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AI Dependency in Education: A Bibliometric Analysis and Psychological Research Directions

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A B S T R A C T

The proliferation of artificial intelligence (AI) tools in higher education has raised growing concerns about students' excessive reliance on AI in completing academic tasks, a phenomenon referred to as AI dependency. No comprehensive bibliometric synthesis on this topic currently exists. This study aimed to map the research landscape of AI dependency in education by identifying publication trends, intellectual structure, and emerging thematic directions. A bibliometric analysis was conducted on 88 articles published between 2023 and 2025, indexed in the Scopus database. Descriptive analysis, keyword co-occurrence networks, co-authorship networks, and thematic mapping were performed using Bibliometrix and VOSviewer. Findings reveal an exponential annual growth rate of 724.62%, with China, France, and Southeast Asian countries dominating research output. Four thematic clusters were identified: Generative AI and Educational Ethics, AI Dependency and Cognitive Impact, Human Factors and Psychology, and Educational Research Methods. Thematic mapping indicates that AI dependency occupies an emerging theme position with near-zero centrality, suggesting the construct remains in early conceptual consolidation. The co-occurrence of self-efficacy and psychological variables points to possible directions for developing standardised theoretical frameworks and evidence-based interventions to support responsible AI use in education.

1. Introduction

The rapid proliferation of artificial intelligence (AI) technology in educational contexts has fundamentally transformed teaching and learning practices across the globe. Among the most notable developments, the emergence of generative AI tools, most notably ChatGPT which was launched in November 2022, demonstrated an unprecedented rate of adoption in higher education (OpenAI, 2022). Within two months of its release, ChatGPT amassed 100 million users, making it the fastest-growing consumer application in history and driving its widespread integration into academic activities (Hu, 2023). This development has generated considerable optimism regarding AI's potential to enhance learning quality, while simultaneously raising serious concerns about its implications for students' cognitive development and academic integrity (Kung et al., 2023).

Prior research has extensively examined the use of AI in education, encompassing intelligent tutoring systems, adaptive learning environments, and automated assessment tools (Luckin et al., 2016; Zawacki-Richter et al., 2019). However, one increasingly prominent yet systematically underexplored phenomenon is AI dependency. AI dependency refers to the excessive reliance of students on AI tools to complete academic tasks to the extent that it potentially impairs their critical thinking abilities, problem-solving skills, and capacity for independent learning. Unlike instrumental uses of technology, dependency reflects a maladaptive behavioral pattern in which individuals become reluctant or unable to engage in cognitive tasks without AI assistance, a condition that threatens the development of higher-order thinking skills regarded as essential competencies for twenty-first century education (Griffin et al., 2012).

Conceptually, this phenomenon draws upon two well-established constructs in cognitive psychology: automation bias (Goddard et al., 2012) and cognitive offloading (Risko & Gilbert, 2016). Automation bias describes the tendency of individuals to over-trust automated systems, while cognitive offloading refers to the delegation of internal cognitive processes to external devices. In educational settings, AI dependency can be understood as a manifestation of both constructs, amplified by the generative and interactive capabilities of large language models (LLMs) that enable the instantaneous replacement of effortful thinking (Sullivan et al., 2023). The persistent engagement with such systems may progressively erode students' cognitive autonomy in ways that conventional technology use does not.

A growing body of empirical evidence suggests that intensive AI use is associated with reduced engagement in critical analysis, diminished originality in academic work, and declining confidence in independent problem-solving (Chan & Hu, 2023; Kong et al., 2023). Unrestricted access to AI-generated answers risks producing conditions analogous to learned helplessness (Seligman, 1975), wherein students are no longer motivated to struggle with academic challenges independently, thereby bypassing the productive struggle that is fundamental to deep learning (Kapur, 2008). Conversely, students with higher levels of academic self-efficacy tend to be better equipped to preserve their cognitive autonomy when confronted with the ease of AI access (Bandura, 1997; Kong et al., 2023). This suggests that AI dependency is not a uniform phenomenon but is moderated by individual psychological factors, including self-regulation, learning motivation, and cognitive engagement. Accordingly, AI dependency can be positioned as a psychological construct closely related to self-regulated learning, motivational dynamics, and higher-order cognitive processes, and therefore warrants sustained scholarly attention from both educational and clinical psychology.

Despite growing interest in this topic, the field remains fragmented and poorly structured. Terminological ambiguity is pervasive, with terms such as AI dependency, over-reliance, automation complacency, and digital dependence used interchangeably without clear conceptual boundaries (Dwivedi et al., 2023). Furthermore, no comprehensive bibliometric synthesis currently exists that maps the development, intellectual structure, and thematic landscape of AI dependency research in education. This gap is particularly pressing given the accelerating integration of AI into educational institutions and the increasing demand for evidence-based policies that ensure responsible AI adoption (UNESCO, 2023). Without a systematic mapping of the existing literature, efforts to develop theoretical frameworks, standardized measurement instruments, and targeted psychological interventions risk being redundant, inconsistent, or poorly grounded in the accumulated evidence base.

Bibliometric analysis offers a rigorous and systematic approach to addressing this gap. By applying quantitative methods to the analysis of scientific publications, citations, and collaboration patterns, bibliometrics enables the identification of publication trends, key contributors, intellectual networks, and thematic clusters within a research domain (Aria & Cuccurullo, 2017; Donthu et al., 2021). This approach is particularly well-suited to emerging fields such as AI dependency, where the volume of literature is growing rapidly but its structure remains unclear. Therefore, this study aims to map the research landscape of AI dependency in education through a bibliometric analysis of 88 articles published between 2023 and 2025 and indexed in the Scopus database. Specifically, the study addresses three research questions: (1) What are the publication trends and distribution patterns of AI dependency research in education? (2) What is the intellectual structure and collaboration network of this research domain? and (3) What are the emerging thematic directions in AI dependency research, and what do they imply for future scholarly and psychological inquiry? The findings of this study are intended to provide a conceptual and empirical foundation for advancing theoretical development, psychological intervention design, and evidence-based educational policy in the context of responsible AI use.

2. Methodology

Research Design

This study employed a bibliometric approach to map the research landscape of AI dependency in educational contexts. Bibliometrics is a quantitative method that analyses the scientific literature through statistical measurement of publications, citations, and collaboration patterns (Donthu et al., 2021). This approach was selected for its capacity to provide a systematic overview of research developments, identify emerging trends, and map intellectual structures through network analysis (Aria & Cuccurullo, 2017). Document selection followed the *Preferred Reporting Items for Systematic Reviews and Meta-Analyses* (PRISMA) guidelines adapted for bibliometric studies, as illustrated in Figure 1 (Page et al., 2021).

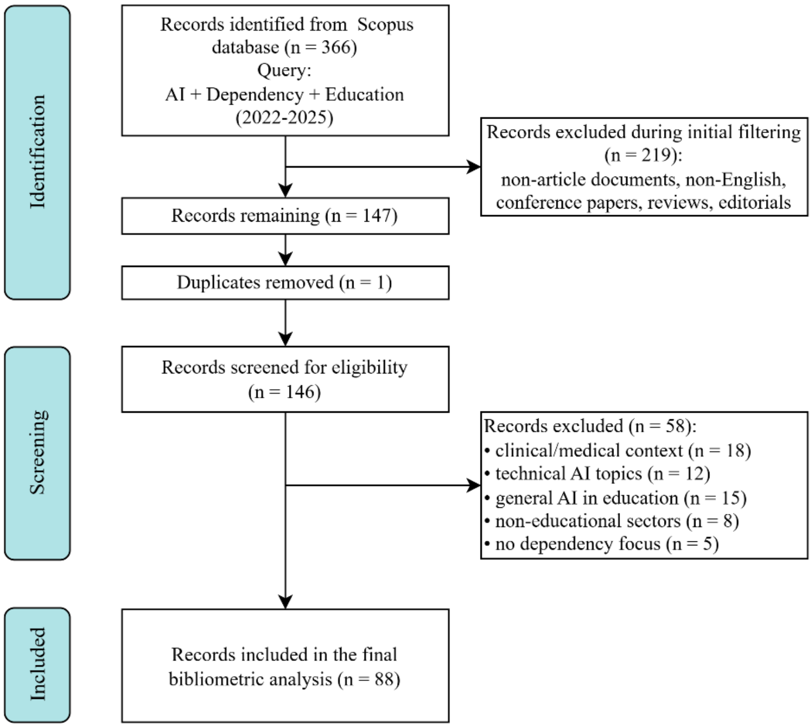

Figure 1. PRISMA Flow Diagram

Instrument

The analysis was conducted using a combination of software tools to ensure validity and triangulation of results (Cobo et al., 2011). The primary analytical tool was Bibliometrix and its web interface Biblioshiny, an open-source R-based package developed specifically for comprehensive science mapping. Bibliometrix was used to perform descriptive statistics, Bradford's Law analysis, Lotka's Law analysis, and thematic mapping via Correspondence Analysis (Aria & Cuccurullo, 2017; Moral-Munoz et al., 2020). The second tool was VOSviewer, a software program developed by Leiden University for constructing and visualising bibliometric networks. VOSviewer was used to generate keyword co-occurrence networks and co-authorship networks (van Eck & Waltman, 2010). Both tools are freely available and widely adopted in bibliometric research, ensuring replicability. Prior to analysis, author name standardisation and institutional name normalisation were performed manually to address spelling variations and ensure the accuracy of collaboration analysis (Zhu & Liu, 2020).

Data Collection

Data were collected from the Scopus database on 17 February 2026. Scopus was selected as the sole data source due to its broad coverage of more than 25,000 indexed journals, structured metadata that supports bibliometric analysis, an integrated citation tracking system, and full compatibility with both Bibliometrix and VOSviewer (Baas et al., 2020; Moral-Munoz et al., 2020). The following search query was applied to the Title, Abstract, and Keywords fields:

TITLE-ABS-KEY ((("artificial intelligence" OR "AI" OR "generative AI" OR "ChatGPT" OR "large language model" OR "LLM") AND ("dependency" OR "dependence" OR "over-reliance" OR "reliance" OR "over-dependence")) AND ("education*" OR "student*" OR "learning" OR "academic" OR "university" OR "school" OR "teaching")) AND (PUBYEAR > 2021) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English"))*

The initial search retrieved 366 records. After excluding non-article document types (conference papers, reviews, and editorials), 147 articles remained. Eligibility screening was subsequently applied based on the following criteria. Inclusion criteria required that articles address AI dependency within the context of formal education. Exclusion criteria removed articles focused on non-educational contexts or purely technical AI research without an educational dimension. Following the removal of one duplicate identified via DOI matching, a final corpus of 88 articles published between 2023 and 2025 was retained for analysis. No articles from 2022 were identified, which is consistent with the November 2022 launch date of ChatGPT, meaning that empirical research on AI dependency in education only began to emerge in 2023 (OpenAI, 2022).

Data Analysis

Data analysis was conducted in three sequential stages, each corresponding to one of the study's research questions (Donthu et al., 2021). Stage 1. Descriptive Analysis (RQ1). Descriptive bibliometric analysis was performed using Bibliometrix to address publication trends and distribution patterns. This stage included the calculation of annual growth rate, Bradford's Law to identify core journals, Lotka's Law to examine author productivity distribution, and geographic distribution analysis based on author affiliations (Aria & Cuccurullo, 2017).

Stage 2. Network Analysis (RQ2). Co-occurrence and collaboration networks were constructed using VOSviewer. For keyword co-occurrence analysis, a minimum threshold of 3 occurrences per keyword was applied. For co-authorship network analysis, a minimum threshold of 2 documents per author was set. These parameters were chosen to balance network density with analytical manageability, following established bibliometric practice (van Eck & Waltman, 2010).

Stage 3. Thematic Analysis (RQ3). Thematic mapping was conducted using the Thematic Map function in Biblioshiny, which applies Correspondence Analysis to classify research themes into four strategic quadrants: Motor Themes (high centrality, high density), Basic Themes (high centrality, low density), Niche Themes (low centrality, high density), and Emerging Themes (low centrality, low density) (Cobo et al., 2011; Moral-Munoz et al., 2020). Validity was maintained through the use of an indexed and curated database, systematic document selection following PRISMA guidelines, and the triangulation of results across multiple analytical tools (Donthu et al., 2021). Acknowledged limitations include the use of a single database, a short publication window inherent to a newly emerging topic, and restriction to English-language publications (Baas et al., 2020).

3. Results and Discussion

Overview of the Dataset

The bibliometric analysis was conducted on 88 articles addressing AI dependency in educational contexts, published between 2023 and 2025, as summarised in Figure 2.

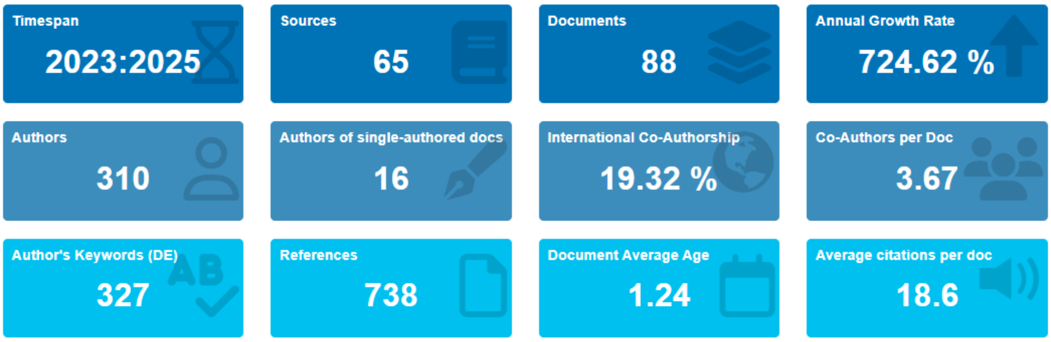

Figure 2. Overview of the Dataset

The annual growth rate of 724.62% visible in Figure 2 represents the most significant indicator across the entire dataset. From a bibliometric standpoint, this figure reflects a pattern of quantitative growth in the literature. While it is tempting to interpret this acceleration as confirmation that AI dependency in education is undergoing a research acceleration phase driven by technological disruption rather than gradual disciplinary development, it is important to note that bibliometric data indicate patterns of publication activity and do not, in themselves, establish causal or structural explanations for such growth. The observed growth rate may suggest, but does not conclusively confirm, the nature of the underlying disciplinary dynamics. Despite the recency of the literature, an average citation rate of 18.6 per document indicates that its academic impact is already substantial, pointing to the high relevance of this topic across multiple scientific communities.

The terminological diversity reflected in 327 author keywords also carries important conceptual implications. It suggests that the research community has yet to reach consensus on the constructs being used, a condition typical of the early formation stages of a new field of inquiry (Donthu et al., 2021). An international collaboration rate of 19.32% further indicates that while global awareness has formed, cross-national integration still needs to be strengthened to build a more robust empirical foundation.

Publication Trends and Distribution (RQ1)

a. Annual Publication Trends

Figure 3 presents annual publication growth patterns over the 2023-2025 period.

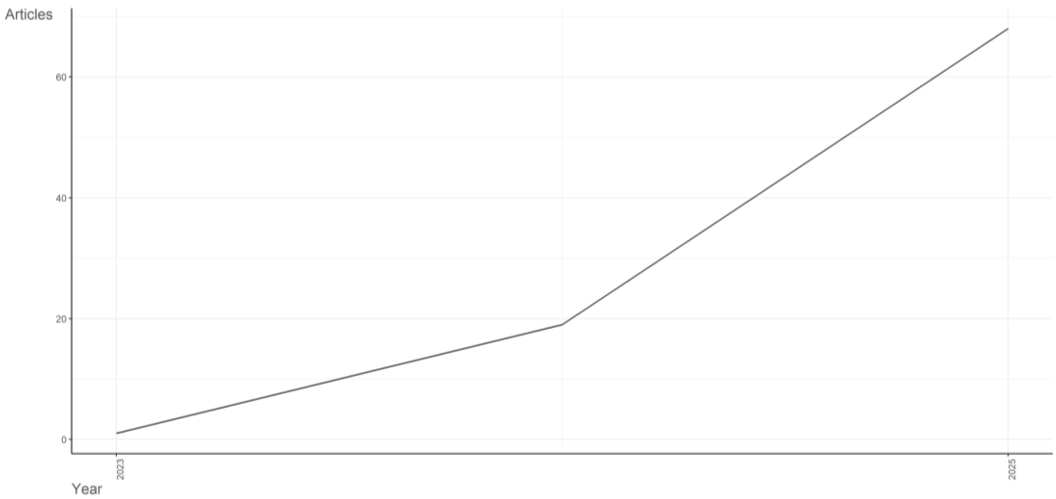

Figure 3. Annual Scientific Production

The J-curve pattern visible in Figure 3 is the most significant finding of this trend analysis. In the bibliometric literature, such a pattern generally indicates that a topic has passed its critical adoption threshold and entered a phase of exponential growth (Rogers, 2003). In this study, the inflection point can be directly attributed to the launch of ChatGPT in November 2022, which triggered systematic scholarly concern about the impact of AI on students' cognitive processes (Hu, 2023; OpenAI, 2022). What warrants emphasis is not merely the rate of growth, but its implication: the academic community has responded to the AI dependency phenomenon at a speed that has outpaced the development of standardised theoretical frameworks, resulting in massive growth in literature that has yet to achieve conceptual consensus (Sullivan et al., 2023).

b. Journal Distribution and Bradford's Law

Figure 4 presents the Bradford's Law visualisation, while Table 1 lists the ten journals with the highest publication contributions.

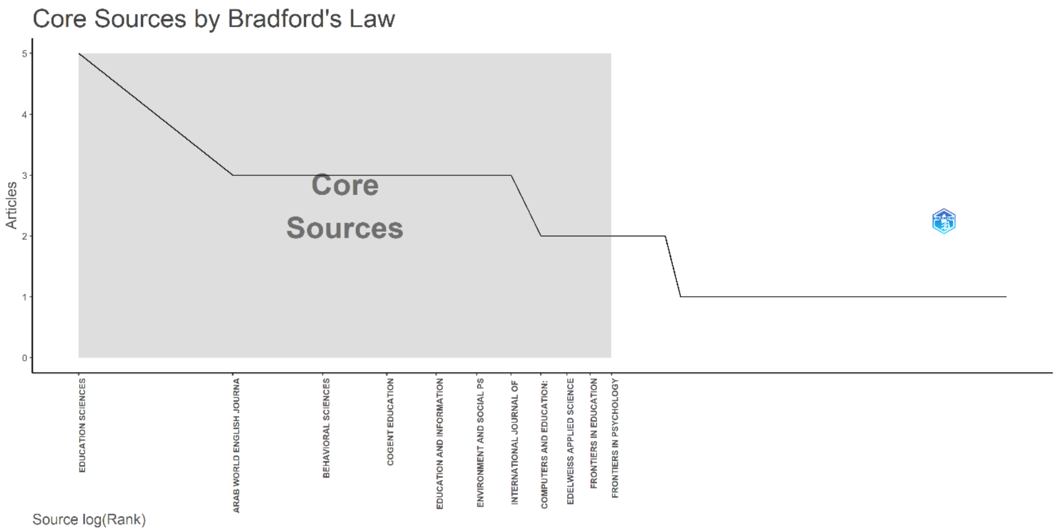

Figure 4. Bradford's Law

Table 1. Top 10 Journals

Sources	Articles
Education Sciences	5
Arab World English Journal	3
Behavioral Sciences	3
Cogent Education	3
Education and Information Technologies	3
Environment and Social Psychology	3
International Journal of Learning, Teaching And Educational Research	3
Computers and Education: Artificial Intelligence	2
Edelweiss Applied Science and Technology	2
Frontiers in Education	2

The most meaningful finding from the journal distribution is not the productivity ranking itself, but the disciplinary diversity represented. The presence of journals from psychology (Behavioral Sciences, Environment and Social Psychology), educational technology (Education and Information Technologies, Computers and Education: Artificial Intelligence), and language learning (Arab World English Journal) within Bradford's core zone collectively suggests that AI dependency may be an inherently interdisciplinary phenomenon, though this observation is based on publication venue diversity and should be interpreted as an indicative pattern rather than a definitive structural conclusion (Zawacki-Richter et al., 2019). This carries important methodological implications: future research cannot rely on a single-discipline perspective, but must instead adopt cross-disciplinary approaches that integrate psychological, pedagogical, and technological frameworks simultaneously. The recognition of this topic by a specialist AI journal such as Computers and Education: Artificial Intelligence also marks the legitimisation of AI dependency as a research area in its own right, rather than a mere sub-theme of educational technology more broadly (Fitria, 2021).

c. Author Productivity and Lotka's Law

Figure 5 shows the comparison between empirical and theoretical author productivity distributions based on Lotka's Law.

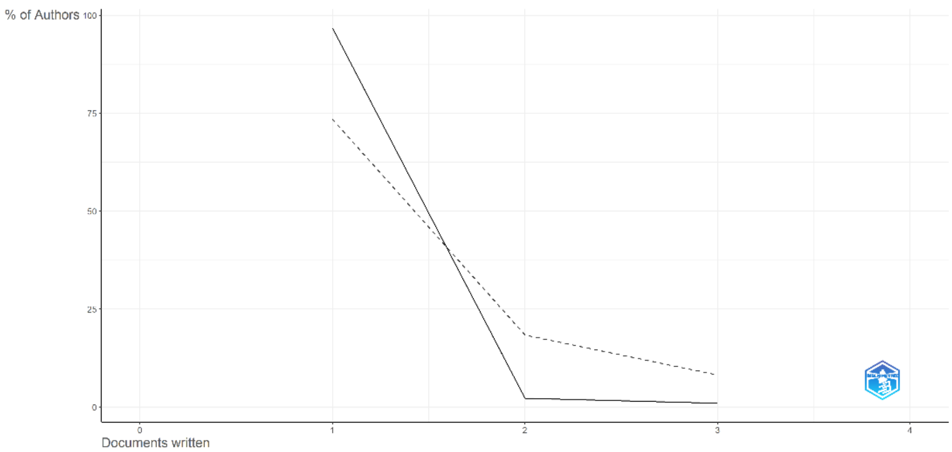

Figure 5. Author Productivity through Lotka's Law

The gap between the empirical and theoretical curves in Figure 5 carries strategic significance for the development of this field. The deviation from Lotka's prediction toward dominance by single-contribution authors confirms that the AI dependency research community has yet to develop an established core group of researchers (Zhu & Liu, 2020). This reflects a characteristic feature of emerging research fields, where academic interest arrives broadly but has not yet concentrated (Donthu et al., 2021). Practically, this means the field is highly open to researchers willing to build a consistent and sustained research agenda, as the space to become a thought leader remains considerably wide.

d. Geographic Distribution of Research

Figure 6 presents the global scientific production map, while Table 2 details the contributions of the top ten countries.

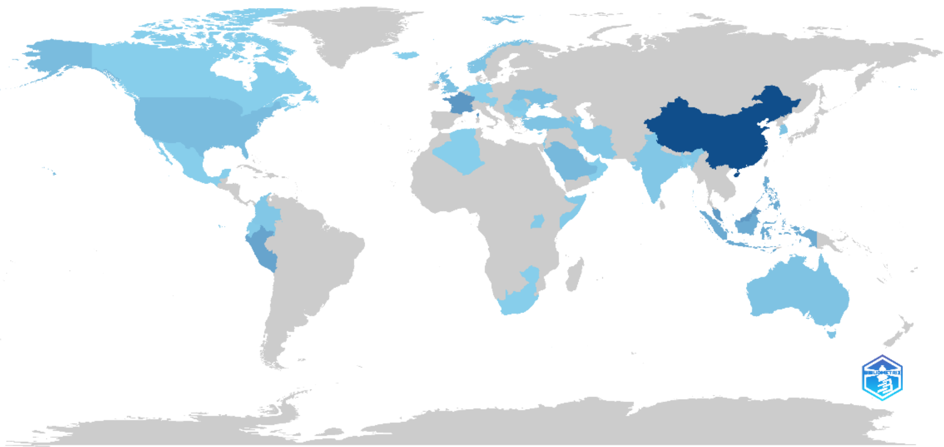

Figure 6. Countries' Scientific Production Map

Table 2. Top 10 Countries

Country	Freq
China	40
France	17
Malaysia	16
Peru	13
Indonesia	11
Philippines	11
Saudi Arabia	7
USA	6
UK	5
Ukraine	5

The most notable finding from the geographic analysis is not China's dominance as the largest producer, but the contrast between publication volume and citation impact. Australia, which does not appear among the top ten producing countries, leads in total citations with 569, far exceeding China's 197. This gap indicates that publication quantity does not correlate linearly with intellectual influence, and that foundational articles with high theoretical impact tend to originate from countries with more established research traditions (Bornmann & Leydesdorff, 2013). The collectively high contribution of Southeast Asia is also contextually significant: the region is not only quantitatively productive, but also represents a unique sociocultural context for AI dependency research, given its high smartphone penetration rates and educational dynamics that differ substantially from Western contexts (Kemp, 2023). The presence of Peru from Latin America further suggests that AI dependency research may not be limited to specific regions, pointing to its potentially global relevance across diverse educational systems, though more balanced geographic representation in future studies would be needed to substantiate this interpretation. China's dominance can largely be attributed to its national strategic commitment to AI development, the enormous scale of its higher education ecosystem, and the dramatic acceleration of digital technology adoption following the COVID-19 pandemic (Chen et al., 2020; Statistics, 2022; Zhang et al., 2020).

Thematic Structure and Intellectual Networks (RQ2)

a. Keyword Co-occurrence Network

Figure 7 presents the keyword co-occurrence network formed from 44 keywords with a minimum of three occurrences, while Table 3 lists the twenty keywords with the highest frequencies.

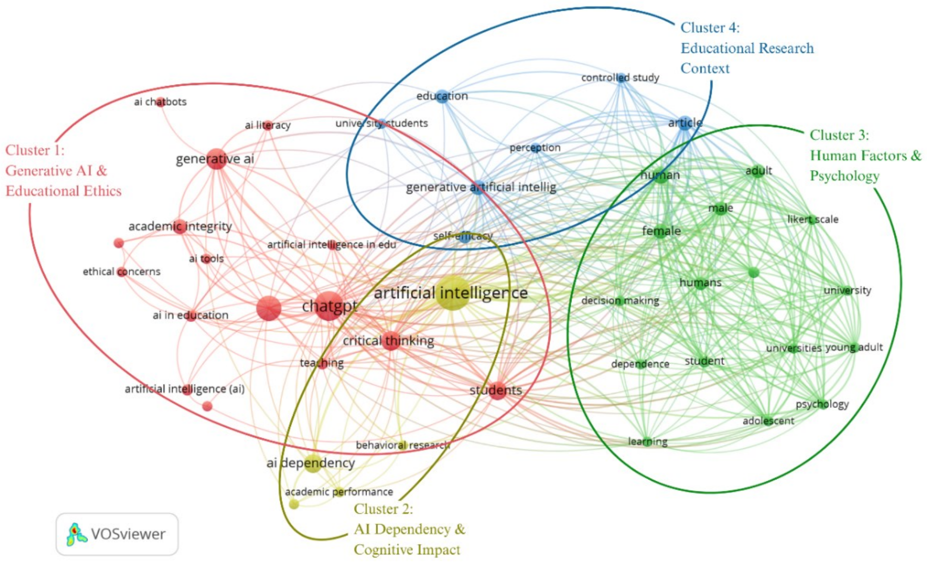

Figure 7. Keyword Co-occurrence Network

The most significant finding from Table 3 is not the frequency ranking itself, but the explicit presence of "ai dependency" as a standalone keyword at sixth position. This may indicate that the AI dependency construct has begun to be articulated independently by some researchers, rather than being merely implied within broader discussions about AI in education. This could be interpreted as a possible early sign of emerging conceptual consolidation, though it remains at a very nascent stage and should be regarded as a tentative observation rather than a confirmed trend.

Table 3. Top 20 Keywords

No	Words	Occurrences
1	artificial intelligence	36
2	chatgpt	26
3	higher education	18
4	generative ai	13
5	critical thinking	11
6	ai dependency	10
7	students	10
8	human	8
9	academic integrity	7
10	article	7
11	female	7
12	generative artificial intelligence	7
13	adult	6
14	education	6
15	male	6
16	humans	5
17	self-efficacy	5
18	ai in education	4
19	artificial intelligence (ai)	4
20	questionnaire	4

Figure 7 identifies four thematic clusters that reflect the intellectual structure of AI dependency research. The Red Cluster (Generative AI and Educational Ethics) indicates that the AI dependency discourse cannot be separated from academic integrity considerations, particularly around the risks of plagiarism and the erosion of originality in student work (Sullivan et al., 2023). More theoretically significant, the Yellow Cluster (AI Dependency and Cognitive Impact) positions "critical thinking" as a central node, confirming that cognitive implications constitute the core of academic concern about AI dependency. The presence of "behavioral research" within the same cluster signals a positive methodological shift: the field is beginning to move from phenomenological description toward explanations grounded in psychological and behavioral frameworks (Kapur, 2008; Risko & Gilbert, 2016).

The Green Cluster (Human Factors and Psychology) is particularly relevant from an educational psychology perspective. The co-occurrence of "self-efficacy" alongside gender and demographic variables indicates that the research community is beginning to recognise heterogeneity in vulnerability to AI dependency. This opens an important psychological research agenda: students with lower academic self-efficacy are likely to exhibit different dependency patterns compared to those with higher levels of academic confidence (Bandura, 1997; Kong et al., 2023). The Blue Cluster (Educational Research Methods), meanwhile, signals a stage of methodological maturation, with controlled study emerging as an approach being increasingly adopted, indicating that the field is beginning to shift toward more rigorous evidence-based research.

b. Co-authorship Network

Figure 8 presents the co-authorship network structure of authors meeting the minimum threshold of two publications.

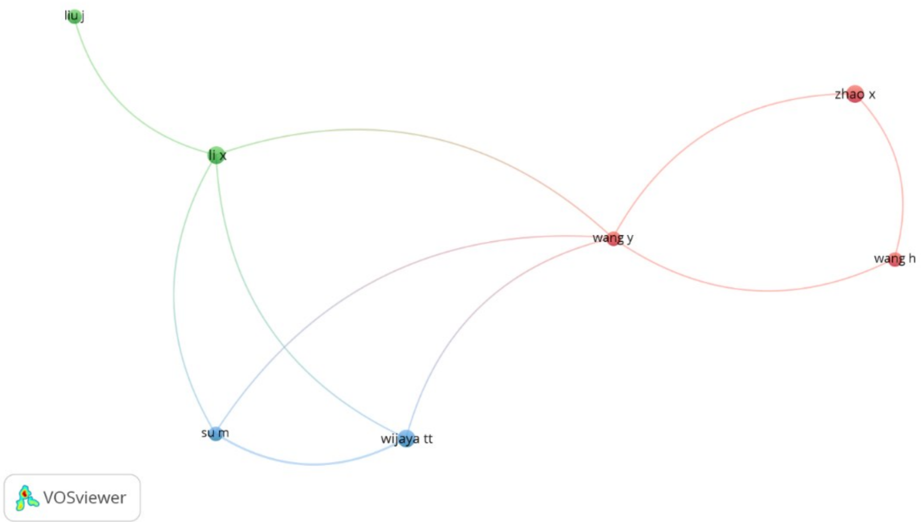

Figure 8. Co-authorship Network

The network fragmentation visible in Figure 8 is the most meaningful finding of the collaboration analysis. Three clusters operating independently without cross-group connections reflects a condition typical of emerging research fields, where the academic community has not yet formed dense collaboration networks (Donthu et al., 2021). Of particular note is the position of Wijaya TT as a productive Indonesian researcher who remains isolated from the dominant Chinese researcher clusters. This represents an untapped opportunity: collaboration between Southeast Asian and East Asian researchers has the potential to produce highly valuable comparative studies, given that both regions share high AI adoption rates but operate within distinct sociocultural contexts and educational systems. This fragmentation ultimately impedes theoretical integration and the development of the conceptual consensus necessary to mature the field (Zhu & Liu, 2020).

Thematic Mapping and Research Directions (RQ3)

Thematic Map and Theme Classification

Figure 9 presents the Thematic Map classifying research themes along the dimensions of centrality and density, while Table 4 details the classification by quadrant.

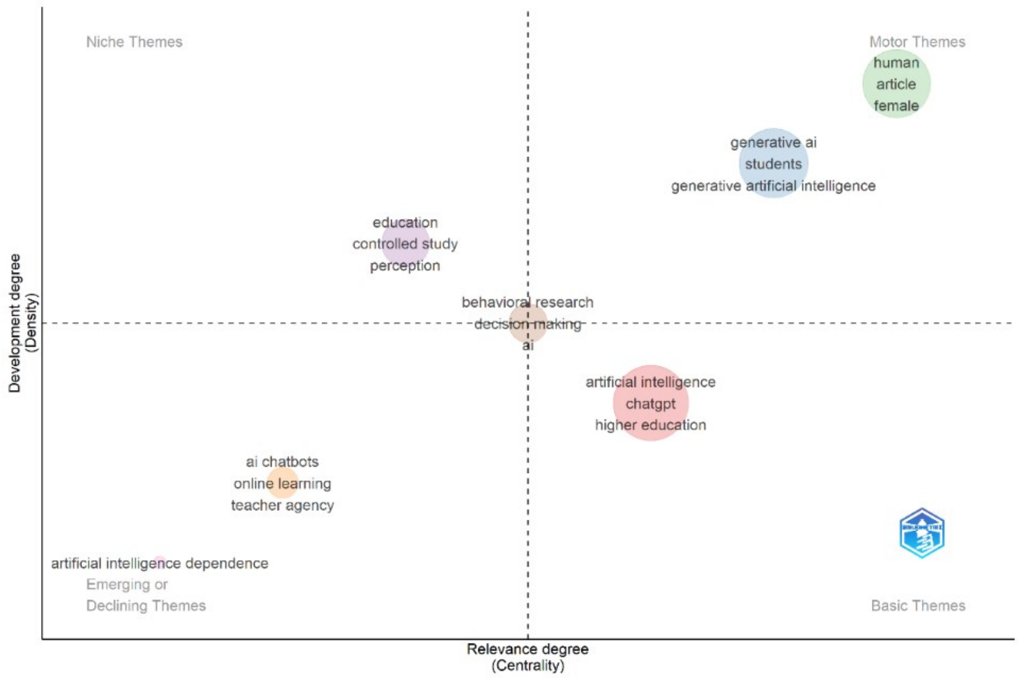

Figure 9. Thematic Map

Table 4. Thematic Quadrants

Quadrant	Theme (Cluster)	Freq.	Top Keywords
Motor Themes	**human** (24 keywords)	8	Human
		7	Article
		7	Female
		6	adult, male
	generative ai (27 keywords)	13	generative ai
		10	students
		7	generative artificial intelligence
Basic Themes	**artificial intelligence** (21 keywords)	36	artificial intelligence
		26	chatgpt
		18	higher education
		11	critical thinking
		10	ai dependency
	behavioral research (5 keywords)	3	behavioral research
		3	decision making
		2	ai
Niche Themes	**education** (8 keywords)	6	Education
		3	controlled study
		3	perception
Emerging Themes	**ai chatbots** (3 keywords)	3	ai chatbots
		2	online learning
		2	teacher agency
	artificial intelligence dependence (1 keyword)	2	artificial intelligence dependence

The most critical finding from Figure 9 and Table 4 is the positioning of "artificial intelligence dependence" as an emerging theme with centrality approaching zero. As an empirical observation, this finding indicates that the keyword "artificial intelligence dependence" occupies a peripheral and underdeveloped position within the current thematic map of the literature. It is important to distinguish this bibliometric finding from its theoretical interpretation: while bibliometric methods can reveal patterns of co-occurrence and thematic positioning, they do not directly measure conceptual depth or the quality of theoretical development within the studies concerned. With this methodological caveat in mind, the low centrality of this theme may be interpreted as a possible indicator that AI dependency as a theoretically autonomous construct is still in early stages of conceptual development, though this interpretation should be understood as a plausible direction for further inquiry rather than a conclusion directly derivable from the thematic map alone. The gap between the substantial volume of practical attention directed at AI in education and the relatively limited thematic centrality of AI dependency as a construct represents an important observation that warrants further theoretical investigation.

The Motor Themes quadrant, occupied by the "human" and "generative ai" clusters, indicates the most actively developing research directions at present. The dominance of demographic and gender perspectives within the "human" cluster suggests that the research community is in the process of building an understanding of who is most vulnerable to AI dependency. This is consistent with a differential psychology approach that emphasises the importance of individual-level variables in understanding responses to technology. The "generative ai" cluster, centred on its impact on students, reflects an urgent need to understand the specific mechanisms through which LLMs such as ChatGPT contribute to the formation of dependency patterns.

The Basic Themes, encompassing the "artificial intelligence" cluster with high centrality but low density, signal an interesting condition: these themes have become stable conceptual foundations, but are no longer in a phase of active development. This actually reinforces the argument that the true space for theoretical innovation lies within the emerging themes clusters, not in themes that have already reached maturity. The Niche Themes cluster, represented by "education," indicates the presence of a research community specialising in specific methodological aspects, particularly controlled studies. Although relatively isolated, this community represents an important foundation for the development of a stronger evidence base in the future.

Most relevant to the future research agenda are the two Emerging Themes clusters. The "ai chatbots" cluster, which includes "teacher agency," indicates that the role of educators in mediating student-AI interactions has not yet received adequate attention in the literature, despite being a crucial dimension for the design of pedagogical interventions. The positioning of "artificial intelligence dependence" as an emerging theme with the lowest frequency provides the strongest justification for this study: there is an urgent need to develop conceptual frameworks, psychometric measurement instruments, and an empirical evidence base that specifically address AI dependency as a standalone construct, rather than treating it merely as a side effect of broader discussions about AI in education (Cobo et al., 2011; Moral-Munoz et al., 2020).

Synthesis and Implications

The three principal findings of this study together form a coherent narrative about the current state of AI dependency research in education. The exponential growth rate of 724.62% points to the field being in an acceleration phase, while the collaboration fragmentation and the peripheral positioning of "artificial intelligence dependence" as an emerging theme together suggest that this quantitative growth has not been accompanied by commensurate conceptual consolidation. It should be emphasised, however, that these observations reflect patterns discernible from bibliometric data, and should not be read as direct measures of conceptual maturity or theoretical quality in the underlying literature.

From a psychological perspective, the bibliometric findings carry potential implications that warrant careful interpretation. It is important to acknowledge upfront that bibliometric methods map patterns of keyword co-occurrence and thematic positioning in the literature; they do not directly assess the quality, depth, or psychological content of the studies themselves. The interpretations that follow should therefore be understood as theoretically informed possibilities suggested by the thematic structure of the literature, rather than conclusions that can be directly inferred from the bibliometric data alone. With this epistemological limitation in mind, the peripheral positioning of "artificial intelligence dependence" as an emerging theme may suggest a potential need for the development of standardised psychological constructs.

Psychology as a discipline has a long tradition of defining, operationalising, and measuring dependency constructs, ranging from substance dependence to internet addiction, and is therefore well positioned to lead the development of valid and reliable psychometric instruments for measuring AI dependency. The emergence of self-efficacy within the Motor Themes provides an empirical basis for designing psychological interventions aimed at enhancing academic self-efficacy as a preventive strategy against AI dependency, for instance through growth mindset programmes and the reinforcement of mastery experiences (Bandura, 1997). The prominence of gender variables opens an important cross-cultural research agenda, particularly regarding whether differences in locus of control and need for cognitive closure mediate patterns of AI dependency. Drawing on learned helplessness theory (Seligman, 1975), sustained exposure to instantaneous AI-generated answers risks creating conditions in which students progressively lose the motivation to engage with cognitive challenges independently, a condition that requires a psychoeducational response grounded in a cognitive-behavioral approach, rather than technological regulation alone.

Theoretically, there is an urgent need to develop conceptual frameworks that distinguish AI dependency from related constructs such as automation bias, digital dependence, and technology addiction. Methodologically, the field would benefit considerably from longitudinal studies, experimental designs, and mixed-methods approaches. Contextually, comparative studies across cultural settings and educational levels are necessary given the dominance of Asian contexts in the existing literature.

Policy implications are equally significant. Educational institutions require evidence-based guidance to promote responsible AI use without inhibiting its potential benefits. Faculty development programmes need to equip educators with strategies for designing learning experiences in AI-rich environments, and assessment practices need to be reviewed to reduce incentives for excessive reliance on AI-generated content. This study acknowledges several limitations. Its focus on Scopus and English-language publications risks excluding relevant research from other databases or published in other languages. The short time window, inherent to the novelty of the topic, limits the ability to identify long-term trends. Furthermore, bibliometric methods capture publication patterns and thematic linkages, but do not directly assess the quality or theoretical depth of individual studies (Baas et al., 2020).

4. Conclusion

This study successfully mapped the research landscape of AI dependency in education through a bibliometric approach, addressing all three stated research objectives. First, the field is demonstrably in a phase of exponential growth driven by the emergence of generative AI, confirming that AI dependency has become a rapidly expanding global research priority. Second, the intellectual structure of this domain is inherently multidisciplinary, integrating perspectives from psychology, educational technology, linguistics, and behavioural science, though the fragmented collaboration network indicates that the field has not yet reached structural maturity. Third, AI dependency as a theoretically autonomous construct remains at an early stage of conceptual development, confirming the urgency for more targeted scholarly inquiry. Taken together, the findings affirm that AI dependency is fundamentally a psychological and cognitive phenomenon that requires active contributions from educational and clinical psychology. Future research should prioritise the development of standardised conceptual frameworks, valid psychometric instruments, and longitudinal as well as cross-cultural comparative studies. Furthermore, the role of educators in mediating student interactions with AI represents a critically underexplored dimension that holds considerable potential for future investigation.

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