methodologies (Anwar et al., 2025).

According to Du (2022), these tools provide previously unheard-of capabilities for forecasting student performance, customizing instruction, distributing resources, and forming educational policy. There is an urgent need to comprehend how this growth affects strategic and operational decision-making in education, nevertheless, as educators and administrators frequently struggle to keep up with technological advancements due to the quick influx of digital tools (Levantis & Sgora, 2024). Even though technology is widely used in education, little is known about how decision-makers handle the opportunities and challenges brought on by the quick changes in technology (Trianung et al., 2024). The pedagogical implications of digital tools or technological integration in the classroom are the main topics of much of the present writing, which frequently ignores the larger, systemic consequences for leadership and policymaking (Yan, 2023).

High-stakes decisions on anything from investing in digital infrastructure to ethical issues with data usage and algorithmic bias are routinely expected of institutional executives (Levantis & Sgora, 2024). Technology can advance more quickly than institutions are ready, which might result in reactive rather than strategic decisions (Li et al., 2024). Furthermore, many education stakeholders are left navigating uncertainty due to the absence of formal frameworks and empirical data to inform decision-making in the face of rapid technological change (Chang, 2020).

The current body of educational research lacks a thorough, longitudinal understanding of how the changing technological landscape affects decision-making structures, behaviors, and outcomes, which is reflected in this misalignment between technological advancement and decision-making readiness (Asfaw et al., 2023). This bibliometric analysis aims to map and assess the intellectual and thematic structure of research on educational decision-making and technology. Through a thorough analysis of current literature, this study aims to determine the following:

- To determine the intellectual structure of the field through co-citation analysis.
- To identify emerging trends in relevant educational contexts through co-word analysis.

2. Method

This bibliometric analysis aims to thoroughly examine the body of scholarly literature on how educational decision-making is impacted by the rapid rate of technological development. This study uses three bibliometric approaches: co-occurrence analysis, co-citation analysis, and performance analysis. Performance analysis helps determine the most influential contributors to the subject by assessing the output and impact of publications, authors, institutions, and nations (Murnaka et al., 2021).

Co-citation analysis reveals core notions and important academic works by mapping the discipline's intellectual structure by detecting groups of texts that are frequently mentioned together (Vílchez-Román et al., 2020). Co-occurrence analysis, on the other hand, looks at the frequency and connections between terms in different articles, which makes it possible to find recurring themes and new lines of inquiry (Zou et al., 2025).

Using the Web of Science (WoS) database, a well-defined search technique was utilized to guarantee a targeted and high-quality dataset (Zou et al., 2025). The following advanced search string (Table 1) was used: ((TS = ("technolog")) AND TS = ("decision")) AND TS = ("educat")). Technology, decision-making, and education-related terms in the title, abstract, and keywords (TS) were the focus of this Boolean search. The first search produced 10,901 records. A period filter was used to limit findings to articles from 2020 to 2024 in order to assure relevance and fit with recent scholarly conversation, bringing the total down to 4,802. Following a document-type filter that only included articles, the set was further reduced to 3,774 entries.

Table 1: Inclusion Criteria for Bibliometric Analysis

WoS Database	ALL
Time period	2020 to 2024
Search field	TS
Search keywords	"technolog*" AND “decision” AND “educat*”
Document Types	Article
Research Areas	Education Educational Research
Open Access	All Open Access
Language	English

The PRISMA flowchart in Figure 1 illustrates a methodical and transparent screening procedure. 1,028 of the 4,802 documents that were reviewed were disqualified because they did not fit the definition of research publications. After evaluating the eligibility of the remaining 3,774 full-text publications, 3,403 records were excluded because they were not in English, did not fall into the Education or Educational Research subject areas, or were not Open Access. Ultimately, 371 papers in all satisfied all inclusion requirements and were kept for bibliometric examination. Performance, co-citation, and co-occurrence studies were based on these papers.

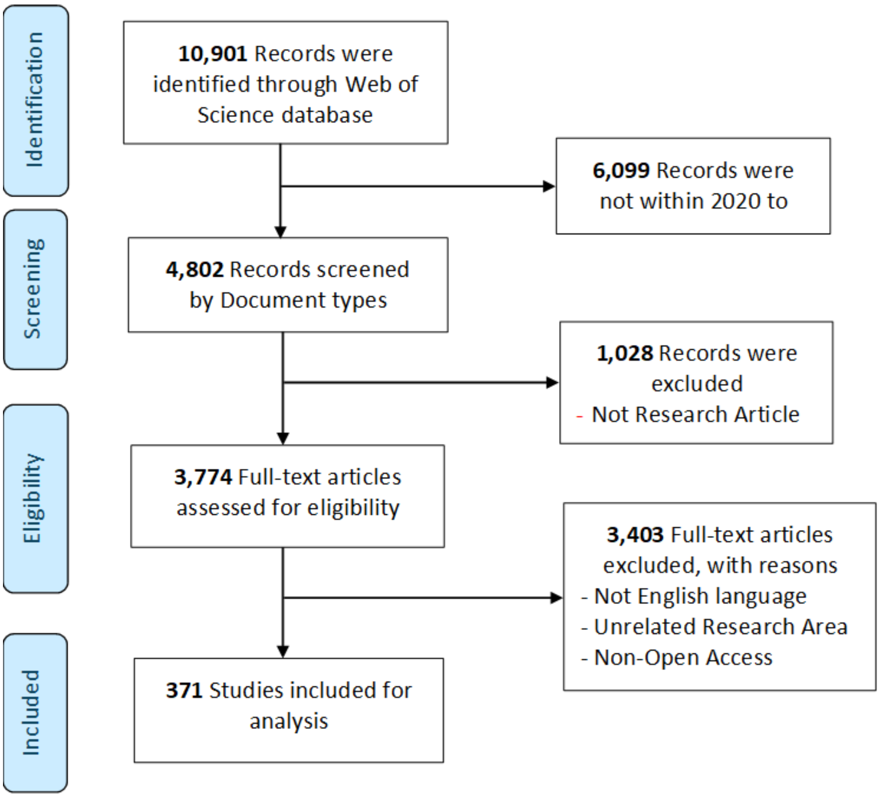

Figure 1: PRISMA Flowchart

3. Results

3.1 Performance Analysis

The performance analysis reveals a vibrant and globally distributed research environment. Strong publication activity in both established and emerging educational contexts, the importance of acceptance models, and the expanding role of ethical issues in AI adoption are all highlighted. It also identifies important organizations and publications that act as centers of thought leadership in this new area, providing insightful guidance for future research cooperation and communication.

3.1.1 Document-Level Performance

According to the performance analysis by documents, Rafique et al.'s (2020) article is the most influential work in this field, with 226 citations. This suggests that TAM-based frameworks for educational technology are of great scholarly interest. Abbad (2021), which emphasizes the UTAUT model in understanding e-learning system adoption in developing contexts with 220 citations. Additional noteworthy contributions that demonstrate a thematic shift towards ethics, learning outcomes, and technological implementation include Nguyen et al. (2023) on AI ethics in education (196 citations) and Hillmayr et al. (2020) on digital tools in STEM education (177 citations). Despite only being published recently, Zhai et al. (2024) has 59 citations, indicating that academics are becoming increasingly concerned about the cognitive effects of excessive AI use in the classroom.

3.1.2 Source-Level Performance

Education and Information Technologies have established itself as a primary publication platform for technology-driven educational research, ranking first in terms of source performance with 27 articles and 767 citations. Significant output is also shown by BMC Medical Education (21 papers, 218 citations) and Education Sciences (26 articles, 234 citations), indicating the topic's cross-disciplinary appeal. Notable contributions are made by Frontiers in Education and the International Journal of STEM Education, especially in the areas of pedagogy and technology in educational reform. Despite having less citations, the Australasian Journal of Educational Technology and Electronic Journal of e-Learning provide substantial exposure for specialized subjects and innovative approaches in educational technology.

3.1.3 Author-Level Performance

The performance of the author highlights a number of notable contributors. Stains, M. is notable for having the highest link strength (24), indicating substantial co-authorship or citation network linkages, with 3 publications and 40 citations. In the meantime, a group of authors, Arrona-Palacios, Escamilla, Hosseini, and Okoye—produced three documents apiece, each of which was mentioned 110 times, indicating highly influential teamwork. Notable for their research on virtual reality in arts education, Abad-Segura and Gonzalez-Zamar rank highly with 87 citations in 3 articles, which is consistent with more general themes in immersive learning technology. The authors' differing citation counts, and overall connection strengths reveal different levels of cooperation and influence throughout the academic community.

3.1.4 Organization-Level Performance

With nine publications and 172 citations, Tecnológico de Monterrey stands out as the most prolific institution from an organizational standpoint. This indicates that the university places a high priority on educational technology research in Latin America. With several publications and citation counts between 40 and 44, the University of South Florida, the University of Michigan, and the University of Virginia come next, demonstrating the active participation of American universities. Curiously, despite the fact that some universities, such as the University of Edinburgh and the National Autonomous University of Mexico, are mentioned more than once, their comparatively low citation counts point to either new research outputs or a localized concentration.

3.1.5 Country-Level Performance

The United States is at the forefront of educational technology research, as evidenced by its substantial lead of 57 documents and 611 citations at the country-level. With 25 publications and 396 citations, England comes in second, followed by China (306 citations) and Germany (271 citations), demonstrating the significant contributions made by both Europe and Asia to the area. Perhaps as a result of focused research on the uptake of e-learning during the pandemic, Saudi Arabia stands out for having a high citation-per-article average with 510 citations spread across 16 papers. Though with differing degrees of scholarly influence, the inclusion of South Africa, Mexico, and Russia in the top 10 indicates a growing worldwide interest.

3.2 Co-Citation Analysis

The bibliometric analysis's top 10 co-cited papers in Table 2 are seminal works that have greatly impacted studies on educational methodology, decision-making, and technology adoption. Braun and Clarke (2021) top the list because of their groundbreaking work on reflexive theme analysis, which has been a mainstay of qualitative research, especially when examining how educators view and react to technological change. The Technology Acceptance Model (TAM) and UTAUT, which are widely used to comprehend user behavior and decision-making in educational technology contexts, were first developed and expanded by Venkatesh et al. (2003) and Davis (1989).

Table 2: Co-citations (Top 10 Articles)

Rank	Authors	Title	Citations	Total Link Strength
1	Braun & Clarke (2021)	One size fits all? What counts as quality practice in (reflexive) thematic analysis?	28	46
2	Venkatesh et al. (2003)	User acceptance of information technology: Toward a unified view.	25	100
3	David (1989)	Perceived usefulness, perceived ease of use, and user acceptance of information technology.	23	93
4	Hair et al. (2010)	Multivariate data analysis.	14	65
5	Ajzen (1991)	The theory of planned behavior.	14	61
6	Zawacki-Richter et al. (2019)	Systematic review of research on artificial intelligence applications in higher education–where are the educators?	13	37
7	Fornell & Larcker (1981)	Evaluating structural equation models with unobservable variables and measurement error.	13	72
8	Cohen (2013)	Statistical power analysis for the behavioral sciences.	12	57
9	Bandura (1986)	Social foundations of thought and action.	10	26
10	Venkatesh & Davis (2000)	A theoretical extension of the technology acceptance model: Four longitudinal field studies.	9	47

3.2.1 Co-Citation Analysis by Clusters

The focus of Cluster 1 (in Figure 2) is on qualitative research techniques and how they can be used to comprehend how technology is integrated into classrooms.

Along with landmark works by Miles et al. (2014) and Creswell and Creswell (2018) (in Table 3) that offer thorough frameworks for interpreting qualitative data, Braun and Clarke's (2021) work on reflexive thematic analysis is essential to this cluster. While Mishra and Koehler's (2006) TPACK framework provides a conceptual model connecting technological knowledge with educational efficacy, Hsieh and Shannon's (2005) content analysis provides a valuable lens.

The transition to emergency remote teaching during crises, particularly COVID-19, is highlighted in other publications like Bozkurt and Sharma (2020) and Hodges et al. (2020), which frame technology as a pedagogically placed activity rather than a neutral tool. With a heavy emphasis on teacher autonomy and instructional quality, this cluster generally highlights interpretive approaches to comprehending how technology affects instructional design and educational reform.

The Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003) is the most often co-cited work in Cluster 2. It is supported by the Technology Acceptance Model (TAM) by Davis (1989) and the longitudinal TAM extension by Venkatesh and Davis (2000). These theories describe how users' propensity to accept digital technology is influenced by perceived utility and usability. This is further developed by Ajzen's (1991) Theory of Planned Behavior (TPB), which takes behavioral control and social norms into account.

Fundamental statistical techniques, especially in structural equation modeling, are contributed by Fornell and Larcker (1981) and Hair et al. (2019) and are frequently used to test these behavioral frameworks. The cluster offers analytical tools for evaluating technology implementation at scale and emphasizes the importance of quantitative, theory-driven investigation in analyzing tech adoption.

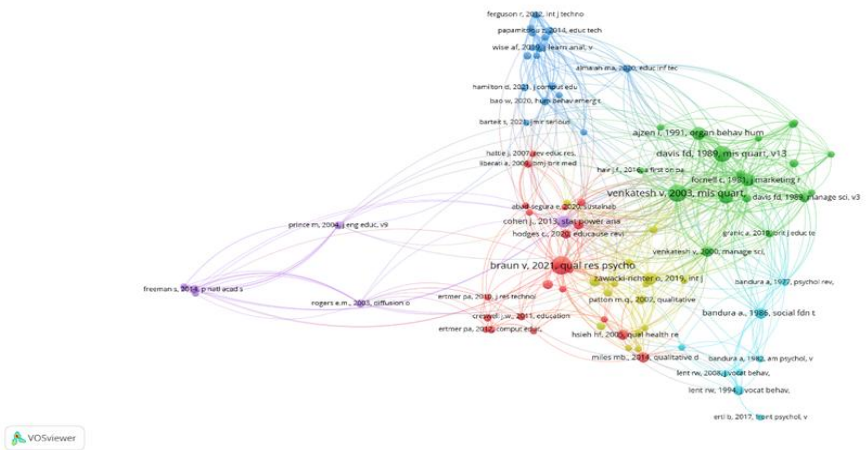

Figure 2: Co-citations Analysis (VOSviewer Visualization)

Cluster 3 focuses on the rise of learning analytics and the use of technology in education during the COVID-19 epidemic. Critical obstacles to the adoption of e-learning during global crises, especially in higher education, are examined in articles by Almaiah et al. (2020) and Bao (2020). A basis for comprehending how data is utilized to inform instructional decisions is provided by Papamitsiou and Economides (2014), who provide a systematic overview of empirical research on learning analytics and educational data mining. A situated model of analytics-based instructional decision-making is presented by Wise and Jung (2019), emphasizing the necessity of context-sensitive interpretations of learning data.

Additional contributions by Barteit et al. (2021) and Crawford et al. (2020) demonstrate a wider trend toward immersive technologies (such AR/VR), emergency digital pedagogy, and cross-national responses to disruption. This cluster highlights the pressing need for learner-centered interventions, adaptive digital infrastructures, and real-time instructional decisions under pressure by illuminating the nexus of institutional agility and technological capabilities.

Cluster 4 combines strong research design approaches with AI applications in higher education. A thorough analysis of AI's incorporation into educational systems is provided by Zawacki-Richter et al. (2019), who also raise concerns regarding the ethical application of intelligent systems and educator agency. The basic texts in mixed-methods and qualitative assessment, which are frequently used to evaluate intricate, multi-variable technology interventions, are Creswell and Clark (2017) and Patton (2002).

Recent studies on generative AI (such as ChatGPT) and its effects on academic integrity and instructional quality include Dwivedi et al. (2023) and Sullivan et al. (2023). In his theoretical contributions to instructional content knowledge, Shulman (2019) emphasizes that profound discipline expertise must be complemented by AI, not replaced. This cluster reflects expanding interdisciplinary involvement with the governance, assessment, and implementation of emerging technologies in education.

Cluster 5 focuses on evidence-based educational improvement, the spread of innovation, and active learning strategies. Methodological rigor for impact studies in this area is provided by Cohen's (2013) work on statistical power analysis. With an emphasis on enhanced student performance and engagement, Prince (2004) and Freeman et al. (2014) provide meta-analytic and empirical evidence for active learning methodologies in STEM education.

The key to comprehending how new teaching methods and technological advancements proliferate throughout educational institutions is Rogers' (2003) groundbreaking idea of innovation diffusion. By documenting patterns in instructional conduct and institutional norms, Stains et al. (2018) investigate STEM teaching practices in North American colleges in more detail. This cluster indicates a strong interest in the diffusion, scaling, and sustainability of innovative teaching practices across educational ecosystems.

Social cognitive theory and motivational research serve as the foundation for Cluster 6, with Bandura (1986) serving as the primary source. Bandura's theory is applied to the development of academic and professional interests, especially through the Social Cognitive Career Theory (SCCT), as demonstrated by the inclusion of Lent et al. (1994; 2008). By examining gender stereotypes and motivational factors in underrepresented STEM communities, Ertl et al. (2017) and Wang (2013) expand on this. Cluster 6 shows how student psychology, identity, and equity are impacted by technological development, especially when students are expected to use digital tools, coding, artificial intelligence, and data literacy more and more.

Table 3: Co-citation Clusters

Cluster No and Colour	Cluster Labels	No. of Articles	Representative Publications
Cluster 1 (Red)	Qualitative Research and Pedagogical Frameworks	22	Braun & Clarke (2021); Miles et al. (2014); Hsieh & Shannon (2005); Mishra & Koehler (2006); Hodges et al. (2020); Creswell & Creswell (2018); Bozkurt & Sharma (2020)
Cluster 2 (Green)	Technology Acceptance and Behavioral Theories	18	Venkatesh et al. (2003); Davis (1989); Ajzen (1991); Fornell & Larcker (1981); Hair et al. (2019); Venkatesh & Davis (2000)
Cluster 3 (Blue)	E-learning, Analytics, and Pandemic-Era Adaptation	17	Almaiah et al. (2020); Wise & Jung (2019); Papamitsiou & Economides (2014); Bao (2020); Crawford et al. (2020); Barteit et al. (2021)
Cluster 4 (Yellow)	Artificial Intelligence and Mixed Methods in Educational Research	15	Zawacki-Richter et al. (2019); Creswell & Clark (2017); Patton (2002); Dwivedi et al. (2023); Shulman (2019); Sullivan et al. (2023)
Cluster 5 (Purple)	Active Learning, Diffusion, and Learning Efficacy	8	Cohen (2013); Prince (2004); Rogers (2003); Freeman et al. (2014); Stains et al. (2018)
Cluster 6 (Turquoise)	Social Cognitive Theory and STEM Motivation	8	Bandura (1986); Lent et al. (1994); Lent et al. (2008); Ertl et al. (2017); Wang (2013)

3.3 Co-Occurrence Analysis

The co-occurrence analysis of keywords in Table 4 reveals important thematic topics that are guiding research at the nexus of educational technology and decision-making. The most common term (68 times; link strength 180) was "education," which further supported the study's wide disciplinary scope. Following closely after is "technology" (65 occurrences; 184 link strength), indicating that the discourse revolves around technological integration. Additionally prevalent are the terms "students" and "higher education," suggesting that tertiary education settings are the focus of research. "Science" (29) and "teachers" (27) are two keywords that imply interest in STEM education and instructional viewpoints.

Table 4: The 15 Most Frequent Keywords in the Co-Occurrence Analysis

Rank	Keyword	Occurrences	Total Link Strength
1	Education	68	180
2	Technology	65	184
3	Higher education	53	142
4	Students	39	140
5	Science	29	91
6	Teachers	27	92
7	Decision-making	25	59
8	Model	24	84
9	Covid-19	23	58
10	Performance	22	84
11	Impact	22	76
12	Higher education	21	77
13	Adoption	20	81
14	Knowledge	20	54
15	Achievement	18	78

The words "model" and "adoption" refer to the broad use of theoretical frameworks like TAM and UTAUT, while "decision-making" (25 instances) connects educational research to leadership and policy questions. Notably, the pandemic's temporal effects on digital change are reflected in "Covid-19" (23). Impact, performance, and attainment are examples of keywords that point to an emphasis on outcome-based research, namely assessing the efficacy of tech adoption. The fact that "higher education" and "higher education" are both used shows semantic redundancy, but it also emphasizes how important it is. Overall, the co-occurrence patterns demonstrate a robust interaction between stakeholder emphasis (teachers, students), setting (higher education, COVID-19), and theory (adoption, model).

3.3.1 Co-Occurrence Analysis by Clusters

Keywords (in Figure 3) like "technology," "decision-making," "knowledge," "Covid-19," "artificial intelligence," "educational technology," and "acceptance" are found in Cluster 1. This cluster focuses on decision-making in the face of technological disruption; specifically, how educational and administrative decisions are being impacted by digital tools like artificial intelligence. The fact that Covid-19 is a co-keyword indicates that research on emergency digital transitions and the necessity of adaptive decision-making is on the rise.

Acceptance and knowledge suggest a dual focus on the behavioral and epistemic elements influencing the use of technology. This cluster, which emphasizes how innovation impacts planning, adaptation, and assessment in educational institutions, serves as the technological foundation of the research field. In uncertain times, it shows the increased interest in tech adoption habits, data-informed methods, and the alignment of digital tools with learning objectives.

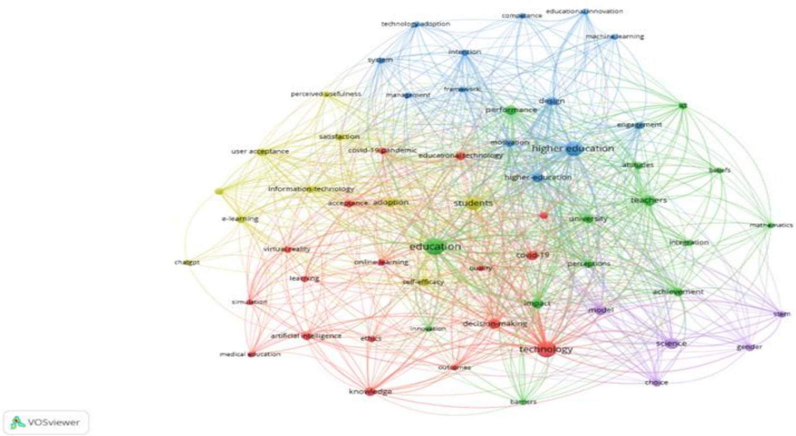

Figure 3: Co-Occurrence Analysis (VOSviewer Visualization)

Cluster 2 encompasses "achievement," "performance," "impact," "education," "teachers," and "university." The impact of pedagogical and technological interventions on teachers and institutions is examined in this cluster. The focus on teachers and performance points to the need for a substantial amount of research on how teachers adjust to new tools and how these tools impact student learning and classroom delivery.

Achievement and impact are often used buzzwords, which suggests a persistent focus in gauging results at the institutional and individual learner levels. This cluster emphasizes the interaction between pedagogy and digital tools, educator agency, and assessment of educational efficacy. It indicates an increasing tendency toward evidence-based education, in which the use of technology is not only adopted but also evaluated critically for its impact on institutional performance and student progress.

The words "higher education," "higher education," "design," "engagement," "motivation," and "educational innovation" predominate in Cluster 3. This cluster displays a strong emphasis on transformative methods in higher education, which are fueled by institutional innovation, learner engagement tactics, and design thinking. Although it may be a reflection of differences in term usage, the repetition of "higher education" and "higher education" highlights its crucial position in literature.

A methodological orientation toward curriculum innovation, learning experience design, and instructional models suited to contemporary learners is suggested by the existence of educational innovation and design. Important psychological factors like motivation and engagement are frequently researched in conjunction with technology-enhanced learning, especially when using gamification, blended learning, or flipped classroom strategies. This cluster of research frequently focuses on student-centered methods and the digital reinvention of educational practices.

Cluster 4 combines terms like "students," "adoption," "e-learning," "information technology," and "user acceptance." This cluster is mostly student-centered and places a lot of emphasis on how students use digital tools and platforms. The use of information technology and e-learning situates this study within digital learning ecosystems, especially those that gained popularity during and after the epidemic. This cluster focuses on how educational institutions may enhance students' experiences with digital tools and how students understand, adjust to, and gain from them. This cluster provides crucial insight into the user-centered design of educational technology, ensuring that they reflect the expectations, behaviors, and objectives of learners as educational institutions progressively digitize their learning environments.

Among the keywords in Cluster 5 are "science," "model," "gender," "STEM," and "choice." The intersection of identity, motivation, and learning in STEM fields is the focus of this cluster, which emphasizes a significant yet frequently specialized area of study. The inclusion of gender suggests that representation and equity, particularly for underrepresented groups, are important in science and technology professions.

In order to comprehend learning pathways and professional decision-making, the term "model" most commonly refers to theoretical constructs like Social Cognitive professional Theory (SCCT) or conceptual frameworks. Choice and STEM recommend research on how students, especially women and minorities, decide to pursue STEM disciplines or not, and how digital learning environments affect these choices. Particularly in fields that are conventionally perceived as challenging or exclusive, this cluster positions technology not only as an instructional tool but also as a factor impacting student identity and aspiration.

Table 5: Co-Occurrence Analysis of Keywords on Decision-Making

Cluster No and Colour	Cluster Label	Number of Keywords	Representative Keywords
Cluster 1 (Red)	Technology-Driven Decision Systems	17	‘technology’, ‘decision-making’, ‘knowledge’, ‘Covid-19’, ‘artificial intelligence’, ‘educational technology’, ‘acceptance’
Cluster 2 (Green)	Educational Impact and Teacher Performance	14	‘education’, ‘teachers’, ‘university’, ‘achievement’, ‘performance’, ‘impact’
Cluster 3 (Blue)	Innovation in Higher Education	13	‘Higher education’, ‘higher education’, ‘design’, ‘engagement’ ‘motivation’, ‘educational innovation’
Cluster 4 (Yellow)	Student Experience and Technology Adoption	10	‘students’, ‘adoption’, Information-technology’, ‘e-learning’, ‘user acceptance’
Cluster 5 (Purple)	STEM, Identity, and Learning Pathways	5	‘science’, ‘model’, ‘gender’, ‘STEM’, ‘choice’

4. Discussion

This bibliometric study provides a cohesive perspective on the thematic and philosophical evolution of research relating technological change and educational decision-making, a relationship that was previously exclusively examined in disparate subfields (Manarbek et al., 2024; Jing et al., 2023). The study maps popular theoretical underpinnings, such as the Technology Acceptance Model (Davis, 1989), Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), and Theory of Planned Behaviour (Ajzen, 1991), by combining co-citation and co-occurrence analyses. It also highlights new areas, such as AI ethics (Zawacki-Richter et al., 2019), remote decision-making (Bao, 2020), and adaptive learning models in the post-COVID-19 context.

This dual emphasis develops theory by placing adoption models in larger institutional and leadership contexts, highlighting the fact that systemic, policy-driven processes, rather than just individual actions, frequently influence educational decisions (Hair et al., 2019). It also identifies shortcomings in current models, especially with regard to addressing ethics, inclusivity, equity, and crisis-responsive decision-making (Hodges et al., 2020), which promotes the creation of multi-theoretical or hybrid frameworks for the changing educational environment (Sullivan et al., 2023).

From a practical standpoint, the results offer educators, administrators, and legislators' useful information. Keywords like "acceptance," "technology," "decision-making," and "COVID-19" are frequently linked, indicating that many institutional responses during the pandemic were reactive. This highlights the necessity of proactive decision-making models that incorporate scenario planning, real-time analytics, and predictive tools (Du, 2022). Finding authors, organisations, and sources with a high effect provides a road map for evidence-based investments, directing funding priorities and strategic partnerships (Srivastava et al., 2024).

Furthermore, topics like "educational innovation," "artificial intelligence," and "STEM choice" are prominent, suggesting that curriculum creation, professional development, and resource allocation can be in line with new technology advancements. In the digital age, this study supports tech-aligned pedagogy, evidence-based policy, and resilient educational systems that stay relevant and responsive by connecting theoretical ideas with strategic implementations.

5. Conclusion

This bibliometric analysis offers a thorough summary of the changing body of research on how technological advancements affect educational decision-making. In order to demonstrate the dynamic confluence of technological innovation, leadership behavior, educational reform, and institutional policy, the study conducted an integrated performance, co-citation, and co-occurrence analysis of 371 selected articles from 2020 to 2024. The results show that while more recent topics like artificial intelligence, emergency digital transitions, and ethical decision-making have become significant focal points, fundamental theories like the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Social Cognitive Theory (SCT) still serve as the framework for the conversation.

This study supports the significance of inclusive, equitable, and creative teaching methods that use technology to improve access, responsiveness, and learning results, all of which are in line with SDG 4: Quality Education. This study acts as a strategic knowledge map to make sure that technological integration is both pedagogically sound and purposeful as education systems throughout the world continue to change in the face of digital disruption. The report concludes by advocating for an educational ecosystem that is prepared for the future and where decisions are inclusive, well-informed, and resistant to the rapid advancement of technology.

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