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ARTIFICIAL INTELLIGENCE DEPENDENCY AND COGNITIVE OFFLOADING AMONG UNIVERSITY STUDENTS: A PRISMA-BASED SYSTEMATIC REVIEW

[1]Dr. Mohammad Akram, [2]Fayize P V
[1]Assistant Professor, Faculty of Education, Desh Bhagat Uuniversity, Mandi Gobindgarh
[2]Research scholar, Faculty of Education, Desh Bhagat Uuniversity, Mandi Gobindgarh
Corresponding Author: Fayize P V, Corresponding Email: fayizepv@gmail.com

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Abstract

The rapid adoption of artificial intelligence (AI) in higher education has transformed student learning behaviors and engagement patterns. While AI tools enhance efficiency and reduce cognitive load, concerns have emerged regarding cognitive offloading and potential dependency. This PRISMA-based systematic review synthesized findings from 16 peer-reviewed studies published between 2015 and 2026. Results indicate that students increasingly delegate cognitive tasks such as memory retrieval, idea generation, and problem-solving to AI systems. High reliance was associated with reduced analytical depth, automation bias, and lower metacognitive monitoring. However, structured and reflective use of AI was found to mitigate these negative effects. Memory outcomes varied depending on the level of cognitive engagement. The review also highlights a significant gap in the lack of standardized measures for AI dependency. Overall, AI functions as both a cognitive support tool and a potential source of dependency, emphasizing the need for balanced integration and further research on long-term cognitive effects.

Keywords: *Artificial intelligence, AI dependency, cognitive offloading, generative AI, higher education, critical thinking, cognitive load, metacognition*

Introduction

The integration of artificial intelligence (AI) into higher education has significantly transformed academic environments. Tools such as generative AI systems and automated assistants are increasingly used by university students for tasks including writing, summarization, and problem-solving. While these technologies enhance efficiency and accessibility, concerns are emerging regarding their cognitive and psychological effects. Unlike traditional tools that primarily support information retrieval, generative AI systems perform higher-order functions such as reasoning and synthesis. This raises important questions about whether students are merely offloading memory tasks or increasingly delegating analytical thinking processes. Research on automation bias suggests that users may over-rely on AI-generated outputs, potentially reducing critical evaluation and independent reasoning. AI reliance may also extend beyond functional use to psychological dependency, influencing confidence, motivation, and self-regulation. Despite growing interest, current research remains fragmented, with inconsistent findings regarding cognitive outcomes and a lack of standardized measures for AI dependency. This systematic review aims to synthesize existing literature on AI dependency and cognitive offloading among university students, identify conceptual gaps, and provide directions for future research. This review addresses these gaps by offering a structured integration of empirical findings and theoretical perspectives.

Aim of the Study

The primary aim of this systematic review is to synthesize existing empirical and theoretical literature examining the relationship between artificial intelligence dependency and cognitive offloading among university students.

Research Objectives

This study seeks to:

1. Identify how artificial intelligence dependency is defined and operationalized in higher education research.
2. Examine patterns of cognitive offloading behaviors associated with AI use among university students.
3. Analyze cognitive outcomes linked to AI dependency, including memory retention, critical thinking, and metacognitive engagement.
4. Evaluate the theoretical frameworks used to explain AI-mediated cognitive processes.
5. Identify research gaps and methodological limitations within the existing literature

Research Questions

Based on the objectives, the review addresses the following research questions:

1. How is artificial intelligence dependency conceptualized and measured in current research involving university students?
2. What forms of cognitive offloading are associated with AI usage in academic contexts?
3. What cognitive and psychological outcomes are linked to AI dependency?
4. Does existing evidence suggest that AI reliance enhances or diminishes critical thinking and learning processes?
5. What theoretical frameworks best explain the relationship between AI use and cognitive offloading?

Theoretical Framework: The relationship between artificial intelligence dependency and cognitive offloading can be understood through multiple theoretical perspectives drawn from cognitive psychology, human–computer interaction, and educational theory. Integrating these frameworks provides a comprehensive understanding of how AI technologies may reshape cognitive processes among university students.

Extended Mind Theory: Extended Mind Theory (Clark & Chalmers, 1998) proposes that cognitive processes are not confined to the biological brain but may extend into external tools when these tools are consistently and reliably used. In educational contexts, generative AI systems may function as advanced cognitive extensions by assisting students in reasoning, writing, and problem-solving tasks. Unlike traditional tools, AI systems actively generate responses and structure information, thereby participating in higher-order cognition. However, when reliance becomes excessive, cognitive extension may shift toward dependency, potentially reducing independent cognitive engagement and cognitive autonomy.

Cognitive Offloading Theory: Cognitive offloading refers to the use of external tools or actions to reduce internal cognitive demands (Risko & Gilbert, 2016). Individuals tend to offload tasks when cognitive load is high or when external tools offer greater efficiency. Empirical research shows that the availability of external storage reduces internal encoding efforts (Sparrow et al., 2011). In AI-assisted environments, offloading extends beyond memory to include reasoning, idea generation, and problem structuring. While this enhances efficiency, repeated reliance on AI outputs may reduce deep processing and weaken metacognitive monitoring if learners engage passively with AI-generated outputs.

Automation Bias and Over-Reliance: Automation bias describes the tendency to over-rely on automated systems and favor their outputs over independent judgment (Parasuraman & Riley, 1997; Parasuraman & Manzey, 2010). In academic contexts, this may lead students to accept AI-generated responses without sufficient verification, even when inaccuracies are present. Such over-reliance may reduce cognitive vigilance and analytical evaluation. As AI systems often present information in structured and authoritative formats, they may increase perceived credibility, further reinforcing dependence.

Transactive Memory Systems: Transactive Memory Theory (Wegner, 1987) explains how individuals distribute cognitive responsibilities across external systems. In digital environments, technology increasingly functions as a transactive memory partner. AI tools may serve this role by allowing students to rely on external systems for information retrieval rather than internal storage. However, unlike human transactive systems, AI lacks reciprocal interaction and shared responsibility, which may limit deeper cognitive processing and engagement with knowledge.

Cognitive Load Theory: Cognitive Load Theory (Sweller, 1988) distinguishes between intrinsic, extraneous, and germane cognitive load. AI tools can reduce extraneous load by simplifying tasks such as information search and content organization, thereby improving efficiency. However, if AI use reduces germane load-the effort required for meaningful learning and schema development-students may engage less in deep processing. Therefore, effective AI integration must balance cognitive support with active engagement to ensure that efficiency gains do not compromise deep learning.

Method: Study Design and Reporting Framework

This study employed a systematic review methodology guided by the PRISMA 2020 framework to ensure transparency and methodological rigor. A systematic approach was appropriate given the rapidly expanding yet conceptually fragmented literature on AI dependency and cognitive offloading across disciplines. The review aimed to provide a structured synthesis while minimizing selection bias. The following sections describe the search strategy, selection process, and data analysis procedures.

Search Strategy Development: A structured search strategy was developed using Boolean operators (AND, OR) by combining keywords related to artificial intelligence, dependency, and cognitive processes. Key terms included "Artificial Intelligence," "Generative AI," "ChatGPT," "AI dependency," "cognitive offloading," "automation bias," "critical thinking," "metacognition," and "higher education." Example search string: ("Artificial Intelligence" OR "Generative AI" OR "ChatGPT") AND ("AI dependency" OR "Cognitive offloading") AND ("Higher education") retrieved were conducted between January 2023 and February 2026.

Information Sources: Studies were identified from Scopus, Web of Science, PsycINFO, PubMed, and Google Scholar to ensure comprehensive interdisciplinary coverage. Additionally, reference lists of included studies were manually screened using a snowballing technique.

Eligibility Criteria

Inclusion Criteria:

- Peer-reviewed articles (2015–2026)
- English language
- Focus on AI use in educational contexts
- University or higher-education samples
- Measured cognitive, psychological, or academic outcomes

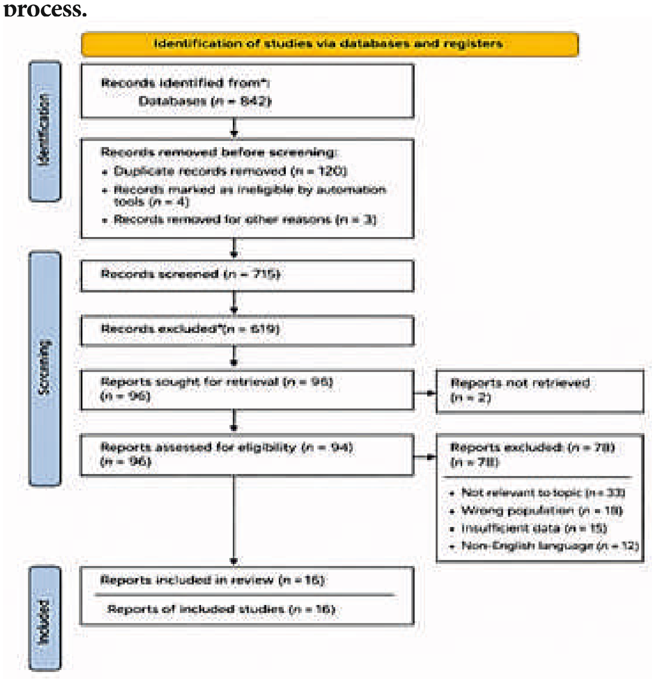
Exclusion Criteria:

- Technical AI development studies
- School-level samples
- Non-peer-reviewed sources
- Studies without cognitive or psychological variables

Duplicate records

Screening and Selection Process: All records were imported into reference management software, and duplicates were removed prior to screening. The selection process followed three stages: title screening, abstract screening, and full-text assessment based on predefined inclusion and exclusion criteria. Discrepancies were resolved through discussion to ensure consistency and reliability

Figure 1. PRISMA 2020 flow diagram of the study selection process.



Data Extraction Procedure: A standardized data extraction sheet was used to systematically record key information from included studies. Extracted variables included author details, country, study design, sample characteristics, type of AI tool, operationalization of AI dependency, cognitive and academic outcomes, key findings, and theoretical frameworks. This ensured consistency in data collection and comparison across studies.

Quality Appraisal: Methodological quality was assessed based on research design clarity, measurement validity, sample adequacy, statistical rigor, and reporting transparency. Studies were categorized as high, moderate, or low quality to guide interpretation of findings.

Data Synthesis Approach: Due to heterogeneity in study designs and measurement approaches, a narrative synthesis was conducted rather than a meta-analysis. Findings were grouped into thematic categories, including AI dependency, cognitive offloading, memory effects, critical thinking, automation bias, and academic performance. The synthesis focused on identifying common patterns, inconsistencies, and research gaps.

Results

Study Selection and Publication Trends: The systematic search identified 842 records across five databases. After removal of 127 duplicates, 715 titles and abstracts were screened. A total of 96 full-text articles were assessed for eligibility, of which 16 studies met the inclusion criteria. Most studies (n = 11) were published between January 2025 – February 2026, reflecting the rapid emergence of generative AI tools such as ChatGPT. Earlier studies (2018–2021) primarily focused on digital offloading and algorithmic systems. This distribution indicates that research on AI dependency remains recent and rapidly evolving.

Study Characteristics

- The included studies demonstrated methodo logical diversity in design, sample characteristics, and geographic distribution (see Table 1). Cross-sectional studies (43.8%) were the most common, followed by experimental and mixed-method designs.
- The combined sample size exceeded 5,200 participants, with individual samples ranging from 78 to 1,240 students. Most participants were undergraduate students. Studies were conducted across North America, Europe, and Asia, reflecting the global adoption of AI tools in higher education.

Table 1

No	Author (Year)	Country	Design	Sample (N)	AI Tool	Cognitive Outcome	Key Findings
1	Gerlich (2025)	Germany	Cross-sectional	312	Generative AI	Critical Thinking	Higher AI use linked to reduced analytical depth
2	Tian (2025)	China	Survey	450	ChatGPT	AI Dependency	AI dependence associated with cognitive fatigue
3	Nasr (2025)	UAE	Mixed-method	210	ChatGPT	Critical Thinking	AI use reduced independent reasoning
4	Al-Mamary (2025)	Yemen	Survey	380	ChatGPT	Academic Performance	Improved performance but reliance increased
5	Shuhaiber (2025)	Jordan	Survey	420	Generative AI	Adoption Behavior	High adoption influenced by ease of use
6	Mosoi (2025)	Romania	Experimental	120	AI Tool	Problem-solving	Faster solutions but reduced cognitive effort
7	Hassan (2026)	Malaysia	Experimental	150	AI Learning Tool	Engagement	AI increased engagement but reduced deep learning
8	Baines (2026)	UK	Experimental	90	ChatGPT	Academic Writing	Improved output quality but less originality
9	Shishakly (2025)	USA	Survey	600	ChatGPT	Academic Performance	Increased efficiency with shallow processing
10	Blahopoulou (2025)	Greece	Survey	340	Generative AI	Perception	Students reported dependency on AI tools
11	Farnon (2025)	Sweden	Survey	270	ChatGPT	Adoption	Trust in AI influenced usage patterns
12	Rabidi (2025)	Lebanon	Survey	310	ChatGPT	Learning Behavior	AI reliance reduced independent effort
13	Fajt (2025)	Czech Republic	Mixed-method	180	ChatGPT	Attitudes	Positive attitudes with concerns about overuse
14	Mo (2025)	China	Experimental	140	AI Tool	Learning Outcomes	AI improved performance but reduced retention
15	Owan (2025)	Nigeria	Cross-sectional	520	ChatGPT	Usage Behavior	High frequency use linked to dependency patterns
16	Martin-Alguacil (2025)	Spain	Experimental	110	ChatGPT	Critical Thinking	Guided AI use improved reasoning skills

Characteristics of Included Studies (N = 16)

Conceptualization of Artificial Intelligence Dependency: A key finding is the lack of standardized conceptualization of AI dependency (see Table 2). None of the included studies employed validated psychometric instruments; instead, dependency was inferred through indicators such as usage frequency, self-reported reliance, trust in AI outputs, and task delegation (Gerlich, 2025; Tian, 2025; Owan, 2025). This reflects an early-stage construct similar to early internet addiction research (Kuss & Griffiths, 2017). Several studies framed AI reliance in terms of automation bias, where users favor automated outputs over independent judgment (Parasuraman & Riley, 1997). However, most studies did not clearly distinguish between functional reliance and psychological dependency, indicating a need for standardized measurement frameworks.

Table 2: Operationalization of AI Dependency

Indicator	Description
Usage Frequency	Frequency of AI tool usage
Self-reported Reliance	Perceived dependence on AI
Trust in AI Outputs	Acceptance without verification
Task Delegation	Offloading cognitive tasks
Perceived Indispensability	Feeling unable to perform without AI

Cognitive Offloading Patterns: All included studies reported cognitive offloading behaviors, with students relying on AI tools to reduce cognitive effort (Gerlich, 2025; Tian, 2025; Nasr, 2025; Owan, 2025). Commonly offloaded tasks included memory retrieval, text generation, idea development, and problem-solving. Experimental findings showed reduced independent reasoning and fewer self-generated responses in AI-assisted conditions, consistent with Cognitive Offloading Theory (Risko & Gilbert, 2016). These results indicate that generative AI extends offloading beyond memory to higher-order cognitive processes.

Memory and Encoding Depth: Four studies examined memory outcomes, with most reporting reduced recall performance when students relied on AI-generated summaries (Mo, 2025; Martín-Alguacil, 2025). This was attributed to lower encoding depth, consistent with the "Google effect" (Sparrow et al., 2011). However, improved conceptual understanding was observed when AI use required active engagement, supporting Cognitive Load Theory (Sweller, 1988). These findings suggest that memory outcomes depend on level of cognitive involvement.

Critical Thinking and Analytical Depth: Eight studies examined critical thinking, with six reporting reduced analytical depth under high AI reliance (Gerlich, 2025; Nasr, 2025; Baines, 2026). Eight studies examined critical thinking outcomes (see Table 3), with six reporting reduced analytical depth under high AI reliance. Students frequently engaged in surface-level editing rather than deep reasoning. Evidence of automation bias was observed, where students accepted AI outputs without verification (Parasuraman & Manzey, 2010). However, structured AI use improved reasoning in some cases (Martín-Alguacil, 2025), indicating that instructional design moderates outcomes.

Table 3
Cognitive and Psychological Outcomes

Variable	No. of Studies	Main Trend
Critical Thinking	8	Declines under high reliance
Memory Retention	4	Reduced with passive use
Metacognition	5	Lower monitoring
Cognitive Load	6	Reduced effort
Problemsolving	3	Faster but shallow
Academic Performance	5	Short-term improvement

Metacognitive Calibration: Five studies reported that high AI users exhibited overconfidence and reduced monitoring, indicating distorted metacognitive calibration (Blahopoulou, 2025; Fajt, 2025). However, moderate AI use combined with reflective scaffolding improved awareness of reasoning gaps, suggesting that AI can both hinder and support self-regulation depending on usage patterns.

Cognitive Load and Efficiency Trade-Offs: Six studies found that AI tools reduced cognitive load and increased efficiency, enabling faster task completion (Moșoi, 2025; Hassan, 2026). However, reduced effort may also limit deep processing (germane load) (Sweller, 1988), creating an efficiency–depth trade-off where improved performance may come at the cost of reduced learning depth.

Academic Performance Outcomes: Five studies reported improvements in short-term academic performance, including task accuracy and writing quality (Al-Mamary, 2025; Shishakly, 2025). However, these gains were not consistently linked to deeper conceptual understanding, suggesting that heavy reliance on AI may reduce independent cognitive engagement.

Integrated Synthesis: Across all 16 studies, findings indicate that AI dependency remains under-theorized, while cognitive offloading is consistently observed (Gerlich, 2025; Tian, 2025; Owan, 2025). Evidence suggests that passive AI use may reduce memory retention and critical thinking (Sparrow et al., 2011; Parasuraman & Manzey, 2010), whereas structured use can mitigate these effects. Overall, AI functions as both a cognitive support system and a potential source of dependency, depending on usage patterns. A thematic summary of these findings is presented in Table 4.

Table 4: Summary of Key Findings

Theme	**Summary**
Cognitive Offloading	Widely observed across studies
Critical Thinking	Reduced with high AI use
Memory	Lower retention with passive use
Metacognition	Overconfidence in AI outputs
Cognitive Load	Reduced but less deep learning
Performance	Improved short-term outcomes

Discussion

The present review of 16 studies indicates that artificial intelligence (AI) in higher education functions as both a cognitive support system and a potential source of cognitive dependency. Across studies, AI tools consistently improved efficiency by reducing cognitive load, enabling faster task completion, and supporting academic performance. These findings align with Cognitive Offloading Theory, which suggests that individuals use external tools to reduce internal cognitive demands (Risko & Gilbert, 2016). However, the findings also reveal important cognitive trade-offs. Under conditions of high reliance, students demonstrated reduced independent reasoning, lower analytical depth, weaker memory encoding, and diminished metacognitive monitoring. These patterns suggest that while AI enhances performance efficiency, it may also limit deeper cognitive engagement when used passively.

A key shift identified in this review is the expansion of cognitive offloading from memory-based tasks to higher-order cognitive processes, including reasoning, idea generation, and problem-solving. Unlike traditional digital tools, generative AI actively produces structured responses, effectively functioning as a cognitive extension (Clark & Chalmers, 1998). However, when reliance becomes excessive, this extension may shift toward cognitive substitution, where AI replaces rather than supports core thinking processes. This transition highlights a continuum from cognitive support to dependency, emphasizing the need to distinguish adaptive use from over-reliance.

The findings also demonstrate the role of automation bias, where students tend to trust AI-generated outputs without sufficient verification (Parasuraman & Manzey, 2010). This can reduce critical evaluation and analytical engagement, particularly in unstructured learning environments. However, studies incorporating reflective prompts and guided interaction showed that such negative effects can be mitigated. This suggests that instructional design is a key moderating factor, influencing whether AI supports or undermines cognitive development.

From a cognitive perspective, AI use appears to influence both critical thinking and metacognitive processes. High reliance was associated with surface-level engagement and overconfidence in AI-generated responses, indicating distorted metacognitive calibration (Bjork et al., 2013). At the same time, structured use of AI encouraged evaluative thinking and improved awareness of reasoning gaps. Similarly, findings related to Cognitive Load Theory indicate that while AI reduces extraneous cognitive load, it may also reduce germane load if learners disengage from deep processing (Sweller, 1988). This creates an efficiency-depth trade-off, where improved speed and convenience may come at the cost of reduced conceptual understanding.

Another important issue identified is the lack of standardized measurement of AI dependency. Most studies relied on indirect indicators such as frequency of use or trust in AI outputs, limiting conceptual clarity and comparability. This reflects a stage similar to early internet addiction research (Young, 1998), highlighting the need for validated multidimensional scales to assess behavioral, cognitive, and psychological aspects of AI reliance.

Overall, the findings suggest that AI should be understood as a cognitive amplifier, with effects shaped by the degree of reliance, nature of academic tasks, and level of student engagement. When used in a structured and reflective manner, AI can enhance learning and support cognitive processes. However, when used passively, it may lead to cognitive substitution and dependency. Therefore, the impact of AI in education depends not on the technology itself but on how it is integrated into learning environments. Developing clear theoretical frameworks and effective pedagogical strategies will be essential to ensure that AI supports rather than undermines higher-order cognitive functioning.

Limitations

This review has several limitations that should be considered when interpreting the findings.

- Inclusion limited to English-language, peer-reviewed studies (2015-2026), potentially excluding relevant research from other sources.
- Predominance of cross-sectional study designs, restricting conclusions about long-term cognitive effects.
- Lack of standardized measures for AI dependency, with reliance on indirect indicators (e.g., usage frequency, self-reports).
- Samples largely composed of undergraduate students, limiting generalizability to other populations and contexts.
- Rapid evolution of AI technologies, meaning earlier findings may not reflect current or future systems

Conclusion

This systematic review highlights that artificial intelligence (AI) in higher education serves as both a cognitive support and a potential source of dependency. While AI tools improve efficiency, reduce cognitive load, and enhance short-term performance, excessive reliance may lead to reduced critical thinking, weaker memory encoding, and diminished metacognitive engagement. The findings suggest that AI is not inherently detrimental; rather, its impact depends on how it is used. Structured and reflective integration of AI can support learning, whereas passive reliance may result in cognitive substitution. A major gap remains the lack of standardized measures of AI dependency, which limits theoretical and empirical development. As AI continues to expand in educational contexts, it is essential to balance cognitive augmentation with independent thinking, ensuring that AI enhances rather than replaces core cognitive processes.

Conflict of Interest

The author declares no conflict of interest.

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