Awareness of Artificial Intelligence and its Potential Usability in Higher Education - Systematic Literature Review

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Abstract. This study aims to explore the rapidly changing technology of Artificial Intelligence (AI) and its relationship with Higher Education (HE). This profound technology has become a significant part of everyday life with the emergence of generative AI (GenAI) such as ChatGPT. In recent years, this has also imploded in the life of HE, which was not ready for it and has still not adapted properly. The research is a systematic literature review whose primary objective is to explore current studies to date and determine the current state of understanding of this technology within the higher education system and the level of adaptation of AI tools. This systematic review of the literature categorizes previous studies based on three conditions stated in the different studies: (1) the level of understanding and awareness of the technology by students, (2) the level of knowledge and acceptance of AI by higher education faculty, and (3) the proposed or implemented solution. The field is changing rapidly; therefore, most previous research is outdated, although those included in the review were mainly published in the last 4 years. The success of this technology's proper application depends on the understanding and education of HE faculty and students. Furthermore, the study reveals gaps in previous research, which mostly reached the same conclusion: that higher education in an uncontrolled environment is characterized by these tools becoming a significant part, with limited solutions to this problem.

Keywords: Systematic literature review, Artificial intelligence, Higher education, Artificial intelligence awareness, Digital well-being

1 Introduction

The evolution of information technology has given rise to successive generations of artificial intelligence models. The earliest "if...else..." statements were limited in their ability to create decisions based on pre-determined and hard-coded conditions. These conditions were straightforward to formulate in controlled environments, but challenging and often impossible to implement in a multivariable industrial context.

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Contemporary neural networks, the most advanced AI models, are complex to develop but process the capacity to adapt and learn in real-time, effectively processing new data. Gen AIs emerge from the collaborative and synchronized efforts of multiple AI models. The advent of novel AI models, such as ChatGPT, has profoundly integrated technology into daily life, thereby enhancing the performance of individuals who utilize it. Concurrently, this integration has given rise to numerous challenges in the context of institutional regulations.

This innovative technology rapidly became a part of everyday life due to its ability to adapt to any environment and solve monotone problems with greater efficiency than humans. The integration of this technology into the fabric of daily life has become a pervasive phenomenon, manifesting in the ubiquity of smart devices. These devices have become indispensable tools, offering a range of functionalities aimed at simplifying and enhancing our daily lives. Their ability to address mundane tasks autonomously has significantly reduced the burden on individuals, allowing them to focus on more complex or creative endeavors. (Haenlein & Kaplan, 2019)

It is an integral component of the educational experience, facilitating learning processes and enhancing personal efficacy. Given the rapid growth and evolution of this technology, the implementation of centralized regulations is imperative. However, the cumbersome regulatory process enables the advancement of local policies. The unregulated use of artificial intelligence (AI) in education has given rise to a multitude of issues, particularly in higher education (HE). These issues include plagiarism and the production of AI-generated texts that are increasingly difficult to distinguish from those created by humans. This situation has led to significant challenges for educators, exacerbating the already difficult nature of their work. A multitude of studies have identified these issues; however, the measures that can be implemented to address them remain unclear. (Krstić et al., 2022)

The objective of this study is to ascertain the responses to the following research questions (RQ):

RQ1: How intensely is the topic of "the relations between AI and HE" being investigated in the scientific research?

RQ2.1: What exactly is the current level of awareness of AI among students according to the found literature?

RQ2.2: What exactly is the current level of awareness of AI among HE faculties according to the found literature?

RQ3: What solutions are implemented or suggested by researchers if there are any?

The remaining sections of the study are organized as follows. The following is a synopsis of the history of artificial intelligence, accompanied by a literature review that elucidates the methodology and a collection of standardized literature. The following sections present the findings, discussion, and conclusion. The findings are discussed, followed by suggestions for future studies.

2 Backgrounds

Artificial intelligence has been around since the 20th century, and it has a rich history even though the technology is not older than 60 years. The following paragraph will give a brief insight into the history of technology. Its past could be sectioned into 4 period, “AI Spring: The Birth of AI”, “AI Summer and Winter: The Ups and Downs of AI”, “AI Fall: The Harvest”, “The Present: California Management Review”. (Haenlein & Kaplan, 2019)

2.1 AI Spring

The precise time and date when the bases of AI were set is unknown, the only sure is that it was somewhere in the early 1950’s. The first mention of the word Artificial Intelligence was in the Darthmouth proposal about Artificial Intelligence (DPAI) which was an eight week-long research conference about Artificial Intelligence held . (Chao et al., 2020)

2.2 AI Summer and Winter

In the following years after the DPAI almost for two decades, the field of Artificial Intelligence was significantly researched and greatly improved. The first significant breakthrough was ELIZA, which was the first natural language tool that came close to passing the Turing test. (TURING, 1950)

In 1973, the United States Congress began critiquing the substantial federal funding devoted to artificial intelligence (AI) research, prompted by reports and concerns over exaggerated progress claims, which precipitated the first AI winter (1974–1980). This skepticism intensified after the United Kingdom discontinued public support for AI projects, leading the U.S. to similarly reduce its investments. Despite Japan's government substantially escalating AI funding in the 1980s via the ambitious Fifth Generation Computer Systems initiative, the U.S. Defense Advanced Research Projects Agency (DARPA)—established in 1958 amid the Cold War as the Department of Defense's premier research and development entity—countered with its Strategic Computing Initiative (1983–1993), yet these concerted efforts failed to yield transformative breakthroughs in the ensuing years, underscoring the era's persistent challenges in achieving general AI advancements.

2.3 AI Fall

The fall back in progression in the early state of AI development was caused by the way they tried to replicate human intelligence. The main base of these so-called Expert Systems was “if-then” statements which assumed every action can be formalized and solved by using top-down approach. One of the most famous machines using this approach was IBM’s - International Business Machines Corporation, which is a U.S.

based International technological company - Deep Blue chess playing program which was able to beat the world champion Gary Kasparov in 1997. (Campbell et al., 2002)

These machines were able to perform tasks that could be formulated according to the set rules, but they performed poorly in areas that do not give opportunities to be formalized like others, such as complex multivariable environments and tasks such as distinguishing a muffin from a Chihuahua on pictures. For such tasks it is necessary that the system is capable of extracting data correctly from given datasets and use them to generalize a solution for each problem individually. (Hutson, 2018)

The artificial neural networks gain importance in 2015 when google released a deep learning algorithm named AlphaGo, that was able to beat the world champion in the board game Go. (Silver et al., 2016) Go is a far more complex game than chess while the second has only 20 possible opening moves, the one mentioned before has 361 moves for first, which is why it was long believed that no computer program will be able to play it effectively not to mention beating a human in the game. AlphaGo achieved this performance by using a type of neural network called Deep Learning. (Janiesch et al., 2021)

2.4 Present

The paragraphs above make it clear that Ai has become a part of our life just like the social media in previous years. The main question is not whether AI will have any effect on our life and if it will make a part of the lives of companies and institutions, but rather how the humans and corporations will adjust and how these systems will work together with humans. On of the questions is what will bring the future and how these systems will reshape the society and job market. (Vochozka et al., 2018) How will and how should the education system adapt to this new and changed environment of present days. In the following sections this will be the main topic to find answers to.

3 Systematic Literature Review

. In accordance with the objectives of this research, a systematic literature review was conducted. For this purpose, the well-known Prisma model, which has been used in numerous other reviews, was applied. (Page et al., 2021) The foundation of the model is based on a checklist to categorize the sources and a diagram to differentiate and organize the collected studies.

In the first period keywords were identified according to the scope of the research. The following terms were chosen “AI”; “Artificial Intelligence”; “machine learning”; “Awareness”; “Higher Education”. After that, advanced Boolean queries were established according to the previous terms for Scopus and Web of Science (WoS) databases which can be seen below in Table 1. Quarries.

Table 1. Quarries

Scopus	TITLE-ABS-KEY ("artificial intelligence" OR "AI" OR "machine learning") AND TITLE-ABS-KEY ("Awareness") AND TITLE-ABS-KEY ("Higher" AND "Education")
Web of Science	TS = ("artificial intelligence" OR "AI" OR "machine learning") AND TS = ("Awareness") AND TS = ("Higher Education")

To maintain close relation with computer science and the practical applications, a filter was implemented with the objective of including only those relevant to the field of computer science. Concurrently, a filter was implemented for temporal constraints on the publication date, with the aim of ensuring the relevance of the findings, the restriction only allowed those research that has been conducted between 2015 and 2025. Furthermore, the implementation of additional criteria filter was required to ensure that the findings were limited to those derived from the final state of conference papers and articles. Language restrictions were not necessary arising from the nature of the field researched. The number of findings after each restriction is shown in Table 2. Findings arranged by the databases used to find them.

Table 2. Findings

Database	Total results	Published final conference papers and articles	On the field of Computer science	Year 2015-25
Scopus	335	268	113	109
Web of Science	125	119	36	36
Total	460	387	149	145

The initial search yielded a total of 460 results, including 335 from the Scopus database and 125 from the Web of Science. Following the application of the initial filter, which was designed to identify conference papers and articles in the final stage, the number of results was reduced to 387. Follow-up criteria were applied to narrow the results to those conducted in the field of computer science and published within the last decade; this reduced the total to 145 documents. After the application of all the criteria, a preliminary review of the titles and abstracts was conducted to identify relevant documents. This step resulted in the selection of 49 documents for further consideration. Following a preliminary analysis, a comprehensive review was conducted to identify the relevant documents, resulting in the exclusion of 20 documents. This process ultimately led to the inclusion of 29 documents in the final research study. The flow diagram of the inclusions and exclusions according to the Prisma model is shown in Figure Fig. 1. Prisma Diagram - (Page et al., 2021)

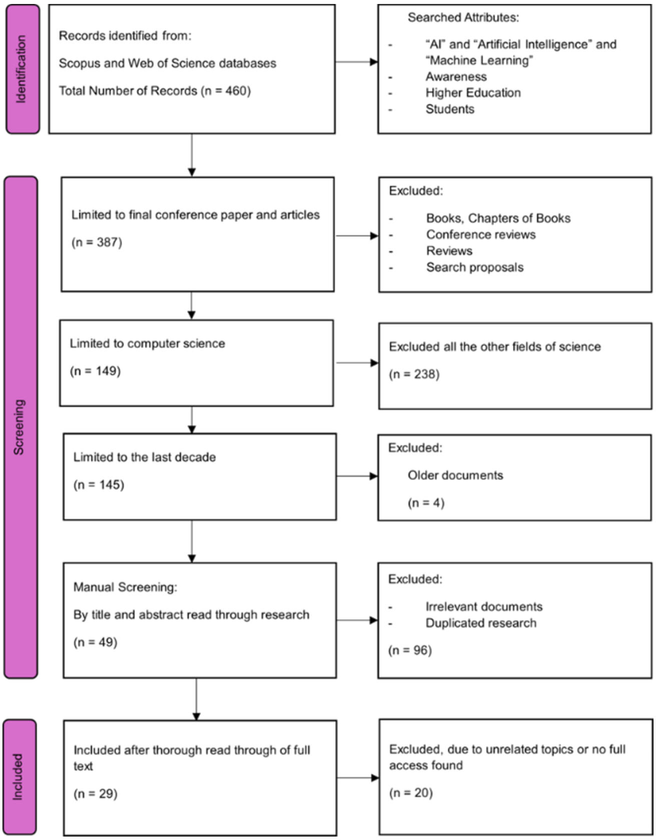

Fig. 1. Prisma Diagram - (Page et al., 2021)

Most of the findings are only focusing on the GenAI and its usability and the problems arising from its adoption, which generally creates a huge gap in the knowledge about the other AI tools used these days. These findings are mostly outdated not by the year they were written in but by the point of view they research this technology which is one of the fastest evolving even in informatic context too, which is a rapidly evolving field of science. Most of the articles are only useable for references to have bases for changes in this technology.

4 Findings

During the systematic review, there were several complicating factors, the most important of which was the rapid evolution of technology, which made even research done within a year outdated. Most of them used data from 2023, which is no longer relevant, and used versions of technologies that are no longer current. All of this made all the inclusions theoretical, only to be referenced in future research as examples of what has changed. The field of connection between education and AI is a researched field, having numerous articles written about. (Guan et al., 2020) But HE as a restricted topic is much less researched and there are smaller number of articles written about.

The research was designed to answer the following questions:

4.1 RQ1: How intensely is the topic of "the relations between AI and HE" being investigated in the scientific research?

The field is relatively new, which is one of the reasons for its under research, the other reason is that the technology is changing rapidly which makes any research outdated within a year or so. All this makes it hard to research properly and all the studies are focused trying to find out the current level of awareness which is changing with the evolution of AI. The field still has many gaps in its research, although there are several new studies conducted every month in the topic. Most of the current research is conducted in eastern countries rather than in the western, which trend is rather unusual in terms of its being an IT topic. (Crompton & Burke, 2023)

4.2 RQ2.1: What exactly is the current level of awareness of AI among students according to the found literature?

Of the 29 included studies, almost all gave an answer to this question. In these studies, it can be observed that the older the publication date, the less relevant and accurate the answer. For this question, the studies could be categorized in two ways.

4.3 By acceptance and awareness level

They could be classified into three group, mostly those written more than one year ago "low acceptance and low awareness", the following two class is commonly mentioned in studies not older than one year "low awareness, but high acceptance", "high acceptance and high awareness". In Table 3. Awareness, acceptance level you can see the fourteen article that could be put into these three categories.

Table 3. Awareness, acceptance level

low acceptance and low awareness	low awareness, but high acceptance	high acceptance and high awareness
(Wang et al., 2023)	(Bae et al., 2024)	(Shahzad et al., 2024)
(Chao et al., 2020)	(Krupp et al., 2024)	(Almassaad et al., 2024)
	(Alharbi, 2024)	(Sarwanti et al., 2024)
	(Sokele et al., 2024)	(Sova et al., 2024)
	(Gouveia et al., 2023)	(Tick, 2024)
	(Syzdykbayeva et al., 2021)	(Stöhr et al., 2024)
		(Balahadia et al., 2023)

4.4 By the impact of AI tools on students' lives.

Earlier studies only mention the negative impact on students' lives by lowering their level of critical thinking. There are newer studies that mention positive impact, some even opposite to those earlier ones that AI helps improve creative and critical thinking, but most mention brainstorming and the ease factor of these tools. There is one thing that all the studies have in common: these effects are only relevant if the tools are used correctly. Table 4. Effect on students' life below shows the distribution of the findings regarding these criteria.

Table 4. Effect on students' life

Negative effects	Positive effects
(Krupp et al., 2024)	(Shahzad et al., 2024)
(Stöhr et al., 2024)	(Almassaad et al., 2024)
(Wang et al., 2023)	(Sarwanti et al., 2024)
	(Jia & Tu, 2024)
	(Sokele et al., 2024)
	(Stöhr et al., 2024)

4.5 RQ2.2: What exactly is the current level of awareness of AI among HE faculties according to the found literature?

There are only a few studies that have addressed this question, and their conclusions fall into two groups. The older ones mainly concluded that teachers' awareness and understanding is slightly higher than students' and that they use it more frequently. (Balahadia et al., 2023) The more recent ones concluded that teachers' knowledge and acceptance has fall behind students' and that students use it more frequently. (Alharbi, 2024)However, there was a common conclusion that the level of AI ethics needs to be raised, and rules need to be established. They also agreed that future lectures and workshops are needed to improve the understanding and acceptance of this new technology. (Christian et al., 2024; Gouveia et al., 2023)

4.6 RQ3: What solutions are implemented or suggested by researchers if there are any?

The articles raised many issues, such as ethical concerns about the lack of regulation, which leads to uncertainty and plagiarism, and as technologies evolve, it is becoming increasingly difficult to distinguish between texts written by humans and those generated by artificial intelligence. This makes it harder for the authorities to correctly identify plagiarized or generated essays and gives more opportunities for students to use this as a tool to take advantage on the system by using these on not permitted ways. Not many have brought real solutions to this problem, only mentioning that institutional and governmental regulations and policies need to be put in place to control the way AI can be used at the academic level.(Bukar et al., 2024; Kamali et al., 2024; Stöhr et al.,

2024) There were some examples of the implementation of AI in the learning environment, but they were field specific which makes it almost impossible to be included in other areas of higher education.(Bukar et al., 2024; Jagadeesan et al., 2023)

5 Discussion

5.1 The Temporality of AI Perpectives: Pre- and Post-ChatGPT Divergence

A systematic analysis of the 29 reviewed studies reveals a critical temporal divide that explains apparent contradictions in the literature more robustly than claims of obsolescence. A review of studies published prior to 2023 reveals a predominant emphasis on theoretical ethical risks and speculative harms associated with artificial intelligence (AI). Prominent examples include works by Chao et al., 2020; Wang et al., 2023; and Syzdykbayeva et al., 2021. These studies position AI as a distant threat to academic integrity and critical thinking skills. Conversely, publications subsequent to the ChatGPT era (2024 dominance: As evidenced by the works of Bae et al., Alharbi, Shahzad et al., and Stöhr et al. (2024), there is an urgent need to address critical practical governance challenges, including the detection of plagiarism under technological parity, the immediate adaptation of pedagogical methods, and the absence of institutional policy. This phenomenon does not stem from a simple contrast between outdated and current research; rather, it reflects a profound paradigm shift in scholarly concern, driven by ChatGPT's qualitative leap in accessibility and capability. Prior to 2023, literature on AI addressed it as an emerging risk necessitating proactive ethical guidance. However, subsequent literature has confronted a reality that is already embedded within the system, necessitating a reactive institutional response (Figure 2).

Fig. 2. Temporal Shift in Research Concerns: Pre- and Post-ChatGPT Paradigm Transition

The temporal analysis undertaken has far-reaching implications. Earlier studies proposed generalized frameworks for AI literacy and abstract safeguards; newer work interrogates the failure of these ex-ante approaches when confronted with tools that students already possess and deploy without institutional guidance. For instance, Chao et al.'s 2020 focus on general awareness establishes a fundamental baseline; however, it does not address the particular detection and assessment challenges identified by Sokele et al. (2024) or the emergent distinction between passive awareness and active adoption documented by Balahadia et al. (2023) versus Alharbi (2024). The temporal layering of AI's integration into institutions is a distinctive scholarly contribution. The review demonstrates that this integration does not follow a linear path; rather, it follows a discontinuous path, marked by technological inflection points that reshape both the problems and the validity of proposed solutions.

5.2 Synthesizing Awareness Disparities: Drivers Beyond Simple Gaps

The findings section categorizes awareness levels into discrete groups (low awareness/low acceptance; low awareness/high acceptance; high acceptance/high awareness). However, synthesis reveals underlying systemic drivers that explain why these disparities persist. The discrepancy in awareness between students and faculty is not merely a matter of differential exposure; it reflects fundamentally misaligned incentive structures and institutional readiness constraints.

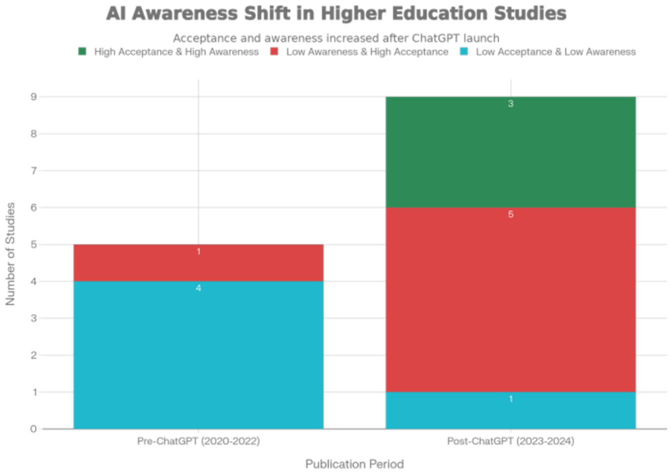

Fig. 3. Evolution of Student AI Awareness and Acceptance Across Pre- and Post-ChatGPT Literature

Student-Faculty Divergence: The relationship between generational proximity and risk tolerance warrants further investigation. In recent years, younger cohorts have begun to encounter artificial intelligence (AI) tools through consumerized interfaces, such as ChatGPT, which are designed for intuitive use. This accessibility has contributed to the rapid adoption of these tools, despite the presence of fragmented technical literacy among users. Conversely, faculty encounter dual barriers: a lack of familiarity with tool mechanics and professional vulnerability (e.g., concerns about pedagogical disruption, reputational risk if endorsing tools that are later deemed problematic). The classification presented in Table 3 indicates that studies conducted prior to 2023 document a higher level of faculty awareness compared to student awareness. Conversely, post-2023 studies demonstrate a reverse hierarchy, with student awareness surpassing that of faculty awareness. This phenomenon, however, does not necessarily indicate a decline in literary quality. Instead, it is more indicative of a compressed adoption timeline for technological tools. Students are adopting these tools at a faster rate than institutions can establish governance frameworks to regulate their use. The discrepancy identified by Alharbi (2024) cannot be resolved through generic awareness campaigns; rather, it is a structural consequence of asynchronous institutional responsiveness.

Institutional Readiness as the Underlying Constraint. Beyond the mere awareness of AI integration, its effective implementation necessitates three interconnected substrates: The technical infrastructure encompasses LMS integration and content flagging systems. Incentive alignment involves faculty rewards for ethical tool use and student consequences for misuse. Ethical literacy is supported by prompt engineering workshops and contextual decision-making frameworks. The extant literature addresses awareness (RQ2.1, RQ2.2) extensively, yet it offers few solutions (RQ3 primarily calls for regulation rather than actionable interventions). This discrepancy underscores the limitations of awareness campaigns in addressing the knowledge gap, particularly in instances where institutions lack the necessary infrastructure and incentive mechanisms to operationalize the acquired knowledge. Christian et al. (2024) and Gouveia et al. (2023) both call for "future lectures and workshops." However, they do not examine why existing institutional training frameworks have not materialized at scale, nor do they address the zero-sum dynamics. Faculty time spent in AI literacy workshops is time unavailable for disciplinary pedagogy, creating rational institutional resistance absent countervailing incentives.

5.3 The Scarcity of Practical Solutions: Systemic Fragmentation

The findings indicate a critical bottleneck: RQ3 identifies a substantial amount of problem articulation but a paucity of solution implementation. Bukar et al. (2024), Kamali et al. (2024), and Sthr et al. (2024) document ethical concerns surrounding plagiarism and regulation, yet propose only macro-level interventions (institutional/governmental policies). Conversely, Bukar et al. (2024) and Jagadeesan et al. (2023) have noted field-specific AI implementations in learning environments, yet these implementations are not universally applicable across disciplines. This discrepancy does not signify a deficiency in individual researchers; rather, it is a consequence of a mismatch in scale-disciplinarity. Solutions that are effective in domains such as engineering education, where there is an abundance of algorithm-intensive contexts, may prove to be counterproductive in humanities instruction. In humanities instruction, the application of AI gives rise to distinct risks, including stylistic homogenization. The fragmentation of higher education suggests that a universal policy is not sufficient; rather, a modular governance framework calibrated to disciplinary epistemologies is required. This finding is entirely absent from the reviewed literature.

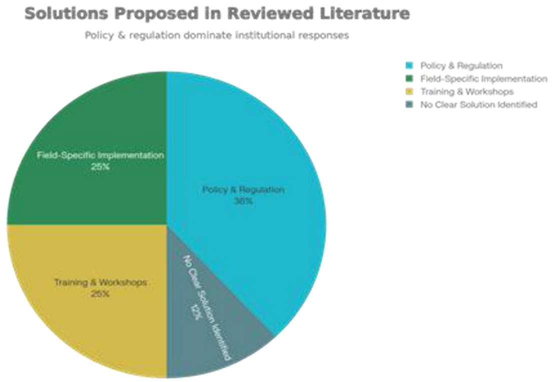

Fig. 4. Breakdown of Solution Types Proposed in the Reviewed Literature (RQ3)

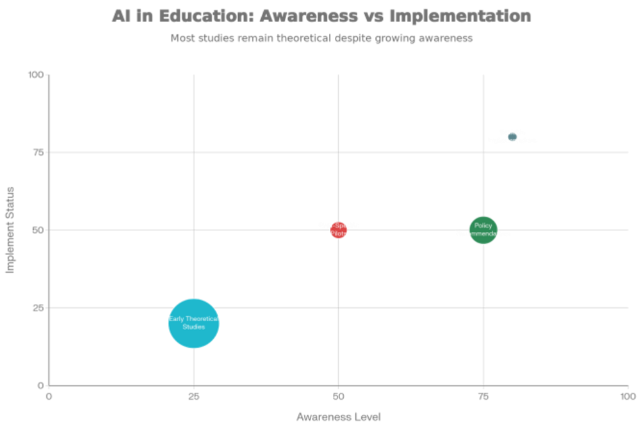

Fig. 5. Awareness-Implementation Gap: Scarcity of Scalable Solutions in the Literature

Furthermore, the predominance of Eastern-region research (as noted by Crompton & Burke, 2023) obscures Western institutional contexts, wherein faculty governance traditions, accreditation structures, and student expectations differ markedly. European and North American higher education systems have established (if legacy) processes for curricular innovation and professional development that could scaffold AI integration. However, their underrepresentation in the extant literature suggests the presence of regional blind spots in solution design.

5.4 A Nuanced Framework: Institutional Readiness, Incentive Structures, and Ethical Literacy

To move beyond awareness-centric analysis, this review synthesizes the findings into a three-dimensional framework that illuminates why awareness alone has proven insufficient:

Fig. 6. Three-Pillar Framework for Institutional AI Integration in Higher Education

Table 5. Institutional Readiness, Incentive Structures, and Ethical Literacy

Integration Factor	Definition and Current State	Key Barriers Identified in Literature	Exemplary Studies
Institutional Readiness	Technical infrastructure (detection systems, LMS integration) and policy apparatus aligned with pedagogical goals; currently fragmented across fields	Field-specific solutions not generalizable; regulatory lag; legacy systems incompatible with AI governance	Bukar et al. (2024); Jagadeesan et al. (2023)
Incentive Structures	Reward mechanisms for faculty experimentation and ethical use; consequence frameworks for student misuse; alignment of individual and institutional interests	Absent at scale; faculty anxiety outweighs adoption incentives; no recognition protocols for responsible AI integration	Christian et al. (2024); Alharbi (2024)
Ethical Literacy	Multi-layered capability spanning tool mechanics, contextual decision-making, bias recognition, and governance participation; currently segmented into awareness vs. technical competence	Workshops called for but not resourced; ethics framed as abstract principle rather than situated practice; competence-assessment absent	Kamali et al. (2024); Stöhr et al. (2024); Christian et al. (2024)

This framework transcends the conventional question, "To what extent are students and faculty aware?" and advances to a more generative inquiry: "What systemic conditions enable institutions to translate awareness into sustainable, ethically grounded practice?" The dearth of longitudinal studies that systematically monitor institutions as they navigate the integration of AI into their operations signifies a significant research deficit. Furthermore, a paucity of reviewed studies has examined the relationship between institutional readiness maturity and awareness accumulation. That is, there is a lack of research on whether awareness campaigns prove counterproductive when institutions are unable to act on the heightened awareness they aim to achieve.

5.5 Non-Obvious Research Gaps This Review Identifies

Utilizing the aforementioned framework as a foundation, this review identifies specific gaps that are obscured by a superficial evaluation of the existing literature:

1. **Technological Pluralism Neglect:** The majority of reviewed studies concentrate on generative AI (e.g., ChatGPT), thereby creating a dearth of research on other AI modalities, such as recommender systems, automated grading algorithms, and predictive student success models. These AI modalities are already embedded in numerous institutions and pose distinct governance challenges.
2. **Longitudinal Absence:** To date, no study has systematically tracked a cohort of institutions or individuals over time to examine whether awareness accumulation translates to behavioral change or institutional policy adoption. Temporal snapshots (e.g., Balahadia et al., 2023) are inadequate for discerning signal from noise in rapidly evolving adoption patterns.
3. **Cross-Cultural Governance Silence:** The predominance of Eastern frameworks, derived from collectivist, centralized education systems, over decentralized, Western models, characterized by faculty autonomy and institutional heterogeneity, underscores a significant gap in research (Crompton & Burke, 2023). The necessity for alternative coordination mechanisms in these models is evident, yet they remain under-explored.
4. **Incentive Dynamics Unexamined:** Literature offers prescriptions for solutions, such as workshops and policies, yet it does not engage with the analysis of the rational choices that faculty members must make. It is imperative to explore the reasons behind faculty members' underuse of tools designed to alleviate the grading burden. Which institutional signals give rise to adoption resistance? To the best of our knowledge, no reviewed study employs organizational behavior or economic perspectives to understand incentive failure.
5. **Circularization of Solutions:** The solutions that have been repeatedly proposed—institutional regulation and educator training—have been discussed for a decade (pre-2023 literature) without implementation progress. The question of whether these barriers are technical, political, or structural merits further investigation. The central question guiding this inquiry is whether solutions to these challenges falter due to the necessity of orchestrating activities among actors with conflicting objectives.

5.6 Toward Actionable Integration

The synthesis indicates that while awareness is necessary, it is insufficient in the absence of operational infrastructure. Institutions that aspire to transition from rhetoric to implementation must prioritize and address three key areas in a sequential manner. First, a diagnostic readiness assessment is necessary to determine which AI tools are already in use, what governance exists, and what technical capacity is available. Second, discipline-specific governance design is required, which should not be universal policy but rather modular frameworks reflecting disciplinary epistemologies. Third, incentive restructuring is necessary to ensure that ethical, integrated AI use is professionally rewarding for faculty and academically beneficial for students, rather than merely risk-minimized.

6 Conclusion

This systematic review of 29 studies reveals four key findings that enhance our understanding of AI integration in higher education. Pre-ChatGPT literature (2015–2022) treated AI as a manageable risk requiring proactive governance and ethical scaffolding. In contrast, post-ChatGPT literature (2023–2024) addresses the already-embedded reality of AI, demanding reactive institutional adaptation. This temporal shift reflects a genuine reformulation of the problem rather than a decay of the literature. Students now adopt AI tools faster than faculty, despite having lower technical literacy. This phenomenon is driven by consumerized interfaces that enable adoption without institutional gatekeeping. While 28 out of 29 studies identified governance gaps, only about 25% of them proposed field-specific implementations. The rest offered generic policy recommendations that lacked operational specificity. No studies validated the efficacy of solutions through implementation assessment. Most critically, variation in awareness across studies does not correlate with institutional governance maturity. This indicates that awareness alone is insufficient for integration readiness, which requires technical infrastructure, incentive alignment, and ethical literacy—dimensions that were rarely addressed systematically in the reviewed literature.

The scope and conclusions of this review are constrained by several methodological limitations. A review of the literature reveals several limitations in the Scopus and Web of Science databases. Firstly, the scope of the databases excludes educational research and non-Anglophone scholarship. Secondly, the computer science field filter limits the breadth of the databases. Thirdly, the publication lag underrepresents late 2024 developments. Finally, the absence of reviewed studies precludes the possibility of empirical evidence on solution effectiveness. Additionally, the Eastern-dominant research may not generalize to decentralized Western systems with established faculty governance traditions. Subsequent research endeavors must address six specific priorities that have been logically derived from these findings, which have undergone rigorous validation. The following six points comprise the research framework:

1. Longitudinal institutional tracking over 18–24 months assessing whether baseline awareness predicts policy adoption and sustained faculty behavior change;

2. Comparative institutional case studies identifying discipline-specific governance models that succeed across research universities, teaching-focused institutions, and professional schools;
3. Randomized controlled trials on professional development testing variants of faculty training to measure efficacy and sustained implementation;
4. Organizational incentive analysis examining why adoption lags despite tool benefits and identifying effective incentive restructuring;
5. Scoping review of non-generative AI tools (recommender systems, automated grading, learning analytics) to document governance challenges beyond ChatGPT; and
6. Investigation of solution stasis analyzing why decade-long policy recommendations remain unimplemented despite evidence of their necessity.

This review makes three interrelated contributions to the field. Firstly, it employs temporal analysis as a tool for understanding technology-driven paradigm shifts. Secondly, it presents an integrated framework that moves beyond awareness-centric approaches to encompass institutional readiness, incentive structures, and ethical literacy. Thirdly, it identifies concrete, operationalized research gaps that will inform future investigations. The integration of artificial intelligence (AI) within higher education does not follow a linear progression from a state of ignorance to one of adoption. Rather, it is a discontinuous institutional process that is constrained by misaligned incentives and the absence of adequate infrastructure. Future research must transition from the descriptive inquiry, "To what extent are stakeholders aware?" to the diagnostic question, "What systemic conditions facilitate the translation of awareness into sustainable, ethically grounded practice?" This review facilitates a reframing of the research agenda that aligns with this shift in inquiry.

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