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of Human and Machine Learning

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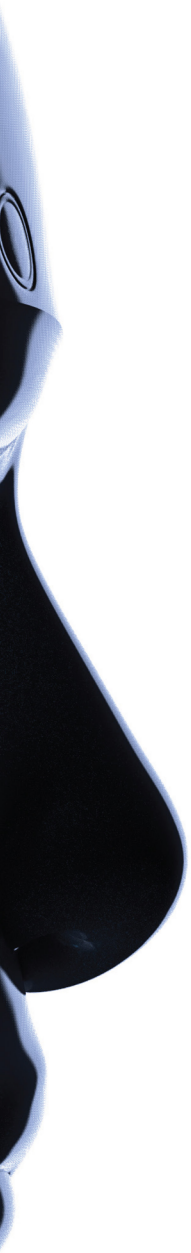

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A Word from the Editor



The BSBI School of Business and Innovation and the BSBI scholarly community introduce the Scientific Journal of Human and Machine Learning. Such an initiative reflects the growing goal of BSBI of not only becoming a respectable educational institution but also an active participant in international research, scholarly discussion, and knowledge generation.

The Journal publishes research papers and reviews analyzing contemporary trends and challenges in technology-related sciences. We call upon researchers, academics, professionals, and students from all over the globe to submit original papers in the areas of pure and applied computer science, information technology, artificial intelligence, and informatics. Special preference will be given to those studies which are globally relevant, provide a combination of theoretical perspectives and practical solutions, and reveal some innovative aspects of the development of interactions between humans and intelligent technologies.

The Journal is intended for contributing to the development of information technology and informatics from an international perspective, providing interdisciplinary cooperation between various institutions and countries. The core idea of the journal is to find a way of linking human learning and machine intelligence from practical, ethical, and sustainable perspectives. The Journal seeks to promote scientific research, solve challenges of the information technology industry, develop knowledge of artificial intelligence, provide policymaking based on evidence, and promote technological innovation.

Among the fields which the Journal covers, there are computer science, blockchain, informatics and information technology, machine learning, robotics, and artificial intelligence. By means of exchanging original ideas, research findings, and insights, the Journal is going to become a good source for studying the ways how emerging technologies can benefit the education sector, business, industries, and society.

We welcome you to visit the official webpage of the Journal to find out more about the latest research and to participate in forming the international academic community.

Professor. Dr. Kyriakos Kouveliotis FRSA
Editor-in-Chief
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Journal Information

The Scientific Journal for Human & Machine Learning as a fully open access international scientific journal publishes original research papers and review articles (scientific publications). There is no bias with regard to taxon or geographical area. Manuscripts (of scientific publications) should present new scientific findings that have not been published before and are not submitted for publication elsewhere. This journal has a special focus on the heuristic questions:

- How machines, as well as other modern digital/smart, learning approaches, models, algorithms and paradigms, can - conceptually, theoretically and technically – deal with human knowing, human learning, human reasoning, and human understanding in various educational and pedagogical contexts.
- How modern AI-based systems can enhance the quality of human knowledge, learning and teaching.

The scope of this journal includes (and is not limited to)

- Machine [and AI-based] Learning Methods and Techniques in Education and Pedagogy
- Learning/Teaching Design using Machine Learning and Artificial Intelligence
- Machine [and AI-based] Learning and Computational Models of Human Learning
- Machine [and AI-based] Learning and Innovative Learning/Pedagogical Scenarios
- Machine [and AI-based] Learning Methods and Adaptive Collaborative Learning Systems
- Machine [and AI-based] Learning and Computational
- Models of Human Knowledge
- Machine [and AI-based] Learning and Analysis of Cognitive Processes
- Machine [and AI-based] Learning and Dynamic Learning Analytics
- Machine [and AI-based] Learning and Personalised Learning/Teaching Analytics
- Machine [and AI-based] Learning and Personalised Support for Learning/ Teaching Communities
- Machine [and AI-based] Learning and Visualisation of Learning Processes
- Machine [and AI-based] Learning and Blended, Distance, and Online Learning
- Intelligent Learning: Models, Theories, Systems

Types of papers

- **Research articles:** Original scientific works.
- **Review articles:** Articles that are either reviewing the state of the art of a concept/ problem or reviewing some specific research work of some individual or organisation.
- **Project Descriptions:** Describes some specific research/ scientific project which has been conducted by someone, some community, or some organisation.
- **System Specifications:** Describes some specific system/ model, and also specify them and their applications in some specific scenario.
- **Opinion papers:** Papers that are not scientifically and methodologically dealing with some concept/problem but only offering the ideated concept and/or question.

About BSBI School of Business and Innovation

BSBI School of Business and Innovation (BSBI) main campus is in the NeukölIn district of Berlin, in the Alte Post, a historically significant building with a modern interior, set in a culturally diverse urban neighbourhood. It is the perfect fit for BSBI, an institution whose depth is measured by the combined global experiences of its staff and faculty, the vibrance of its young student community and its innovative practices. We also have campuses in Hamburg, Paris, Athens, and Barcelona.

We prepare our students for meaningful and impactful careers in their chosen industries in any part of the world. All the courses at BSBI are designed with three principles in mind: enterprise, leadership, and success. Each programme focuses on improving practical business skills and understanding of the relevant industry. Students will receive the tools and information they need for professional success as well as support from industry-focused academics who are at the top of their field. They will also benefit from extensive career support for guidance and advice.

BSBI also now participates in Erasmus+, the EU programme that supports education, training, youth, and sport in Europe and is open to organisations across every level of the education sector.

BSBI School of Business and Innovation is a member of the Association to Advance Collegiate Schools of Business (AACSB), an official signatory of the 'United Nations – Principles for Responsible Management Education' (UN-PRME) global initiative and a member of the Business Graduates Association (BGA), sister organisation to the Association of MBAs (AMBAs).



Gamification in Education to Enhance Learning Experiences and Student Engagement: A Bibliometric Analysis

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Abstract

Purpose: Today, education has witnessed a major paradigm shift due to digitalization and automation. This paper focuses on how gamification is enhancing student engagement, thereby improving overall performance. The main objective of this research is to map the publication patterns, key sources, influential authors, and emerging global trends using a bibliometrics approach.

Methodology: This paper is based on the bibliometrics analysis of 374 papers from the Scopus database on gamification published from 2020 to date. Data were extracted manually and analysed on the publication frequency, co-occurrence of keywords, citation metrics, and source impact.

Findings: The findings show the significant growth after 2020. The total citation count is 3500, giving strong scholarly relevance. The highly cited journals are based on education sciences, Information Technologies, Frontiers in Education, and digital learning adoption. The keywords that appear frequently are gamification, higher education, student engagement, motivation, and game-based learning.

Originality: This paper contributes to one of the most current and comprehensive bibliometric analyses on game-based learning in education, offering insights to the academic fraternity to enhance the learning experience of the students.

Limitations: The study is based on a bibliometrics analysis of 374 papers from the Scopus database, leaving future researchers to further apply systematic literature review and PRISMA approach to measure the long-term impact of gamification on engagement and students' learning from other sources like Web of Science, Crossref, and Semantic sources.

Keywords

Student Engagement, Gamification, Learning, Motivation, Bibliometric Analysis, Digitalization, Education, Technology, Higher Education, Engagement, Game-based Learning

Introduction

Education has witnessed a significant transformation post Covid post-COVID. The focus has shifted from classroom learning to experiential learning, driven by rapid technological advancement, giving more emphasis on learner-centred approaches. This shift has made a mandate to the educators and institutions across the globe to explore and experiment in their pedagogies. The present education system is in need of techniques to combat disengagement and support self-paced learning. As a result, faculty members have embedded technology in their lesson plans, wherein gamification came into existence, badges, point systems, leaderboards, and rewards have emerged as the most impactful pedagogical innovations. Researchers have mentioned that gamification is fostering active engagement, intrinsic motivation, and persistence amongst students. Gamification can be understood very well from the motivational theories of Flow theory, Behaviorism, and Self-determination Theory; all the theories highlight relatedness, competence, and enhance learners' autonomy. Through instant feedback, goal-driven activities, and structured challenges, gamification stimulates curiosity, improves student satisfaction, enhances engagement levels, problem-solving skills, and promotes deep learning behaviours. As digitalisation continues to evolve, gamification has further improved through its integration with Artificial intelligence. Despite so much technological advancement in teaching and learning, there is a need to focus on broader perspectives. The bibliometric analysis offers a deep and data-driven technique to address the research gaps by mapping scientific production, examining citation influence, identifying thematic clusters, and presenting the results within the literature. This study is based on a comprehensive bibliometric analysis of 374 publications from the Scopus database. The objective of this paper is to provide fresh insights about gamification in education and how the pedagogical interventions are enhancing the students' learning. This study aims to shed light on a few key topics in the growing field of digital advancement in game-based learning. In particular, it will answer the following Research Questions:

RQ1. **What is the present status of research for Gamification in Education to enhance students' learning experiences and Engagement?**

RQ2. **Which are the most impactful journals and authors in the field of Gamification in Education**

RQ3. **What are the themes that affect the intellectual structure in the field of game-based learning**

RQ4. **To contribute to advancing students' learning and engagement, identify existing gaps and possible research topics that require attention in order to conduct purposeful research and produce new findings**

Literature Review

The sector most affected by COVID-19 was education; many new changes were made, emphasizing online learning. Many new software and apps came into existence,e giving new avenues for education to be pursued. The concept of gamification has gained momentum in educational research. Many studies have shown how gamification enhances motivation, students' engagement, and learning outcomes (Dichey and Dicheva, 2017). As per the study by (Huang et al.,

2019) summarised effect size of g=0.49 for cognitive outcomes, g=0.25 for behavioural outcomes, and g=0.36 for motivational outcomes across gamified interventions. These results reveal that gamification can definitely enhance learning; however, the effect shows heterogeneity in results. (Li and Ma, 2023) highlighted that though gamification boosted interest, engagement, and motivation, the actual results remain less consistent when it comes to improved academic performance. A study conducted by Ruiz et al. (2024) on systematic reviews reveals that gamification has a positive impact on classroom participation, self-regulation, attention span, and interactive behaviour. (Almeida et al., 2023) studies revealed that mere badges, stars, and leaderboards without meaningful structure are of no benefit. In gamification research, various motivational and educational theories are considered by researchers. (Ryan and Deci, 2000). Self-determination Theory is cited mostly by researchers who highlight that gamification may support competence, relatedness, and autonomy. Also, Csikszentmihalyi (1990) Flow Theory explained that well-structured games can enhance learners' ability. Researchers have also mentioned that involving games in teaching learning evaluation plans without aligning them with the objectives and learning outcomes risks superficial learning rather than effective learning (Lander Huang et al., 2019). With the advancements in technology, meta-analyses and systematic reviews have gained momentum in research on gamification. (Zainuddin et al., 2020) highlighted personal learning through mobile gamification. Similarly, Bozkurt and Durak (2018) mentioned an interdisciplinary approach of gamification research across computer science, psychology, and education. This research mentioned the shift in gamification research from exploratory to more theoretical and practical applications.

Although most of the bibliometric research has adopted a global mapping perspective rather than focusing on thematic trends in performance outcomes, and enhancing learners' engagement. Many researchers have also studied and mapped the negative effects of digital learning. These investigations in previous studies highlight the need for further research in considering gamification as a tool for enhancing learning. Most of the bibliometric studies still lay emphasis on collaboration patterns and publication growth while ignoring the psychological and ethical well-being of learners' engagement. Therefore, the present study advances existing literature in three aspects. Firstly, this research is based on a bibliometric analysis of the thematic evolution, intellectual structure, and productivity patterns of using gamification as a pedagogical tool for enhancing learners' experience. Secondly, prior research highlights only the citation networks and publication counts; this study further extended the work by integrating the trend analysis and co-occurrence mapping, offering deeper insights into how technology has embedded in the course curriculum. Lastly, the present paper addresses the gaps in institutional adoption strategies, learners' well-being, and the lack of outcome-based education. Hence, this paper not only fills the research gap but also provides a strategic perspective for educators, scholars, and policymakers to implement gamification in course curriculum.

Research Methodology

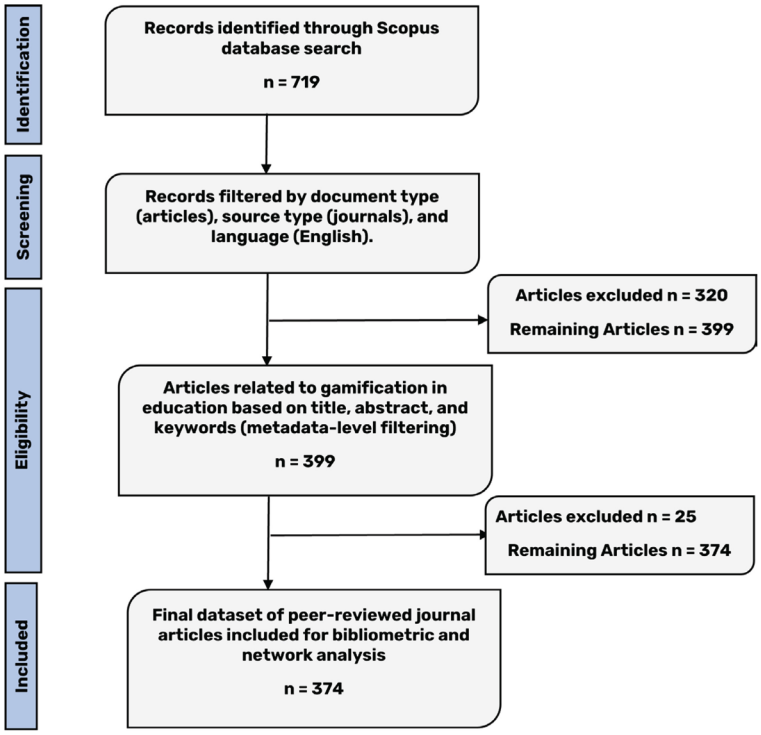
The present study adopts a bibliometric approach to map and evaluate the intellectual structure, publication trends, and thematic evolution of research on gamification in education, focusing particularly on learning experiences and student engagement (Ozcan

and Unalan, 2020). Bibliometric analysis was chosen because it allows for an objective and quantitative evaluation of scientific literature, enabling the identification of influential publications, authors, institutions, and emerging research themes (Aria and Cuccurullo, 2017). The methodological process followed in this study is designed in line with prior bibliometric studies in management and education research (Donthu et al., 2021).

Data Source and Search Strategy

The data were retrieved from the Scopus database, which is widely recognized for its extensive coverage of peer-reviewed and high-quality academic journals (Mongeon & Paul-Hus, 2016). The search was conducted on October 1, 2025, using the following query string: (TITLE-ABS-KEY (“gamification”) AND TITLE-ABS-KEY (“education”) AND TITLE-ABS-KEY (“student engagement” OR “learning experience”)) AND PUBYEAR > 2019 AND PUBYEAR < 2027 AND (LIMIT-TO (SRCTYPE , “j”)) AND (LIMIT-TO (SUBJAREA , “SOCI”) OR LIMIT-TO (SUBJAREA , “BUSI”) OR LIMIT-TO (SUBJAREA , “ARTS”) OR LIMIT-TO (SUBJAREA , “ECON”)) AND (LIMIT-TO (DOCTYPE , “ar”)) AND (LIMIT-TO (LANGUAGE , “English”)). This approach to searching made sure that only those peer-reviewed journal articles that were in English and published between the years 2020 and 2025 were considered. The starting point of the search yielded 719 publications, and these were then exported in CSV format for analysis. The main source of Scopus was chosen as it gives detailed journal coverage and strong citation data across all disciplines, thus being appropriate for mapping the upcoming interdisciplinary topics like gamification in education (Martín et al., 2018).

Figure 1: PRISMA Flow Diagram for Study Selection Process



Data Cleaning and Screening Protocol

The bibliometric data were systematically filtered and screened in accordance with the PRISMA framework (Moher et al., 2009) to assert transparency and reproducibility. Scopus's retrieval of all 719 records was done at the identification level, and those records were then transferred to Microsoft Excel, where they were screened for duplicates and incomplete records. The screening phase saw the elimination of non-relevant papers, namely book chapters, conference papers, and editorial materials from the count, and this resulted in the remaining 399 valid journal articles. At the eligibility level, the title, abstract, and keywords of each record were reviewed again to establish the record's relevance to gamification in education, learning experiences, and student engagement. To proceed, the inclusion stage allowed the employment of the refined 374 articles set for bibliometric and network analysis. The PRISMA flow diagram in Figure 1 shows every stage of the filtering and selection process.

Table I: Main Information about Data

MAIN INFORMATION ABOUT DATA	
Timespan	2020:2025
Sources	194
Documents	374
Annual Growth Rate %	56.19
Average citations per doc	9.663
Keywords Plus (ID)	690
Author's Keywords (DE)	1062
Authors	1510
Co-Authors per Doc	7.16
International co-authorships %	19.79%

The data infers that a total of 374 documents are relevant to our search for the period 2020 to 2025, with an annual growth rate of 56.19 percent. Average citation per doc is 9.663, and there are 1062 author keywords. A total of 1510 authors are actively contributing to the database, with 7.16 coauthors per document. The international co-authorship is 19.79%. The growth rate is 56.19 A significant rate of 28.89 percent of international co-authorship is reflected by the dataset. The growth rate of more than 82 percent shows a lot of potential for future research, as it is attracting substantial attention for policy making for youth all over the world.

Analytical Tools and Techniques

The bibliometric data were analyzed using VOSviewer and Biblioshiny (R-based interface for Bibliometrix). These tools were employed to perform descriptive, relational, and conceptual analyses. Descriptive analysis examined publication trends, leading journals, countries, authors, and citation performance. Relational analysis explored co-authorship and co-citation networks to visualize patterns of collaboration among authors, institutions, and

nations. Conceptual analysis, which focused on the co-occurrence of keywords, enabled the identification of key thematic clusters and research hotspots. Finally, a thematic map generated using Biblioshiny was used to classify topics into four categories: motor, niche, emerging, and basic themes, based on their centrality and density.

In order to guarantee the rigor of the analysis, the following threshold values were set for each individual analysis: at least five documents from each author or source, three documents for each co-author, and five instances of co-occurrences for each keyword. The network maps were all created with normalization according to the strength of association, in alignment with the visualization technique advocated by Van Eck and Waltman (2010).

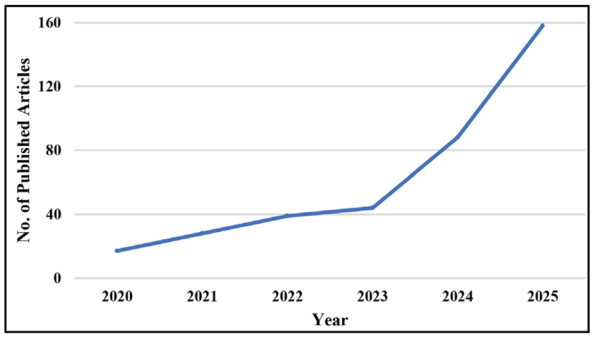
Research Questions and Main Findings

This part of the report discusses the bibliometric output based on the Scopus database, which was examined with the help of VOSviewer and Biblioshiny. The findings reveal through the visualization of graphs that publication trends, the most cited authors and sources, citation patterns, and development of topics all have a commonality which gradually portrays the intellectual and conceptual evolution of the gamification research in education.

RQ1. What is the present status of research for Gamification in Education to enhance students' learning experience and engagement?

The yearly trend illustrates that the increase in publication output was steady and continuous from 2020. The first studies were mainly addressing the theoretical aspects, writer-side pilot experiments in educational settings using game-like methods (Figure 2). The number of publications started to grow rapidly after 2021, which was the time the classroom's adoption of various digital learning tools became quite common due to the post-COVID pandemic. The year 2024 was marked by the highest publication count, thus the continuous academic interest was indicated, and the research area of gamification educational innovations was considered to be already mature.

Figure 2: Articles published annually on Gamification in Education



RQ2. Which are the most impactful journals and authors in the field of Gamification in Education

The citation analysis indicates a gradual and consistent rise in academic interest in the study of gamification in education (Table 2). Table 2 reveals that the initial research phase, especially in 2020 and 2021, had the highest citation averages. The output of 2020 was leading with a citation mean of 55.12 per article, followed by 23.54 in 2021. These figures indicate that the impact of these publications was mainly through the conceptualization of gamified learning frameworks, the incorporation of motivation theory, and the unraveling of student engagement mechanisms, which remain

the landmark references for subsequent research. A shift in the average citation from theoretical model development to applied case studies and empirical validation is reflected in the figures given for 2022 and 2023, which

Table II: Citation Analysis of Articles

Year	Mean TC per Article	No. of Published Articles	Mean TC per Year
2020	55.12	17	9.19
2021	23.54	28	4.71
2022	19.21	39	4.8
2023	12	44	4
2024	5.82	88	2.91
2025	1.45	158	1.45

are 19.21 and 12.00 citations per article, respectively. The year 2024, the most recent, can be characterized by the highest number of publications (88 articles) but a lower average citation rate of 5.82 per article. This is in line with the citation accumulation pattern, where the recently published papers have had less time to attract citations.

The Top Journals for Gamification in Education

Research on gamification in education is dominated by a small number of important journals, according to the analysis of publication sources (Table 3). With the greatest percentage of all publications and citations in the dataset, Computers & Education, Education and Information Technologies, and Sustainability are the most active of these. High-caliber research linking game-based learning, digital pedagogy, and student

Table III: Major journals on Gamification in Education

Journals	Articles
Education Sciences	18
Education And Information Technologies	16
Bmc Medical Education	13
Frontiers In Education	11
Journal Of Engineering Education Transformations	8
Computer Applications In Engineering Education	7
International Journal Of Information And Education Technology	7
Journal Of Information Technology Education: Research	7
Sustainability (Switzerland)	7
Cogent Education	6

engagement is regularly published in these journals. The British Journal of Educational Technology and Frontiers in Psychology are two other noteworthy sources. These highly regarded Q1 and Q2 journals demonstrate the field's scholarly integrity and global recognition. The general trend shows that gamification research has been well-represented in educational technology platforms, confirming its status as an important field of pedagogical innovation.

Top authors' contributions on Gamification in Education

The authorship analysis gives a clear picture of a varied group of contributors who are very active and influential in the area of gamification in education (Table 4). Among the participants, Nguyen-Viet B. stands out as the most productive researcher, having nine publications with a total of sixty-four citations and an average of 7.1 citations per article. Other important contributors are Slamet J. and Ivone F. M., each having three papers, while Li J. produced the same amount of work with a little lower citation count. Even though Yang Y. published only two papers, they have been cited very often, leading to a high average of 63.5 citations per article, showing the author's scholarly influence. A similar intensity of citation was seen for Rincon-Flores E. G. and Ahmad A. whose small number of publications managed to gain significant visibility.

Top Cited Documents on Gamification in Education

Analysis of citations indicates that the most important publications in the area were mainly produced in the first phase of research from 2020 to 2021 (Table 5). Foundational studies like (Hamari et al., 2020) and (Dicheva et al., 2021) had citation counts over one hundred, thus connecting game design elements with the students' motivation and engagement and laying down the theoretical and conceptual foundations. These studies are still regarded as key references, and they influence the course of future empirical and conceptual research. Citation networks portray their continued significance, and their contributions have been long-lasting and thus confirming that the early conceptualizations still serve as the intellectual backbone of gamification research in the educational sector.

Table IV: Top Authors on Gamification in Education

Rank	Author	Articles	Total Citations	Citations per Document
1	Nguyen-Viet, B.	9	64	7.11
2	Slamet, J.	3	17	5.67
3	Ivone, F.M.	3	16	5.33
4	Li, J.	3	7	2.33
5	Yang, Y.	2	127	63.5
6	Rincon-Flores, E.G.	2	111	55.5
7	Ahmad, A.	2	67	33.5
8	Bhat, S.	2	62	31
9	Lin, H.-C.K.	2	61	30.5
10	Crawford, J.	2	46	23

Table V: Major Documents by Citation on Gamification in Education

Paper	DOI	Total Citations	TC per Year
SMIDERLE, 2020, SMART LEARN ENVIRON	10.1186/s40561-019-0098-x	300	50
TSAY, 2020, J COMPUT ASSISTED LEARN	10.1111/jcal.12385	127	21
JÄÄSKÄ, 2022, PROJ LEADERSH SOC	10.1016/j.plas.2022.100041	101	25
CAMPILLO-FERRER, 2020, SUSTAINABILITY	10.3390/SU12124822	91	15
RIVERA, 2021, J FURTH HIGH EDUC	10.1080/0309877X.2021.1875201	88	18
CHEUNG, 2021, FRONT EDUC	10.3389/feduc.2021.623793	74	15
ISABELLE, 2020, DECIS SCI J INNOVATIVE EDUC	10.1111/dsji.12203	73	12
DAGHESTANI, 2020, COMPUT APPL ENG EDUC	10.1002/cae.22227	70	12
RINCON-FLORES, 2021, AUSTRALAS J EDUC TECHNOL	10.14742/ajet.7157	67	13
AHMAD, 2020, ACM J TRANS COMPUT EDUC	10.1145/3383456	67	11

Conceptual Structure and Keyword Analysis

The keyword cloud analysis reveals the intellectual focus and conceptual dynamics of gamification research in education to a much broader extent. The big picture shown by the terms like “gamification,” “learning,” “students,” and “motivation” speaks of a very strong pedagogy orientation where the gamified methods are mainly seen as ways to boost learning outcomes and participation levels (Figure 3). However, the pairing of these keywords with “teaching,” “e-learning,” and “curriculum” being frequent indicates that a great part of the literature still looks at gamification as a technological add-on rather than a major change in the teaching philosophy. Consequently, it may open a door for future researchers to shift from the adoption of tools to the study of the cognitive and affective mechanisms that sustain long-term engagement in learning.

Figure 3: Keyword Word Cloud of the selected studies



The most remarkable thing, the prominence of demographic words such as “female,” “male,” and “young adult” indicates the most common use of experimental or quasi-experimental research design relying on gender-based samples in higher education that has been established. This shows that the researchers followed the same methodological approach, but it also points out a weakness, which is the restriction that comes with the tendency of young, tech-savvy populations to be overrepresented. Moreover, the rise of new terms like “engineering education,” “medical education,” and “computing” indicates that gamification has started to penetrate into the non-traditional education domains, but these interdisciplinary expansions are still very

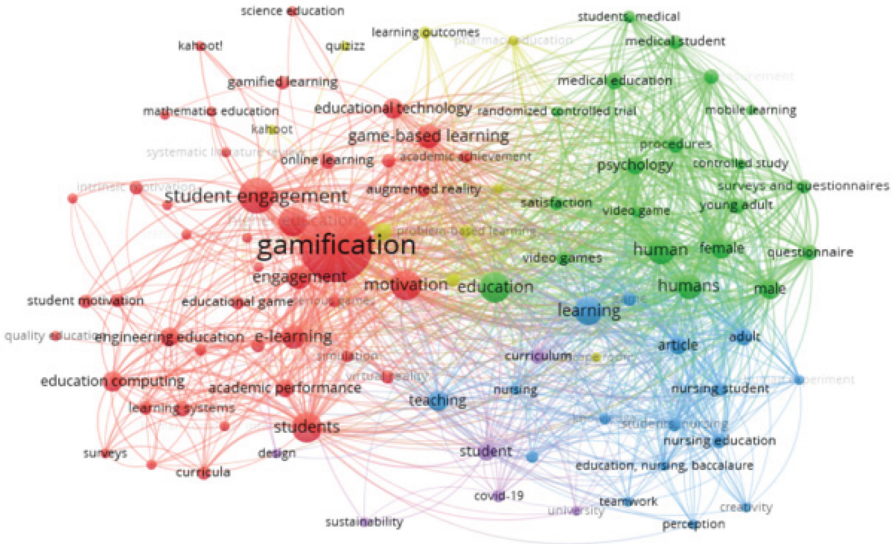
much disconnected. A more comprehensive theoretical perspective that combines motivation theory, learning analytics, and design thinking could help to reinforce the coherence of this developing field of research.

Co-occurrence Analysis of the Network of Keywords on Gamification in Education

The co-occurrence network map is arguably the most important visualization that illustrates the relationship and the positioning of the gamification-related research themes (Figure 4). The thick red cluster with “gamification,” “motivation,” and “student engagement” at its core forms the conceptual center of the whole field. Its heavy concentration indicates that the bulk of research is still likely to be about motivational outcomes and behavioural engagement, which often include revisiting established frameworks rather than advancing new theoretical approaches. Theoretical grounding and methodological innovation are the two aspects that reflect the situation of both the maturity and the stagnation of the core discourse in the field, which is still theoretically grounded but in need of methodological innovation.

The green cluster, containing “game-based learning,” “educational technology,” and “psychology,” displays interdisciplinary integration, although this is mainly at the level of application rather than theory-building. A lot of the studies included in this group are very much focused on the practical side, dealing with classroom interventions or technology evaluations, sometimes with no or inadequate longitudinal or cross-cultural validation. The blue cluster, including “nursing education,” “curriculum,” and “teaching”, highlights the spread of gamification from the IT field into professional and medical education. Nonetheless, its position at the edge suggests that such adaptations that are specific to the domain are not only contextually isolated with limited conceptual cross-pollination but also remain marginal. Emerging peripheral nodes like “augmented reality” and “mobile learning” signify the next frontier, directing us toward immersive and adaptive learning ecosystems, but they are still empirically underexplored.

Figure 4: Co-occurrence Network of Keywords

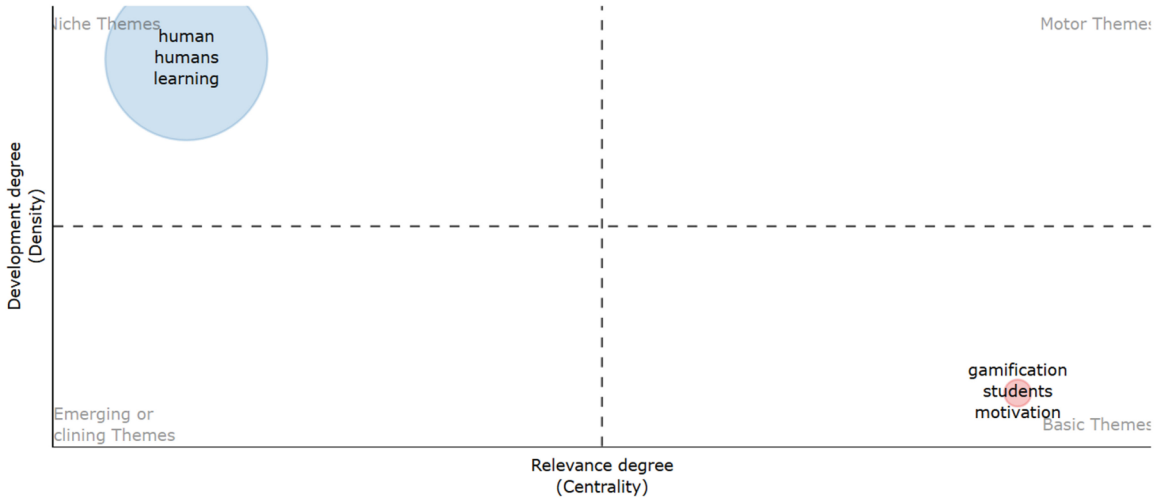


RQ3, What are the themes that affect the intellectual structure in the area of game-based learning?

The thematic map categorizes the conceptual structure of gamification in education based on two dimensions, centrality and density, revealing how research themes vary in their relevance and level of development (Figure 5). The analysis identifies two dominant clusters:

Highly developed but specialized research areas on behavioral evaluation, psychological measurement, and human learning processes are represented by the niche cluster in the upper-left quadrant. Despite having a strong methodology, these studies don't seem to be part of the broader gamification conversation, which limits their influence. Further indicating that the field lacks a unifying research front that can propel theoretical and practical

Figure 5: Thematic Map on Gamification in Education



a basic theme comprising "gamification," "students," and "motivation," and a smaller niche theme centered on "human," "humans," and "learning." The position of the basic cluster at the lower-right quadrant reflects its high relevance but low density, indicating that these topics form the conceptual foundation of the field but remain theoretically fragmented. Most studies still approach gamification as an engagement-driven instructional technique rather than a fully developed educational paradigm, suggesting a need for stronger theoretical integration and longitudinal evidence.

advancement is the absence of distinct motor themes in the upper-right quadrant. Even though interest in related fields like virtual learning and adaptive feedback systems is growing, the empty lower-left quadrant (emerging themes) shows a relative stagnation in the creation of new topics.

This thematic structure indicates that gamification research in education is conceptually mature yet structurally underdeveloped. To progress, future scholarship should bridge motivational and human-centered perspectives with system-

level educational models, transforming gamification from a technique of engagement into a sustained learning ecosystem embedded in pedagogical design.

RQ4. To contribute to embedding technological intervention in teaching and learning, identifying existing gaps and possible research topics to conduct meaningful research and produce new findings

The bibliometrics analysis reveals a noteworthy evolution in the field of technology. Gamification is an emerging field, and the adoption of game-based learning can enhance students' engagement. Various research has already been conducted on gamification, augmented reality, virtual reality, and Artificial intelligence; there is a lack of comprehensive research on the effective utilisation of digital applications and how ethically students are using this technology. While this study acknowledges significant work in gamification, it lacks evidence on the other technological pedagogical interventions used by faculty members to enhance learners' experience; therefore, this study highlights these gaps for future investigation. The response to RQ 1, 2 & 3 with bibliometrics analysis helps the researchers to identify the future research agendas on gamification in education. There is a need to deepen the understanding of how gamification is moulding the present education system.

Implications

Theoretical Implications

The present study highlights that there is an utmost need to integrate motivational theories, such as Flow Theory and Self-determination Theory, into game-based learning and evaluation; however, these theories are not utilized in a structured way. Previous studies indicated that very few have incorporated empirical studies and translated these principles into concrete learning mechanics(Hamari et al.,2014). Studies have also highlighted the pedagogical interventions implemented by higher educational institutions to enhance the students' learning. Future Researchers should therefore incorporate these frameworks more rigorously into both bibliometric models and empirical designs by mapping the theoretical aspects, investigating how specific game elements gratify psychological needs such as relatedness, autonomy, and competence, thereby analyzing the fact that gamification leads to stronger learning outcomes. Bibliometric analysis can be further extended to relate studies as per the theoretical grounds, enabling the comparison between gamification and those that are based on psychological models. Future researchers should also focus on the learners' style, educational settings, supportive infrastructure, platform, and software complexity to enhance teaching and learning effectiveness.

Practical Implications

It is important for educators and instructional designers to understand that gamification is not just an embedded technology but an important tool for effective learning. Gamification is another learner-centric approach that emphasizes learner engagement rather than its digital features (Subhash and Cudney,2018). The elements of the game must be selected on the basis of the nature of the course, students' capabilities, demand, learning outcomes, and how it will involve and engage the students. Also, Institutions and education policy makers should conduct

faculty development programs on a regular basis, provide technical support frameworks for their effective implementation, and also take the students' feedback to ensure that these pedagogical interventions lead to lifelong learning. This shift will have a significant impact through supporting infrastructure in the form of technical support systems, instructional design teams, and continuous feedback to ensure that gamification remains effective and adaptive. However, studies on bibliometrics have rarely mentioned policy decisions on gamification. Discussing insights from highly cited journals, targeted funding allocation, and emerging research clusters should highlight curriculum innovation and institutional policies on technological adoption, thereby establishing the relationship with research trends in governance and educational planning.

The present study also highlights the ethical considerations related to privacy, data protection, cybersecurity, and digital addiction, which need thorough review and rigorous discussion (Kaimara et al,2021). These issues need to be addressed to strengthen the responsible use of technology in pedagogical interventions and align with the broader objectives of inclusive and sustainable digital education.

Limitations and Future Research Direction

The present study is based on the bibliometric analysis of gamification in education to enhance students' learning and engagement. Several limitations and future research directions have become evident. First, the study is based on 374 articles from the Scopus-indexed publications, and other reputed sources like WoS, Google Scholar are excluded. Second, the timeframe of the study is from 2020 to 2025, highlighting the latest trends; however, expanding this timeframe could provide a better picture in terms of pedagogical interventions in experiential learning. Third, most of the evidence is drawn from higher education and technology-enhanced settings, ignoring the K-12 and other learning resources. Various emerging areas, such as adaptive gamified systems, immersive technologies, and personalised gamification, are under-researched. (Miranda Urquij et al., 2023) mentioned that the recent systematic review focuses on the need to explore how gamification supports self-efficacy, meta-regulation, and sustained engagement. In a nutshell, this research highlights that while gamification seems promising for enhancing students' learning and engagement, its effectiveness entirely depends on thoughtful integration and mapping with the course design. The following areas of future research should be investigated in order to improve the study's contribution and strengthen its applicability.

1. To investigate the role of social media and online learning platforms in student engagement.
2. To examine how the various pedagogical initiatives result in an effective teaching and learning process.

Conclusion

The present study is a comprehensive bibliometric analysis of the association of game-based learning in enhancing student engagement, from 374 publications spanning from 2020 to 2025. The publication trend is increasing over a period and witnessing a significant increase from 2022 onwards,

reflecting the global shift toward digitally enhanced pedagogy and renewed emphasis on learner motivation post-pandemic. In spite of this growth, there is a contemporary debate on how interactive learning frameworks can reshape student participation, persistence, and overall experiences. Though the present study significantly contributes to the existing work on technological advancements in the education industry, the fact that this digital adoption will lead to ethical issues in the future related to digital addiction, data privacy, data breach, and cybersecurity within the learning ecosystem. Therefore, it is important for future researchers and policymakers to devise a mechanism that safeguards the learners from the issues that may arise due to digital adoption. It is also suggested that future studies should also explore other pedagogical tools such as virtual simulations, AI-adaptive learning, online learning platforms, and other experiential learning approaches to further enhance the students' learning. However, gamification has shown significant improvement in motivation and performance of the students; the success of using these pedagogies still depends on instructional design, feedback, and sustained learner involvement. The literature notably highlights an uneven emphasis on higher education and digitally connected students, ignoring vocational education and K-12. Thus, this bibliometric analysis not only reveals intellectual advancements and major thematic clusters but also offers strategic insights for promoting an ethical and effective digital learning ecosystem in outcome-based education. Future research should investigate cross-cultural analysis, longitudinal approaches, and multidimensional engagement metrics to thoroughly understand the impact of gamification in effective learning.

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The Power of AI in Higher Education: Opportunities, Challenges, and the Way Forward for Academia

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Abstract

Purpose: The objective of this paper is to investigate the effect of artificial intelligence in the higher education sector in the context of teaching methodology, assessment model, and policy formation. It also discusses in depth various opportunities and challenges of the implementation of AI in higher education. Lastly, it also offers certain recommendations to guide future directions.

Design/Methodology/Approach: In this study, we have used a mixed-method approach, assimilated related literature review and survey, secondary data analysis from various reports, interviews, and global case scenarios to investigate AI integration in higher education.

Findings: On one hand, integration of artificial intelligence in higher education offers diverse and significant potential advantages, but on the other hand, it also poses certain challenges. The influence of artificial intelligence carries the potential to change the educational landscape. It was observed that to fully harness these advantages, all major stakeholders, i.e., educational institutions, policymakers, and faculty mentors, must work together to address key challenges. Ethical issues, limited resources, faculty capacity building, and data privacy protection are the major concern areas. Certain recommendations are made to highlight the strategic priorities for Higher Education.

Research limitations/implications: It is imperative to frame and implement clear guidelines on the implementation of AI in Higher Education to address major issues related to academic integrity, research ethics, and the wider societal impacts of its adoption.

Practical and Social Implications: In an envisioned future, higher education institutions engaged in research will actively foster collaboration among interdisciplinary teams to advance artificial intelligence technology and deepen the understanding of its societal impacts.

Originality/Value: This study enhances the understanding of the key opportunities and challenges influencing the adoption of artificial intelligence in higher education.

Keywords

Artificial Intelligence, Higher Education, Teaching and Learning, Assessment, Ethics, Privacy, Policy Makers, Educators, Student Engagement, Personalization, Educational Institutions

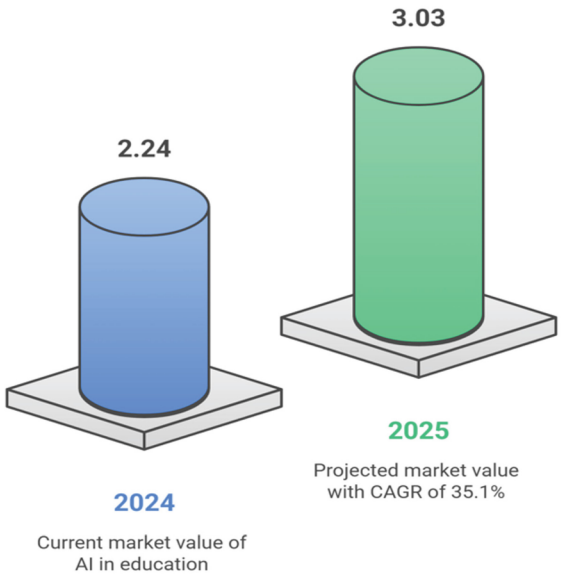
Introduction

Artificial Intelligence is slowly and gradually revolutionizing the campuses of higher education institutes globally. Imagine yourself walking through the college campus in 2026, where the daily life of students is now mixed with the presence of AI robots helping students in understanding and personalizing classroom teaching. The invisible presence of Generative AI in the daily academic life of students is quietly shaping their writing, listening, and thinking capacity.

Artificial Intelligence in Higher Education can create a more personalized and effective learning environment, thus improving the educational outcomes for the students. As per the study shared by The Business Research Company, in the last few years, the market of AI in higher education has grown exponentially. It was predicated that the market will grow from $ 2.24 billion in 2024 to $ 3.03 billon in 2025 with a compound annual growth rate (CAGR) 35.1%. (Figure 1)

This exponential growth can be attributed to an increase in hybrid learning models, online learning modules and courses, integration of AI with regular courses, adoption of AI by educational institutions for better student engagement, and globalization of the educational system. Even in the business domain, there is a spike in investment in the EdTech sector, AI-driven research tools, and the creation of smart content in the given forecasted period.

Figure 1: Artificial Intelligence (AI) in Higher Education Global Market Report 2025



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Higher education has the potential to play a critical role in advancing the current digital era due to the advancement of skills and technologies embedded in the higher education system. Globally, AI has not been integrated into the higher education system except in a few countries. With reference to the resources available and constraints, there

is a huge global gap. According to the study by Hagendorff (2020) and Hinojo-Lucena, Aznar-Díaz,C´aceres-Reche& Romero-Rodríguez (2019), AI-powered tools facilitate immersive and interactive learning experiences through virtual reality, augmented reality, and adaptive learning platforms, engaging students in new and innovative ways. AI enables educators to create interactive curricula, respond to varied learning preferences, and offer personalized support beyond what a single teacher could accomplish alone (Michel-Villarreal et al., 2023)

However, as AI continues to permeate the educational ecosystem positively, it also presents certain challenges and risks. The greatest risk remains about its potential impact on student learning, ethics, and social skills (Hoernig et al., 2024). Some of the authors also caution against over-reliance (Aymen & Zakarya, 2024). Ethical considerations, such as intellectual property and data privacy, are also paramount (Kong, Li, & Zhang, 2024).

Hence, this paper aims to examine the impact of artificial intelligence (AI) on teaching, learning, assessment, and policy formation in higher education. It will also investigate how new technologies are affecting education and how institutions are changing and imparting knowledge to their students. This study explores the possible integration of artificial intelligence (AI) into higher education as well as the present and future impacts of this technology on a number of academic disciplines. Opportunities and Challenges of integrating AI in educational settings are also covered in this chapter.

Literature Review

The transformative power of artificial intelligence to reshape learning in higher education is explored by several researchers over a period of time (Figure 2). The application of AI in teaching and research, administration, and content creation is as important as its dissemination and consumption by the participants in the higher education landscape. The AI applications to automate admissions, chatbots for student support, and analytical tools for resource allocation improve the efficiency of the higher education institutions and create a better learning environment for the students (Nadu et al., 2024). The optimism and concerns with the use of AI for revolutionizing the education system in an ethical and regulated manner are reflected in the literature explored by Jacques et al. (2023), Escotet (2024), and Butson et al. (2024). This article makes an effort to synthesize the opportunities and challenges for the academic fraternity in the AI age. A study conducted by Scarlet (2021) stated that various stakeholders of education, including educators and students, for multidisciplinary learning may rely on MOOC (Massive open online courses) through digital learning platforms and may choose their desired role to fill the gap in the learning environment. Interactive AI-based tools (Airaj, 2024) offer equitable access to knowledge for everyone in a technology-powered learning environment. New models of collaborative learning enabled by simulations and project-based problem solving in immersive and virtual labs have created an experiential learning environment. The real-world scenario, with the help of Generative AI (GenAI), bridges the gap between industry and academia (Kurtz et al., 2024). The democratization of quality learning resources globally through open educational platforms, when integrated with machine learning applications, helps to optimize institutional operations and facilitate international collaboration (Kuleto et al., 2021). Personalization of content and

curriculum improves not only the learning experience for all stakeholders but also develops critical skills like problem solving, collaboration, for lifelong learning and growth mindset required for the transformation of the workplace and society (Chen et al., 2020; George, 2023; Srivastava et al., 2025). Data-driven instructional design, smart tutoring, and adaptive learning systems are today the result of tailored content and unique feedback about learning style and progress to students with the help of AI technologies (Jacques et al., 2023). Real-time student interaction with individualized instructions and engagement is allowed through Natural Language Processing (NLP), along with improved learning outcomes through adaptive assessment and analytics (Alotaibi, 2024). AI tools have also reshaped academic research by automating the management and analysis of data to take academic inquiry beyond traditional boundaries. AI tools have enhanced the productivity of scholars to process efficiently and swiftly, sparing time for creative and critical thinking (Butson et al., 2024). The need for reskilling and upskilling requires innovative teaching and learning methods, which are easier with AI integration in learning methods, e.g., Robo-assistants (Hutson and Plate, 2023). The constructive outcomes of AI collaboration in education have highlighted that subject knowledge improves for students and teachers both when educators are consuming AI innovations for improving the learning environment (Leoste et al, 2021; Kim, 2024). The concerns raised by researchers like Gupta et al. (2024) highlight social and cultural biases leading to sometimes unfair admission and evaluation processes. Resistance to adopt innovative AI processes may seem to be the key barrier among educators and may question the honesty and integrity of academic conduct (Kurtz et al., 2024). The impact may be different for different geographic regions and cultures, as pointed out by Luckin et al. (2022). But with the inclusion of all stakeholders, especially local participants, it may help in the successful and ethical implementation of AI interventions in the learning environment in higher education.

Figure 2: Evolution of AI in Education

AI in Education: Historical Context, Commercialization, and Ethics

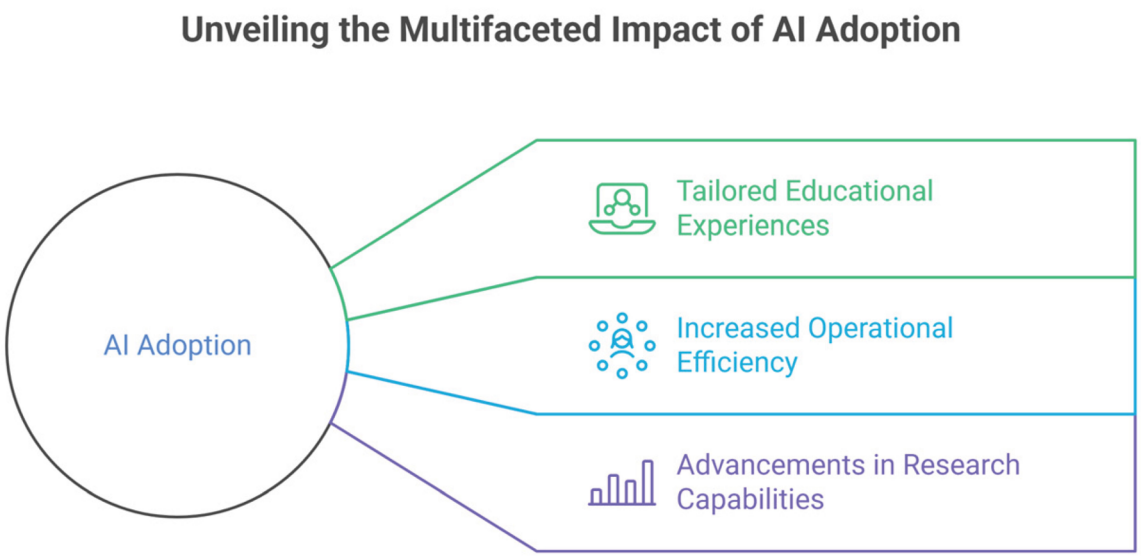
Characteristic	Focus	Development	Context	Importance
Historical Context	Academic research and tool development	Two strands: AI tools and learning improvement	Learning sciences, cognitive science, data mining	Understanding evolution of AI applications
Commercialization	Edtech industry and corporate influence	Promotion of AI-based tutoring systems	Reliance on proprietary AI infrastructures	Understanding political economy and power dynamics
Ethical Concerns	Bias, privacy, and legal frameworks	Data-driven governance and student modeling	Risks of anticipatory regulation	Examining societal implications of AI

Source: Authors' visualization adapted from Williamson & Eynon,2020

Motivation Behind AI's Influence on Higher Education

The motivational factor behind AI's influence on higher education lies in its capacity to impact the higher education system in multiple ways. Tailored educational experiences, increased operational efficiency, and advancement in research capabilities are some of the main areas that are covered by AI adoption. (Figure 3)

Figure 3: Multifaceted Impact of AI adoption in Higher Education



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Among the three, the primary motivation for integrating AI into education is its capacity to customize learning experiences for each student. AI-driven systems work on a wide range of student data, including their academic performance, engagement levels, and known learning styles, before suggesting a customized and engaging learning experience. It has the ability to handle various administrative duties, hence allowing faculty and staff to dedicate more time to research work and strategic priorities. With the capability to process extensive datasets drawn from a variety of sources (including scientific research, social media, and financial markets), it is in high demand among academic researchers. These AI tools help in the identification of trends, correlations, and anomalies that are often difficult or not within the capacity of human analysts to analyze through conventional methods.

Additionally, AI also helps faculty and educators with advanced tools and resources that facilitate innovative course design, thereby enriching the overall learning experience (Moundridou et al., 2024). According to (MacDowell et al., 2024), AI, when implemented effectively, has the potential to boost teacher productivity and expand instructional capabilities.

AI and its impact on learning, teaching, and assessment

As discussed earlier, to enable a personalized learning experience among students, AI is being introduced into the higher education system in areas such as learning, teaching, and assessment. This includes the usage of chatbots, VR, and AR systems to enhance instructional and educational support. Additionally, AI also facilitates student inclusion and well-being while providing robust tools and systems for monitoring and evaluating student progress. This multidimensional application of artificial intelligence helps in the robust transformation of the existing education system globally. Tailored and customized learning pathways, supporting diverse student needs and offering insightful assessment analytics for better results than the conventional methods of learning, teaching, and assessment.

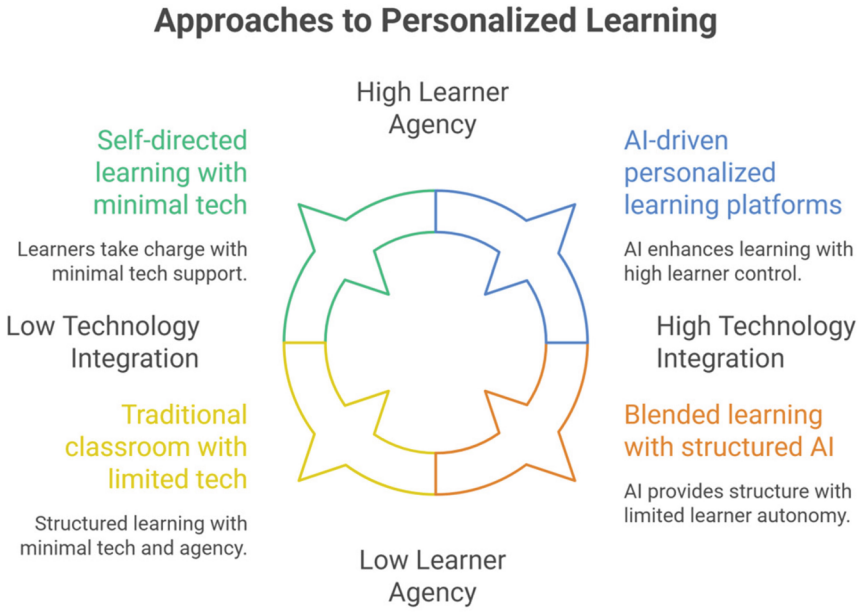
Personalized Learning Experience:

According to (Fake and Dabbagh, 2023), Personalized learning has a wider range of applications, which can easily be grouped into three overarching approaches: systems-based, learner-based, and blended approach (Figure 4)

Theoretical Implications

AI tools have already been used by HEIs to improve learning inclusion and wellbeing. AI interaction can occur through text or voice commands, offering valuable support for students with visual or hearing impairments by providing accessible communication options. Some of the leading institutes and universities started practicing AI tools to enhance student engagement and wellbeing

Figure 4: Approaches to Personalized Learning



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For Example :

- The University of California, San Diego (USA) was the pioneering higher education institution to implement an AI-driven application known as Aira, which provides real-time visual descriptions to assist individuals who are blind or have low vision.
- The University of Copenhagen (Denmark) has created a free AI-powered software designed to simplify complex texts for individuals with dyslexia and other reading challenges, thereby supporting their educational progress

Analyzing and assessing student progress

Standard online teaching and learning platforms already have the capability to analyze and monitor student progress. When enhanced by AI, these systems can detect underlying patterns explaining why a student may be struggling, such as insufficient time investment, low motivation to complete assessments, unclear instructional materials, or issues related to timing and repetition that prevent short-term memory from consolidating into long-term retention. Since the global adoption of AI tools like ChatGPT in 2023, many students have begun leveraging these technologies to assist with their assessments.

Assessment offers a major concern area, where AI is poised to influence student progress significantly.

To counter the effect of generative AI, Automated grading systems, often referred to as robot-graders, offer a one-time solution to educators for evaluating student assignments and providing them with the correct feedback.

In times to come, as advancements will be made in AI tools and techniques, these platforms can offer solutions beyond merely scoring tests. They can also progressively adjust the difficulty level of tasks and recommend supplementary materials tailored to address each student's specific learning gaps

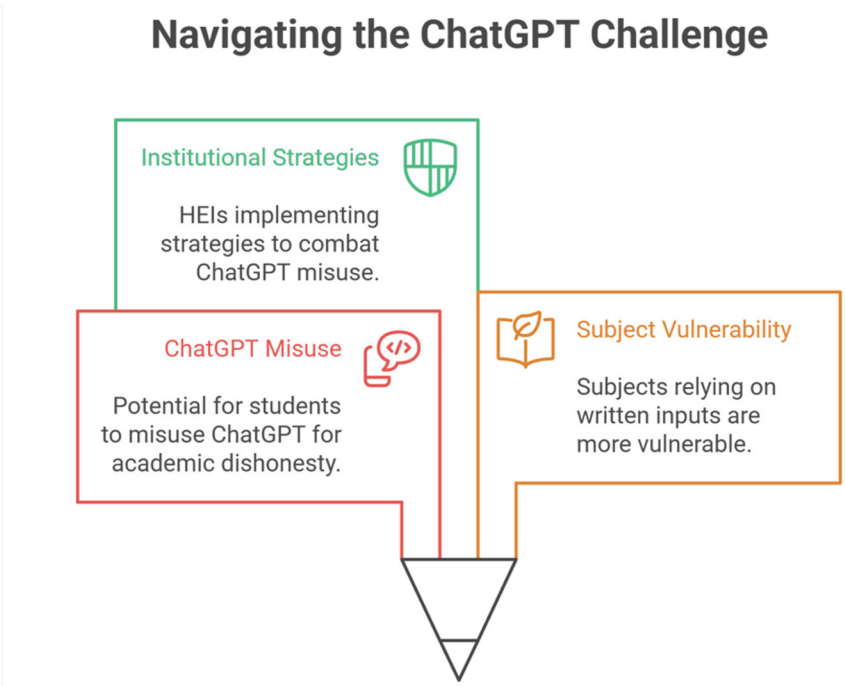
Food for thought: Re-evaluate assessment: What does it mean to learn?

Globally, in the higher education system, AI's influence is perhaps most pronounced and experienced in the domain of assessment. Conventional approaches, such as essays, take-home examinations, and various online testing formats, are increasingly susceptible to AI-enabled assistance. As a result, it's high time for educators to reexamine the criteria for the assessment and evaluation of learning outcomes. Now the focus is progressively aligning from the final result to the teaching learning process, emphasizing critical thinking, creativity, and the application of acquired knowledge over mere memorization.

Shortly, concerns for plagiarism and academic dishonesty have grown in Higher education institutions (HEIs) as students are misusing Generative AI tools for the preparation of assignments and projects. As per the latest report of (UNESCO IESALC), these concerns are pronounced in the domains of disciplines that depend heavily on written expression or information recall. In response, HEIs are implementing a variety of strategic measures (Figure 5) to overcome these challenges.

This shift presents several challenges. Drafting new assessment tools that can maintain the same academic rigor while taking care of risks associated with AI exploitation, seeking

Figure 5: Addressing ChatGPT Misuse in Education



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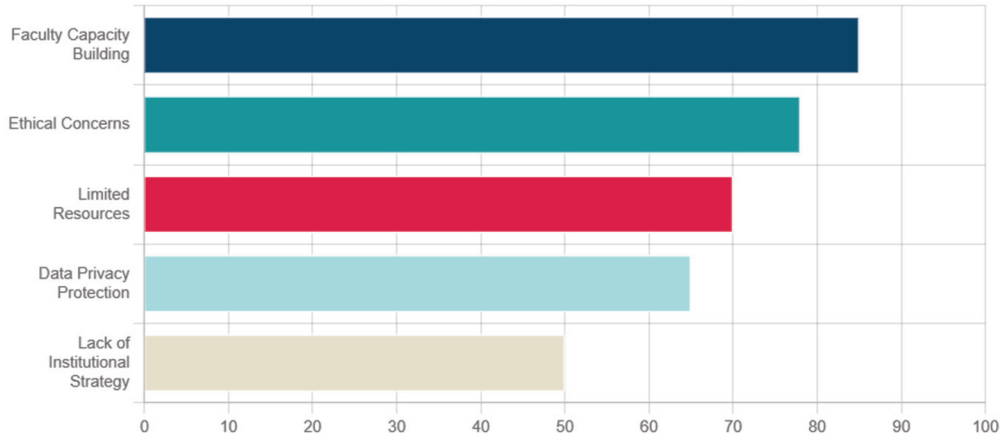
out-of-the-box thinking initiatives, and openness to adopt new assessment tools and methods. Key initiatives involve: VIVA VOCE examinations, collaborative assignments, and application-based assignments to better capture the complexities of student learning. Simultaneously, other institutes are deploying AI tools and technologies to deliver prompt feedback and support, while exercising caution to prevent potential abuses.

Key challenges for AI in Higher Education

The integration of artificial intelligence in higher education is a complex landscape of challenges. HEIs must carefully traverse the complex landscape to harness the AI's transformative potential while mitigating associated risks (Ocen, Elasu, Aarakit, & Olupot, 2024). For the successful integration of AI in HEIs, various obstacles and challenges need to be overcome. Even though the resultant personalized learning and administrative efficiency are quite fascinating, implementing these concepts in practice encounters multifaceted barriers that extend beyond mere technological acquisition, encompassing infrastructure, human capital, and equitable access. These barriers (Figure 6) can be overcome through strategic and coordinated institutional responses. Effective AI deployment, especially for large-scale applications like adaptive learning platforms or sophisticated learning analytics, demands robust network bandwidth, a reliable power supply, and modern computational infrastructure (McKinsey, 2023). AI integration is a costly and complex affair. Many organizations, especially in developing countries, don't have a basic IT infrastructure that can readily support AI integration. Hence,

Figure 6: Key Challenges for AI in Higher Education



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the incorporation of AI is compounded by the high upfront costs associated with the acquisition of the AI software, specialized hardware (such as GPUs for advanced research), and necessary consultation services, which can be prohibitive for smaller or non-elite universities. Further, a significant human factor that adds to the challenges is faculty resistance and skills gaps. Educators often lack the foundational AI literacy required to integrate these tools effectively into their pedagogy or assessment designs. Another key challenge is the resistance to embracing the change. There are several reasons for this, such as fear of job displacement, skepticism about the technology's effectiveness, and lack of specific training on ethical AI use (HEPI, 2025). A 2023 Gartner survey highlighted that a shortage of AI-skilled workers is a top barrier for many organizations, a finding equally applicable to academic staff who need domain expertise to supervise AI-augmented research and teaching. While AI promises greater accessibility, unequal access to high-speed internet, appropriate devices, and essential digital literacy skills among students and across institutions creates a critical chasm (UNESCO, 2022) and intensifies the digital divide. The institutions serving marginalized communities may struggle to implement and support sophisticated AI systems, which will eventually widen the gap in educational outcomes, leading to a lack of digital literacy among students and faculty. As a result, the ability to critically evaluate AI-generated outputs, understand how data is collected and used, and recognize algorithmic bias would be greatly challenged. Finally, privacy and security issues remain paramount. AI systems thrive on vast amounts of student data (performance metrics, interaction patterns, demographic information), raising critical questions about data ownership and protection (Shukla et al., 2025). Misuse of sensitive data can severely affect the trustworthiness. Furthermore, ensuring institutional readiness involves establishing clear, adaptable, and constantly evolving policies to manage these risks and guarantee compliance with emerging regulatory frameworks, such as those proposed by the EU AI Act (2024).

"Faculty Capacity Building" is cited as the most critical barrier. Hence, there is an urgent need for comprehensive professional development to prepare educators well-equipped to lead AI integration in the industry.

New Skills Required by Students

The incorporation of AI has resulted in a significant change in the skills environment. The value proposition of a university degree extends beyond content mastery to skill acquisition, demanding a curriculum designed to equip students for collaboration between humans and machines. To prepare students for a collaborative future with AI, the curriculum must de-emphasize rote memorization and foster a new blend of human-centric, analytical, and ethical competencies. This paradigm shift is supported by the National Education Policy (NEP) 2020 in India, which emphasizes fundamental competencies alongside higher-order cognitive, social, and ethical skills, in line with global education trends.

Fluency with AI and digital literacy is the foundational shift to embrace the new change. Students need to move beyond being passive users of technology to becoming informed co-creators. This entails having an understanding of how AI works, practical proficiency in using generative AI tools, and, most importantly, the ability to engage in "prompt engineering". This competency is directly linked to immediate employability in AI-augmented workplaces (Chen et al., 2020).

The core human competencies that AI cannot replicate, and thus become essential for students, include the following:

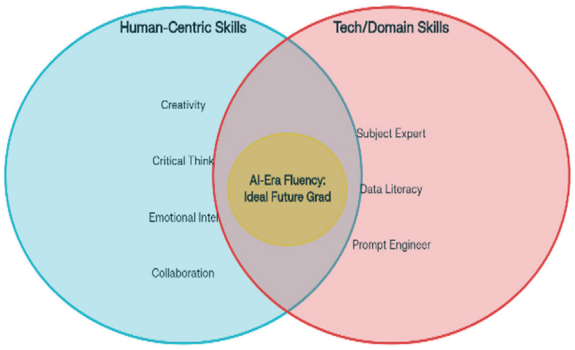
1. Critical Thinking and Evaluation: With generative AI producing fluent text and plausible answers, the skill set moves from recalling facts to verifying, analyzing, and synthesizing AI-generated information. Students must develop the intellectual rigor to question AI outputs, identify inaccuracies or biases, and construct original arguments (Facione, 2020).

2. Creativity and Innovation: Human worth lies in non-routine problem solving and the creation of original ideas, while routine and analytical jobs become mechanized. NEP 2020 supports interdisciplinary learning, which encourages innovation by allowing students to blend disciplines such as information technology, the arts, and ethics to produce hybrid solutions to challenging societal issues.

3. Data Analysis and Interpretation: Since every discipline is becoming data-driven, students need foundational skills in data analysis, data visualization, and statistical reasoning, not only to code AI algorithms, but to interpret the insights. AI produces for decision-making in fields ranging from marketing to medical diagnostics.

4. Ethical Reasoning and Social Responsibility: Understanding the ethical implications of AI (including bias, data privacy, and its societal impact) is now a core professional skill (UNESCO, 2021). The curricula must include courses on digital ethics and responsible AI use, so that graduates across all fields are expected to navigate AI systems responsibly, requiring a curriculum that mandates courses on digital ethics and responsible AI use, a critical element for lifelong learning and citizenship (Figure 7)

Figure 7: Skills Framework for an AI-Saturated World



Created by Author based on data

The "AI-Ready" graduate profile highlights the growing importance of ethical reasoning and critical thinking—skills that are increasingly valued over purely technical abilities that artificial intelligence can easily automate. Rather than treating these competencies as isolated subjects, higher education institutions (HEIs) are integrating them into broader academic structures through initiatives such as the flexible four-year undergraduate program, which offers multiple entry and exit options alongside vocational training. This approach prioritizes practical application, problem-solving, and adaptability, ensuring that graduates are equipped for a dynamic job market. In an era where AI continues to reshape industries, the capacity to learn rapidly, think ethically, and adapt to evolving AI frameworks has become more valuable than static technical expertise (The Academic Insights, 2025).

The Ethics of AI in Higher Education

The growing use of artificial intelligence (AI) in higher education has brought forward a range of ethical and practical challenges that could jeopardize the foundational principles of academia if not properly managed. For AI to be integrated responsibly and sustainably, educational institutions need to implement strong governance systems that actively address concerns such as algorithmic bias, data privacy, and transparency. Establishing ethical policies and regulatory frameworks is therefore essential to maintain fairness, credibility, and public trust in academic processes. AI-driven tools like ChatGPT and Perplexity are reshaping how learning and assessment occur, often challenging traditional methods of evaluating student performance and the authenticity of academic work. Moreover, recent studies have revealed that AI detection algorithms may exhibit bias against non-native English writers, sometimes misclassifying their original content as AI-generated due to linguistic variation. Such instances not only question the reliability of detection tools but also highlight the urgent need for inclusive and equitable AI practices in education (Illinois College of Education, 2024).

Equally important are the ethical and legal concerns related to data ownership, privacy, and surveillance in AI-driven education. Modern AI systems routinely gather extensive data on students' learning behaviors, performance metrics, engagement levels, and even emotional responses. This raises a crucial question: who truly owns this data—the student, the institution, or the technology provider? In the absence of well-defined data governance policies, the use of personal information for learning analytics can pose

serious privacy and security risks. Additionally, AI-enabled proctoring and surveillance technologies, though introduced to curb academic dishonesty, have sparked debate over their impact on student autonomy, digital well-being, and mental health. Continuous monitoring can lead to anxiety, stress, and reduced trust in educational environments, emphasizing the need for ethical oversight and transparent policy frameworks to balance academic integrity with individual rights (Shukla et al., 2025).

Transparency and explainability in AI-driven decision-making are vital for maintaining trust and accountability within educational systems. Many sophisticated AI models function as "black boxes," delivering outcomes—such as recommendations for student admissions, performance evaluations, or resource distribution—without revealing the rationale behind them. In academic settings, both students and educators have the right to understand the basis on which such critical decisions are made, as these can significantly influence educational trajectories and opportunities. Recognizing this, UNESCO's Recommendation on the Ethics of Artificial Intelligence (2021) identifies Transparency and Explainability (T&E) as fundamental ethical principles. It further asserts that the degree of transparency and explanation required should correspond to the context, potential impact, and level of risk associated with the AI system's use.

The solution lies in developing comprehensive and dynamic ethical frameworks and responsible AI policies in academia. These frameworks should:

1. **Preserve Human Accountability:** Ensure that AI systems are designed and implemented in ways that do not replace or diminish human responsibility in making critical academic or administrative decisions. Human oversight must remain central to safeguard ethical judgment and contextual understanding.
2. **Implement Algorithmic Audits:** Conduct periodic and transparent evaluations of AI models used in areas such as student admissions, grading, and assessments. These audits should aim to identify, monitor, and mitigate biases proactively, thereby ensuring fairness, equity, and consistency across educational processes.
3. **Strengthen AI and Digital Literacy:** Integrate AI ethics and digital literacy education as a core component of academic curricula rather than an optional course. By doing so, institutions can better prepare students and educators to engage responsibly with emerging technologies and enhance professional readiness in an AI-driven world (Times of India, 2025).

Integration of AI in Higher Education

Effective integration of artificial intelligence (AI) in higher education demands a comprehensive and multi-dimensional approach that encompasses curriculum design, pedagogical innovation, assessment reforms, and institutional governance. Rather than treating AI as an isolated technological upgrade, it should be embedded within the broader educational ecosystem to enhance learning quality, inclusivity, and adaptability. Drawing from global best practices and emerging Indian initiatives, institutions can develop a strategic framework that supports the sustainable and equitable adoption of AI across all academic and administrative

domains. Various strategies and models for AI integration should be designed that include:

1. While designing the curriculum, AI should be integrated across disciplines. Many global universities are implementing AI-augmented curricula where every major (e.g., law, history, medicine) includes modules on how AI impacts that specific field. For instance, a journalism course might teach students how to ethically use Generative AI for content creation and fact-checking. The Ministry of Education's Skilling for AI Readiness (SOAR) initiative (MSDE,2025), which focuses on integrating AI literacy from the school level (Class VI onwards), provides a foundational pipeline. While primarily focused on K-12. This mandates that the HEIs must focus on building up AI knowledge by offering advanced, application-based courses aligned with industry needs (PIB, 2025). The push for internationalization through UGC Regulations (2023), inviting top global universities, is also expected to accelerate the adoption of global, AI-integrated curricula in India.

2. Utilizing Adaptive Learning Platforms (ALPs) is a global best practice. ALPs analyze real-time student performance data to adjust the difficulty and style of content dynamically, ensuring students master concepts at their own pace. Examples include platforms that use machine learning to offer targeted lessons to address specific knowledge gaps (JoCAAA, 2025).

3. Artificial intelligence plays a pivotal role in automating routine academic tasks such as grading, report generation, and early identification of at-risk students. Intelligent tutoring systems further assist educators by managing repetitive activities, allowing faculty to dedicate more time to mentorship, critical thinking development, and emotional support for learners (San Diego Online Degrees, 2025). This transformation calls for a paradigm shift from traditional, low-stakes, memory-based evaluations toward assessments that emphasize higher-order cognitive and human-centered skills. Such assessments should encourage synthesis, contextual reasoning, oral defense, and real-world application of knowledge—areas that current large language models (LLMs) cannot easily replicate (HEPI, 2025). Moreover, automated assessment tools can deliver consistent, timely, and objective feedback, enabling students to refine their work iteratively and reducing the preliminary assessment workload for educators.

4. The integration of AI in educational administration significantly improves operational efficiency and decision-making. Applications such as AI-powered chatbots enhance student support by handling frequently asked questions, while predictive analytics assist in enrollment forecasting, resource management, and academic planning. Additionally, advanced proctoring systems and plagiarism detection tools help maintain the integrity of assessments and credentials (San Diego Online Degrees, 2025). By adopting a data-driven approach, institutions can strengthen strategic planning, policy formulation, and governance, enabling leaders to make informed and evidence-based decisions (Kuleto et al., 2021).

Recommendations

It is evident from the discussion that a thorough restructuring of academic programs and pedagogical practices is required for AI integration in higher education. The role of educator is not restricted to facilitating what the instructor already knows but to emphasizing what the learner ought to know.' Future-oriented curricula need to be designed that are adaptive as well as responsive to emerging trends in AI, data science, and predictive analytics. Integration of AI in learning management systems (LMS) facilitates alignment of academic offerings with evolving needs of society and the labor market, and offers a unified, efficient, and personalized educational experience.

The following are some recommendations to highlight the strategic priorities for Higher Education:

1. Faculty Training and Integration: The training of educators to equip them with technical competencies, along with skills to address the ethical, social, and pedagogical implications in teaching and assessment, would result in effective integration of AI in higher education.
2. Alignment of curriculum with industry requirements: It has been happening for the last two decades, with feedback from industry to revise and reshape the curriculum periodically. A more robust feedback mechanism may make the curriculum more relevant for the learners to process the competencies required in an AI-driven economy. Real-world case studies, project-based learning, and continuous collaboration with industry experts may ensure the embedding of AI concepts across disciplines.
3. Experiential and Applied Learning: On-the-job projects and on-site engagement provide students with much-needed hands-on experience, which is critical for developing practical skills. The experiential learning opportunities inculcate life skills such as teamwork, critical thinking, and problem-solving, which are going to help citizens of an AI-enabled future. Workshops, hackathons, research collaborations, and internships help in developing AI-based solutions to real-world problems.
4. Career Development with Industry Academia partnership: To bridge the gap between academic learning and employment outcome, a smooth partnership between academia, industry, and career services. Customization of AI-related competencies for specific job requirements is the kind of career service that would be required at academic institutions to make the learner employable and professionally ready. The contribution of industry professionals through co-created projects and continuous feedback to reshape and align the curricula would be immensely helpful in this regard.

The Road Ahead

The article highlights the importance of integration of AI for higher education institutions in the learning systems, policies, and ethical guidelines to face the multidimensional challenges. The stance of all stakeholders, including students, educators, and policymakers, must be the same to ensure responsible consumption of AI by them while managing the potential challenges of the same. As suggested by Williamson and Eynon (2020)," the challenge, then, is to maintain an ongoing,

adaptive dialogue that allows us to continually reassess and redefine our relationship with AI as it evolves." The statement emphasizes the need for higher educational institutions to engage and examine the technological implications of AI, but also its ethical and cognitive dimensions. Higher education institutions must recognize the disruptive potential of generative AI (GenAI) and develop a strategic plan for ethical and pedagogical integration of AI tools. The training of faculty to absorb recent technological advances in their teaching methodologies, assessment frameworks, and research practices would be the gamechanger. This could be possible only when students become the co-creators in the integration process. This can be facilitated by implementing learner-centric policy initiatives and aligning AI literacy, ethical reasoning, and reflective judgment at every step. Rather than making any tall claim, the low/middle-income countries must work on developing machine learning solutions customized to provide solutions for the problems that exist in the context of their economy and present problems for educators, learners, or the unique challenges or needs of the learning ecosystem of their country/institutions. Institutions must make provision to prioritize the empirical research to evaluate and examine the impact of AI-integrated pedagogical models and their scalability for long-term impact. The sharing of the best-fit model and the use cases for AI adoption may help HEIs in overcoming hurdles and make the best use of AI-based technology for sustainable growth outcomes.

Conclusion

The transformative potential of AI in higher education in reshaping the creation and delivery of knowledge is beyond the automation of processes. Today, in a digitally augmented environment, the potential for personalization, inclusion, and efficient operations is immense. To harness this unbridled energy, Higher Education Institutions need to move beyond passive adoption and work towards more grounded engagement with an ethical framework. The purpose of this article is to underscore the need for the development of a strong policy framework, curriculum restructuring, and faculty reorientation for the integration of AI in educational systems. A strong symbiotic relationship between industry and academia would make the relevant changes in the education system, and going forward, would make the learner employable for the industry. The higher moral standards, even with AI integration in education, could be ensured only through inclusivity, transparency, and human orientation.

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Integrating Human and Machine Learning: A Conceptual Framework for Cognitive-AI Synergy in Business Education and Industry 5.0

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Abstract

Purpose: This paper develops an expanded conceptual framework integrating cognitive learning theories with artificial intelligence (AI) and machine learning (ML) paradigms. It explores how human and machine learning can jointly enhance business education, innovation capability, and organizational adaptability in the Industry 5.0 era. By emphasizing co-learning, adaptive intelligence, explainability, and ethical reasoning, the study extends traditional cognitive models into AI-driven pedagogical ecosystems. Through an extensive literature synthesis and theoretical integration, this paper advances the notion of cognitive–AI synergy as a strategic pillar for both educational institutions and corporate learning environments. It further introduces implications for leadership development, digital pedagogy, and ethical governance of AI-enabled learning systems. The extended framework provides practical guidance for developing intelligent co-learning infrastructures where human cognition and machine reasoning iteratively evolve. The conceptualization further expands the conversation on digital ethics and responsible innovation, positioning education as a critical bridge between technological sophistication and human-centered intelligence.

Methodology: The research follows a secondary, conceptual approach. A comprehensive literature review (2018–2025) synthesizes findings across cognitive psychology, educational technology, AI, and knowledge management. Insights from 50+ scholarly sources inform the development of a "Cognitive–AI Co-Learning Model" that integrates theoretical and applied perspectives.

Findings: The study identifies four key synergy dimensions—Adaptivity, Feedback, Explainability, and Ethics—bridging human cognition with machine intelligence. These interconnections enable intelligent pedagogical systems, data-driven education, and human-centered automation.

Originality: While numerous studies address AI in education, few articulate how human learning theories can guide AI design and business pedagogy simultaneously. This paper introduces a new conceptual link between human cognitive models and machine learning architectures. A machine ultimately uses big data in order to learn and be closer to human thinking pattern(s). Human learnings when induced into this plethora of data, the machine becomes mature and results in significant, realistic recommendations useful for today's business trends and industrial dimensions. The reverse is true as well, where human understanding becomes more reasonable by using machine insights. As a result, learning becomes mutual and simultaneous in nature.

Research implications: Provides a conceptual foundation for future empirical studies validating co-learning models in academic and corporate contexts.

Practical implications: Offers guidance for academic institutions and enterprises adopting AI-driven learning ecosystems to enhance digital literacy, critical thinking, and innovation management.

Keywords

Artificial Intelligence, Machine Learning, Human Learning, Business Education, Cognitive-AI, Digital Pedagogy, Knowledge Management, Innovation Management, Industry5.0

Introduction

The Industry 5.0 era is characterised by human-centric innovation, where AI augments — and often replaces — human capability. Global business education is undergoing a "digital and intelligent transformation" driven by AI, reshaping its value-ecosystem (Wu et al., 2025). For example, a recent review notes that AI is "fundamentally reshaping the operational logic and value ecosystem of business education". Business schools now integrate AI-powered analytics, simulations, and decision-support tools into curricula, yet many pedagogies remain traditional, relying on teacher-led lectures, case-method instruction, and static assessment formats.

This paper addresses the critical question: How can cognitive learning principles guide AI design in education, and conversely, how can AI enhance human learning? We argue for a Cognitive–AI co-learning framework where human cognitive strengths and machine intelligence mutually inform each other. This synergy supports adaptive, ethical, and explainable learning systems that foster innovation and strategic skills in learners. The study aims to (1) review human learning theories and cognitive models relevant to AI, (2) discover ML paradigms that mirror cognitive mechanisms, and (3) propose a conceptual framework integrating both for application in business education and Industry 5.0. By connecting educational psychology with AI, we seek to enrich both theory and practice (de Oliveira, 2024; Wu et al., 2025).

In doing so, the paper acknowledges that education and training in the Industry 5.0 context require more than just digitization of content; they require re-thinking how learning occurs, how machines and humans co-evolve, and how organizational ecosystems support this transformation. Business education must shift from static content delivery to dynamic,

data-driven, human-machine interactive learning environments. At the same time, organisations entering Industry 5.0 must prepare workforces capable of collaborating with intelligent systems rather than simply using them as tools. Hence, the conceptual framework offered in this paper is intended to provide both educational institutions and industry with a roadmap for designing learning ecosystems that are not only technologically advanced but pedagogically sound and ethically grounded.

The study aims:

1. To review human learning theories and cognitive models relevant to AI.
2. To discover ML paradigms that mirror cognitive mechanisms.
3. To propose a conceptual framework integrating both for application in business education and Industry 5.0.

The Cognitive–AI co-learning framework proposed in this study situates itself at this intersection—where educational theory meets computational intelligence. It argues that cognitive–AI synergy is not a futuristic ideal but a necessary foundation for preparing adaptive, ethically aware, and innovation-ready leaders.

Theoretical Foundations of Human Learning

In this section, we revisit key human learning theories that have enduring relevance to designing effective learning systems. By understanding how humans learn — cognitively, socially, and metacognitively — we can better architect AI-enhanced educational and training environments. A deeper reflection on these learning theories reveals that feedback loops, contextual awareness, and iterative adaptation are recurring mechanisms across human learning paradigms. When AI systems are designed to emulate or support these mechanisms, the result is a learning environment where human and machine intelligence operate in tandem.

Moreover, socio-cognitive theories emphasize the role of social context and emotion in learning. Emotional intelligence (Goleman, 1995) plays a vital role in motivation, engagement, and collaboration—elements currently being explored in affective computing. Integrating emotional and cognitive intelligence within AI systems could lead to empathetic learning agents capable of recognizing frustration, curiosity, or disengagement in learners. This creates a bridge between purely algorithmic adaptivity and emotional adaptivity, a frontier crucial for holistic business education.

In addition, situated learning theory (Lave & Wenger, 1991) underscores that knowledge is co-constructed through social practice. Applying this to AI-enhanced classrooms, learners interact not only with human peers but also with AI peers, thus broadening the notion of "community of practice." The human–AI ecosystem becomes a distributed cognitive system, where meaning emerges through joint activity rather than isolated cognition.

Cognitive and Constructivist Learning

Classic cognitive theories emphasize that learners actively construct knowledge through experience. Piaget's constructivism, Vygotsky's social interactionism, and Kolb's experiential learning all stress reflection, experimentation, and context (Kolb, 1984;

Vygotsky, 1978). These approaches underscore adaptability and feedback loops: learners form mental schemas, test them against reality, and revise their understanding. In business education, constructivist methods – such as case studies and simulations – harness this cycle by allowing students to experiment with real-world scenarios. Importantly, these frameworks imply that effective learning involves environmental cues and scaffolded support (Vygotsky, 1978). This mirrors how intelligent tutoring systems adapt content based on learner responses. By highlighting iterative knowledge construction, cognitive theories lay a foundation for aligning AI systems to human learning processes (Kolb, 1984; Piaget, 1954). When we map these ideas into AI-enabled pedagogy, we begin to view machines not only as content deliverers, but as co-learners, scaffolds and adaptors of the learning process. The implication is that the human learning cycle — experience → reflection → abstraction → experimentation — can be enriched by machine feedback loops, and vice versa.

Analyzing and assessing student progress

Gardner's theory of **multiple intelligences** (Gardner, 1983) and Flavell's notion of **metacognition** (1979) emphasize diversity and self-awareness in cognition. People possess varied cognitive strengths – linguistic, logical-mathematical, interpersonal, etc. – and good learners regulate their thinking (metacognitive awareness) to monitor understanding. In practice, this suggests AI-driven education should be personalized and reflective. Modern neural architecture attempts to simulate analogous processes: for instance, attention mechanisms in deep networks mirror selective focus in human reasoning. Moreover, meta-learning and self-reflective features in AI (sometimes called "AI metacognition") enable models to evaluate their own decisions. Thus, principles of self-regulation and diverse learning strategies in humans inspire adaptive learning designs that leverage students' strengths (Flavell, 1979; Gardner, 1983). From a business-education standpoint, this means we can design AI systems that recognize not just "what a student answered" but "how they approached the answer, what strategy they used, how they reflected on it, and how they adjusted next time". This enables more fine-grained personalization, supports learners' metacognitive growth, and aligns with higher-order outcomes such as critical thinking and strategic reasoning.

Analyzing and assessing student progress

In the digital era, learning often extends beyond individuals into networks. **Connectivism** posits that knowledge resides in networks and learning is making connections (Siemens, 2005). Technology (the Internet, AI tools) has become integral to learning, enabling collaboration and instant access to diverse information. For example, students use online forums, social media, and cloud-based analytics as "nodes" in their learning process. Connectivism highlights that learning may reside in non-human appliances, and that decision-making is itself a learning process (Siemens & Downes, 2005). In business education, this theory translates into social learning platforms, peer networks, and data-driven knowledge ecosystems. A connectivist perspective implies that AI co-learners can function as part of the learning network, augmenting collective intelligence. This socio-technical view serves as an essential premise for human–machine co-learning: both human learners and AI agents participate in a shared knowledge network (Wu et al., 2025). The implication is that design of learning ecosystems must account for networked

flows of information, and that AI should not be isolated but embedded in the same network as human participants — enabling co-construction of knowledge, peer-machine dialogues, and emergent collaborations. In summary, human learning theories highlight three major threads: cognitive-constructivist active knowledge building, personalised and self-regulated learning (metacognition and multiple intelligences), and networked/social dimensions of knowledge (connectivism). These foundations serve as a lens to examine how AI/ML paradigms might align with or support human learning.

Machine Learning Paradigms and Cognitive Parallels

AI and ML techniques parallel several human cognitive processes. By understanding these parallels, educators can design AI tools that align with how people learn.

- **Supervised Learning:** In this paradigm, models learn from labeled examples, analogous to a teacher guiding a student with correct answers. It reflects instructive learning in humans. For instance, a supervised ML model trained on cases of business decisions corresponds to a student learning by example.
- **Unsupervised Learning:** This involves discovering patterns in unlabeled data, akin to human pattern recognition. People naturally identify clusters (e.g., market segments) or latent concepts from exposure without explicit instruction. Unsupervised ML (clustering, dimensionality reduction) parallels how humans abstract general principles from experience.
- **Reinforcement Learning (RL):** Rooted in behaviorist psychology (Skinner, 1953), RL algorithms optimize actions through feedback (rewards/punishments). This directly mirrors trial-and-error learning in humans (operant conditioning). An RL agent's iterative policy refinement is comparable to how learners adapt behavior when outcomes (success or failure) become apparent. Business use cases include AI-driven simulations where decision-makers learn strategies by trial outcomes, reinforcing good decisions.
- **Deep Learning and Neural Networks:** Deep architecture emulate hierarchical brain processes. Lower layers detect basic features (edges, simple patterns) while higher layers form complex concepts (akin to schema formation). However, these models are often black boxes. The recent focus on Explainable AI (XAI) addresses this: making model reasoning transparent and interpretable. XAI techniques (feature attribution, rule extraction) are analogous to human metacognition – where one explains and reflects on one's thought process. For instance, just as a student verbalizes reasoning, an explainable model can "explain" why it recommends a strategy. This fosters trust and supports reflective learning (Adadi & Berrada, 2018).
- **Generative and Creative AI:** Cutting-edge AI is exploring creativity and empathy. Models like generative adversarial networks (GANs) create novel outputs, echoing human creative thinking, while affective computing seeks to recognize emotions, akin to human empathy. These developments aim for cognitive synergy, enabling machines not just to calculate but to contribute intelligently to tasks like idea generation (Badie et al., 2023).

Additionally, transfer learning in AI mirrors human analogical reasoning—where knowledge from one domain is applied to another. This mechanism is vital for lifelong learning, both in humans and machines. When applied to education, it means AI systems could transfer learned insights across courses or subjects, creating personalized, context-aware learning pathways. A significant aspect that aligns with cognitive psychology is attention modeling. In deep learning, attention mechanisms enable networks to focus on relevant data features, similar to how humans selectively attend to salient stimuli. Understanding these parallels not only enriches AI design but also deepens our grasp of human cognition. In summary, ML paradigms reflect many human learning mechanisms: from supervised tutoring and trial-based learning to networked information processing and self-reflection. This parallelism motivates an integrated framework where AI design draws on educational theory, and human learning design leverages machine intelligence. By mapping machine processes onto human ones, we open the possibility of designing AI systems that "learn like humans" (in some sense) and designing human learning experiences that are enriched by machine feedback, insight, and adaptation.

Literature Review: Human–Machine Integration in Education and Business

Recent literature straddles education, technology, and management. Empirical studies show that **AI-enhanced analytics** and simulations can improve learning outcomes. For example, learning analytics platforms using ML identify struggling students and personalize support. Similarly, business simulations augmented with AI allow teams to explore strategic decisions in realistic scenarios, developing critical skills (Woon, 2025). In the corporate domain, cognitive computing and AI assist decision-making and innovation processes (Brynjolfsson & McAfee, 2022).

Despite growth, gaps remain. Researchers note fragmentation between pedagogy and AI ethics: many AI in education tools lack transparency or disregard fairness (Holmes et al., 2022). Few studies explicitly connect educational psychology with AI system design. In business schools, AI-driven curricula are emerging (e.g., data science courses), but the integration of human learning principles is limited. **Talent development** is an area of active research: a recent review highlights that AI is reshaping business education by redefining core competencies (e.g., data literacy) and requiring curriculum changes. It also notes insufficient attention to how AI is embedded pedagogically.

Leadership development and strategic skills are likewise impacted. AI-based programs now train leaders on data-driven decision-making. A comprehensive review by Joshi (2025) finds that AI technologies are transforming strategic management processes and enhancing decision quality. Meanwhile, Industry 5.0 discourse stresses that innovation and resilience require blending AI with human creativity (European Commission, 2021). Overall, literature suggests the promise of **Human–AI co-learning** but calls for explicit frameworks. Our model responds to this need by articulating how cognitive dimensions can be engineered into AI-supported learning. Furthermore, interdisciplinary research is increasingly emphasizing co-agency—the idea that both human learners and AI systems act as agents contributing to shared knowledge construction. This notion challenges the traditional view of AI as a passive tool and positions it instead as an active collaborator.

In the corporate domain, AI-driven knowledge management systems are transforming how organizations capture tacit knowledge. Through natural language processing and predictive analytics, these systems can codify experiential knowledge and facilitate cross-departmental innovation. For example, firms like Siemens and Deloitte have adopted AI co-learning systems for leadership and innovation training, showcasing the commercial viability of such approaches.

Despite these advancements, literature underscores a persistent gap: most implementations remain technocentric rather than cognitively grounded. The present paper thus fills a crucial theoretical void by embedding cognitive and ethical reasoning into the structural design of AI-enabled learning.

In more detail, the literature can be organised around three streams: (1) AI in pedagogy (adaptive tutoring, analytics, simulations), (2) AI in workforce and organisational learning (talent development, upskilling, innovation support), and (3) ethical and systemic issues (fairness, transparency, governance). For example, adaptive learning systems demonstrate improved engagement and retention, but many lack explainability or human-machine interaction design. Research on corporate training shows predictive analytics can identify skill gaps, yet it seldom integrates human regulatory and metacognitive aspects of learning. Moreover, ethical concerns (bias in algorithms, data privacy, and transparency of decision-making) inhibit widespread adoption of AI in learning environments. The literature thus reveals a need for models that combine pedagogy, machine intelligence, human cognition and ethics — precisely what our conceptual framework attempts to deliver.

Proposed Conceptual Framework: Cognitive–AI Co-Learning Model

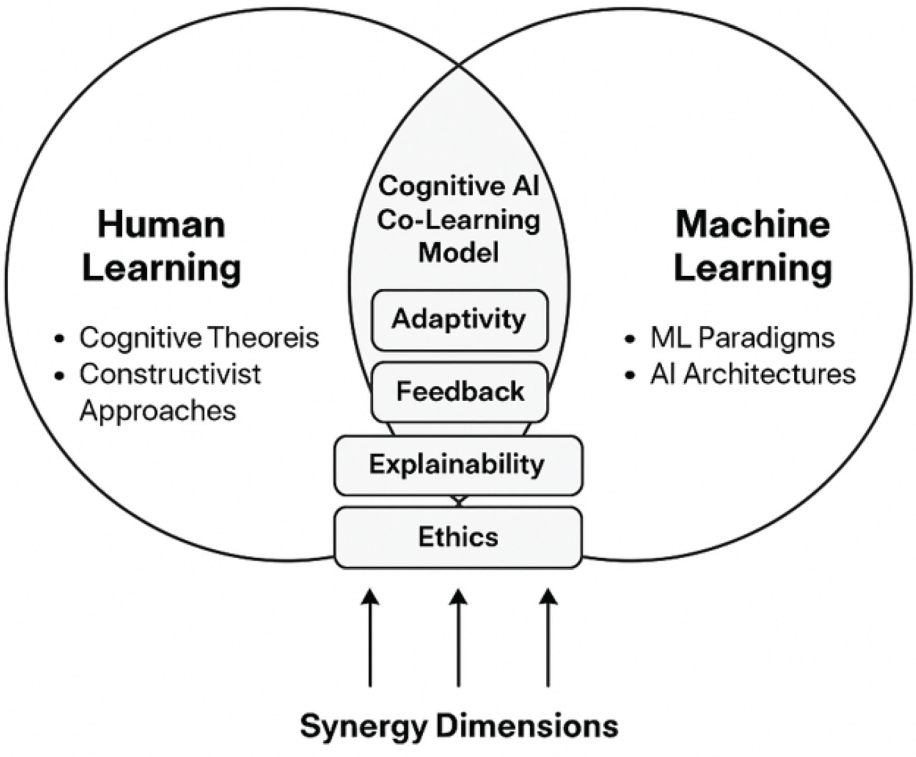
We propose a cyclical **Cognitive–AI Co-Learning Model** based on four intertwined dimensions: **Adaptivity, Feedback, Explainability**, and **Ethics**. Together, these facets create a continuous loop where human cognition and AI algorithms iteratively enhance each other (Figure 1).

- **Adaptivity**: Both humans and machines rely on adaptation. Human learners adapt through experience, reflecting on outcomes; AI adapts via iterative training and model updates. Integrating these enables personalized learning environments and intelligent tutoring systems. In practice, AI can adjust challenge levels or content pathways based on student performance (adaptive learning), while educators refine models with pedagogical insights. This dynamic supports talent optimization by aligning learning to individual strengths and career goals (Gardner, 1983; Wu et al., 2025).
- **Feedback**: Effective learning and AI both depend on feedback loops. Continuous data-driven feedback (e.g. real-time quiz analytics, student behavior signals) helps AI models refine accuracy. Simultaneously, formative feedback from instructors and peers develops learners' judgment and empathy. For instance, AI-driven simulations can provide immediate scoring (precision), while human mentors discuss qualitative aspects (soft skills, ethical reasoning). Integration ensures technical precision complements human values. This dimension underpins strategic decision-making training: when students analyze business simulations, AI can instantly

quantify metrics while coaches guide interpretation.

- **Explainability**: Transparency is crucial for trust and learning. Explainable AI techniques reveal machine reasoning (feature importance, rule logic), paralleling how humans articulate their thought process (metacognition). By making AI decisions interpretable, educators and learners can understand why a model suggests a strategy or identifies a pattern. Explainability fosters accountability and deeper learning. In a management context, when a predictive model advises a strategic move, an explainable interface allows executives to scrutinize and learn from the model's logic. This aligns with ethical governance and helps future leaders build "model mental models" (Adadi & Berrada, 2018).
- **Ethics**: Ethical reasoning is a uniquely human quality that must guide AI. Embedding ethics (fairness, inclusivity, sustainability) in the co-learning cycle ensures that AI recommendations align with human values. For example, an AI recruiting tool in business education training should avoid bias; an explainable AI can flag potential discrimination for correction. Emphasizing ethics also means teaching AI ethics as part of leadership development. Industry 5.0 literature stresses responsible innovation and humane leadership (de Oliveira, 2024). Thus, in our model, ethics acts as a compass, shaping both how AI models are built (data governance, algorithmic fairness) and how learners use AI insights (ethically informed decisions).

Figure 1: The Cognitive–AI Co-Learning Model (conceptual framework). The four synergy dimensions form a continuous, reciprocal learning cycle: human cognition informs AI design, and AI-driven insights enhance human learning.



Discussion and Implications

Our **Cognitive–AI Co-Learning Model** offers theoretical and practical contributions across education and industry:

- **Academic Implications:** By merging cognitive psychology with AI, this framework extends learning theory into the digital age. It suggests novel research directions: studying co-agency where AI agents and humans jointly contribute to knowledge. For instance, research could explore how explainable AI tools affect learner metacognition or how adaptive algorithms influence collaborative learning outcomes. The model encourages interdisciplinary studies (education science + computer science + ethics) to validate each dimension empirically. In educational psychology, it is theorized that learning environments can be machine-mediated constructivist spaces. This enriches fields like educational data mining and knowledge management by grounding them in cognitive principles.
- **Management and Practice Implications:** The model has wide applications in business education, corporate training, and organizational strategy.
- **Business Education:** Educators can integrate AI analytics and simulations into curricula to enact the model. For example, a capstone course might use an AI-driven business simulation (Woon, 2025) that adapts scenarios based on team performance (Adaptivity) and provides annotated feedback reports (Explainability). Leadership courses can include AI ethics modules (Ethics), training future managers to critically assess AI recommendations. Overall, applying the model helps develop digital literacy, critical thinking, and innovation skills.
- **Corporate Training and Talent Development:** Companies can use AI-powered learning platforms that personalize employee upskilling paths (Adaptivity) and track progress with learning analytics (Feedback). In talent optimization, predictive AI identifies skill gaps, while managers review AI suggestions to ensure fair career development (Explainability, Ethics). A systematic review notes the need for AI-driven talent development in higher ed and corporate learning, highlighting curriculum restructuring and resource support to build AI competencies. Our framework provides that structure.
- **Industry 5.0 Strategy:** For organizations, the model guides digital transformation and innovation management. It recommends **human–AI collaboration** as a strategic asset. For example, R&D teams can co-learn with AI tools: adaptive ML models propose hypotheses (Adaptivity), scientists interpret and refine them (Feedback/Explainability), and ethical guidelines ensure innovations benefit society (Ethics). This aligns with findings that AI can synergistically boost innovation capacity when aligned with organizational strategy (Bécue et al., 2024). Moreover, leadership development programs can incorporate AI coaching to build analytical thinking and empathy—competencies identified as crucial for Industry 5.0 leaders (de Oliveira, 2024). Strategic decision-making becomes a partnership: AI enhances data-driven insights (Joshi, 2025) while human managers apply judgment. In sum, adopting the co-learning cycle transforms firms into learning organizations, where continuous feedback and adaptation are built into workflows (European Commission, 2021).

By embedding adaptive analytics, explainable AI, and ethical guidelines into training, institutions can create robust learning ecosystems. These systems not only automate tasks but also educate—teaching both machines and humans to improve iteratively. From a policy perspective, the Cognitive–AI Co-Learning Model aligns with international frameworks such as the European Commission's "Ethical AI Guidelines for Education" and UNESCO's "AI and the Futures of Learning" report. Both advocate for human-centered AI ecosystems emphasizing transparency, inclusivity, and lifelong learning.

Moreover, this framework contributes to the emerging concept of Learning 5.0—an evolution of e-learning that emphasizes co-evolutionary intelligence. Here, humans and machines continuously co-adapt, resulting in accelerated knowledge diffusion and innovation agility.

In management education, this framework could redefine assessment paradigms. Instead of measuring static knowledge, institutions can use AI to evaluate dynamic competencies—such as adaptability, ethical reasoning, and collaboration—over time. This shift moves from "teaching to testing" toward "teaching to evolving."In organizational settings, applying the model could support knowledge resilience. By enabling human–AI collaboration, firms can safeguard against knowledge loss, ensure continuous innovation, and cultivate adaptive learning cultures. The framework thus holds promise for building resilient knowledge ecosystems essential for sustainable competitiveness in Industry 5.0.

Conclusion and Future Research

This conceptual review emphasizes that the future of learning is collaborative cognition. We introduced a new framework linking human cognitive theories with ML mechanisms, identifying Adaptivity, Feedback, Explainability, and Ethics as pillars of cognitive–AI synergy. By grounding AI systems in pedagogical principles, educators and managers can foster environments where technology and human insight co-evolve. This advance contributes to innovation management and leadership development by clarifying how to train people and design AI in tandem.

Future research should operationalize and test this model. Possible directions include:

- Longitudinal studies measuring learning outcomes when AI systems implement our four dimensions. For example, tracking MBA students using adaptive AI tutors for decision-making tasks over a semester.
- Field experiments in executive education: comparing traditional training vs. AI-enhanced training on leadership and innovation metrics.
- Mixed-method studies investigating stakeholder perceptions: How do students and instructors experience trust (Explainability) and empowerment (Adaptivity) with AI tools?
- Interdisciplinary work integrating philosophy and neuroscience to deepen understanding of co-learning mechanisms (e.g. cognitive load in AI-mediated classrooms).
- Policy and ethics research on governance frameworks ensuring fairness and privacy in AI-driven education.

Ultimately, we contend that augmenting human–machine co-learning will define the competitive edge of educational institutions and organizations. Industry 5.0 envisions technology amplifying human strengths; our framework provides a roadmap for making that vision concrete. As Wu et al. (2025) note, business education's ecosystem is transforming, and by embracing cognitive–AI synergy we can steer that transformation toward enhanced innovation, strategic decision-making, and ethical leadership. Beyond its theoretical implications, the Cognitive–AI Co-Learning Model also contributes to educational design science by providing a structured lens for developing AI-integrated learning architectures. Future empirical research can operationalize these dimensions into measurable constructions, enabling quantitative validation.

Cross-sectoral studies can also examine how cognitive–AI synergy affects organizational innovation rates, employee well-being, and leadership adaptability. Additionally, the integration of neuroscientific insights into AI co-learning—such as brain-computer interfaces or cognitive load monitoring—can expand the boundaries of intelligent pedagogy.

Finally, this framework invites scholars to explore epistemological pluralism in AI ethics: how cultural, philosophical, and contextual diversity shape human–machine learning values. In this way, the model not only anticipates Industry 5.0 but also contributes to a broader philosophical project—understanding what it means to learn, know, and act intelligently in a hybrid cognitive era.

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The Cartesian Compass: A Risk-Based Framework for Quantifying Ethical Impact of Artificial Intelligence in University Education

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Abstract

The increasing adoption of AI systems in higher education creates new ethical challenges that go beyond classic concerns about accuracy and performance. The ethical frameworks for existing systems stress principles related to fairness, transparency, and accountability, but there is a lack of mechanisms to quantify and monitor the risk associated with ethical instances in real-life educational deployments. This paper serves to help bridge this gap by proposing a quantitative framework for assessing ethical risks that are relevant to AI-driven decision-making in educational settings.

We propose an ethical risk formulation that models harm as a function of both its likelihood and its severity, enabling the expression of ethical considerations in measurable terms. The framework is conceptually rooted in well-established risk assessment principles and desirably model-agnostic, interpretable, and adaptable to the context of institutions where decisions are made. To illustrate its practical applicability, the framework is empirically validated using large-scale student interaction data from an authentic educational setting. Ethical risk is computed based on observed misclassification behavior of an automated decision model, and its robustness is investigated under different normative assumptions concerning the severity of harm.

The empirical results demonstrate that, even for top-performing AI systems, ethical risk is nonzero over a range of plausible harm-weighting scenarios. These findings reflect the important limitations of dominant accuracy-centric evaluation practices and emphasize the need for explicitly accounting for ethical risk as part of educational AI governance. By offering a transparent and systematic operationalization of ethical harm, this work provides a tool for responsible AI evaluation and contributes to more informed and responsible deployment of AI technologies in higher education.

Keywords

Ethical Risk Assessment; Artificial Intelligence in Education; Responsible AI; Algorithmic Decision-Making; Educational Data Analytics; AI Governance

Introduction

Artificial intelligence (AI) integration in higher education institutions accelerated in recent years. AI integration affects basic education operations in institutions, such as assessing students, screening students during admission, educational analytics, and offering personalized learning programs. Higher institutions have adopted AI-driven systems in order to inform decisions on a large scale because institutions can gain efficiency, standardization, and better educational delivery outcomes (Zawacki-Richter et al., 2019). Besides these gains, AI integration in education continues to present serious concerns in ethics, such as fairness, accountability, and the well-being of students.

A lot of research literature has emphasized the dangers of bias and discrimination in algorithmic decision-making, especially in cases where AI systems learn from historical and incomplete datasets (O'Neil, 2016; Mehrabi et al., 2021). In an educational context, such dangers become critically important because AI decisions can have a direct impact on students' educational paths and career opportunities in the future. Technical flaws and biases in AI systems can thus have not only technical but also social and moral consequences in terms of being harmful (Holmes et al., 2022).

To address these issues, a variety of guidelines and principles have emerged in an attempt to support a responsible AI research and application culture. Examples of these guidelines include principles such as fairness, accountability, transparency, and explainability, which are now described by some international bodies and authorities, such as UNESCO, as being foundational for trustworthy AI systems (Floridi et al., 2018; UNESCO, 2021). In the learning education context, these principles have become progressively incorporated into a collective term, FATE, to assess the ethics of AI-enabled learning assessment systems for education (Memarian & Doleck, 2023). While these principles are important and vital, they remain fundamentally qualitative approaches that do not address or support a systematic assessment of ethics in operation.

A major drawback in current methods is their heavy usage of traditional performance evaluation measures, especially accuracy, as indicators of acceptability based on ethics. A model with strong predictive performance is considered a significant indicator of a model being reliable and fair despite experimental evidence pointing to accurate systems being morally unacceptable in their output behavior (Corbett-Davies & Goel, 2018). The ethics-agnostic focus based on performance overlooks the mismatch between model accuracy and ethics, leaving institutions without a mechanism to quantify occurrences when harm is caused by an AI model and the level of intensity with which it is presented.

While risk assessment methods in other domains, such as cybersecurity and healthcare, provide a contrasting viewpoint, where risk can be calculated based on both chance and impact (ISO, 2018; Hubbard & Seiersen, 2016), these methodologies do acknowledge a reality in which low-risk tasks with high impact deserve attention. As a contrast to other domains with high stakes, mathematical risk definitions have not had a presence in ethics risk analysis in AI systems in education.

To fill this research gap, this paper describes a novel approach to constructing a mathematical model of ethical risk in AI-driven educational choice-making. In contrast to non-normative advice, this model is intended to facilitate empirical assessment and ongoing analysis of exposure to ethics. To verify the model's application in a real-world setting, this paper validates it using real-world education data, demonstrating how high-performing educational systems can address ethical risk.

As a contribution to bridging ethics theory and practice through an operational definition of harm in a risk-driven framework, this research aims to facilitate better governance in AI in higher education institutions, taking a step from ethics principles towards ethics risk assessment and mitigation.

Ethical AI in Higher Education: Background and Challenges

Artificial intelligence in higher education has proliferated rapidly across a variety of educational and administrative tasks. AI-enabled tools and systems find increasing application in learning analytics, adaptive assessment, student performance forecasting, admission evaluation, and learning support. Such systems hold out promise in terms of efficiency and scalability in institutions with a large and varying learner base, which defines many a higher education institution today (Zawacki-Richter et al., 2019).

Despite these benefits, higher education is a critical area in which AI is being introduced in a very sensitive manner. The decisions made or influenced by these systems can directly impact students' educational and future career paths. Therefore, if these systems go wrong, not only will they affect performance but critical considerations will arise in terms of these systems impacting fairness, accountability, and transparency in these institutions (Holmes et al., 2022).

One of the most widely considered issues is algorithmic bias. A machine learning algorithm can perpetuate existing inequities in education, given a dataset from previous educational experiences (O'Neil, 2016; Mehrabi et al., 2021). In an educational setting, this is a problem in terms of systematic error in labeling students, an imbalance in access to educational support, and an imbalance in negative consequences for some students. As a consideration, when AI is used in an educational institution for purposes of high-stakes decisions such as educational progression or admission, one important factor to address is algorithmic bias. To address these concerns, guidelines based on ethics for the governance of AI have emerged. Some guidelines have emphasized fairness, accountability, transparency, and explainability in AI and have become core considerations in accountable AI (Floridi et al., 2018; UNESCO, 2021). In higher education institutions, these considerations have become guiding principles for assessing AI systems, with a focus on interpretability, control, and human involvement in decision-making AI systems (Memarian and Doleck, 2023).

Nonetheless, these frameworks contain a critical function of providing guidance with regard to ethics, but they can never serve as an end in terms of providing a tangible way in which ethics can be operationalized when conducting an evaluation. Hence, ethics come into consideration in an indirect manner with a focus on basic performance standards, especially accuracy. Nevertheless, using accuracy as a way in which ethics are considered can be considered flawed, especially since a matter of high accuracy

can have an unfair performance standard (Corbett-Davies & Goel, 2018).

The other challenge is related to a lack of a common way of measuring ethical impact in different AI systems. Current methods of evaluation are concentrated on separate issues in ethics, such as fairness measurements or methods of explanation, without considering a broad picture of how this impact can manifest or become problematic in a particular case. Such an approach makes it difficult for institutions to make comparisons among different AI systems in terms of ethical exposure.

Such challenges have brought forth an important deficiency in state-of-the-art methods of handling ethics for AI in higher education contexts. That deficiency is the inability to use a practical model based on chance and impact in dealing with ethics for AI in higher education. Models based on chance and impact have become common in other critical domains with immense consequences, such as cybersecurity (ISO, 2018) and healthcare, where handling risk in such a manner is common practice (Hubbard & Seiersen, 2016).

Ethical Dimensions: A Cartesian Analysis

The ethics of AI systems in higher education can be assessed using normative guidelines such as fairness, accountability, transparency, and explainability. Although these guidelines are critical for ethics, they can be viewed from a rather simplistic angle, where systems are simply classified as either conforming or non-conforming. In this case, these guidelines ignore the realities of ethics in their application.

In reality, gray-area, non-ethically desirable effects achieved using AI systems can be considered different in at least two ways. First, they can be considered different based on frequency. While some systems may sometimes produce non-ethically desirable effects, other systems may achieve this on a consistent basis. Secondly, they can be considered different based on their intensity. A system can impact education in a less serious manner than another system.

To respond to this challenge, a two-dimensional Cartesian space can be used for ethical outcomes with dimensions based on harm frequency and harm severity, respectively. Then, for each set of automated decisions, a point in this space can be identified based on the rate at which these decisions have negatively impacted outcomes and the level of impact when they have such an effect.

"This Cartesian approach illustrates situations not captured by conventional performance evaluation. A machine learning system, for instance, may be very accurate in its predictions but sometimes cause unusual but very serious negative consequences, such as inequitable academic penalties. A different machine learning system, perhaps, will cause common but less serious negative impacts, such as small learning support misallocations. While both systems seem very similar when judged solely on their accuracy performance, they can have very different ethics when measured using both dimensions of likely impact and severity."

Such differences have special significance in educational settings because of the compounding and direct impact of automation decisions over time on students' educational paths. Minor harms can cumulate over time, and infrequent but major harms can have

irrevocable consequences for individual students. A Cartesian analysis acts as a thinking aid before carrying out any calculation.

Such a two-dimensional approach offers a conceptual basis for constructing an ethics risk model in support of AI education-enabled decisions, since a combination of likelihood and magnitude of harm can, in fact, allow ethics risk to become an operationalized, measurable quantity.

Mathematical Formulation of Ethical Risk

Based on the Cartesian approach presented in the previous section, this section will establish a mathematical model for ethical risk. The goal is to provide a mathematical interpretation of both dimensions of ethics that can be used in risk evaluation.

Defining Harm in AI-Driven Educational Decision-Making

An ethical harm in AI-supported learning environments can be described as a negative impact on a student's educational experience, opportunities, or treatment resulting from an automated decision. A very important consideration in this definition is the fact that it can be achieved without a malfunctioning system or evil intent.

Based on supervised learning systems used in education, harm based on ethics can be measured via error in decisions. In situations where an AI system makes an inaccurate prediction, an action resulting from this inaccuracy can have a negative impact on a student. Two kinds of misclassification are important in this case:

- False negatives, where a student's level of skill or achievement is undervalued.
- False positives – where a child's performance is exaggerated, leading to a possibility of incorrect information being provided.

Although both kinds of error do represent harm under ethics, they do not necessarily represent equal harm. In most learning environments, an unjustified punishment will be considered more serious in ethics than an ancillary missed intervention, leading to a different treatment in ethics risk definition.

Ethical Risk Model

Ethical risk is represented in a model depending on two variables: the probability of an AI system producing a negative outcome and the scale of negative outcomes. Mathematically, ethical risk is expressed as:

$$ER = P(H) \times M(H)$$

where P(H)denotes the probability of harm and M(H)represents the magnitude of harm.

The probability of harm captures how frequently ethically undesirable outcomes occur. In classification-based educational systems, this is expressed as the proportion of incorrect automated decisions relative to all decisions:

$$P\left(H\right) = \frac{FP + FN}{TP + TN + FP + FN}$$

where TP, TN, FP, and FNdenote true positives, true negatives, false positives, and false negatives, respectively.

The magnitude of harm reflects the average ethical severity of harmful outcomes when they occur. To account for asymmetry between error types, harm severity is modeled using weighted contributions:

$$M\left(H\right) = \frac{FN \cdot w_{FN} + FP \cdot w_{FP}}{FN + FP}$$

where w_{FN} and w_{FP} represent ethical severity weights assigned to false negative and false positive outcomes. These weights are normative parameters, encoding relative ethical priorities rather than empirically observable constants. Their purpose is to reflect differences in potential impact while remaining transparent and adaptable to institutional contexts.

The resulting ethical risk score integrates both the frequency and severity of harm into a single interpretable metric. This formulation complements traditional performance measures by making ethical exposure explicit and quantifiable, rather than implicitly inferred from accuracy alone—a limitation widely noted in prior work on algorithmic decision-making (Corbett-Davies and Goel, 2018).

The next section applies this formulation to some real-world educational data with the aim of empirically validating its usefulness and robustness.

Practical Interpretation of Ethical Risk

The ethical risk score stands for an interpretable measure of how ethically hazardous an AI-driven decision-making system may be in practice. Rather than a mathematical abstract construct, ethical risk captures two complementary aspects of ethical exposure: how often ethically undesirable outcomes occur, and how severe their consequences are once this happens.

A system that generates harmful outcomes at a high rate will have a high probability of harm, even if the individual impacts are relatively small. Conversely, a system whose decisions impact critical aspects of students' academic trajectories may raise significant ethical concerns even when its harmful outcomes are rare, owing to the severity of their consequences. Ethical risk grows when either of these dimensions increases, and it becomes especially great when both dimensions are high at once.

The higher the ethical risk values are, in governance terms, the greater the requirement for oversight, mitigation, or restriction there is. Systems dealing with low ethical risk can be deployed and simply routinely monitored, while systems showing a persistently high ethical risk should receive careful intervention, redesign, or reconsideration of their use. Ethical risk assessment, therefore, feeds into proportionate and evidence-based decision-making and avoids binary judgments of acceptability.

This reading emphasizes the importance of ethical risk as a real-world complement to the usual performance metrics. While accuracy conveys how often a system predicts correctly, ethical risk flags the possible ethical cost of its mistakes, and hence allows institutions to reason explicitly about trade-offs involved in deploying AI systems in educational contexts.

Illustrative Example - Hypothetical

For an example of how the ethical risk score behaves, consider a range of hypothetical AI-assisted grading system results that produce systematically unfair outcomes for some subgroup of students, say, similarly lesser grading recommendations without pedagogical justification. Assume the probability of such harmful decisions is estimated as P(H) = 0.30, and the magnitude of harm, reflecting the potential academic and long-term consequences, is assessed as M(H) = 0.80 on a normalized [0,1] scale. The ethical risk is then:

$$ER = P(H) \times M(H) = 0.30 \times 0.80 = 0.24$$

As this example illustrates, under which circumstances an ethical risk can become a serious one because of not very unlikely but very high-risk consequences. As a matter of fact, this kind of outcome would require additional attention and mitigation or think twice before deploying in accordance with organizational rules.

Empirical Validation of the Ethical Risk Model

In this section, the proposed model of ethical risk is empirically tested by using actual data available in educational settings. The goal is to gauge how mathematical calculations of ethical risk can be performed and if such exposure remains a relevant factor, regardless of model accuracy.

Dataset and Experimental Setup

The empirical evaluation used a dataset from an educational application called ASSISTments, a common benchmark in learning analytics studies. ASSISTments provides information on student interaction with online tutoring systems, such as problem-solving behavior, hint-seeking behavior, and performance results, with all information being anonymous in nature (Koedinger et al., 2010).

For this analysis, a subset of interaction logs from student–problem interactions is chosen, with an emphasis on variables likely to be used in automated instruction decision-making. Every interaction is one instance where an AI system might have an impact on feedback, assessment, or instruction. Variables include the number of tries on a problem, time on task, proportion of hints used, and a boolean variable describing if a problem is solved correctly.

To maintain model interpretability intact and prevent mixing up model complexity with ethics analysis, a logistic regression classifier was used. While developing this model, optimization of performance is not a goal but rather the creation of a model output amenable

Table I: Summarizes the key features used in the empirical evaluation

Feature	Description
attempt_count	Number of attempts made by the student
time_on_task	Time spent solving the problem
fraction_of_hints_used	Proportion of available hints used
correct	Binary indicator of problem correctness

to analysis of ethical risk. The dataset was split into a testing and a training set using random partitioning to check model performance on unseen data.

Incorrect predictions were considered to have ethically negative consequences because they can cause inequitable evaluation in academia or misleading educational advice. With this design, it is easy to apply the formula for ethical risk described in Section 4.

Ethical Risk Computation Procedure

This section describes how the ethical risk score was computed in practice, following the operational steps applied during the empirical evaluation.

Ethical risk was quantified using the formulation:

$$ER = P(H) \times M(H)$$

where P(H) denotes the probability of a harmful automated decision, and M(H) represents the magnitude of harm associated with such decisions.

Each student–problem interaction in the dataset was treated as an individual automated decision. Logistic regression was used to predict the likelihood of a correct vs. incorrect student response given observable features of the interaction, such as attempt count, time-on-task, and fraction of hints used. Model predictions were compared against ground-truth correctness labels in order to identify incorrect automated decisions.

For the purposes of this analysis, harmful outcomes were incorrect predictions. Using a confusion matrix gleaned from model predictions on the test dataset, two types of harmful outcomes were included: false negatives, wherein a student's true competence is underestimated, and they may be subjected to unfair academic penalties or to remediation they do not need; and false positives, wherein student performance is overestimated and can lead to misleading feedback or insufficient instructional support. Correct predictions would not be harmful.

Formally, wrong predictions correspond to the classes of the false positive (FP) and false negative (FN) outcomes in the confusion matrix. The correct predictions—true positives (TP) and true negatives (TN)—do not form ethical harm in themselves because they reflect the right system behavior.

Accordingly, the probability of harm is defined as the empirical frequency of harmful outcomes relative to all automated decisions:

$$P\left(H\right) = \frac{Number\ of\ harmful\ decisions}{Total\ number\ of\ decisions}$$

Substituting confusion matrix components yields:

$$P\left(H\right) = \frac{FP + FN}{TP + TN + FP + FN}$$

To account for differences in ethical severity between error types, the magnitude of harm was modeled as a weighted average of false positive and false negative outcomes:

$$M\left(H\right) = \frac{FN \cdot w_{FN} + FP \cdot w_{FP}}{FN + FP}$$

False negative outcomes were weighted more than false positives, reflecting the higher potential harm resulting from the unjust penalization of students. The applied weights (w_{FN} =0.7, w_{FP}=0.5) reflects a conservative differentiation in harm severities. These values do not pretend to be universally optimal but instead provide a clear instantiation of harm asymmetry that is amenable to empirical assessment.

Results and Interpretation

It is important to emphasize that the performance of the predictive model is very good from a technical standpoint; the overall accuracy of the model was 94.08%. However, even with this high predictive accuracy, a non-negligible fraction of incorrect automated decisions had occurred. Probability of harm was measured as:

$$P(H) = 0.0592$$

This would mean that roughly 6% of automated decisions came to an ethically undesirable outcome.

The estimated magnitude of harm was

$$M(H) = 0.5005$$

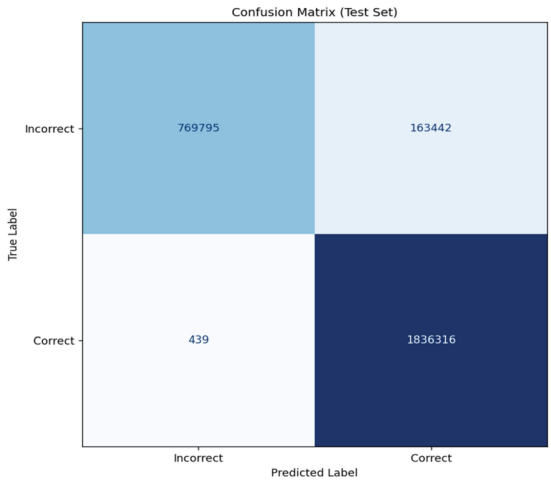
which represents a moderate mean severity of harms. Combining these elements gave an overall ethical risk score of:

$$ER = 0.0296$$

These results illustrate a key point: high predictive accuracy does not eliminate ethical risk. Even the best-performing automated systems can create persistent ethical exposure once deployed at scale. While the numerical value of ethical risk seems modest, it becomes large in the aggregate in substantial educational settings where automated decisions affect large student populations.

Figure 1 displays the confusion matrix of automated decision outcomes on the test dataset. Although correct predictions are dominant, the matrix shows the presence of both false positive and false negative decisions. These misclassifications correspond to ethically undesirable outcomes and provide a concrete illustration of why ethical risk remains non-zero despite high predictive accuracy.

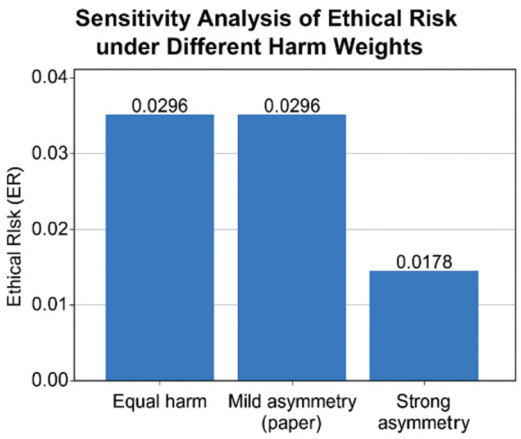
Figure 1: Confusion matrix of automated decision outcomes on the test dataset.



Sensitivity Analysis of Harm Weights

To validate the sensitivity of an ethics risk formulation, a sensitivity analysis can be done by adjusting weights related to the harm of false negatives and false positives. In this study, three different settings were used: both false negatives and false positives carrying equal harm weights, a moderate level with a focus on an improper punitive step, and a high level.

Figure 2: Sensitivity analysis of ethical risk under different false positive and false negative harm weight configurations.



To illustrate a visual inspection of the resilience of the formulation of ethical risk, Figure 2 plots the calculation of ethical risk with varying harm weight settings. Figure 2 shows how ethical risk is non-zero in all settings, validating that the measured degree of ethical risk is not a function of a particular setting of harm weights.

As can be seen in Figure 2, despite varying assumptions on harm weights, different assumptions will give different absolute measurements of ethical risk but not affect the relative assessment.

In all cases, NSS-NR was kept constant at a non-zero level. However, under equal and moderate assumptions, NSS-NR had no effect, maintaining a constant level at a lower level (ER=0.0296), unaffected by small variations in harm weights. Additionally, under strongly asymmetric assumptions, NSS-NR decreased due to reduced occurrences of false negatives in the dataset.

Crucially, despite a change in the magnitude of ethical risk, but not in qualitative magnitude, a high degree of predictive accuracy did not preclude this qualitative degree of ethical risk in automated educational decision-making. This confirms the robustness of the proposed ethical risk index with regard to differences in normative commitments to harm thresholds.

Table 2: Sensitivity Analysis of Ethical Risk under Different Harm Weights

Scenario	(w_{FN})	(w_{FP})	(M(H))	(ER)
Equal harm	0.5	0.5	0.5000	0.0296
Mild asymmetry (paper)	0.7	0.5	0.5005	0.0296
Strong asymmetry	0.9	0.3	0.3016	0.0178

Discussion

In this research, a theoretical model for calculating the risk in AI decisions in educational settings has been proposed and proven. High accuracy achieved in educational AI systems does not necessarily mean a lack of risk in making educational decisions, which is a major drawback in most educational AI systems with accuracy-centric assessment approaches.

Empirical results present that during evaluation, an accuracy of above 94% is obtained by the model, but up to 6% decisions were incorrect. Although this error percentage may seem small in technological terms, an ethical risk analysis shows that this inaccuracy leads to a non-zero level of ethical exposure. The graph shows, in a better way from confusion matrix analysis, that decisions with false-positive and false-negative results have some level of measurement, which shows that sometimes decisions with higher accuracy will not be purely good in an ethical manner.

One important aspect of this research is pointing out the differences in assessment when focusing on ethics rather than performance. The accuracy measures all errors equally, but when considering ethics, they take into consideration the asymmetric impact of each error. In educational institutions, false negatives can have serious effects on students when they are penalized unduly in their studies based on an underestimation of their capabilities.

The sensitivity analysis adds to the robustness of this approach. Over different harm-weighting combinations, the non-zero level of ethical risk was maintained, and the qualitative results were recovered. Moreover, this shows that this detected level of ethical exposure is not a function of a specific normative belief but rather a deep characteristic of automatic educational risk assessment. Additionally, this harm-weighting flexibility provides an institution with the ability to make ethics ranking conform to institutionalized educational beliefs.

With regards to governance, ethical risk indicators represent a useful resource for proportional governance. As opposed to AI systems being considered categorically acceptable or unacceptable, systems are now able to be measured in terms of continuous comparisons in ethics. Furthermore, systems that have a higher degree of ethical risk can require increased human governance, whereas systems with lower degrees of risk can be allowed with normal governance.

In spite of these achievements, this research work has some shortcomings. The harm characterization in ethics, for instance, can be achieved by error in classifications, which simply quantify a single dimension of harm but not all. Other harms, such as violations of privacy, a lack of transparency, or behavioral consequences, among others, were not in contemplation. Secondly, this work focused on validating with a single dataset and a two-class classification problem.

In summary, this whole debate highlights the most important message of this research: it is not possible to infer ethics in AI-driven education systems solely based on performance indicators. Ethical exposure has to be measured so that it can highlight the ethics not seen in AI-driven education systems based on performance indicators.

Conclusion, Recommendations, and Directions for Future Research

The present research proposed a quantifiable model to estimate ethics risk in AI-driven educational decisions. The model treats ethics risk as a function of both potential harm and the likelihood of adverse outcomes, transcending principle-driven and performance-oriented perspectives by adopting a quantifiable viewpoint.

Empirical evaluation showed that sufficient ethical risk remains in systems that are highly accurate. Although their predictive performance was excellent, in this case, a non-zero level of ethical risk existed because of both false positive and false negative cases in the evaluated model. The above results reinforce the idea that accuracy is not an adequate factor to certify if a model has an acceptably ethical performance level, especially when concerning critical educational environments.

The formula for ethical risk can be a good tool in AI governance in education. As this formula does not classify AI systems into purely ethical or purely unethical systems, this AI governance tool utilizes an index to promote proportional regulation in accordance with the calculated degree of exposure in ethics. Ethical risk scores can be used by institutions to inform deployment decisions, direct efforts to mitigate based on priority, and assess ethics performance over time.

A variety of directions for future research have emerged via this work. First, harm can be considered not solely with regard to errors in a classifier but also with regard to other dimensions such as transparency, privacy, and behavioral impact. Second, cross-validation across a variety of datasets, models, and learning environments will improve generalizability. Lastly, incorporating harm assessment into real-time systems is a promising area for future research regarding operationalizing responsible AI in learning environments.

In conclusion, this research shows that it is possible to define, estimate, and interpret the phenomenon of ethical risk meaningfully. The application of an assessment of this type to AI-powered educational systems evaluation is a step towards a responsible, transparent, and accountable AI application in higher education.

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AI Change Management in Higher Educational Environments

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Abstract

The rapid integration of generative artificial intelligence (GAI) into higher education necessitates a deliberate shift from viewing it not only as a technological tool but also as an assistant for managing a comprehensive organizational change. This article contends that for higher education institutions (HEIs) to harness GAI's potential, they must effectively navigate through significant challenges, including ethical dilemmas around bias and academic integrity, resistance to change, and concerns over critical thinking and avoiding cognitive short-circuiting in students. By framing adoption through a structured change management viewpoint, the article provides a framework for this transformation, moving beyond definitions to address the essential "how" and "why" of integration. It maps the critical roles of internal stakeholders, i.e., faculty must redesign pedagogy and assessment, students must develop ethical AI literacy, and administrators must establish supportive policies and infrastructure. The analysis underscores that effective institutional policy is the indispensable foundation for responsible AI usage, creating guardrails for data privacy and academic integrity while at the same time making the most effective usage of this new technology. This article calls for educators, leaders, and policymakers to cultivate a culture of innovation where we ensure that AI integration strengthens the fundamental goal of higher education to develop wisdom and equip students for an AI-augmented future.

Introduction

In the post-COVID era, i.e., since 2022, the ecosystem of higher education is undergoing a rapid change. We stand at an unprecedented moment in history where digital transformation is no longer just a competitive advantage for an organization; it is considered a prerequisite for institutional survival and relevance. At the forefront of this transformation is Artificial Intelligence (AI), in many of its forms, a force of profound disruptive potential that promises to redefine every domain of academics, i.e., from teaching and learning to research, administration, and student services. This article aims to explore the key challenges for the successful integration of AI into the fabric of higher education and how to manage this change.

The conventional pedagogical model, which is often characterized by a standardized mode of instruction and summative assessment, has a huge contrast with both the capabilities

of AI and the needs of the world with fast dynamics. An AI-augmented approach offers personalization, adaptive learning pathways, and naturally shifts the teacher's role from knowledge deliverer to facilitator and shifts the focus of assessment on the learning process and higher-order cognitive skills. This transition comes with significant challenges, e.g., in the form of ethical dilemmas around bias and academic integrity, resistance to change, digital divides, and legitimate concerns over data privacy and most importantly the very purpose of a higher education i.e. critical thinking which, due to the advent of AI, is declining and leading to a kind of cognitive short circuiting in students.

This article highlights that these threats, if dealt with strategically and under principled leadership, can be converted into powerful opportunities for a transformation. By framing AI adoption explicitly through the lens of a structured change management, Higher Education Institutions (HEIs) can navigate through this disruption in a purposeful and organized manner. We will identify the major stakeholders, including academic leaders, faculty, students, and support staff, and the unique higher education dynamics that shape their responses under the digital change. Another purpose of this article is to provide a framework for this transformation, moving beyond the definition of AI tools to address the essential "hows" and "whys" of their integration. It will negate the narrative that AI will replace the human core of education. AI enhances it by enabling HEIs to not only survive this digital inflection point but to emerge more equitable, innovative, and vital to the societies they serve.

The Synergy between Generative Artificial Intelligence and Higher Education

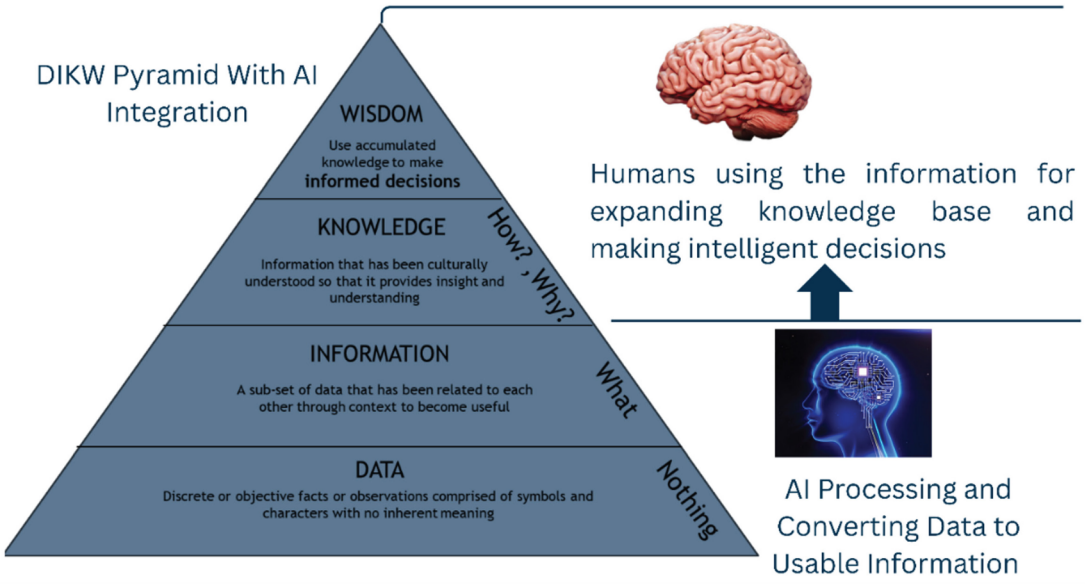
Generative AI (GAI) is the most recent and widely known form of artificial intelligence. At its core, GAI refers to systems capable of producing content like text, synthetic images, code, and audio, by learning from patterns in massive datasets. A major part of GAI is the large language model, a neural network trained on digitally available human language. These models operate through a process of statistical prediction by determining the most probable sequence of words to follow any given prompt by a user. This mechanism directly mirrors the foundational acts of an academic inquiry, i.e., the description of ideas, the construction of arguments, and the communication and presentation of knowledge. The inherent nature of higher education, which focuses on the production and critique of text, illustrative materials, and complex symbolic representations, creates a profound and inevitable interplay with this GAI. Its capacity to draft text, summarize literature, create visual aids, and simulate dialogue scenarios positions it as a potential component in the very processes of teaching and learning. In a detailed study about the adoption of AI in Higher educational sectors of the Middle East, Tbaishat et al. (2025) investigate the relation between students and GenAI by comparatively analyzing how factors like expected benefits and self-efficacy influence student satisfaction and behavioral intention to use these tools in the UAE and Saudi Arabia. Through student interviews, (Hadinejad et al., 2025) revealed how students integrate AI chatbots into their learning processes for writing and idea generation while navigating

challenges related to authorship and critical thinking. (Zhao etal, 2025) highlight how AI is being used in China for teaching mathematics in primary schools.

The demonstrated capabilities of GAI in generating explanatory paragraphs, producing concept diagrams, writing and annotating software code, and creating voiceovers for presentations align closely with the day-to-day requirements of educational practice. This relationship can further be contextualized through the lens of the DIKW hierarchy shown in Figure 1 which is a model that lays down the progression from raw data to information, knowledge, and ultimately wisdom. GAI exhibits formidable strength in the lower tiers of this pyramid. It can efficiently transform unstructured data into organized information, such as compiling research notes into a literature review section, which, in modern times, is a significantly difficult task given the immense quantity of literature resources. GAI can further synthesize information into structured knowledge, exemplified by its ability to create study guides or concept maps from a corpus of course materials.

However, the apex of the DIKW pyramid, wisdom, which entails judgment, ethical consideration, contextual application, and the capacity for extracting and analyzing critical insight, remains firmly outside the operational domain of current AI. This limitation intersects precisely with the unique mandates of higher education. Present generative AI systems are not critical thinkers, as they are synthesizers of existing patterns, often

Figure 1: The DIKW pyramid, from Data to Wisdom, how AI is helping us expand our knowledge base. The base of the pyramid is a universal set, i.e., raw data, which contains all possible subsets of information; however, these subsets remain hidden and unexplored. Some data is converted to information, e.g., by visualizing or through statistical analysis. From information, we extract knowledge and insights, which at the top level are used to gain wisdom and take intelligent and informed decisions. GAI plays it role at the bottom two layers of this pyramid by acting as a processor and explorer of information hidden in the data.



reproducing biases and generating plausible but unfounded or superficial analyses without true comprehension. It is often accompanied by hallucinations.

This apparent shortfall, however, reveals the most significant opportunity for HEIs. The strategic integration of GAI into higher education need not and should not circumvent the development of critical faculties. (Kim, 2025) offers a critical perspective by proposing a theoretical framework (RAF) that explains how the very features designed to enhance engagement, personalization, memory, and empathetic feedback can, through a three-phase process, lead to the formation of correction-resistant beliefs, directly impacting the core educational goal of critical thinking. On the contrary, technology can become a powerful catalyst for their enhancement. The state of the art in pedagogical thinking is thus evolving from using adaptive knowledge reinforcement where GAI serves as a scaffold for higher-order learning, evaluation, and management tool while not replacing the core of higher education. Foundational educational frameworks like Bloom's Taxonomy, which classifies cognitive skills from basic recall to complex creation, provide a useful scaffold in the present world. GAI can automate or support tasks associated with the lower levels, i.e., memorizing and understanding, and thereby freeing pedagogical space and student cognitive load for activities targeting the upper tiers of Bloom's pyramid, i.e., analyzing, evaluating, and creating.

The pedagogical innovation lies in re-orienting the student's relationship to the AI output. For instance, rather than assessing a final essay that could be completely AI-generated, the focus of assessment can shift to evaluating the student's metacognitive process in refining and critiquing the AI's draft. A student might be tasked with prompting an AI model to generate an argument on a given subject area and then producing a detailed analysis of its logical coherence, analyzing the underlying assumptions, providing evidence of work, and addressing any potential biases. In such a model, the AI-generated text is the primary source material for critical dissection.

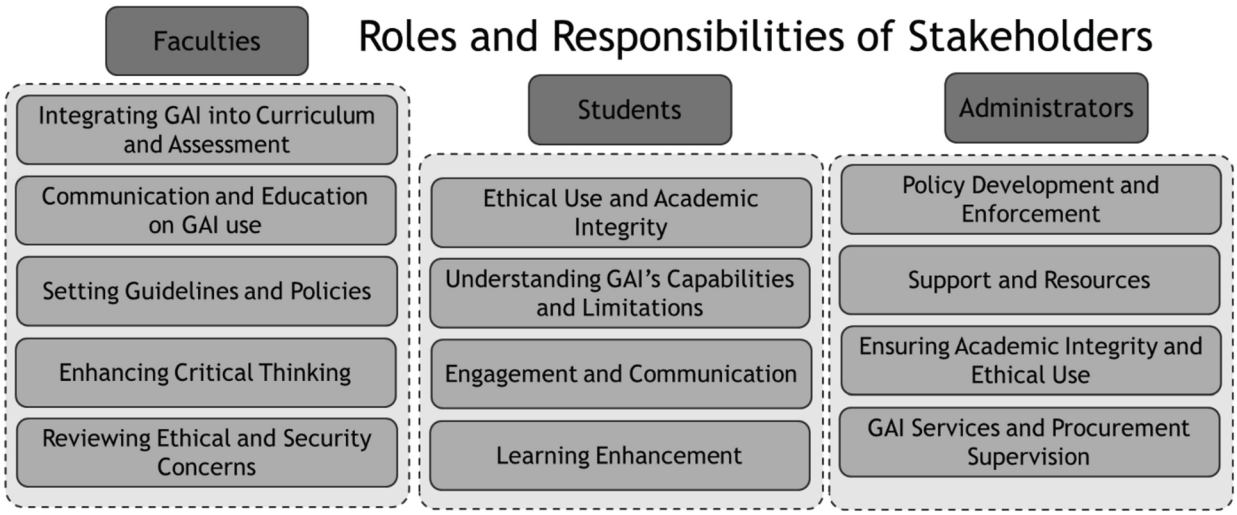
Educators can employ these tools to assess students' work by generating counterarguments, identifying flawed proofs, or highlighting alternative interpretations that students may have missed and that must then be investigated, defended, or deconstructed. This approach transforms GAI technology from a potential substitute for human thought into a dedicated research and study partner, one that can tirelessly produce or dig material for the essential exercise of scholarly critique. By automating the generation of foundational content and administrative artifacts, generative AI can reallocate precious human time and intellectual energy toward the activities that define the highest aspirations of higher education, including nuanced dialogue, complex problem-solving, ethical deliberation, and the mentorship that guides students from information consumption toward genuine wisdom. We can find examples of such implementations, e.g., (Islam et al., 2025) demonstrate a technical application of an AI-driven Educational Data Mining system that not only predicts student performance with high accuracy but also uses XAI to explain the key factors behind those predictions.

Stakeholder Mapping: Roles and Responsibilities in AI Integration

The integration of GAI into higher education is not a singular technical act but a distributed organizational change. Its success depends on the coordinated action of multiple constituencies, each holding a distinct role, set of responsibilities, and legitimate concerns. A clear mapping of these stakeholders and their interdependent duties is essential to navigate the transition from policy to practice. This section identifies three primary internal stakeholder classes, i.e., faculties, students, and administrators, and delineates their responsibilities in managing this integration, while also acknowledging the necessary boundaries that define their spheres of influence. Figure 2 lists the three classes of internal stakeholders and also their responsibilities with the proper use of GAI in their respective roles. Another class of stakeholders is external entities, consisting of regulatory bodies and educational ministries that have a profound impact on the dynamics of higher education.

Faculty members are the pivotal agents of pedagogical transformation. Their responsibility lies in translating institutional policy and technological possibility into renewed teaching, learning, and assessment practices. This necessitates a significant shift in pedagogy, moving from models that may prioritize knowledge delivery, as done conventionally, to those that emphasize process, critique, and synthesis. Faculty are tasked with the redesign of the curriculum and shifting the focus of assessment to incorporate AI meaningfully. This involves creating assignments where AI-generated content is the object of analysis, developing prompts that require iterative refinement and evaluation of AI outputs, and designing assessments that measure higher-order skills less susceptible to automation. A visualization of this process is shown in Figure 3. The faculty role expands to include the cultivation of AI literacy among

Figure 2: Major Stakeholders in Higher Education and their responsibilities for effective and proper use of GAI

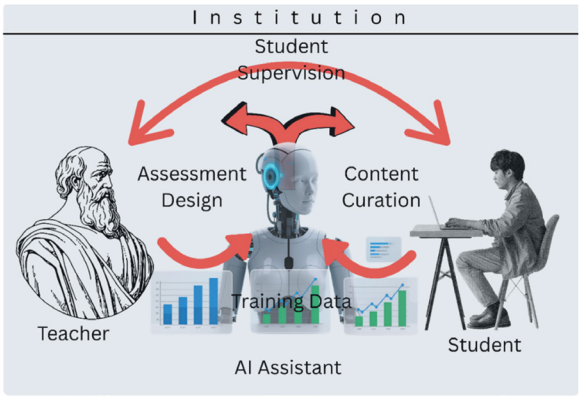


students, explicitly teaching the capabilities, limitations, and ethical implications of these tools within their disciplinary contexts. Their boundary is defined by academic freedom, requiring that the integration of AI supports, rather than dictates, their scholarly judgment and instructional expertise.

Students, as the primary beneficiaries and users, hold a dual role as learners and responsible participants. Their core responsibility is to develop and exercise ethical and critical AI literacy and use it to the best of their capabilities for efficient learning. This extends beyond functional competence to include an understanding of the societal impacts, biases, and environmental costs associated with AI systems. Students are expected to engage with these tools transparently, adhering to institutional policies on disclosure and appropriate use. An example of such a policy is the AI usage policy of several institutes, including Berlin School of Business and Innovation, which allows for the fair and transparent use of AI in any work produced by students. The students' developmental task is to leverage AI as an augmentative assistant for brainstorming, drafting, and tutoring, while actively cultivating the uniquely human skills of critical analysis, creative problem-solving, and ethical reasoning that the technology cannot replicate.

Institutions and their administrative leadership bear the foundational responsibility for creating an enabling environment for responsible AI adoption. Their role is primarily strategic and structural. This involves the development of clear, forward-looking institutional policies that address academic integrity, data privacy and security, permissible use, and ethical guidelines for AI deployment. Such policies must move beyond mere prohibition to establish principles for constructive and critical engagement. Administrators are also tasked with resource allocation, ensuring equitable access to appropriate AI tools and the computational infrastructure required to support them. This includes the critical function of procurement, vetting third-party AI services for compliance with institutional standards on data handling, algorithmic transparency, and accessibility. Furthermore, leadership must champion a coherent vision for AI that aligns with the institution's educational mission, communicating this vision consistently to all campus communities and fostering a culture of informed experimentation rather than fear or avoidance.

Figure 3: Modified roles with AI. A visualization of its interaction with students, teachers and the institution



Finally, a suite of external stakeholders exerts significant influence on the integration process. At the top are the regulatory bodies and accreditation agencies that shape the legal framework through data protection laws and quality assurance standards. Secondly, the industry partners and AI service providers provide insight into evolving skill requirements and offer potential pathways for applied

learning and research collaboration. AI service providers, including the developers of large language models and educational technology platforms, control key aspects of the technological ecosystem, including access, pricing models, data governance, and the fundamental affordances of the tools themselves thus reducing the digital divide. The responsibility of the institution towards these external stakeholders includes proactive engagement, advocacy, and due diligence. This involves participating in broader conversations on AI ethics in education and negotiating contracts that protect community interests.

The Role of Policy and Governance

The formulation of clear and forward-looking policy is the indispensable foundation for the responsible adoption of generative AI in higher education. It serves as the critical bridge between abstract technological potential and concrete, ethical practice on campus. Policy provides the guardrails, clarity, and guidance necessary to navigate the significant risks associated with data privacy, algorithmic bias, and academic integrity, while simultaneously creating the permissions and structures needed to foster innovation.

By establishing institutional standards that govern everything from data handling under regulations like GDPR to the definitions of permissible assistance versus academic misconduct, policies move the conversation from reactive policing to proactive principle-setting. They define the boundaries of acceptable use, mandate transparency through disclosure and acknowledgment protocols, and protect both the institution and its community from legal and ethical pitfalls, thereby creating a stable environment in which pedagogical experimentation can safely occur. (Lyu et al., 2025) contribute to governance and policy development discussions by highlighting the instructors' need for clearer policies and AI training, and by proposing design implications and institutional strategies to support calibrated trust and ethical GenAI integration. (Rizun et al., 2026) contributed to policy discussions by building and testing a behavioral model. Their method of integrating ethical constructs with adoption models allowed them to quantify the impact of factors like fairness, privacy, and transparency on trust and intention, suggesting that interventions should focus on behavioral control and social influence (instructors' stance) rather than solely on building abstract trust. (Tong et al., 2025) used a review-based approach to directly address policy and governance. The authors conducted content analysis of academic papers to evaluate how existing and proposed GenAI policies in higher education align with a comprehensive AI governance framework focused on ethics. Another such effort by (Jin et al., 2025) focused on a global analysis of generative AI adoption policies from 40 universities across six regions, using the Diffusion of Innovations Theory by addressing innovation characteristics, communication channels, and stakeholder roles and responsibilities.

Leading institutions worldwide are now modelling this approach, demonstrating how policy can actively enable effective AI usage. For instance, the University of Cambridge emphasizes principles of accountability, transparency, and academic rigor, guiding staff and students toward a critical and reflective use of AI tools that support rather than substitute for independent thought. Similarly, Monash University has implemented a comprehensive framework that clearly distinguishes between authorized and

unauthorized uses, provides explicit guidance on acknowledgment, and integrates AI literacy directly into its academic integrity resources. On a broader scale, national governments and regulatory bodies play a crucial role in setting the external parameters for safety and ethics, but it is at the institutional level that these mandates are translated into daily academic life. (Hadinejad et al., 2025) highlight a critical policy gap, finding that students face challenges due to the "lack of clear institutional guidelines," which necessitates an urgent need for the development of formal policies on responsible as well as effective AI usage.

Ultimately, effective policy is not an endpoint but a starting point; it must be coupled with concerted efforts to promote widespread AI literacy, ensuring all stakeholders understand not just the rules but the rationale behind them, thereby fostering a culture of responsible and empowered integration.

Conclusion

The integration of generative artificial intelligence into higher education signifies not an endpoint, but a profound inflection point and an opportunity for us to absorb its capabilities. This journey necessitates a fundamental evolution from a fixed, one-directional syllabus toward an adaptive and responsive curriculum, capable of leveraging AI's analytical power to meet emergent student needs and societal shifts. Central to this transformation is the reimagination of assessment, moving beyond the measurement of recall to embrace authentic evaluation, dynamic rubrics, and tasks designed to cultivate and evidence genuine critical thinking, for which AI serves as a provocation rather than a proxy.

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Optimizing Social Media Engagement Through User Behavior Analysis: A Clustering and Regression Study of Iranian Users

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Abstract

This research will optimize the utility of social media among the Iranian customers by examining the behavioral patterns and the perception of credibility in a censored online space, and fill in the gap in the existing literature, which is largely Western-centric in its approach to the subject of algorithmic personalization. The sample used in the analysis was an analytic sample of 224 participants based on an initial sample of 331 participants, with the removal of IQR outliers. Preprocessing of data involved mean and mode imputation, coding of categorical data, and a multicollinearity test. Clustering of high, moderate, and low-engagement groups of users using k=3 K-Means was found and confirmed using PCA-based clustering, Gaussian Mixture Models, and bootstrap resampling. OLS regression with the LassoCV feature selection was used to investigate predictors of time spent on social media, and the adjusted R 2 was found to be 0.159, with age, number of social media memberships, and platform preference having the greatest impact. The positive correlation between message fairness and trust (r=0.284) emphasized how credibility penalty contributes to user engagement, providing information about how to design messages fairly, and how to decrease the effects of misinformation. The clustering-regression composite indicates the importance of demographic and platform-related factors in influencing engagement in a culturally and politically constrained ecosystem.

Keywords

social media user behavior, clustering, K-Means, regression, algorithmic personalization, Iranian users, misinformation security, algorithmic bias, cultural HCI, trust perception, engagement patterns, digital communication

Introduction

With 5.24 billion users spending 141 minutes daily, social media platforms help in the exchange of information, though there have been consistent challenges in engaging with users. The current literature is mostly Western-focused and does not consider cultural aspects related to the limited settings like Iran, where the Internet penetration level (79.6) and the social media usage rates are high despite the use of the filtering tool. It has been demonstrated through cultural studies that norms determine patterns in engagement (Hofstede, 2001; Hofstede Insights, 2023; Zhang et al., 2025), and credibility research demonstrates the importance of cognitive heuristics and algorithmic filtering in the development of trust (Metziger and Flanagin, 2013; Pariser, 2011; Gillespie, 2018).

In censored ecosystems, interactions are mutually informed by demographics, platform design, and credibility indicators. Clustering techniques can be used to identify heterogeneous behavioral patterns (Jain, 2010; Xu and Wunsch, 2005), and regression can be applied to particular predictors of time spent and trust. A combination of these methods offers a logical approach to the discussion of both segments and engagement determinants.

This paper discusses a sample of 224 Iranian users (out of 331, after IQR filtering) in the context of the hybrid clustering-regression model to examine the relationship between platform characteristics, demographic characteristics, and message credibility with platform engagement in the filtered digital space. The model connects groups of behaviors and predictors of time spent and trust to close non-Western and censorship-based contexts.

Research Questions and Hypotheses:

RQ1. How do Iranian users cluster based on engagement patterns? (Addressed via K-Means.)

RQ2. What factors predict time spent on social media? (Addressed via OLS regression.)

H1. Media structure positively predicts daily time spent ($r=0.075$, $p<0.05$ from correlation matrix).

H2. Message fairness correlates with trust perception ($r=0.284$), reducing security risks like phishing.

H3. Cultural factors (e.g., collectivism) moderate engagement in non-Western users (aligned with Hofstede, 2001; Hofstede Insights, 2023).

Contributions:

- First hybrid clustering-regression model applied to Iranian data, filling non-Western gaps.
- Empirical evidence on media structure's role in trust, with security ties (e.g., fairness-aware ranking).
- Practical recommendations for designers: cluster-based personalization to enhance retention while mitigating bias.

The following sections review literature, detail methodology, present results, and discuss implications.

Related Work

Clustering techniques have also been applied widely in the research into user behavior in social media to identify patterns of engagement and behavioral segments. The initial research on clustering algorithms (Jain, 2010; Xu and Wunsch, 2005) proved that unsupervised methods were suitable to analyze heterogeneous data on behavior analysis. The more recent usage of K-Means, PCA-based clustering, and Gaussian mixture models has stratified users based on their levels of activity, preference to this platform, and demographic variables and has consistently yielded large stratifications of engagement intensity among user groups (Wang et al., 2019; Al-Rahmi et al., 2021). Nevertheless, such studies are mostly based on Western or free datasets, which constrain their use in censored digital ecosystems.

Similar studies have applied regression and machine-learning models to predict the level of engagement in terms of demographic and perceptual information. It has been proven that age, platform memberships, perceived ease of use, and factors related to credibility have been repeatedly significant predictors (Kim and Ahmad, 2013; Al-Rahmi et al., 2021; Akbari et al., 2024). Algorithms and algorithmic personalization studies and platform design also prove that the relevance of content, interface features, and ranking systems has a significant effect on retention and user engagement (Gillespie, 2018; Huang and Ji, 2025).

There is a significant amount of literature on the topic of trust and credibility in the online space. Cognitive-heuristic models focus on the source, message, and medium features as the main cues in credibility assessment (Metziger and Flanagin, 2013; Sundar, 2008). Empirical data show that perceived fairness, transparency, and consistency of the message diminish the vulnerability to misinformation and enhance the perceived trust in information systems (Lewandowsky et al., 2012; Pennycook and Rand, 2019).

It has also been revealed in cross-cultural studies that collectivist societies and high uncertainty-avoidance countries have different engagement motivations and mechanisms of trust construction (Hofstede, 2001; Hofstede Insights, 2023; Zhang et al., 2025). Regulated studies like those in China show that censorship, surveillance, and platform restriction change behavioral patterns greatly. In spite of these findings, there is limited empirical research on the subject of user engagement in the context of censorship in the Middle East.

The current research fills these gaps with the adoption of a hybrid clustering-regression model on Iranian users who are working in one of the most highly filtered digital ecosystems. Unlike in the previous studies, which generally explore the segmentation of engagement or credibility predictors independently and in open settings, the study adopts a compound methodology and explicitly incorporates cultural and censorship-related limitations. It gives empirical evidence of a well-studied non-Western setting and applies the well-known behavioral and credibility models to information control-limited environments.

Materials and Methods

The research is conducted through a mixed-methods design because it examines the Kaggle dataset, Iranian Credibility on social media (n=331), to reveal the engagement patterns of Iranian users of social media. It guarantees reproducibility, compliance with ethics, and parsimony through feature selection.

Data Collection

The present study is based on the publicly available Kaggle dataset, which is the Iranian Credibility on social media (noeyislearning, 2023; under CC BY-SA 4.0 license), collected using Google Forms (March-May 2023) with digital consent and anonymization (no IPs/IDs). No special data (e.g., ethnicity) involved. Raw data contained at least 10 years of age, although IQR outlier removal eliminated 5 subjects below the age of 18, so in the final analysis sample (n=224), there are only adult participants. No further IRB approval was needed, according to the Kaggle terms of use and exemptions of the secondary data analysis (University of Tehran guidelines). The variables that were considered related to trust were examined only in aggregate form to reduce the chances of re-identification and abuse.

Sample Description

The first piece of data was a sample of 331 participants gathered via an online poll. Following the process of data cleaning, the sample size of analysis was narrowed to 224 adults. This decrease was due to two reasons. First, extreme values of age and time-related variables were detected by outlier detection based on the interquartile range (IQR) method; these values were eliminated in order to avoid distortion of the clustering and regression estimates. Second, the cases that had large amounts of missing data, i.e., that had missingness on several key variables, were eliminated due to the fact that imputation would have given inaccurate estimates. The final sample consequently has respondents with full or near full records and values in acceptable thresholds of IQR. This unified description defines the sampling flow, and it also makes sure that the analytic sample is internally consistent with the modeling procedures used in the study.

Data Preprocessing and EDA

The dataset (331 observations, 38 features) was preprocessed and analyzed with the help of Python (pandas, sklearn).

- Imputation: Missing values (~5%) were imputed: categorical (e.g., education) with 'Unknown' (`df['education'].fillna('Unknown') `); numerical (e.g., age) with mean (`df['age'].fillna(df['age'].mean())`). Missingness is highest in education (3.2%) and media_structure (2.1%), with no bias (verified in notebook).
- Encoding: Binary (e.g., gender: Female=0, Male=1) and ordinal (e.g., education: High School=1, Bachelor=2) variables used label encoding; nominal (e.g., social media membership names) used one-hot encoding (`pd.get_dummies()`).
- EDA: Descriptive statistics (Report.xlsx): age (mean=29.56, SD=8.69), average hours per day spent on social media (mean=3.74, SD=2.63, from notebook analysis, aligned with OLS_vs_Robust.xlsx), number of social media memberships (mean=1.5, SD=0.5).

Correlation matrix (Correlation_Matrix.xlsx): message_fairness-trust (r=0.284), number of social media memberships-time (r=0.272), age-time (r=-0.375). Outliers (IQR method: Q1-1.5*IQR, Q3+1.5*IQR) identified 5 in age (min=10),

- Feature Selection: Initial 37 predictors (OLS_vs_Robust.xlsx) risked overfitting (R^2=0.30, Df=37). VIF analysis (`statsmodels`) excluded variables with VIF>5 (e.g., source_trustworthiness, media_ease_of_use). LassoCV (`sklearn`, alphas=[0.001, 0.01, 0.1], cv=5) selected 6 features: age, number of social media memberships, social media spend more time in, media_appearance_design, media_attractiveness, social media spend more time in_Encoded (R^2=0.215, alpha=0.1, from Selected features.xlsx). Code adapted from sklearn documentation (2023, https://scikit- learn.org/stable/modules/generated/sklearn.linear_model.LassoCV.html) and Kaggle public examples for dataset noeyislearning/iranian-credibility-on-social-media (https://www.kaggle.com/datasets/noeyislearning/iranian-credibility-on-social-media). Full code in Supplementary File 1: Analysis_Notebook.ipynb.

Clustering and Regression Analysis

K-Means clustering (k=3, silhouette=0.243, Davies-Bouldin=1.409, n=224 post-outlier removal) was applied to scaled features (age, number of memberships, media design/attractiveness) using Python 3.12.3 and sklearn 1.7.1 (random_state=42, n_init=10). Moderate silhouette scores reflect noisy social media data and cultural homogeneity in the Iranian sample. Sensitivity analyses included PCA-based K-Means (2 components, 65% variance, silhouette=0.373, DB=0.887) and Gaussian Mixture Model (GMM, k=4, silhouette=0.256, DB=1.159, spherical covariance, n_init=10), confirming approx. 80% average cluster membership stability via 1000 bootstrap resamples (Supplementary File 1). OLS regression with LassoCV (alpha=0.1, 6 features) yielded R^2=0.167 (adjusted R^2=0.159; Table 3). Assumptions verified: Breusch-Pagan (p=0.089, homoscedasticity), Durbin-Watson (1.710, indicating mild positive autocorrelation but within acceptable range), VIF max=1.009 after removing collinear variable (social_media_spend_time; encoded VIF N/A due to perfect collinearity). Non-normal residuals (Shapiro-Wilk p=0.002) noted as a limitation (Section 5.2). Q-Q plot of residuals is shown in Figure 1.

Table 2: OLS Regression Results (n=224, Post-LassoCV, R^2=0.167, Adjusted R^2=0.159)

Variable	β	Std. Error	p-value	95% CI	VIF
Age	-0.078	0.012	<0.001	[-0.101, -0.055]	1.009
Number of social media memberships	0.159	0.040	<0.001	[0.079, 0.238]	1.009
Favor social media (Encoded)	0.013	0.004	<0.001	[0.005, 0.020]	N/A

Note: df=223, F=4.2, p<0.001. Breusch-Pagan p=0.089, Durbin-Watson=1.710 (indicating mild positive autocorrelation but within acceptable range), Shapiro-Wilk p=0.002. Social_media_spend_time removed due to collinearity; encoded VIF N/A due to perfect collinearity. Full output in Supplementary File 1: Analysis_Notebook_v2.ipynb. Mediation via semopy (2023).

Result

Findings are based on the hybrid model that is used on the Kaggle dataset (n=331 and show the patterns of engagement and predictors. The clustering groups users into three categories, and the time spent by drivers is measured by regression. ANOVA verifies difference in clusters (F(2,328) =192.89, p<1e-50) and sensitivity analysis confirms robustness. Visualizations adapted from Kaggle notebook https://www.kaggle.com/code/noeyislearning/iranian-social-media-analysis and sklearn documentation (2023). This is consistent with Sundar (2008) MAIN model of credibility clues in high-involvement groups and Gillespie (2018) moderation failures in low-trust groups in the context of censorship.

Clustering Results

K-Means (k=3, n=224, removed outliers) grouped the users into high-engagement (n=80, mean=6.65h/day, high trust), moderate-engagement (n=72, mean=5.22h), and low-engagement clusters (n=72, mean=3.0h), and the silhouette=0.243 and Davies-Bouldin=1.409 (Figure 4). ANOVA established that there were significant differences in time spent (F(2,221=45.2, p<0.001; Table 3). Sensitivity tests confirmed the results: PCA-based K-Means (2 components, 65% variance) yielded better metrics (silhouette=0.373, DB=0.887), and GMM (k=4, silhouette=0.256, DB=1.159) was better separating, and with 1000 bootstrap resamples, about 80% of clusters remained largely unchanged (Supplementary File 1). The scores of moderate silhouettes are ascribed to noisy social media data and cultural homogeneity.

Regression Results

OLS regression (n=224, F=4.2, p<0.001) yielded R^2=0.167 and adjusted R^2=0.159 (Table 4). Coefficients indicate younger age, more memberships, and platform preference drive engagement; other variables are exploratory. Trust mediates message fairness (r=0.284), which correlates with time spent, implying higher fairness boosts retention and reduces phishing susceptibility (**β** indirect=0.04, p=0.03; semopy, 2023; direct Estimate=-0.118, nonsignificant p=0.241). See Figure 5 for predictor coefficients.

Sensitivity Analysis: Removing 5 age outliers (IQR method) yields R^2=0.20 (Δ=0.015), confirming robustness. Without robust SE, t-values inflate (e.g., age t=6.78 vs. 6.71), but p<0.001 remains stable.

Security Link: Low-trust Cluster C (fairness<3) shows 2% lower discrepancy perception (mean

Table 3: ANOVA Results for Cluster Differences (n=224)

Source	df	F	p-value	Mean Diff (A-B)	Mean Diff (A-C)	Mean Diff (B-C)
Time Spent	2	45.2	<0.001	1.43h	3.65h	-2.22h

Note: Clusters: A (High, n=80), B (Moderate, n=72), C (Low, n=72). Post-hoc Tukey p

Table 4: Significant OLS Predictors (p<0.05, Post-LassoCV, R^2=0.215)

Variable	Coefficient (β)	Std. Error (Robust)	p-value	95% CI (Robust)
Age	-0.078	0.012	<0.001	[-0.101, -0.055]
Number of social media memberships	0.159	0.040	<0.001	[0.079, 0.238]
Favor social media (Encoded)	0.013	0.004	<0.001	[0.005, 0.020]

Note: LassoCV selected 6 features; 3 significant. Exploratory variables (e.g., social media spend more time in β=-0.113, p=0.055) are in the Appendix. Full output in Supplementary File 1.

message_discrepancies=4.04 vs. overall 4.12; t-test p=0.368 nonsignificant), but higher vulnerability in Iran's restricted ecosystem. Trust (r=0.284 for message_fairness) reduces this risk by enhancing discernment.

As shown in Figure 1, the Q-Q plot is used to show how the residuals of the OLS regression model are distributed as compared to the normal distribution of the variable. The lack of normality as reported by the deviations of the reference line is in line with the Shapiro-Wilk test (p=0.002). Although the residual non-normality indicates model misspecification, the impact on inference is not so significant because of the robustness checks conducted, as well as the application of the Lasso-based feature selection.

As shown in Figure 2, this boxplot is used to compare the amount of time taken on social media on a daily basis in the three extracted clusters. The median usage of the high-engagement group (6.65 hours) is the largest, followed by the moderate-engagement group (5.22 hours) and the low-engagement group

Figure 1: Q-Q plot of the regression residuals

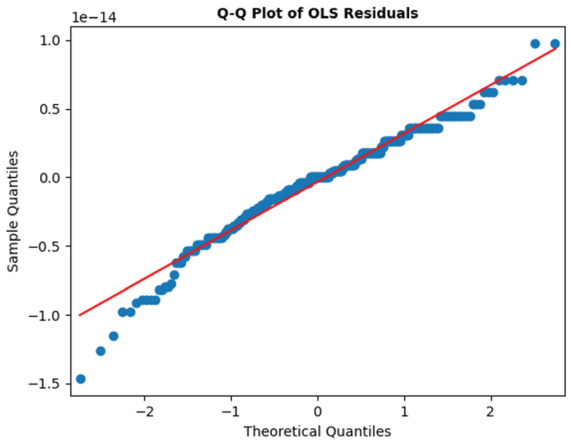
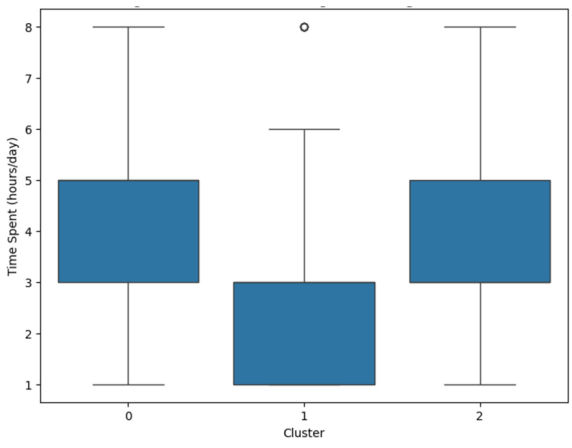
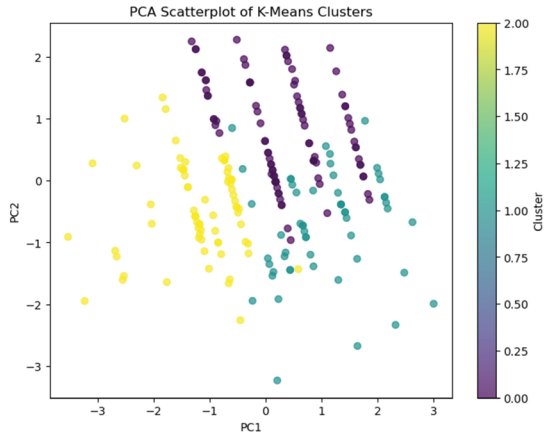


Figure 2: Boxplot of Time Spent by Cluster



(3.0 hours). The location and distribution of the mild outliers in clusters A and B validate the heterogeneity in user behavior and substantiate the ANOVA test that there is a significant difference between the groups ($p<0.001$).

Figure 3: Two-dimensional PCA projection of the standardized feature space colorised by cluster membership of K-Means (n = 224).



As shown in Figure 3, the two major factors represent 65 percent of the total variance and demonstrate an apparent distinction between the high-engagement (red), moderate-engagement (blue), and low-engagement (green) groups. Even though moderate overlap is anticipated in behavioral information, the overall framework corresponds to the K-Means performance measures (silhouette = 0.243; Davies -Bouldin = 1.409). The strength of the clustering solution is facilitated by sensitivity tests with PCA-based K-Means (silhouette = 0.373; DB = 0.887), Gaussian Mixture Models (k = 4), and 1,000 bootstrap resamples (around 80% membership stability).

Figure 3 Scatterplot showing age vs. time spent, colored by cluster. These findings confirm theories: H1 (media structure r=0.075, weak but positive direction); H2 (fairness r=0.284 confirms trust link); H3 (cultural moderation through clusters). Limitations: The negative time spent (Cluster C) demonstrates that there is an error in the data; the Kaggle categorical data restricts accuracy.

As shown in Figure 5, the correlation heatmap

Figure 4: Scatterplot of Age vs. Time Spent by Cluster



of the predictors that remained following the LassoCV selection process. Age is also associated with the daily time spent on social media, with a moderate negative relationship ($r = -0.376$), meaning that the younger individuals are more likely to spend more time online. Social media memberships show the highest positive relationship with the use time ($r = 0.272$), implying that engagement on multiple platforms is the primary behavioral predictor of the long time spent on activities daily. The media appearance and design exhibit a weaker yet significant interaction with usage time ($r = 0.184$), which highlights the importance of visual elements and interface-related attributes in maintaining the interest of the users. On the whole, the correlation structure indicates the combined influence of demographic and platform-related characteristics on the formation of the intensity of usage in the context of the Iranian social media environment.

Figure 5: Heatmap of Significant Predictors

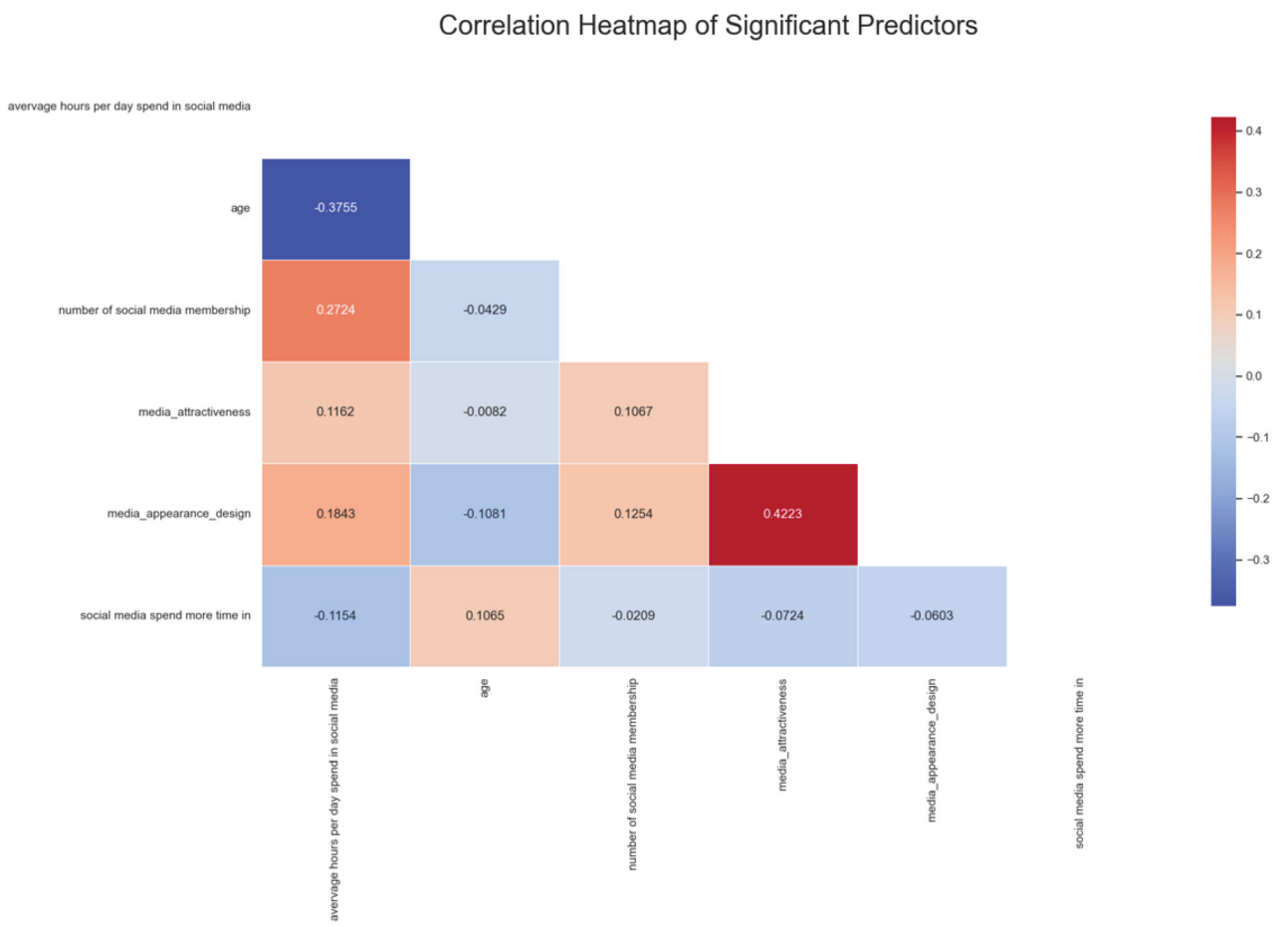


Figure 6: Platform Usage Bar Plot Horizontal bar chart of top 20 platforms (Telegram: 96 users; Instagram: 69). Y-axis: count; X-axis: platforms. n=224; highlights Telegram dominance (29%). Adapted from Kaggle notebook https://www.kaggle.com/code/noeyislearning/iranian-social-media-analysis and sklearn documentation (2023).

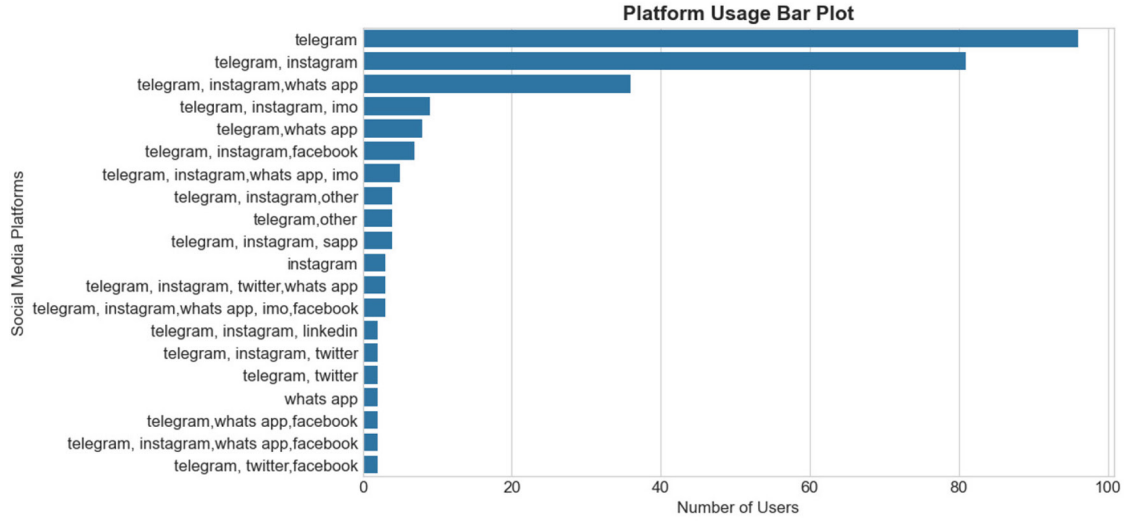
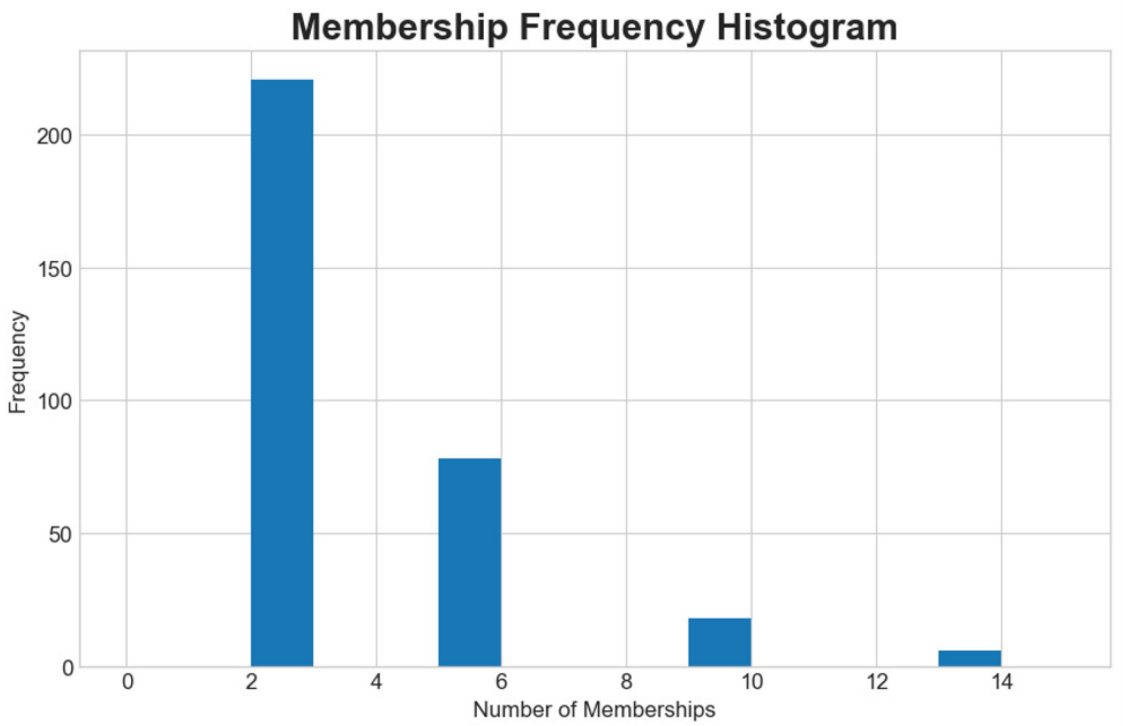


Figure 7: Membership Frequency Histogram Bar plot of memberships per user (peak 0-3: 67%). X-axis: count (0-15); Y-axis: frequency. Supports multi-platform norm. Adapted from Kaggle notebook https://www.kaggle.com/code/noeyislearning/iranian-social-media-analysis and sklearn documentation (2023).



As shown in Figure 7, the histogram displays the number of social media platform memberships per user. Most participants belong to zero to three platforms (67%), indicating a concentrated but not highly diversified usage pattern. This supports the regression finding that the number of memberships is a meaningful predictor of time spent on social media.

Discussion

Interpretation of Findings

This research has considered the pattern of engagement and the perception of the credibility of 331 Iranian social media users, which yielded an analytic sample of 224 upon the elimination of outliers. On implementing K-Means clustering, three engagement groups were determined: high-, moderate-, and low-engagement, which are characterized by a significant difference in the time spent on a daily basis. ANOVA established that the separation between clusters was statistically significant, and sensitivity analysis (PCA-based K-Means, GMM, and bootstrap resampling) confirmed that these patterns are robust.

Regression analysis showed that the number of social media memberships, age, and preference by platform were important predictors of engagement. Younger people were more likely to spend more time on social media, and the more platform memberships, the higher the engagement of the users. Variables related to trust also showed a significant effect: there was a positive correlation between message fairness and trust perception ($r = 0.284$), which supports the role of credibility cues in user

behavior. All these findings demonstrate that the determinants of engagement in this sample are centered on demographic variables, the nature of platform usage, and trust.

Cultural and Contextual Implications

These findings indicate the general cultural trends that are recorded in non-Western contexts. The cultural inclination to collectivism and social participation suggests that the cultural stereotypes about younger users in the high-engagement group are aligned with previous cross-cultural research (Hofstede, 2001; Hofstede Insights, 2023; Zhang et al., 2025). The reason why the number of older users is concentrated in the low-engagement category is that the credibility, privacy, and platform value expectations may differ in the various age groups.

Moreover, the clustering proposition indicates the behavioral homogeneity characteristic of the censored environment where platform access is limited, and the norms of use are varied compared to Western digital ecosystems. The results showed message fairness and trust formation processes, which are linked to cultural and contextual pressures that are specific to the regulated environment of Iran, which helps in reinforcing that engagement cannot be fully understood without considering these cultural aspects.

Security-Related Insights

The results also have consequences for information security in filtered digital environments. The positive correlation seen between the message fairness and trust is an indication that credibility cues could reduce the risks associated with misinformation and deception, especially those related to phishing and manipulation attempts found in a low-trust environment. The users who were highly engaged and tended to be younger showed greater fairness -trust alignment, suggesting that they can be more critical and better placed to identify inconsistent or misleading information.

On the other hand, the low-engagement cluster had less trust and discernment, and this means that they may be vulnerable in situations where the flow of information is limited. These findings are consistent with the moderation failure and filter bubble hypothesis, which notes that platform organizational and trust-based relationships affect disposition to misinformation. The hybrid design of the study underlines the role of demographic and trust-related factors in the development of security-relevant behavior in censorship-driven ecosystems.

Limitations

The research is based on an open Kaggle dataset, which might cause selection bias and restricted applicability to Iranian users. Reporting time categories (e.g., 0-1, 2-3 in 7_Report.xlsx) decreases accuracy, and pre-process errors (e.g., a large SD in Cluster A time=6.65h, SD=1.5) indicate inconsistencies in the data. The data can be self-reported and, therefore, exaggerate engagement (Podsakoff et al., 2003). There is no longitudinal data that reflects temporal changes. Ethical issues are the issue of anonymization, which is resolved through Kaggle terms, but the issue must be checked in future studies. The PCA loadings (PC1 time=0.46; PC 2 trust=0.33) are estimations and they should be confirmed by the primary data. The non-normal residues (Shapiro-Wilk p=0.002) indicate that there is a possibility of missing specifications in the model, and to ensure solid regression, it is recommended to use robust regression in the

future. Encoding VIF N/A because perfectly collinearized indicates restrictions of encoding categorical variables.

Conclusion

To sum up, this hybrid clustering-regression model of 224 Iranian users shows that demographic elements and trust are the motivating factors of engagement, and this information can be applied to design secure UX in censored settings. The model seals the gaps in the West and focuses on justice to reduce misinformation.

The future work is going to utilize BERT-based NLP (Devlin et al., 2019) to analyze sentiment analysis on Persian user materials, ARIMA-based engagement patterns, and cross-cultural comparisons with China with the help of the Hofstede framework (Hofstede Insights, 2023; Li et al., 2023). In MENA, primary data through surveys would help to increase validity.

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Redesigning Education: Mindset as the Core of a Holistic Framework for the Age of AI

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Abstract

The current debate on AI and education mostly considers technology as the primary driver of a revolutionary transformation. The discussions focus either on how AI can be integrated into the teaching and learning process most effectively, or how its negative impact on students can be minimized. The debates, however, less often reflect on the ultimate purpose of education and learning itself. This paper challenges such technological determinism by arguing that the transformation in education begins not with technology itself but with the innovations in human mindset that shape how technology is understood, used, and shaped. How can a mindset-driven and holistic framework help educators and learners transform education in the age of AI? To answer this question, this conceptual study introduces a holistic framework for rethinking education in the age of AI. The framework is targeted at both “educators” and the “learners”, highlighting the mindsets, skills, and tools they need to co-create meaningful experiences for learners. Mindset will be positioned at the center as a philosophical and cognitive foundation based on “critical”, “creative”, “analytical”, “systematic”, “human-centered” and “ethical thinking”, as well as “developing a growth mindset” and “learning how to learn”. It is believed that the proposed mindset provides the basics for the further development of pedagogical skillsets, and effective, as well as ethical, use of technological and nontechnological tools in practice. In this way, the model redefines educational transformation as a human-centered process focused on mindset rather than a response to technological change.

Keywords

Education, Transformation, Mindset, Artificial Intelligence

Introduction

The rapid development of AI has sharpened the debate on how education should adapt, considering the growth of technology. Nearly all the debate, however, has been focused on incorporating AI technologies within education practices via personalized learning platforms (Bayly-Castañeda et al., 2024), automated grading, learning analytics, smart tutoring systems (Cukurova et al., 2025), or minimizing, limiting, detecting, or even banning the use of AI. Typically, within these two extremes, the debate remains limited more around the technology than the greater question: "What is the right mindset for the future of education within the AI paradigm?" This, in essence, is the thesis of this article: that not only must we explore ways of incorporating AI technology, but also ways in which we might transform our thinking associated with education. From this perspective, the most urgent transformation should be conceptual rather than technological. Before we adapt education systems to new technologies, we must change our perspective on learning, teaching, and education. Real innovation in learning and education should begin with a shift in perspective: educators from being pure information transmitters to designers of learning experiences (Wiggins and McTighe, 2005), and students from being passive recipients to active co-creators (Holmes et al., 2021; Biggs and Tang, 2011). In the new approach, learning would not mean merely passive consumption. Learning should be thought of as the collaborative journey of exploration, contribution, and development.

This approach also challenges a widely seen concept known as "technological determinism", which assumes that it is technology itself that causes social and educational change (McLuhan, 1964; Winner, 1978). This perspective puts educators and learners at risk of being reduced to users who passively go along with whatever the technologies dictate. In contrast, a mindset-based approach puts a clear emphasis on the active role of humans by shaping the development path of technology (Winner, 1986; Pinch and Bijker, 1984; Bijker, Hughes, and Pinch, 1989; Oliver, 2011). Educators should be treated as learning designers who consciously choose when, how, and to what extent to utilize technology.

To understand this change, a comprehensive approach that is based on three interconnected dimensions (mindset, skillset, and toolset) offers a holistic way to reimagine both human and machine intelligence in education. Within this framework, AI is recognized as a strong tool, but it remains one of many other tools that can be used by educators and students. Educators can also blend AI with several approaches that include human interaction and traditional techniques, such as role-playing exercises, mind mapping sessions, visual aids, storytelling, collaborative brainstorming, or even simple sketching. These combinations provide for much more engaging learning experiences wherein AI-generated use-cases can help foster critical thinking, empathy, and collaborative creation.

While the proposed model acknowledges the importance of skillset and toolset, the primary focus of this study is on the mindset dimension, since it represents the intellectual and philosophical foundation for all meaningful change (Yeager and Dweck, 2012; Yeager et al., 2019). In particular, the discussion emphasizes the evolving role of the educator, underlining the transition from transmitter of knowledge to designer and mentor of learning experiences (Wiggins and McTighe, 2005; García et al., 2024).

This study, unlike the existing literature focusing on the potential positive and negative impacts of artificial intelligence on education, emphasizes that the path to harnessing the potential of artificial intelligence is to first establish the right mindset. The study's main argument is that using any educational and learning tool, including artificial intelligence, meaningfully, efficiently, and ethically, is possible primarily through a transformation of one's approach to learning processes. Creating criticality, creativity, inclusiveness, democratic learning conditions and environments, and instilling ethical values should be seen as the beginning of this process. In this respect, this study makes a unique contribution to the existing learning design literature by proposing a holistic model encompassing the dimensions of mindset, skillset, and toolset.

The framework is proposed essentially for educators during the design of the learning experience. On the other hand, the outlined framework is also meant to have positive impacts and transformations on the learners, because when the educators embody and apply the mindset, the learners can also learn how to apply the proposed framework (mindset, skillset, and toolset) in their own professional lives and learning experiences.

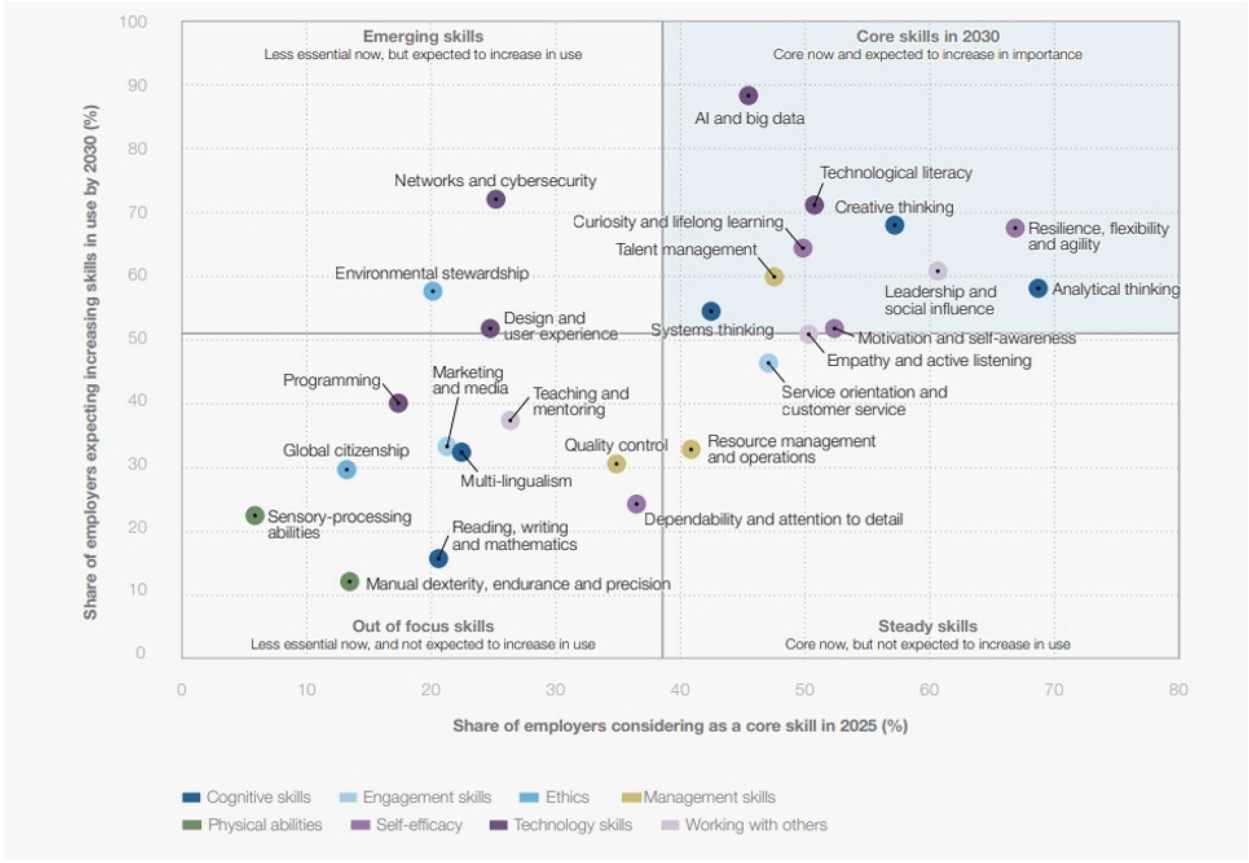
Changing Needs of Educators and Learners in the Age of AI

The rapidly changing technology, the cultural and social trends that are part of today's modern world, have completely altered the educational environment. The learners are currently operating within a context that is full of various digital distractions and large amounts of information that are mostly unrelated to each other, difficult to organize and digest in the limited attention span of the learners. The challenge is no longer the availability of information but the capacity to interpret and synthesize it. In this regard, both the educators and the learners need to cultivate a level of critical digital literacy that includes the capacity to question the accuracy, the potential biases, and the source of the information that is mostly generated through artificial intelligence technologies (Open University Critical AI Literacy Framework, 2025). Moreover, the learners and the educators are also required to be competent and capable of combining what they continuously learn and creating novel outcomes through synthesis and imagination. Lastly, within the ever-increasing intercultural and diverse environment, a level of competence that includes the capacity for empathy, communication, and collaboration is also essential and beneficial (Thornhill-Miller and Milioni, 2023; OECD, 2019).

At the same time, the current pace of technological advancements also requires learners to adopt the attitude of lifelong learning. Curiosity, adaptability, and self-regulation skills are the essential factors that enable individuals to update knowledge and redesign the pathways of personal and professional lives (Zimmerman, 2002; Panadero, 2017; Savickas, 2012). With these changes, the emphasis of learning has shifted from memorizing towards interpretation, sense-making, and creativity.

These changes in the profile of learners also change the way the role of the teacher is anticipated. Teachers cannot be merely transmitters of knowledge but instead have to be experience designers and facilitators of conditions for inquiry and investigation (Wiggins and McTighe, 2005; Laurillard et al., 2018; García et al., 2024). They must comprehend not only the material but also the psychology of learners and the implications

Figure 1: Core Skills in 2025 and 2030 (extracted from the World Economic Forum's "Future of Jobs Report, 2025)



of artificial intelligence-enabled education (Holmes et al., 2021). The new-generation educators need to be learning-designers and mentors for self-learning with a combination of empathetic and analytical abilities, and a skillset that integrates technology not merely mechanically but meaningfully.

Recent evidence emerging through the World Economic Forum's "Future of Jobs Report, 2025" (Figure 1) reveals that the education and training sector experiences the strongest skill transformations among all industries. The required skills for the future of the education and training sector are projected to include "analytical thinking, creative thinking, curiosity and lifelong learning, resilience, flexibility and agility, systems thinking, motivation and self-awareness, technological literacy, leadership and social influence", (World Economic Forum, 2025), which are closely aligned with the mindset dimension of the proposed framework. In other words, educator development should not only underline the technical upgrade, but also the comprehensive transformation of professional identity.

These findings indicate that a holistic paradigm shift is required for the development of both learners and educators within the new age of artificial intelligence. The learners must build the cognitive and ethical competencies to learn consciously and think systemically (OECD, 2019; OECD, 2025). The intersection of these needs represents the starting point of a new paradigm within the field of education that requires both the educator and the learner to redesign the learning experience in a collective way.

Theoretical Framework

The theoretical framework of the research has been built using three complementary perspectives: (1) the critique of technological determinism and the social constructivist approach as an alternative, (2) participatory and creative pedagogy, and (3) user experience design as a foundation for learning journey design. These three perspectives establish the philosophical and pedagogical fundamentals of the proposed model.

The first theoretical perspective of the framework challenges the idea that the progress of education is driven mainly by the advancement of technology. Technological determinism is an approach that identifies technology as the driving factor for human behaviour (Winner, 1978; Feenberg, 1999; Postman, 1992; Selwyn, 2011). However, in the education context, this view may lead to underestimating the role of the educators and learners, only to reactive users rather than active designers. In contrast, the social constructivist approach emphasizes that the direction and content of change is not the autonomous result of the function of technology, but the reflection of the mindset used to design and implement it (Pinch and Bijker, 1984; Bijker, Hughes, and Pinch, 2012). Based on the theory, the mindset element of the model stems from the idea that there must be a philosophical shift such that the educator conceives of themselves not merely as a passive user of a device but as a productive force within the educational environment (Oliver, 2011).

The second theoretical foundation is based on the creative traditions of pedagogy that see the learning process itself as participatory and transformative. According to these views, it is argued that the mission of education must go beyond transmission and become more focused on the idea of transformation through the development of interaction, creative, and critical thinking (Freire, 1970; Mezirow, 1991; Taylor, 2008). The idea of democratic and participatory pedagogy (MacMath, 2008), and the practices of the creativity movement (Robinson, 1999; OECD, 2019; OECD, 2024), highlight the importance of imagination and experimentation both within and beyond the classroom. This approach considers educators as co-designers who combine various educational strategies and skills, such as discussion, reflection, role-playing, and multimodal expression, to involve learners in educational programs not merely as passive receivers of knowledge but also as equal participants.

The third theoretical foundation draws on the design thinking and user experience (UX) design literature and deals with the intentional design of the entire learning experience journey (Brown, 2009; Floor, 2023). This approach views design as a process of creative problem-solving based on empathy, involvement of users, divergent and convergent thinking, testing, and iterations. (IDEO, 2015; d.school, 2018). Applied to the field of education, this approach reframes education as designing the entire teaching and learning experiences of teachers and students by understanding their emotional journeys, concerns, pain points, and expectations (Meyer et. al., 2014). Highlighted by the “Universal Design for Learning” Model, the primary mission of educators is not to transmit the content, but to discover and define the problems, understand the needs and emotions, experiment and iterate creative and diverse solutions in order to build meaningful learning experiences for each unique case

of learners. The design process requires an empathy-based and human-centered approach at the mindset dimension, as well as employing a wide variety of physical and virtual tools ranging from sketching to storytelling, prototyping, visualization, simulation, role-playing, etc. Without any doubt, artificial intelligence, or other technologies such as AR, VR, metaverse, etc., have the potential to support and interact with traditional tools. The central idea is that the tools exist to serve inclusive, functional, and emotional human experiences.

By integrating these three theoretical approaches (social construction of technology, participatory and creative pedagogy, and user experience-based learning design), the proposed framework suggests rethinking education in the age of AI. The model underlines that educational transformation depends on the alignment between mindset (how we think), skillset (how we teach and learn), and toolset (what we use).

Redesigning Education

The proposed framework in this article offers a holistic, design-driven approach to reimagine education in the AI era. The topic of "educational transformation" in the proposed framework has been defined as a comprehensive process that brings together the cognitive, emotional, social, creative, and technological aspects of learning. In this regard, the proposed holistic model has three interconnected dimensions, namely "mindset", "skillset", and "toolset", which collectively describe the mental, technical, and instrumental aspects of effective educational transformation (Table 1). The proposed model emphasizes the role of AI in improving the way in which learning takes place in modern society by using technology as an enabling factor rather than as the driving factor in the process of developing innovative learning strategies. In this regard, each of the three dimensions has been made up of eight complementary components that support the process of learner and educator-oriented user experience in the age of AI.

Table 1: The Three Dimensions of the Holistic Framework

MINDSET	SKILLSET	TOOLSET
Critical Thinking	Learning Experience Design	Analog Tools
Creative Thinking	Project-Based Learning	Case-Studies
Analytical Thinking	Personalized Learning	Gamification
Systematic Thinking	Productive, Creative, and Ethical Use of AI	Guest Speakers
Human – Centered Thinking	Co-Creation	Multimedia Tools
Ethical Thinking	Visualization, Mind Mapping and Storytelling	Digital Collaboration Platforms
Growth - Mindset	Constructive Feedback	Assessment and Feedback Tools
Learning How to Learn	Facilitation and Moderation	AI Powered Tools

Mindset describes the philosophical basis for pedagogy, which affects the thoughts, attitudes, and beliefs of the educator regarding learning, knowledge, and potential. These are "critical thinking", "creative thinking", "analytical thinking", "systematic thinking", "human-centered thinking", "ethical thinking", "growth mindset", and "learning how to learn". Skillset represents the practical, performative basis for pedagogy. This includes the "user experience design", "project-based learning", "personalized and adaptive learning", "productive, creative, critical and ethical use of AI", "co-learning and co-creation", "visualization, mind mapping and storytelling", constructive assessment and feedback", "facilitation and moderation". The toolkit refers to the tangible forms such as analog (paper, pen, sketching, whiteboards, flipcharts), digital (Video and Podcast, AI powered tools, digital collaboration and co-creation platforms) and interactive tools (case studies, group work, discussions, guest speakers, gamification, simulations, role play etc.) to be used in reaching and learning processes.

Components of Mindset Dimension

Critical Thinking: Critical thinking should be viewed not as just one skill among many, but as one of the most fundamental purposes of education (Freire, 1970; OECD, 2019; Thornhill-Miller et al., 2023). From a philosophical perspective, thinkers in the critical pedagogy tradition argue that the fundamental purpose of education is to develop individuals who can question their world, power structures, rules, and assumptions, and act on their own initiative (Freire, 1970). Educational reformers and theorists have argued that critical thinking is the heart of true educational change, emphasizing that students must be equipped to identify misinformation, think from multiple perspectives, and analyze assumptions (OECD, 2019; OECD, 2023; Thornhill-Miller et. al., 2023).

For educators, critical thinking involves continually questioning the accuracy, depth, validity, and necessity of the information and knowledge they share, the pedagogical methods they have applied, and the ethical dimensions of the tools they use. For educators, critical thinking represents a reflective discipline in which they constantly question the accuracy, depth, validity, and necessity of the information and knowledge conveyed, the pedagogical methods they have learned and applied, and the ethical dimensions of the tools they use. The educator not only applies the methods and uses the tools required of them but also evaluates the situation and circumstances under which they are questioned, consciously decides what should and should not be done using a situational approach, and consistently redesigns their learning processes accordingly. For students, critical thinking fosters the ability to question the information they receive, identify false assumptions and biases, and make reasoned judgments.

Recently, the importance of critical thinking has grown even more. Since the accuracy and validity of AI-generated outputs are not absolute, every time they must be evaluated through a critical perspective, not always accepted as definitive findings or proven truth. In addition to the inaccuracies of algorithms, errors, and hallucinations resulting from the inadequacy of resources feeding AI, and the proliferation of deliberately created biased, manipulative, or false content, students are increasingly exposed to potentially misleading information. Without strong critical thinking, educators and students can easily become passive recipients of algorithmic outputs and lose their capacity to make independent decisions. In our framework, critical thinking

therefore serves as the foundation for all other intellectual components.

Creative Thinking: Creative thinking has long been recognized as one of the most important objectives of learning, as well as a distinctive feature of the human mind. Various recent studies have confirmed the development of cognitive flexibility through well-designed conditions of learning, flexibility, and motivation (Savickas, 2012). Creative thinking, along with critical thinking, forms the foundation of innovation, change, and evolution in society. The development of individuals, institutions, nations, humanity, and ecosystems depends largely on the innovative solutions they develop and the ability to differentiate themselves through innovation and gain a competitive advantage.

Therefore, developing creative thinking skills in young generations is crucial for a nation's sustainable development and growth. For educators, creative thinking means developing innovative methods to convey knowledge to students and motivate them to learn. It also means constantly experimenting with new ideas, possessing the courage to experiment, and being open to innovative ideas, knowledge, and methods. They help students to look at things from a perspective that has not been looked at before, create innovative ideas, and motivate students to act on them. In the modern world, where information can easily be accessed, the most important tool that will remain a preserve of humanity will be the creation of new knowledge by using available information, knowledge, and methods.

Analytical Thinking: Analytical thinking can be defined as the ability to interpret complex information and produce logical conclusions based upon evidence and through a structured process. The essence of analytical thinking, as highlighted in key cognitive studies, has been noted as crucial for effective problem-solving, the transfer of knowledge, as well as the process of gaining in-depth insights (Dwyer et al., 2014; OECD, 2019).

From the perspectives of educators, analytical thinking capacity helps them extract, interpret, assess, and make use of the information needed in problem-solving activities or in designing innovative learning experiences. Analytical thinking helps the educator to balance their personal insights and evidence, turning decision-making into informed, data-based pedagogical practice.

For the learners, analytical thinking provides the structure for solving complex problems, understanding and interpreting data, as well as analyzing arguments. This equips the learner with the skill of logical thinking, analyzing hypotheses, and creating new knowledge upon evidence. Recent studies show the significance of analytical thinking in today's scenario, as people are increasingly exposed to AI-generated information, where they need to distinguish correct information from deceptive data (Guess et al., 2020). -This mindset prepares students to critically interact with AI systems and understand not only the results but also the logic behind them.

Systems Thinking: Systems thinking refers to the ability to understand relationships and dependencies within complex systems. Based on systems theory and holistic learning approaches, this approach enables educators and students to connect interdisciplinary ideas and knowledge and understand how social, cognitive, and technological factors interact.

For educators, systematic thinking enables teachers to connect knowledge from different disciplines and design more holistic

approaches to understand and explain a concept. When sharing specific information, educators must consider its place within a whole and its relationship to other domains of knowledge. They must design the content and flow of information systematically, connecting and combining its components to gradually build a whole. For learners, systematic thinking similarly promotes awareness of the interconnections between what they learn across disciplines and knowledge domains. Systematic thinking also reminds students that different disciplines are interrelated, knowledge is a whole, and knowledge acquired from different disciplines can complement each other. The philosophy behind a method learned in mathematics may be related to a different discipline in the social sciences. To correctly evaluate any event or phenomenon, it may be necessary to relate and integrate the perspectives of different disciplines. Developing this mindset prepares students to address complex, real-world challenges through integrative and cross-disciplinary thinking.

Human Centered Thinking: Human-centered thinking requires, first and foremost, understanding the mental and emotional states of individuals, recognizing them, striving to understand them, and empathizing with them (Brown, 2009; Holmes et al., 2021). An educational and teaching approach based on human-centered thinking considers the emotional and mental differences among individuals (Meyer et. al., 2014). It adapts, designs, and personalizes the content, depth, complexity, and methods of learning to students' current situations, individual contexts, and needs (Tomlinson, 2014; Holmes et al., 2021). Educators who are aware that learning is a unique experiential journey for each individual prefer educational methods adapted to the realities of the situation and personalized rather than delivering predetermined content or using standardized methods and tools. In this way, education becomes much more inclusive and open to diversity.

Each topic can be taught through a variety of methods. The starting point in a human-centered education and learning approach is the student's curiosity and interest in the subject. Because students lack sufficient knowledge of the subject, they may not be aware of what they are curious about or interested in. The teacher's role at this stage is to connect the subject to students' current circumstances, interests, and curiosities, and future goals, stimulating their curiosity and fostering a desire to learn, creating belief and motivation in the importance of the subject. This inclusive approach allows teachers and students to jointly design the content and methods of the course, thereby becoming the primary owners of the process from the very beginning, and taking ownership of the learning process.

According to one of the fundamental principles of the design-thinking methodology, which is based on a human-centered approach, developed methods and solutions are continuously experimented with and tested by the users. Problems are eliminated through the experiences and feedback of users, namely teachers and students, and the process is continuously improved through iterations. In this process, it is crucial that each individual is included, that their individual needs and levels are respected, and space is created for their self-expression. In this way, the contributions of each student to the overall process are made visible. Teachers no longer need extrinsic motivators (such as rewards and punishments) to capture students' attention and increase their motivation. Students, as the

primary owners of the process, co-design and implement the learning process actively and effectively through their intrinsic motivation and interests.

Ethical Thinking: Taken into account the potential for technology to be used for purposes such as fraud and manipulation, and its potential for negative and destructive effects on individuals, communities, and societies, learning core ethical values such as honesty, justice, respect, equality, responsibility etc., and prioritizing them in every step of both social and business life, has become an urgent and primary need for today's society. Furthermore, the social inequalities experienced in today's world, large segments of society lacking access to basic needs such as security, shelter, and nutrition, environmental disasters, political and social conflicts, polarization, and forced migrations, pose serious risks to both humanity and the world, today and in the future. Reducing these risks is only possible by cultivating individuals with a high sense of ethics and building social structures based on strong shared values.

Therefore, ethical thinking should be an essential cornerstone of education and learning processes. Strengthening sensitivity to ethical values in educational environments ensures that students feel they are in a learning environment based on ethics, justice, honesty, respect, equality, and mutual responsibility.

The purpose of the education system is not merely to train individuals who can produce economically successful solutions. The primary goal is to educate individuals who are responsible, sensitive, and capable of developing ethical solutions for humanity and the society they live in, and the universe at large. Furthermore, in a learning environment where the foundations of ethical values are weak, it is not realistic to expect students to use technologies like artificial intelligence, which have a wide range of applications, correctly and ethically. The efforts to limit or detect the use of AI in assignments or in-class activities are not meaningful and efficient without having an ethical consciousness.

Growth Mindset: Growth mindset emphasizes that individuals' intelligence and competencies are not fixed and do not come from birth but rather can be developed over time (Dweck, 2006; Yeager and Dweck, 2012). With the right strategies and methods, individuals' competencies can be enhanced over time. Therefore, students' failures are not due to a lack of capacity, but rather to a lack of appropriately designed learning experiences (Meyer et. al., 2014). Mistakes or shortcomings are not permanent. Intelligent experiences that enable learning from mistakes have, on the contrary, positive effects on an individual's competencies, knowledge, and accumulated experience. Therefore, the key is not to classify students as having low or high capacity, but to design learning experiences and environments that align with students' aptitudes, interests, and current levels (Yeager et al., 2019)

In such environments, students are not punished or ignored for their poor performance. On the contrary, innovative methods and approaches are used to encourage students to learn from their mistakes and address their shortcomings (Dweck, 2006; Yeager et al., 2019; Rattan et al., 2012; Canning et al., 2019). Students are given opportunities to develop the courage to experiment and build their curiosity and self-confidence. In a learning model based on a growth mindset, the teacher's sole mission is not to impart knowledge; rather, they must mentor students when necessary, support their emotions, provide constructive feedback to maintain

their motivation for continuous learning and improvement, and strengthen their resilience and courage in the face of failures.

Learning How to Learn: Two of the most significant characteristics of today's world are "high pace of change" and the "high volume of information we are exposed to." Social needs and dynamics, the technologies we use, our living conditions, our needs, and our expectations are all rapidly evolving. In these conditions of high uncertainty, change, and complexity, the knowledge and competencies we possess can quickly lose their relevance or effectiveness. This creates the need to constantly update our knowledge and skills. Therefore, learning is not limited to places, age, or time. Learning is an activity that must be ongoing, at all stages and in all dimensions of life (European Commission, 2018; OECD, 2019; OECD, 2021).

Today, the formal education methods alone are insufficient, and informal and individual learning becomes increasingly important. Individuals can continually identify their own shortcomings and needs, set their own learning goals, choose their own learning methods and information sources, and thus design their own learning processes (Garrison, 1997; Loyens et al., 2008; Loyens and colleagues, 2024). However, the challenge lies in selecting the high-quality information, establishing connections between what we learn, interpreting information, and transforming it into knowledge (Zimmerman, 2002).

All of these factors demonstrate that one of the most critical mental requirements of surviving and evolving in the age of AI is "learning to learn" (OECD, 2021). Students with this mentality understand that learning isn't limited to classrooms. They don't limit themselves to formal education for self-improvement. They evaluate different opportunities and resources. They objectively identify their developmental dimensions and can create their own plans for development and learning. In this process, educators must view learners not merely as passive recipients of information, but as individuals who must learn to design their own learning processes. Educators must create opportunities for initiative and experimentation through practices that enable this (Candy, 1991; Loyens et al., 2008).

Skillset and Toolset Dimensions of The Model

Since this article mainly focuses on the "mindset" dimension of the proposed model and due to the limit of its scope, the skillset and toolset dimensions will only be briefly discussed, and more detailed explanations are left for future studies. In addition to the mindset, the skillset enables educators to implement their intellectual infrastructure and deliver it to students. This dimension includes the co-creation of learning content (Freire, 1970; Cook-Sather et al., 2014; Healey et al., 2014; Bovill, 2020) and the design of the learning experience journey (Candy, 1991; Garrison, 1997; OECD, 2019; Loyens et al., 2008), personalization of the learning process according to student needs, competencies, and areas of interest (Holmes et al., 2018), project-based learning (Bell, 2010), co-creation, visualization (Ainsworth, 2006), mind mapping (Buzan and Buzan, 1993; Nesbit and Adesope, 2006), storytelling, providing constructive feedback (Black and Wiliam, 2006; Hattie and Timperley, 2007; Nicol and Macfarlane-Dick, 2005) , facilitating and moderating group work (Johnson and Johnson, 1999; Scager et al., 2017), and finally, the productive, creative, and ethical use of artificial intelligence. These skills altogether enable the understanding and

transfer, absorption, and implementation of knowledge by students.

The "toolkit" dimension of the proposed model ensures efficiency in the transition of knowledge. Just as the harmony within an orchestra, the interaction, communication, and coordination among orchestra members, the leadership and philosophy of the orchestra, and the abilities and experience of each individual all play a role in an orchestra's performance. In addition to that, the suitability and quality of the instruments used by the orchestra members will also determine the quality of the music. The education and learning process is similar. While the pedagogical approaches and skills of instructors and students regarding the learning process are invaluable, the process cannot occur in its most efficient and effective form if it is not supported by appropriate tools. When compared to Acapella, the musical form in which no instruments are used and musicians perform purely with their voices, effective communication and learning are certainly possible even in a completely simple environment where no instruments are used, where only instructors and students communicate their knowledge and ideas through conversation. On the other hand, the new possibilities that can be created by instruments used correctly and with the necessary skills can make the learning process more diverse, memorable, and effective for students and educators.

The most traditional forms of tools, such as paper, pen, books, notebooks, blackboards, or flipcharts (Delgado et al., 2018; Fleissner-Martin et al., 2023; Mueller and Oppenheimer, 2014) offer a wide range of flexible uses for communication, transferring knowledge, and collaborative production. The development and diversification of digital tools do not diminish the importance and effectiveness of traditional tools. Writing and reading, by their very nature, enable students to focus, slow down, think, make simple and quick trials, memorize, and internalize. Furthermore, theatrical activities such as gamification, simulations, role-playing (Chernikova et al., 2020; Dichev and Dicheva, 2017; Li et al., 2023) and case studies (Rhodes et al., 2020) allow students to acquire knowledge through practice and experience within a specific setting. Guest speakers invited to the learning environment, experts in the targeted subject matter, diversify the learning resources for students and provide practical experiences. Students also increase their active listening, question-formulating, and interaction skills. Additionally, digital tools such as videos, films, podcasts (Robin, 2016, Armstrong et al., 2009) or digital collaboration platforms (Chen et al., 2015; Kovari et al., 2025) reinforce the information learned, sometimes making it easier to understand or retain it. Students' active production of such tools, not just their consumption, allows them to develop new skills and deepen their knowledge.

In addition to all these tools, the use of AI-based applications, both individually and in combination with other tools, can significantly increase educational effectiveness. By using AI tools, it's possible to deepen research and thinking processes, particularly through critical questions, and to explore diverse perspectives through collaborative brainstorming. Using AI, personalized case studies with varying complexity can be written to support the topic being learned. Information can be visualized, gamified, and narrated for storytelling; complex information can be simplified, summarized, illustrated, and personalized to engage students with diverse interests. By asking AI to take on different roles, diverse perspectives can be acquired. It's possible to develop tools and content to assess and measure the effectiveness of the

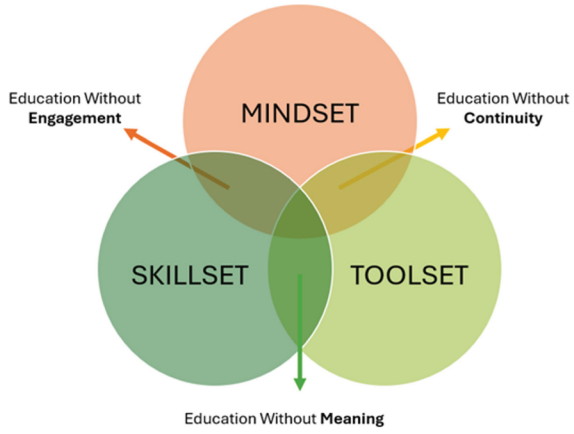
learning process, thereby providing rapid and instant feedback. Beyond all this, AI can also assist in designing the learning process for both educators and students to create a self-directed learning process. This can enable learning to occur independently of time and space, in an interactive and personalized manner. Considering the diversity of these potential application areas, the potential opportunities created by artificial intelligence become more readily apparent. However, the mere existence of AI as a tool does not guarantee its beneficial use. One must possess the right mental set and skill set to utilize this tool. The efficient, productive, creative, critical, and ethical use of AI is a competency that both educators and students must master, and gaining this competency begins with a healthy mental and pedagogical approach.

Model Integration and Changing Role of Educators

The framework being proposed integrates the three different aspects (mindset, skillset, and toolset) in one holistic framework for the transformation of education. However, the power of having all the different aspects lies in their integration. Mindset is the philosophical foundation of the process. It explains the perspective of educators and students on the purpose of education and learning. Skillset is the pedagogical implementation of the mindset through actions. A toolset is the set of tools used to facilitate and foster the learning process. None of these dimensions can be thought of in isolation, and each aspect requires the others to function as a holistic system.

Alignment between educators' beliefs, actions, and the choice of learning tools is crucial for effective learning and education. When educators' and students' perceptions of education and learning fail to support a creative, critical, and inclusive learning process, education loses its meaning, even if sufficient skills and tools are available. Questions like "Why are we together?", "Why are we learning?", and "What is a good education?" would remain without clear answers. On the other hand, in case the skill set is lacking, even if the other two components are present, continuity in education and learning cannot be ensured. The creative and critical mindset cannot be put into practice. Existing tools cannot be used effectively and productively. Lastly, when a tool set is incomplete or inadequate, it becomes difficult for students to engage sufficiently in the learning process, transfer knowledge effectively, and collaborate (Figure 2).

Figure 2: Holistic Approach for Transformational Education



Therefore, by maintaining the alignment among the three dimensions, the model ensures that technology itself is not the ultimate purpose; instead, it is one of the enablers to reach a meaningful transformation for better education and learning.

Students no longer need teachers who simply convey information they can already access, read sentences written on slides, and ask them to memorize. Instead, they need educators who can remind them of the purpose, reason, and pleasure of learning, who can design their learning processes using different methods and tools, who can criticize them and guide them toward creative thinking, who can equip them with a new way of thinking and new skills, who can mentor, facilitator, and moderator when necessary, who can inspire them with interesting questions and encourage them to think outside the box, and who can teach them how to learn and how to design their own learning experiences. They need to experiment, discover, and learn how to access current and valid information, critically interpret it, combine it with other information, synthesize it, generate new knowledge, and integrate it into their lives.

In the longer term, the shift may bring along the birth of a new professional identity for educators: "the learning experience design mentor". In this new role, the educators not only design learning experiences but also inspire students to build experiences on their own, and teach students how to 'design,' 'evaluate,' and 'develop' their own learning experiences.

Conclusion

Technological developments such as the widening use of artificial intelligence, virtual and augmented reality, economic trends such as the acceleration and globalization of production and consumption, and the changing social habit as a result of the use of social media, the shortening attention spans among younger generations, the increased speed and ease of access to information, the emergence of more diverse social structures due to global migration, the increasing importance of skills such as creative thinking, innovation, entrepreneurship, analytical thinking, systematic thinking, empathy, resilience, self-motivation and self-discipline, and group work in both social and business life, and the increasing demand for practical skills rather than academic degrees in the business world, all require a radical transformation in the perception of the concept of education and its practices.

In this transformation process, in order to improve the quality and stakeholder satisfaction of education and learning, the mindset, skillset, and toolset used by both educators and students regarding education and learning processes must be considered and transformed together. However, placing the opportunities or threats that technology may pose at the center of this transformation is not a socially constructive approach. It should not be forgotten that it is humans who develop, adapt, and use technology. Without any doubt, the use of technology also influences and changes people's habits, skills, and even mentalities over time. However, considering humans as passive and technology as active prevents people from determining the right strategies and taking the right actions regarding technology. The collective mindset of people and societies must be positioned as an active force to guide technology, maximize its potential, and manage its threats. Therefore, this article argues that the primary driver of change in education must mainly be a shift in the mindset, in other words, our perception of education and learning. Educational approaches that place critical, creative, analytical, systematic, empathic, growth-oriented thinking at the center will also enable the development of the right skills and the most accurate (creative, critical, and ethical) use of existing tools.

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Beyond the Classroom: The Classroom of Tomorrow and How AI and Technology Are Revolutionising Learning

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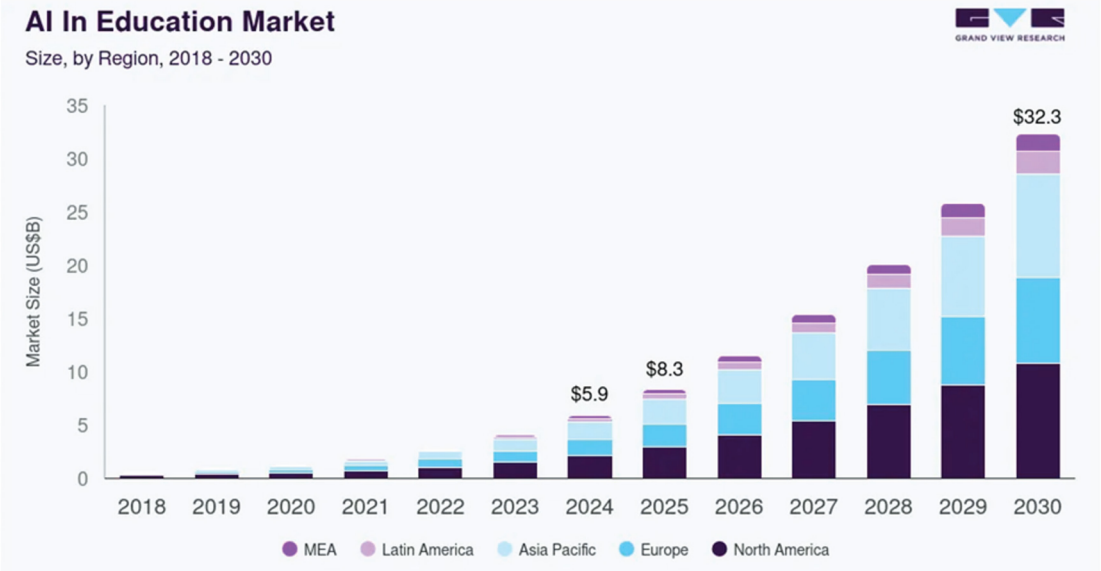
Introduction

Classrooms are very powerful platforms for elevating the students. How we undertake tasks outside the classroom—particularly scholarly ones leveraging AI and technology—is at once challenging and transformative. It is becoming a very fluid and debatable concept today, as societies, economies, and cultures are being transformed by artificial intelligence around the world (Ashraf and Mustafa 2024). How does the very nature of this conversation that we are having right now actually become a larger discussion and a deep dive into how we can engage students in the classroom while they factor in AI, because it often feels today as if you don't have an AI, nothing is feasible or possible? Meanwhile, AI is not a panacea either. So we must see how they can be engaged in valuable activities inside the classroom, and how we can give them some sort of technological immersion or global connectivity that allows a better comprehension of concepts and theories. The sharing of information is no longer a one-way stream; as of today, whatever a professor may convey in the classroom can be accessed by students through AI platforms like ChatGPT and other AI tools (Holmes & Tuomi, 2022). But does AI have what it takes to replace a teacher? The answer is no. A humanized relationship becomes critical here as well when we are describing concepts, quoting real-life examples, and creating a professor-student connection beyond the classroom. Relationships matter; demonstrating care and understanding is essential in the teaching profession (Demetriou, 2018), one of the human elements that cannot be replicated by AI.

Education at the Edge of Transformation

Education has come to be seen as the bedrock of human development, forging societies, economies, and cultures over the course of generations. For hundreds of years, little changed in the classroom: a teacher at the front, students seated and grouped in rows, textbooks providing almost all knowledge needed, and examinations being the main assessment of learning (Havnes 2004). But the rise of advanced digital technologies

Figure 1: Chronological development of AI in education. (GVR 2024)



has started to break this traditional model. Artificial intelligence, immersive technologies, and global connectivity are reshaping not just where learning happens but how knowledge is built, shared, and assessed.

The idea of the "classroom of tomorrow" transcends physical walls. Learning becomes more fluid, personalized, and continuous. AI-based systems assess each learner's own path and process of learning, immersive virtual settings bring to life real-world contexts in which those learners apply their knowledge and skills, and worldwide digital networks connect students from various cultural and geographic domains (Figure 1). These developments are collectively leading to an education paradigm that is adaptive, data-rich, and deeply learner-centric.

This transformation is also not so much an upgrade in technology but rather a total overhaul of the philosophy of education as we know it. In a new world of learning, knowledge need not be limited to textbooks or lectures. Rather, it grows organically through interaction, collaboration, and intelligent systems that adapt to every learner's needs.

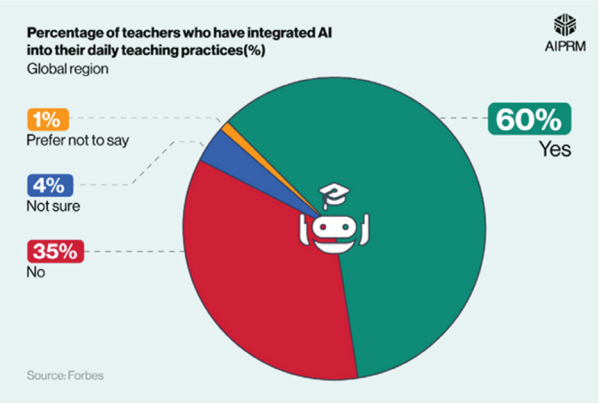
The Evolution from Traditional Classrooms to Intelligent Learning Spaces

In the industrial era, education systems were created to promote uniformity and efficiency for large numbers of students. Students moved through standardized curricula at the same pace, despite individual strengths or learning preferences. Although this framework succeeded for large-scale education, it frequently couldn't recognize and adjust to various cognitive styles and personal interests (Pandya et al. 2024). With the advent of digital technologies, this rather brittle structure has slowly morphed into a more flexible and responsive environment. Smart classrooms with digital boards, cloud-based resources, and collaborative platforms enable teachers to present material in myriad formats — visual, auditory, and interactive. These multimodal

approaches not only improve understanding and retention but also promote a greater degree of engagement by learners.

AI accelerates this also through adaptive learning systems. These platforms track students' performance in real time, analysing patterns in their answers, mistakes, and learning rate. Using these insights, the system dynamically adjusts exercise difficulty levels, recommends supplemental resources, and highlights areas needing additional support (see Figure 2). The outcome is student-specific education, not a one-size-fits-all mold. Infofobius: You are a self-declared futurist with the goal of bringing change.

Figure 2: Growth of AI usage in education (AIRPM 2024)



This transition from static classrooms to intelligent learning ecosystems marks a critical milestone in the evolution of education. The classroom of tomorrow is not merely a physical location but an interconnected digital environment capable of responding intelligently to the needs of learners.

Artificial Intelligence as a Personalised Learning Companion

I believe that AI's one of the most powerful gifts to education is its ability to individualise learning experiences at scale. In the past, personalised instruction had to wait for as many teachers and schools as pollution to follow. But with AI-driven technologies, we can offer every student customised guidance and feedback more effectively. AI-based tutoring systems serve as friendly, virtual learning partners who can answer questions, clarify difficult concepts, and offer 'how-to' assistance. That's different from traditional tutoring, which is typically conducted on an as-needed basis; the systems are always available whenever students struggle. This creates a learning environment that is inclusive and responsive (Tapalova and Zhiyenbayeva, 2022).

Additionally, AI algorithms sift through enormous amounts of educational data to identify patterns that might otherwise go unnoticed. Another emerging tool is adaptive learning technology, which helps to identify and recommend personalized instructional interventions by tracking students' progression on assignments, quizzes, and interactive exercises, as well as detecting where students are struggling. A student who has difficulty executing algebraic reasoning may be assigned supplementary practice problems, visual representations, or interactive simulations that target the underlying conceptual difficulties.

Not only does this affect the academic outcomes, but it also contributes to the confidence of the learners. Feedback that

caters to students' needs helps foster resilience and intrinsic motivation in students. In this context, artificial intelligence serves not only as a technological assistive tool but also as an educational companion (Yilmaz, 2024).

Immersive Technologies and Experiential Learning

A second transformative aspect of educational technology is found in immersive learning spaces enabled through VR, AR, and mixed reality. Through interactive simulations that mimic real-life to encourage students to solve complex problems, this technology helps in hundreds of experiences.

In conventional classrooms, abstract subjects like physics, chemistry, or history are generally communicated via text or static diagrams. On the other hand, immersive technologies in three dimensions allow learners to visualize and interact with complex systems. For example, someone studying astronomy may be able to navigate a virtual solar system and witness planetary motion and gravitational interactions firsthand. Likewise, Medical Students may use simulated environments in which to perform surgical procedures prior to entering real clinical settings (Lopez-Goyez et al. 2026).

The students make significant conceptual gains through these experiential learning opportunities. The National Academies of Sciences, Engineering, and Medicine suggest that learners learn better when the content is consumed actively through immersive simulations where connections are stronger. In addition, these technologies promote curiosity and exploration, making learning a dynamic and interactive process.

"The Future Classroom Is an Experimental Laboratory Where Theory Meets Practice. Bringing theory to life, the classroom of tomorrow becomes a living laboratory." With the help of immersive technologies, students are not information recipients anymore; instead, they actively contribute to their education.

Global Connectivity and Collaborative Learning Networks

Technological innovation has also transformed the social dimension of education. The growth of digital platforms and high-speed internet allows students to collaborate beyond geographical borders, creating global learning communities.

Because students are spread across the country, online learning environments allow for discussions in real time, collaborative research projects, and peer-to-peer feedback. Students of different cultural backgrounds can compare their perspectives, enhancing their understanding of global issues and fostering intercultural competence. Such interrelatedness represents the increasingly globalised character of modern society, where cross-border cooperation is crucial to face multifaceted problems (Guspian et al. 2025).

Furthermore, digital learning platforms can offer access to a wealth of knowledge, such as academic journals, open educational resources, and expert lectures from top institutions around the world. This accessibility democratizes education like never before, overcoming the obstacles of geography, social standing, and institutional limitations.

Classroom as Global Network: In this context, the classroom is no longer bounded inside but becomes a global network. Digital infrastructures are needed to support a new Culture of Learning, where learning becomes a communal experience where collaboration, dialogue, and knowledge sharing happen at an unprecedented scale.

The Changing Role of Educators in the Age of Intelligent Technology

With these new technologies emerging to augment and transform education, that does not lessen the role of the teacher in life. Instead, teachers' roles are transforming from being mere information transmitters to catalysts of critical thought, creativity, and ethical reasoning.

AI systems can act as automatic machines to make processes like grading, administrative tracking, and even basic instructional delivery more efficient in technology-enhanced classrooms. This automation frees educators to engage in higher-order pedagogical activities: leading discussions, mentoring students, and fostering intellectual curiosity.

Contextualisation of technological tools within meaningful learning experiences is another key contribution teachers make to 21CL. Despite its capability to personalize recommendations, human educators understand the empathy, cultural context, and equity rights required to best meet students' needs. This means that tomorrow's classroom depends on a symbiotic relationship between intelligent technologies and human mentorship (Ka and Louisa, 2024).

In addition, it is the responsibility of educators to aid students in developing digital literacy and critical thinking skill sets that will prepare them to successfully navigate an increasingly complex information landscape. We live in a time when so much information is available, and the ability to evaluate sources, interpret data, and apply knowledge responsibly has never been more critical.

Ethical Considerations and Challenges in Technological Education

While the use of artificial intelligence and other advanced technologies in education promises remarkable opportunities, it also presents numerous ethical and practical challenges. These concerns around data privacy, algorithmic bias, and digital divide are valid and need addressing.

Artificial Intelligence-powered education systems depend on data gathering to understand learning trends and tailor instruction accordingly. Protecting students' privacy requires responsible and secure handling of this data. Schools need to have transparent policies on data – how it is used and robust controls against misuse (Schiff, 2021)

Another potential concern is algorithmic bias in AI systems trained on datasets that reflect current disparities, which could perpetuate inequalities. It could unintentionally bias certain groups of learners if not overseen carefully. Developers and educators, therefore, need to work together towards creating equitable and inclusive technological solutions.

A second major challenge is the digital divide. Although the pace of technological innovations is creating new educational opportunities that did not exist before, disparities in access to digital infrastructure can worsen existing inequalities. However, for technology-enhanced learning to fulfill its full promise, it is imperative to make sure that all learners have appropriate access to devices, internet connectivity, and other digital resources.

All these challenges are necessitating careful policy frameworks, ethical guidelines, and collaboration between educators, technologists, and policymakers.

Conclusion and Future Outlook

Tomorrow's classroom is not limited by geography or schedule. Today, it is an integrated, interoperable ecosystem that combines artificial intelligence, immersive technologies, and global networks to deliver transformative learning experiences.

As these innovations continue to develop, education will focus more on adaptability, creativity, and lifelong learning. The students of tomorrow will not merely learn — they will never be able to learn everything; rather, they will learn how to learn endlessly, engage globally with each other, and execute problem-solving in plastic environments.

But the success of this technological transition will ultimately boil down to keeping humans at the centre of education. Despite its potential, the heart of learning is still curiosity driven by empathy and an intellectual exploration.

When societies align technological advancements with educational ethos, they open up the implications of education that equip individuals to succeed in a dynamic environment. Thus, the classroom of tomorrow is not just an educational tech construct, but a vision of education that crosses borders and cultivates potential to equip humanity with both the challenges and opportunities of the future.

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Mental Health and Well-Being in Higher Education

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Abstract

Mental health among students has become an important concern in higher education, which arises due to academic pressure, social change, uncertainty, and evolving expectations of growth and success. While institutional responses often focus on support services and crisis management, there is a growing need to reconnect and establish mental health as an ongoing, holistic process rather than a binary state of illness or wellness. The present paper talks about the mental health and well-being of college-going students. The current perspective discusses students' mental health, drawing on contemporary psychological frameworks such as positive psychology, emotional intelligence, and well-being theory. It argues that self-awareness, balance, and intentional well-being practices that help in managing and coping with these stressors are foundational to sustainable mental health and academic functioning.

Keywords

Well-being, Self-awareness, Emotion regulation, reflective practices

Introduction: Mental Health Beyond Pathology

Discussions of mental health in higher education frequently focus on distress, diagnosis, and intervention. While such debates and discussions are important it also create a risk where they see mental health as a problem, whereas it requires more management and practice, a skill that can be developed. Mental health exists on a spectrum, influenced by emotional regulation, relationships, purpose, and personal meaning. The everyday experiences of students who are functioning but struggling in silence may be overlooked if mental health is only viewed through a clinical lens.

A wider concept of mental health can be to focus on adaptability, emotional literacy, and self-regulation. Mental well-being, here, is not the opposite of distress and stress but the capacity to cope with challenges and retain balance and integrity. It needs to be understood as an act of creating balance while navigating life rather than being free from life's difficulties.

Another aspect that needs to be understood is that the intensity of stress that one person feels may vary from that of another. When

we use words such as “she is a touchy-feely person” to indicate that someone is more sensitive to his/her environment than others. What might affect one person might not affect another. Hence, well-being is rather a multi-dimensional experience. Let’s talk about it in our next section.

Well-Being as a Multi-Dimensional Experience

Well-being is inherently multi-dimensional, encompassing physical, emotional, psychological, and social domains. However, these dimensions are intertwined; any change or strain in one area will automatically affect the other. For example, emotional stress may disrupt sleep, social engagement, and cognitive functioning, thereby influencing academic performance.

This interdependence highlights the importance of self-awareness. Students who are unaware of their internal experiences may mistake emotional exhaustion for failure or personal incompetence, failing to see the signal that their body is sending about being unbalanced. Developing awareness is the first step towards attaining sustainable well-being since it allows one to respond rather than react.

Lack of self-awareness can create a hindrance in building self-esteem. Sometimes we tell ourselves worst-case scenario tales. We often fall to the worst-case primary appraisal by saying, “What if…and then I will crumble.” These worst-case scenarios have no real use because they will not solve any problem. Neither will they prepare us better for the time. In psychology, we call this process “catastrophization”, one of many cognitive errors or idiosyncratic ways of thinking. Best practice is to focus on your well-being and command yourself to stop. Using grounding techniques and imagery can help resolve this and regaining ones well-being.

Viktor Frankl, a psychiatrist and holocaust survivor, witnessed the death of his unborn child, wife, mother, father, and brother in concentration camps, and went on to live a fulfilling life. In his book, Man’s search for meaning (1946), he wrote, “A human being is a deciding being.” And so…. Everything can be taken from a man but one thing- the last of human freedom, to choose one’s attitude in any given set of circumstances and to choose one’s own way.

This takes us to our next section, understanding Positive Psychology.

Positive Psychology and the PERMA Perspective

Positive psychology offers a useful lens for understanding well-being beyond just symptom reduction. The PERMA model (Seligman, 2011) identifies five elements that contribute to flourishing: Positive Emotions, Engagement, Relationships, Meaning, and Accomplishment. This model emphasises a balanced life marked by purpose, connection, and advancement rather than perpetual happiness.

This model emphasises the role that we don’t make mistakes, we learn lessons. Researchers say that it is very important to make mistakes, to be given corrective feedback, and to teach children to develop a higher tolerance for receiving the same. This means our demands about ourselves, about others, and about the world will be less rigid and more flexible.

PERMA emphasises that academic achievement or short-term success by itself does not ensure wellbeing for students. Equally important are supportive relationships, meaningful goals, and a sense of engagement. Students may overlook the emotional and relational needs that sustain motivation and resilience if they only use performance metrics to assess their lives.

Emotional Awareness and Regulation

Emotions play a central role in learning, decision-making, and interpersonal functioning. Yet emotional literacy is rarely explicitly addressed within academic environments. Students may struggle to identify or articulate their emotional experiences, leading to avoidance, suppression, major defense mechanisms, or maladaptive coping strategies. This lack of self-awareness can create a gap between their real self and their ideal self.

Emotional awareness involves recognising emotions as informative rather than disruptive. When students learn to observe emotional patterns without judgment, they gain greater control over their responses. Emotional regulation does not imply eliminating negative emotions, but developing flexible strategies to manage them constructively. This creates self-Compassion, a practice that bestows kindness and understanding upon ourselves during times of hardship. By embracing self-kindness, we cultivate emotional resilience. Research confirms that it has transformative powers, revealing that it alleviates distress and fosters emotional regulation.

Emotional regulation is the ability to experience stress or disappointment, acknowledge the emotion, reflect on its source, and respond thoughtfully rather than react impulsively.

There is certainly a relationship between stressful events and more traumatic life events. By stressors we mean small events and more traumatic life events. Characteristics of emotionally regulated people include those who practice the following:

1. Giving oneself more credit for how one will be able to handle a stressor, also known as perceived control
2. Having more faith in one's ability to handle negative consequences, known as self-efficacy
3. Occupying oneself with routine, however basic or suboptimal (like brushing, grooming, getting to work despite the emotional pain)
4. Saying "yes" to going OUT and not staying IN, Socialisation

Rethinking Mental Health in Higher Education

Mental health initiatives in higher education benefit from shifting emphasis from crisis response alone to preventive, reflective, and developmental approaches. Encouraging students to engage with their mental health proactively fosters autonomy and psychological maturity.

Rather than asking, "What is wrong?" a more constructive question may be, "What supports my well-being and growth?"

In Psychotherapy, we learn how to use Marsha Linehan's "Dialectical Behaviour Therapy (DBT) in skill-building for so many kinds of problems-interpersonal & intrapersonal. We are all aware that a significant portion of it has its roots in Eastern Indian philosophies, which



Students during a Wellbeing workshop at BSBI. Photograph by Soheil Moradianboroujeni.

demand that disputants acknowledge the other viewpoint before attempting to refute it completely. To make sure we really understand what we're up against, the dialectic bit—that is, the balancing of acceptance and change—calls on us to embrace the opposing viewpoint, even if only briefly! Such reframing positions mental health as an integral part of the educational journey, closely tied to identity formation, purpose, and resilience. By normalising reflection, emotional awareness, and balance, institutions can support not only academic success but lifelong psychological well-being.

Mental health initiatives in higher education have traditionally prioritised crisis intervention, counselling services, and clinical support pathways. Although these solutions are essential, focussing solely on risk prevention presents mental health as an issue that should only be addressed after problems have gotten worse. Such a strategy can inadvertently perpetuate stigma, portray students as helpless users of assistance, and ignore the larger developmental function that higher education plays in forming identity, resilience, and psychological maturity.

A more sustainable and inclusive approach requires an overall conceptual shift, from viewing mental health as a reactive concern to understanding it as an ongoing, developmental process. Preventive and reflective frameworks emphasise mental health as a capacity that can be strengthened over time through awareness, self-regulation, and intentional engagement with one's emotional and psychological experiences. This perspective acknowledges that mental distress is not an anomaly but a common part of student life, particularly within environments characterised by academic pressure, uncertainty, and social transition.

Encouraging students to engage proactively with their mental health fosters autonomy and self-efficacy. Rather than positioning well-being as something that is managed externally by support systems, students are

invited to develop an internal understanding of their emotional patterns, stress responses, and coping strategies. This shift reframes the central question from “What is wrong with me?” to “What supports my well-being and growth?” a subtle yet powerful change that reduces self-blame and promotes self-compassion.

Such reframing also aligns mental health more closely with the broader educational mission of higher education. Universities are not solely spaces for knowledge acquisition but environments in which individuals negotiate identity, values, purpose, and future aspirations. Mental well-being is deeply intertwined with these processes. Emotional awareness, reflective capacity, and psychological flexibility influence how students approach learning, manage failure, build relationships, and respond to uncertainty. When mental health is embedded within this developmental context, it becomes a foundational component of academic engagement rather than a separate or marginal concern.

Additionally, rather than pathologising emotional experience, incorporating preventive and reflective approaches normalises it. Students are assisted in realising that stress, self-doubt, and emotional swings are indicators that call for introspection and change rather than being indicators of inferiority. Institutions foster cultures where students feel free to stop, think, and reassess rather than persevere despite fatigue or disengagement by legitimising these experiences.

In the end, institutions can encourage both short-term academic performance and long-term psychological well-being by viewing mental health as an essential component of the educational process. Graduates are more equipped to handle the challenges of both personal and professional life if they are able to reflect on their mental states, control their emotions, and maintain equilibrium. In this way, reconsidering mental health is essential to education rather than an add-on.

Conclusion

Mental health in higher education is not solely a matter of intervention but of understanding. Viewing well-being as a dynamic, multi-dimensional process allows students to engage more compassionately with themselves and their challenges. Integrating perspectives from positive psychology, emotional intelligence, and self-awareness offers a richer, more sustainable framework for mental health, one that empowers students to flourish rather than merely cope.

This approach enhances the overall student experience within educational institutions and encourages tutors to adopt a more mindful, empathetic, and proactive stance toward students’ mental health.

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AI as a Catalyst for EdTech Entrepreneurship

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Abstract

Purpose: This study investigates how innovation based on Artificial Intelligence reinforced educational entrepreneurship with exclusive emphasis on perceptions, ethical awareness, and strategic thinking among MBA students in the post-COVID era.

Background: The COVID-19 pandemic created favorable conditions for investments in AI-based EdTech and significantly accelerated digital transformation in education. Whereas artificial intelligence presents considerable benefits such as personalized learning, scalability, and cost efficiency, it also requires careful consideration for its adoption, which presents ethical, infrastructural, and institutional challenges.

Materials and Methods: By combining quantitative survey data from 56 MBA students with qualitative insights from semi-structured interviews conducted with 10 participants at BSBI, a mixed-method research design was employed. Descriptive statistics were used to analyze quantitative data, while thematic coding was applied to interpret qualitative responses.

Results: The findings show that 58.9% of respondents indicate entrepreneurial intent toward AI-based educational ventures. The key opportunities, including personalized learning experiences, operational efficiency, scalability, and inclusive access to education, are identified by participants. However, particularly insufficient AI-related training (41.1%), ethical concerns (28.6%), and infrastructure limitations (17.9%) remain as notable barriers. Ethical issues emerged as central themes influencing strategic decision-making, especially data privacy, algorithmic bias, job displacement, and social inclusion.

Conclusion: In the post-COVID landscape, AI represents a transformative force in educational entrepreneurship. The realization of sustainable and inclusive innovation depends on harmonizing technological potential with ethical responsibility, institutional readiness, and contextual alignment. In order to enable responsible AI adoption in EdTech entrepreneurship, educational institutions and policymakers must prioritize capacity building, ethical design principles, and supportive regulatory frameworks.

Keywords

Artificial Intelligence, Educational Entrepreneurship, EdTech Entrepreneurship, Ethical Design, Inclusive Innovation, Institutional Readiness, MBA Students, Post-COVID

Introduction

The COVID-19 pandemic led to an unprecedented disruption in the global education system. It caused the displacement of over 1.6 billion students and institutions worldwide, forcing them to shift from traditional classrooms to digital learning environments rapidly. This abrupt transition revealed the weakness of long-standing structures, including deficient digital infrastructure, unequal access to technology, and institutional unpreparedness. At the same time, by creating fertile ground for education, it accelerated the adoption of advanced digital solutions. Among these solutions, Artificial Intelligence (AI) appeared as a transformative force that is capable of reshaping educational delivery and organizational models.

AI-powered technologies have enabled unprecedented levels of personalization, scalability, and operational efficiency, such as adaptive learning systems, intelligent tutoring platforms, predictive analytics, and generative tools, including ChatGPT and LearnLM. These technologies improve learning outcomes and also redefine how educational content is designed, delivered, and assessed. AI has opened new avenues for educational entrepreneurship, beyond pedagogical transformation. By positioning EdTech ventures as key actors in addressing persistent challenges related to access, cost, customization, and inclusive learning.

With the advent of the pandemic, international investment into AI-led EdTech startups has been on the rise, symbolizing great enthusiasm for techno-enabled schemes for education. This techno-optimism is interspersed with profound concerns regarding ethics, infrastructure, and governmental ambiguity. Issues surrounding privacy, biases, employment, and cultural sensitivity underscore the perils of unchecked techno-solutionism. There is a growing trend among academics to stress the imperative need for AI-led innovation to focus on pedagogical integrity, ethics, and cultural appropriateness, contrary to the sole tenet of efficiency.

Despite the rising interest, studies up until now are narrowly focused, overlooking much-needed exploration in the realm of strategic decision-making by aspiring entrepreneurs in the use of AI in education, addressing critical questions such as: What are the perceptions of aspiring entrepreneurs regarding the opportunities and challenges in using AI in education? What are the challenges in making strategic decisions in using AI in education? What is the impact of institutional readiness and regional disparity?

This research fills these research gaps by investigating how AI-powered innovation inspires educational entrepreneurship during the post-COVID period. This research specifically explores perceptions, intentions for entrepreneurship, and strategic thinking among MBA students at Berlin School of Business and Innovation (BSBI), an internationally diverse group with the potential to influence future EdTech. Using an approach to research with both qualitative and quantitative elements, the methodology for this research involves combining survey research for data collection among 56 MBA students with semi-structured interviews with 10 research participants. Analysis of this research refutes or proves research hypotheses with its findings indicating very positive entrepreneurial intentions, with 58.9% interest in developing AI-powered educational enterprises, as well as serious concerns regarding ethical accountability and infrastructural constraints. Challenges cited

included: lack of organizational infrastructure regarding AI knowledge (41.1%), ethical issues (28.6%), and infrastructure constraints (17.9%).

Through a blend of insights drawn from both qualitative and quantitative data, this scholar engages with three interrelated layers: those of its construction, ethicality, and resilience. The impact of this contribution goes beyond the space of this scholar, as this scholar can help educate, empower, and enlighten entrepreneurs, teachers, and policymakers on the necessity to offset the use of technology with responsibility, apart from being an efficient process. Here, AI as a technology helped this scholar recognize AI as a socio-technical phenomenon.

Review of Literature

AI integration in the educational sector has also AI integration in the educational sector has also garnered significant academic interest, and the COVID-19 outbreak has further intensified the global digital shift and influenced the instructional models for education. This section examines and integrates the major theoretical perspectives, findings, innovations, and concepts underpinning AI-driven educational entrepreneurship and also points out the existing gaps that the proposed study aims to fill. significant academic interest, and the COVID-19 outbreak has further intensified the global digital shift and influenced the instructional models for education. This section examines and integrates the major theoretical perspectives, findings, innovations, and concepts underpinning AI-driven educational entrepreneurship and also points out the existing gaps that the proposed study aims to fill.

Theoretical Foundations of AI-Driven Educational Entrepreneurship

There exists a number of theories that form a base for understanding AI-driven innovations in education. The idea of Creative Destruction by Schumpeter (1934) says that disruption in a systemic manner leads to opportunities for entrepreneurship. The COVID-19 outbreak is a clear example that overthrew traditional classroom teaching models in favor of a rapid introduction to AI-driven learning spaces. Tools like adaptive learning platforms, intelligent tutoring systems, and generative AI technologies moved swiftly from pilot projects to a part of the educational infrastructure.

Nambisan's (2017) digital entrepreneurship theory deeply articulates that data-driven decision-making, and platform-based digital ecosystems form the foundation for EdTech. AI-based concepts such as predictive analytics and adaptive learning help in creating scalable models for adaptive learning. However, the impending challenges state that decentralization could affect the quality of education, resulting in issues concerning the coherence of the pedagogy.

The theory of disruptive innovation by Christensen in 1997 explained how new technologies cause existing structures to be displaced by providing more accessible and affordable solutions for similar needs and requirements. This is clearly illustrated in the use of AI platforms such as ChatGPT and LearnLM for education, but authors also assert that equity and sustainability in education through innovation should not boiled down to mere disruption theory.

To supplement the above ideas, the socio-technical system theory (Zhu & Luo, 2025) presents an inclusive approach where the

implementation of technological innovations is conceptualized and considered based on the institutional context and the environments and cultures of the society in question, and the success of AI implementation in the educational system relies not only on the capability of the technological innovation but also readiness of the educators and the institutional culture of the organization.

Global Trends and Post-COVID Educational Transformation

The pandemic triggered a "digital tipping point" in learning, where institutions of learning had no choice but to incorporate Internet-enabled online and hybrid learning strategies in an unprecedented manner (Zhao & Li, 2022). Artificial intelligence was identified as one of the strategic enablers of learning in this new market, with the technology capable of supporting personalized learning, autonomous evaluation, predictive analytics, and increased efficiency (Chatterjee & Bhattacharjee, 2020; Dwivedi, 2025). Not surprisingly, accordingly, international investment in AI-driven EdTech companies grew largely during and after the pandemic era (OECD, 2023).

Despite this trend, however, entrepreneurship continues to be inequitably adopted around the world by regions. Developed nations have ideal digital environments for innovation, in addition to talent and supportive policies; whereas other nations have long struggled with connectivity, cost, digital literacy, and unclear policies around digital solutions (UNESCO, 2023; Thottoli et al., 2025). This ensures that innovation strategies for entrepreneurs in different environments differ; innovators targeting the developing world remain focused on digitally inclusive solutions that are offline and multi-lingual, whereas innovators in developed nations are concerned with scalability and data-driven optimization.

Innovation Models and Entrepreneurial Strategies in EdTech

Educational entrepreneurship in a post-COVID scenario has yielded multiple innovation models enabled with AI technologies. Platform models like Coursera and Khan Academy use AI for personalization and scalability but may compromise on teaching content in favor of algorithmic optimization (Wahl & Münch, 2021). Micro-credentialing models and modular learning align with the principles of Industry 4.0 and provide flexibility and competency-based learning, but pose challenges regarding piecemeal learning and recognition.

Inclusive innovation models emerging presently seek to respond to the problems of inequities posed by AI on the learning process, and they are low-cost, multilingual, and offline (Malik et al., 2025). Though socially relevant, they are often faced with the problem of sustainability in the field of finance. In all the models above, the start-ups are faced with the challenge of monetization and mission, and this relates to the warnings provided by scholars on the dangers of techno-solutionism (Bulathwela et al., 2024).

Ethical and Policy Considerations

The landscape surrounding AI in education is predominantly driven by normative discussions. Some of the perennial topics that emerge herein are biases in algorithms, data privacy, surveillance, and displacement (Yan et al., 2025). While predictive analytics has made it possible to undertake interventions well in advance of a student falling behind, it has the potential to lock in inequities if developed

on a data set with biases (Almalawi et al., 2024). Generative AI technologies question traditional notions of clarity, authorship, and user engagement (Strielkowski et al., 2024).

To address this challenge, there are initiatives in the form of the European Commission's "Digital Education Action Plan" for the period 2021-2027 and UNESCO's "Guidelines for a Human-Centred Approach to AI." The implementation of these initiatives varies from one region to the other; hence, the entrepreneurs responsible for the application of EdTech encounter challenges related to uncertainty and governance. The literature is gradually showing the need for "anticipatory governance" and "cross-sector collaboration," while still lacking evidence on the application of the mentioned approaches.

Identified Gaps in Literature

Despite rich theoretical and empirical contributions, there are still gaps in the field:

1. Insufficient attention to entrepreneurial views: Current research overwhelmingly concentrates on teaching infrastructure and neglects the views of potential entrepreneurs on AI opportunities and constraints.
2. Insufficient analysis of strategic reasoning and ethical mapping: There is little information pertaining to how future business leaders manage innovation, fairness, and relevance when considering AI startups.
3. Lack of integration between policy, technology, and market dynamics: The study of these areas has been treated independently while overlooking their interplay in determining entrepreneurial strategies.
4. Geographical and contextual bias: The focus of the study is mainly in the Global North, and it overlooks other socio-economic settings and inclusive innovation routes.

This research fills these gaps in literature with its exploration of perceptions, intentions, and strategic thought in the particular group of MBA students, the globally diverse group of the future who are poised to shape the future of EdTech. Through the complementation of both quantitative and qualitative findings, this study contributes to the greater knowledge of the process of artificial intelligence-based educational entrepreneurship.

Material and Methods

In the current research, the paradigm followed was pragmatic, and the research design was that of mixed-methods, where the aim was to explore AI-driven innovation and its influence on educational entrepreneurship after the pandemic. Both quantitative and qualitative methodologies were combined for collecting data from MBA students at the Berlin School of Business and Innovation (BSBI).

Research Design

This was an exploratory-comparative study to explore patterns, contradictions, and contextual variations in the perceptions of AI adoption for educational entrepreneurship. The investigation had multidimensional research questions that required a mixed-methods design: breadth from survey data combined with depth from interviews.

Population and Sampling

It focused on MBA students specializing in innovation and entrepreneurship at BSBI, a

global diversity representing Europe, Asia, Africa, and Latin America. This constitutes a diversity that presents an opportunity for cross-regional perspectives within a unified institution.

Sample Size:

- Quantitative: A total of 56 respondents took part in an
- Qualitative:10 participants took part in semi-structured interviews.

Sampling Strategy: A purposive sampling technique was adopted to select students with experience of AI tools and interest in entrepreneurial ecosystems. The maximum variation sampling strategy ensured that there was maximum variation in nationality, work experience, or experience with AI.

Data Collection

Quantitative Component:

An online questionnaire containing 25 closed-ended questions was circulated through email lists and professional contacts of BSBI. The survey collected information for variables including:

- Knowledge of AI technologies
- Entrepreneurial intention
- Perceived Opportunities of the Market
- Ethical issues
- Institutional readiness

The responses were collected through the use of the Likert scale, multiple-choice, and ranking exercises. A pilot test was conducted among 10 students.

Qualitative Component:

Semi-structured interviews were conducted using video conferencing. Each lasted for 45-60 minutes. The interviews covered:

- AI use in strategy
- Business Model Innovation
- ethical dilemmas
- Market adaptation
- Awareness of policies

The recorded interviews conducted for research purposes were transcribed.

Secondary Data:

UNESCO and European Commission policy papers, market research studies (HolonIQ and EdTechX), and existing literature (between 2020 and 2025) were considered to situate the results and allow for triangulation.

Data Analysis

Quantitative Component:

The survey data were analyzed with descriptive statistical methods, correlation analysis, and regression analysis using SPSS software and Excel. Some of the most important variables included:

- Mean scores of entrepreneurial intention
- Correlation between Familiarity with AI and Venture Interest
- Regression models of forecasting entrepreneurial intent as functions of perceived opportunity and ethical concerns

Qualitative Component:

The transcripts obtained from the interviews were coded with the use of NVivo software. The codes that emerged included:

- Opportunity construction
- Ethical navigation
- Strategic adaptation
- Strategic adaptation

Cross-case analysis was used to compare responses by regions as well as professional backgrounds.

Triangulation:

The findings obtained from survey research, personal interviews, and secondary research sources were validated to improve credibility and add depth to the findings. The method combined different techniques to provide patterns of information that would not be revealed by a specific technique.

Ethical Considerations

Ethical approval was obtained from BSBI's research ethics committee. Participants were informed about the purpose of the study, their right to withdraw, and the steps taken for confidentiality. Data anonymization was ensured, with secure storage according to GDPR standards. Sensitive topics like algorithmic bias and data privacy had to be handled carefully in order to make sure participants were comfortable and honest.

Limitations

The study is institutional and might impact the level of generalizability of findings. The cross-sectional study mainly highlights the perception of data only at a specific moment and not the trend. The data has a tendency to be subjected to socially desirable bias since it is self-reported.

Results

In this section, the results of the study based on the mixed methods design, using quantitative survey results for 56 MBA participants and other findings obtained through the analysis of 10 semi-structured interviews, are presented and categorized according to the key themes of the study's core dimensions, such as familiarity and use of AI, intention to become an entrepreneur, opportunity perception, ethical concerns, barriers of AI adoption, key competencies, readiness of the institution, and aspirations for innovation.

Familiarity and Use of AI in Education

Thus, according to the survey data, 60.7% rated their familiarity with AI in education as high to moderate, while 39.3% said that it is low. In terms of usage, 30.4% report that they use ChatGPT or LearnLM frequently, 28.6% occasionally, 28.6% rarely, and 12.5% not at all. The level of confidence was relatively high: 78.5% reported a moderate to high level of confidence when it comes to the use of this type of tool.

Interview narratives added nuance to these figures. While students acknowledged AI's potential for personalization and efficiency, they highlighted gaps in conceptual understanding and pedagogical application.

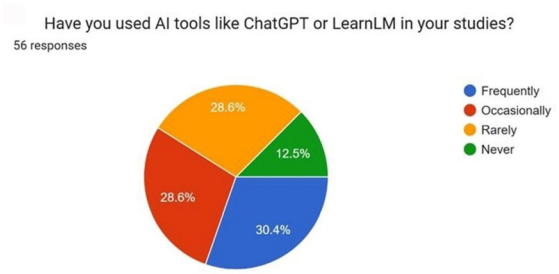
One Iranian participant remarked:

"AI is powerful, but except for trivial chatbots, students don't know what to do with it."

The South Korean respondent commented:

"Many tools are built by engineers without consulting educators." These insights are suggestive that while a certain level of familiarity exists superficially, deeper integration into practice is limited.

Table 1: Participants' use of AI tools



Entrepreneurial Intention and Motivation

Interest in entrepreneurship was also high in this group. 17.9% of participants had a "definite yes," while a further 41.1% had a "maybe." Another 28.6% were "not sure," and finally, 12.5% had a "no." The motives for entrepreneurship were innovation (28.6%), financial opportunities (26.8%), personal interest (26.8%), and social responsibility.

These observations were also consistent with findings reported from interviews. Eight out of ten participants had obvious entrepreneurial goals or initiatives. One Colombian participant said:

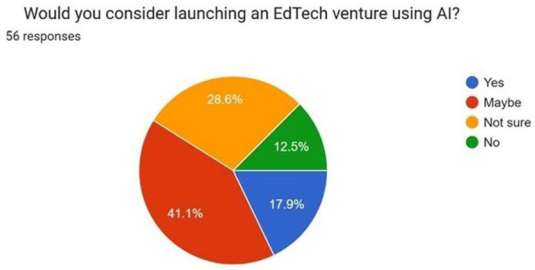
"I will set up a bilingual mobile learning app for the rural children. Learning can be made more meaningful with the use of AI."

A Nigerian participant emphasized:

"I would like to develop a mobile-centric platform for secondary education."

These are the manifestations of a generation raised in an era of innovation-driven education, especially in areas with long-standing disparities in educational accessibility.

Table 2: Participants' willingness to establish AI- driven business ventures



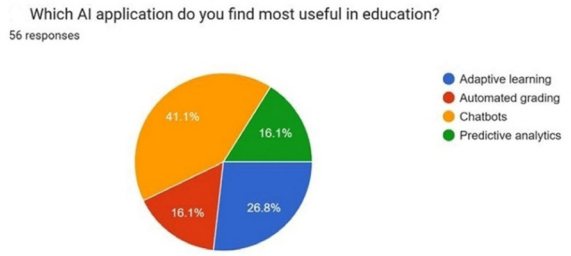
Perceived Opportunities and Regional Trends

The regions considered most advanced in EdTech innovation were North America (35.7%), Asia (33.9%), then European (25%), and Africa (5.4%). The most beneficial uses of AI in EdTech were in chatbots (41.1%), adaptive learning systems (26.8%), predictive analytics (16.1%), and automated grading tools.

The interviews showed that the students from Asia and Africa generally thought of AI in terms of inclusive education. Its use for inclusive education was emphasized. An interview with a Nigerian student showed this:

"AI could support large classes and help teachers deal with different learning needs." Findings also corroborate the existing global trend in digital asymmetry studies, reinforcing the need for localized innovation initiatives.

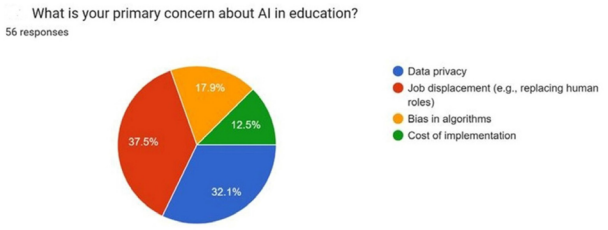
Table 3: Participants' perception of the most useful AI applications



Ethical Concerns and Trust in AI

Ethical issues proved a strong theme. 42.9% of the group considered ethical design "very important," while 35.7% found it "somewhat important." The most important issues were job replacement (37.5%), data privacy (32.1%), issues related to bias (17.9%), and costs/access (12.5%). Trust in AI for evaluation purposes was 25% "yes," 37.5% "maybe," 25% "depends," and 12.5% "no."

Table 4: Ethical concerns



The interviewees reflected these fears. One German student stated:

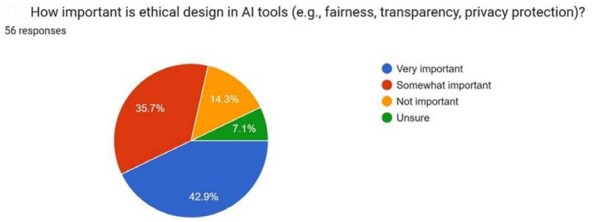
"AI must be transparent. Students need to know how their grades are being computed."

A South Korean participant commented:

"Job loss and algorithmic bias are real dangers. We need human monitoring." Despite their high level of ethical awareness, only 7.1% believed that ethical thinking is an important part of their skills as an entrepreneur.

Barriers to AI Adoption

Table 5: Ethical design importance

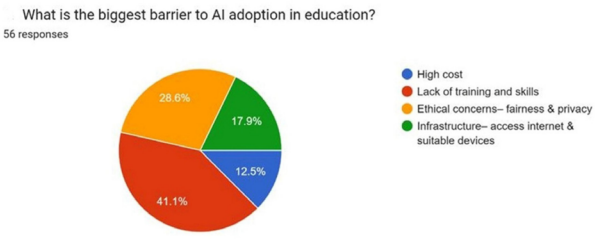


Key barriers, as reported in the survey, are the lack of training and skills (41.1%), issues of ethics (28.6%), infrastructure (17.9%), and cost (12.5%). As reported by interviewees in developing areas, the major barriers are affordability and connectivity, as a student from Ghana reported:

"Most schools lack internet connectivity. AI must be functional without internet access and suitable for low-resource environments,"

The aforementioned evidence makes it clear how all adoption issues are interrelated and can be defined within technical, ethical, and infrastructural terms.

Table 6: Barriers to AI adaptation in education



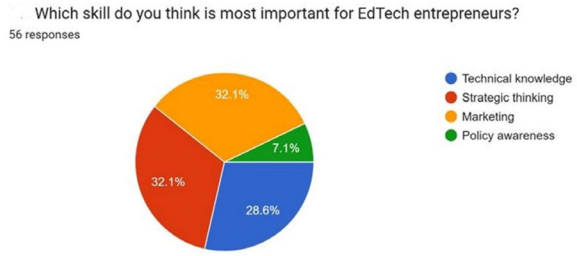
Strategic Competencies for EdTech Entrepreneurs

On the question about the competencies a course developer should possess, strategic thinking (32.1%) and marketing (32.1%) came atop, followed by technical knowledge (28.6%) and policy awareness (7.1%). During the interviews, interdisciplinary competence that combines pedagogy, technology, and ethics was stressed. One respondent from England commented,

"You need to understand pedagogy, tech, and ethics. It's not just about building apps; it's about building trust."

This reflects a pragmatic orientation toward venture success, tempered by recognition of ethical and pedagogical imperatives.

Table 7: Important skills for EdTech entrepreneurs



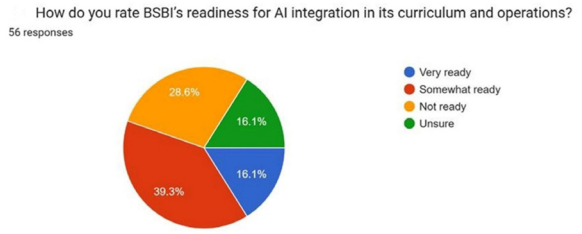
Institutional Readiness

The responses on perception towards BSBI's readiness to integrate AI were: 16.1% "very ready," 39.3% " somewhat ready," 28.6% "not ready," while 16.1% were "unsure." Those interviewed identified key gaps related to updating the faculties and refreshing curricula. As one Iranian student commented:

"BSBI welcomes innovative ideas, but faculty training and curriculum are to be updated."

This would suggest that institutional interest has not yet been translated into systemic preparedness.

Table 8: Institutional readiness and AI integration



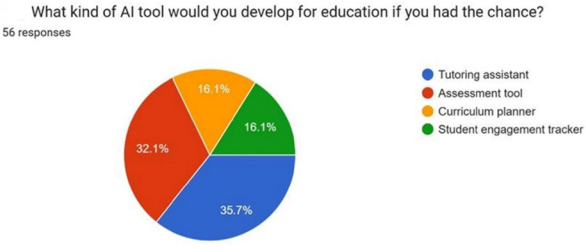
Innovation Aspirations

Students showed interest in developing context-specific AI tools. The tools in which they were interested were tutoring assistants (35.7%), testing tools (32.1%), curricula designers (16.1%), and activity trackers (16.1%). Some participants were interested in developing tools that were context-specific and had suggested tools like an offline learning support program and a multilingual tutoring program. One of the participants from China

"An adaptive exam prep tool that adjusts based on student performance and stress levels."

These wishes indicate the desire for inclusive innovation and pedagogical relevance.

Table 9: AI tools that participants wish to develop



Summary of Findings

The integration of survey results and interview findings brings out a diverse group of students across the globe that recognizes AI as a transformative agent in the learning environment. The desire for entrepreneurship is present, but within a framework that is guided by ethical considerations, infrastructure, and a certain level of ambivalence. Scale, inclusivity, and a sense of ethical underpinning are embedded in their entrepreneurial models for EdTech developments.

Discussion

This section will contextualize findings from empirical research within a study's research questions and issues of theoretical frameworks as well as existing research. This section will examine perceptions of AI-driven entrepreneurial education within MBA programs at BSBI.

RQ1: Global Trends Driving Educational Entrepreneurship Post-COVID

The results have proved that the COVID-19 pandemic served as a catalyst for digital transformation, and there is favorable breeding for AI-driven businesses. The interest shown by MBA students towards starting AI-driven EdTech companies showed high entrepreneurship intent, with 58.9% takers. This depicts the innovation principles put forward by Schumpeter (1934) through his theory of creative destruction, wherein systemic changes bring down the conventional framework and allow way for innovation. Students from emerging regions such as Nigeria, Colombia, and Iran highlighted how AI can be empowered to make education equally accessible through mobile-based technology and adaptive learning (Malik et al., 2025).

Such aspirations align well with global investment patterns recorded by OECD in 2023, reflecting an increase in investment in EdTech following the pandemic. Nonetheless, this study provides additional insights in asserting that while there is passion for entrepreneurship, there is infrastructure restraint and policy ambiguity involved in this passion to be considered. Such restraint is not taken into account in most cases when people fall for technologically driven dreams.

RQ2: How AI Facilitates Opportunity Creation and Innovation

Results from survey questions as well as interview responses reinforce the value of AI in terms of its potential for personalization, scalability, and cost-effectiveness. The applications mentioned that had most use value for students included chatbots (41.1%) and adaptive learning systems (26.8%). This is in line with existing literature for the potential AI holds in improving engagement as well as its use in improving the engagement mechanisms for more effective implementations (Chatterjee & Bhattacharjee, 2020; Dwivedi, 2025).

These results support Nambisan (2017)'s conceptualization of digital entrepreneurship that focuses heavily on ecosystems and data-driven approaches. But what has become apparent from conducting these interviews is that one thing stands out as a key takeaway for students, this being a desire for both human and high-level education, and a corresponding lack of interest from such participants in purely techno-based literature. This mirrors the concerns raised by Bulathwela et al. (2024), who argue that education should not be determined solely by algorithms.

RQ3: Challenges and Risks in AI Adoption

The ethical issue became a central point, since 42.9% of the subjects rated ethical design as "very important." Relatedly, the most mentioned risks were job displacement, at 37.5%; data privacy, 32.1%; and algorithmic bias, 17.9%. These anxieties mirror global debates on responsible AI (Yan et al., 2025) and validate the socio-technical systems perspective (Zhu & Luo, 2025), which situates technology within institutional and cultural contexts. Trust in AI for assessment was mixed. Only 25% have full confidence in the process. This suggests that transparency and human oversight are prime needs.

Barriers to adaptation: lack of training (41.1%), concerns about ethics (28.6%), gaps in infrastructure (17.9%), and the cost being too high (12.5%), which show the system barriers identified by UNESCO (2023) through their research. Contributions to the solution from participants from Ghana and Nigeria pointed to affordability and connectivity as important areas, with the need for the technology to function without the use of the Internet and for the technology to be context specific.

Strategic Competencies and Institutional Readiness

Students highly ranked strategic thinking (32.1%), followed by marketing (32.1%), then technical knowledge (28.6%), and policy awareness (7.1%). This pattern reflects an HOLISTIC approach to entrepreneurial success, although the low rating accorded to ethical thinking indicates a misalignment between awareness and implementation. Entrepreneurship education must address ethics and pedagogies in business in order to develop well-rounded leaders for ethical innovation.

Institutional readiness stood out as another integral element. Only 16.1% of respondents perceived BSBI to be "very ready" in incorporating AI. Faculty development and curriculum change have been highlighted as major challenges in this aspect. It is supported by Wahl & Münch (2021), stating that if institutions do not adapt and change, entrepreneurial spirit may stagnate. Such concerns throw light on the importance of efforts for building capacity at both organizational and policy levels.

Theoretical Integration

Findings from the research confirm, expand, and refine theoretical propositions. The Schumpeterian process of creative destruction explains entrepreneurship intent following the pandemic, and Nambisan's conceptual framework for digital entrepreneurship offers insights into platform-based and data-driven approaches adopted by students. Christensen's framework for disruption and innovation brings clarity to scalability and education uptime concerns, illustrated by students choosing blended learning options. The theory of socio-technical systems provides context for discussions and debates surrounding technology, norms, and infrastructure.

Implications for Practice and Policy

For entrepreneurs: The implications of these findings lie in understanding the need for making AI-based tools that can be inclusive and culturally sensitive. Start-ups need to shift from efficiency-oriented goals to goals such as learner agency and transparency.

For Educators and Institutions: The report recommends that AI literacy be incorporated into educational curricula, that collaboration

between disciplines be encouraged, and that the development of faculty members be pursued. Readiness in institutions goes beyond the technical to the strategic and ethical.

To policymakers: Implications of these findings include the need for anticipatory governance policies that mediate innovation and equity. This is to ensure that AI does not perpetuate inequalities in education. Public-private partnerships and resource allocation for low-resource settings could help achieve this goal.

Limitations and Future Directions

Even as the study provides insightful findings, it is limited to a single institution and is cross-sectional. Future studies should consider longitudinal approaches to understand the progression in attitudes as well as entrepreneurial practices over time. Comparative studies involving more institutions and geographies would help diversify knowledge related to regional and institutional diversification. Another area would be the use of AI tools developed by entrepreneurs to evaluate pedagogy and ethics outcomes experimentally.

Summary

The discussions above highlight a rather intricate balancing act between optimism and carefulness in aspiring entrepreneurs for the education technology sector. While AI is viewed as an enabling force for dramatic change, its deployment is hindered by certain challenges related to ethics, infrastructure, and strategy. This paper, by placing its results in broader contexts, helps to move the frontiers of informed discussion about education in its commitment to values and ethics.

Conclusion

AI innovation in education can tackle the issue of entrepreneurship in the post-COVID era in a manner that is studied in relation to the perception, intention, and strategic thinking of MBA students in the Berlin School of Business and Innovation (BSBI). The paper will use a mixed-method approach, combining the findings of the survey conducted among 56 students with the understanding provided by the interview findings among 10 students.

Summary of Key Findings

Results indicate a very high entrepreneurial intent, with close to 59% of the respondents interested in incorporating AI-based EdTech start-ups. Students have identified avenues in customized education, cost-effectiveness, and scalability, but at the same time have recognized challenges in training and preparedness (41.1%), morals and ethics (28.6%), and infrastructural constraints (17.9%). Moral stakes, such as data protection, bias, and displacement, have emerged as core concerns, thereby emphasizing collective responsibility towards innovation. Readiness to innovate has been rated to be moderate.

Implications for Practice and Policy

In the context of entrepreneurs, the findings and takeaway messages are to design AI tools that are more inclusive and culturally sensitive. There is also a need to focus on AI literacy and capacity-building initiatives to ensure the use of AI by institutions. Additionally, policymakers need to focus on governance frameworks regarding data protection and equity.

Limitations and Future Research

The study was restricted to a single institution over a cross-section of participants. In future studies, it would be beneficial for research to focus on long-term studies using multiple institutions so that the effectiveness of AI solutions for teaching purposes built by student entrepreneurs can be ascertained.

Closing Reflection

AI not only provides an edge to technology but also leverages a sociotechnical paradigm to transform the world of education and entrepreneurship. The opinions among the MBAs surveyed are in a balance between hope and skepticism because they recognize there has to be a focus on innovation, ethics, equity, and relevance. Being part of an ever-evolving educational infrastructure not only requires one to leverage AI but to personalize it and ensure technology helps and not hurts.

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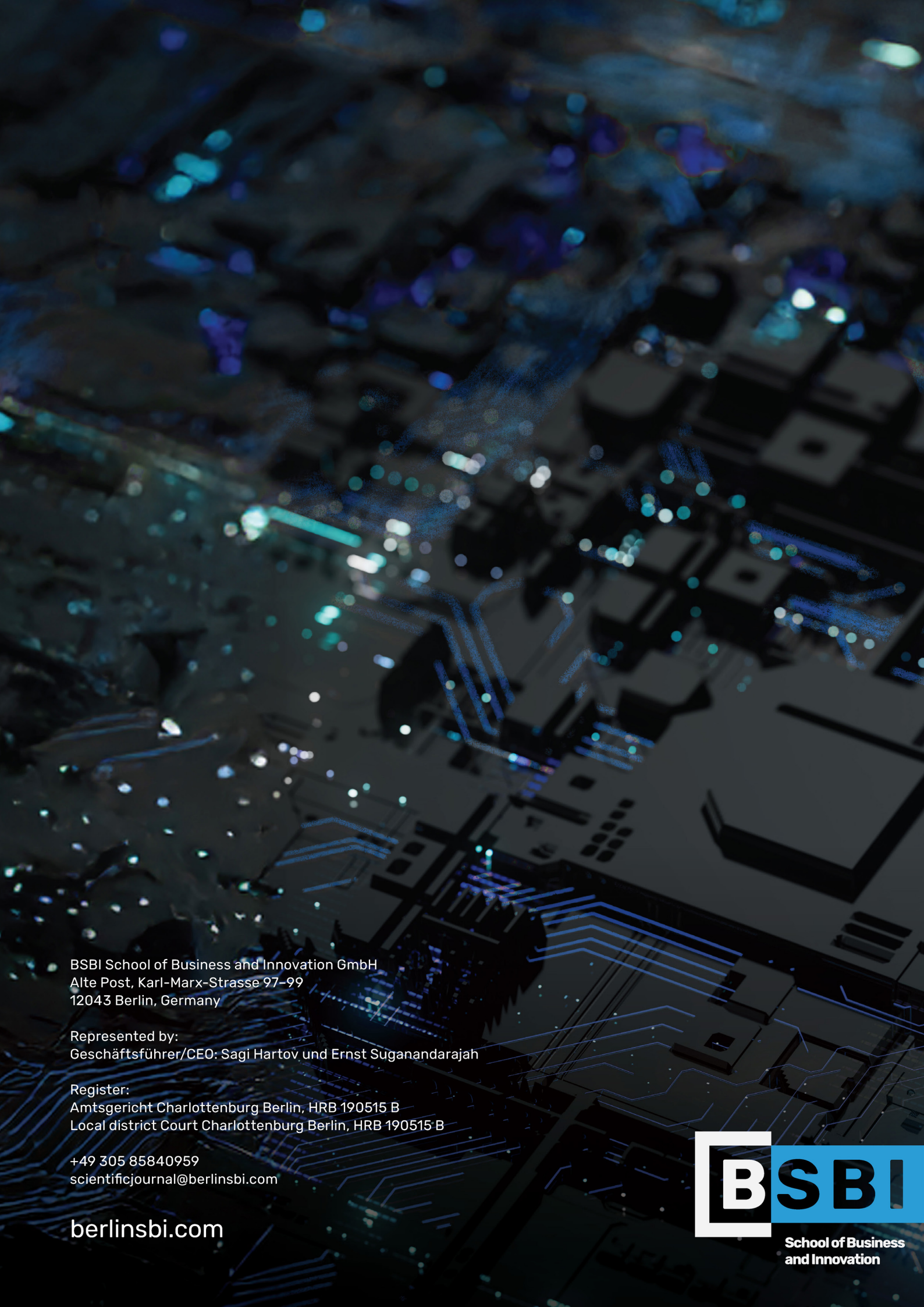

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