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Exploring the Academics' Attitudes toward Opportunities and Challenges of AI in Education Using the ABC Model

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Abstract

With the rapid advancement of technological innovations and the increasingly pervasive integration of Artificial Intelligence (AI) in higher education, universities are undergoing significant transformations. Understanding how the academics perceive and interpret these shifts is of paramount importance, given their pivotal role as key agents in implementing and shaping pedagogical practices. Empirical evidence from studies conducted among the academics in Iran revealed a dichotomy in perspectives regarding the application of AI in educational settings. Consequently, examining the opportunities and challenges associated with the application of AI in higher education is of critical importance for developing appropriate strategies for its effective integration into educational processes. In this context, the academics are well positioned to identify the potentials and limitations of this technology. Therefore, the present study aimed to explore the academics' attitudes toward the opportunities and challenges of using AI in education. This study adopted a qualitative research approach using a deductive qualitative content analysis strategy. Data was collected through semi-structured interviews. The study population consisted of faculty members and postgraduate students, who were selected using purposive and convenience sampling. The sample size was determined based on theoretical data saturation. The collected data were analyzed through systematic coding procedures. Based on the findings, some opportunities and challenges are as follows. In cognitive dimension, opportunities such as enhanced conceptual understanding, accelerated learning, immediate feedback, personalization, and improvement in teaching quality/creativity were identified. In contrast, challenges including technological dependence, reduced critical thinking, weakening of independent/analytical skills, and the risk of inaccurate scientific outputs were noted. In affective dimension, increased motivation, enthusiasm, and learning satisfaction were reported as strengths. However, feelings of anxiety, concerns about the weakening of human interactions, threats to the professional role of academics, and fear of reduced autonomy were reported as challenges. In behavioral dimension, the active use of AI tools for learning management and innovative content creation was identified as an opportunity, whereas resistance to change, infrastructural limitations, reduced human interactions, and concerns related to intellectual property were identified as major challenges. Overall, the results indicated that identifying the academics' attitudes toward the opportunities and challenges of AI in education constitutes a fundamental step toward the informed, responsible, and effective utilization of this technology in higher education.

Keywords

Artificial Intelligence (AI), Academics' Attitudes, ABC Model, Cognitive Component of Attitude, Affective Component of Attitude, Behavioral Component of Attitude.

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Introduction

With the rapid advancement of technology and the increasing use of AI, extensive opportunities have emerged that necessitate significant shifts in orientations and approaches toward the new realities encountered in the digital age. Accordingly, it is not surprising that AI is expected to inevitably transform the functioning of higher education systems (Akinwalere & Ivanov, 2022). From the very outset of AI development, a fundamental question has occupied the scholars' minds: Is it possible to delegate aspects of human learning and reasoning to computers? During the 1960s and 1970s, with the emergence of early computer-based instructional systems, the idea of integrating AI into education gained serious attention. These systems, initially referred to as "teaching machines" and later as "intelligent tutoring systems", sought to recreate teacher–student interactions within relatively simple computer-based environments (Alkhatlan & Kalita, 2018). Subsequently, the 1980s marked a turning point in the history of intelligent education with the widespread adoption of personal computers and advances in artificial neural networks, enabling researchers to focus on personalized learning and intelligent assessment (Joshi, 2023).

In the educational domain, AI has introduced novel teaching–learning approaches and pedagogical solutions. Through adaptive and personalized instructional systems, AI has begun to transform the structure and operation of educational systems (Krstić et al., 2022). Nevertheless, many of these capabilities remain at an early stage of realization. Since 2020, relatively limited scholarly attention has been devoted to examining the potentials and limitations of AI in education systematically, particularly regarding the severe challenges faced by less developed countries (Akinwalere & Ivanov, 2022).

It can be argued that AI has evolved from a largely theoretical concept in the second half of the twentieth century into one of the key pillars driving transformation in contemporary educational systems (Chen et al., 2020). Consequently, AI has rapidly emerged as a transformative force in higher education (Branda et al., 2025). On the one hand, this technology has the potential to enhance the quality of scientific research and scholarly productivity (Chen et al., 2020; Holmes et al., 2019). On the other hand, a growing body of research cautions that the expansion of AI may lead to the erosion of critical thinking, pose challenges to the professional role of teachers and academics, and give rise to ethical and privacy-related concerns (Jose & Jose, 2024; Musslick et al., 2025). This divergence of perspectives is particularly evident among academics, reflecting an ongoing tension between optimism and concern regarding the integration of AI.

In Iran, the growing adoption of AI tools in academic settings has raised increasing debates about their educational and ethical implications. Studies indicated that while Iranian academics recognize the potential benefits of AI, they also express concerns about issues such as students' overreliance on technology and lack of clear guidelines for its educational use. This tension is also clearly reflected in empirical studies (e.g., Alwaqdani, 2024; Hajianvari & Ramezani, 2024; Jose & Jose, 2024; Kim et al., 2025), which document conflicting attitudes toward the opportunities and risks associated with AI in educational contexts. This issue is also noticeably evident in Iran. Some

studies have shown that Iranian academics acknowledge the opportunities offered by AI. However, there remains cautious such as students' excessive dependence on technology and related ethical concerns about its potential consequences (Deljoo et al., 2025; Zarenasab & Jameh Bozorg, 2025;). Given this duality of perspectives, examining attitudes toward both the opportunities and the threats posed by AI systematically is of critical importance for informed decision-making in higher education.

The academics' attitudes can shape the future trajectory of the scientific community's interaction with AI. The findings of this research may serve as a strategic roadmap for Iran's higher education system in the era of AI. Decisions made today regarding the extent and manner of AI adoption will determine the future of universities over the coming decades. Institutions of higher education can either move toward innovation and global competitiveness or, alternatively, face a widening technological gap between Iran and other countries (Hosseini Moghaddam, 2023; Kulkarni et al., 2024).

A substantial proportion of global research has focused on technical applications of AI or on students' attitudes toward AI technologies in universities (Kim et al., 2025; Krstić et al., 2022), whereas comprehensive examinations of the attitudes of the entire academic community—encompassing both faculty members and students—have received comparatively limited attention. Overall, understanding the academics' attitudes toward the opportunities and challenges associated with AI use in education is of particular importance. First, the attitudes of faculty members and researchers play a decisive role in acceptance, adoption, and institutional legitimization of these technologies within academic environments. Second, examining the academics' perspectives enables policymakers and higher education administrators to identify potential opportunities and challenges related to AI implementation and to develop strategies for its effective and responsible use. Finally, awareness of these attitudes can inform the design of faculty development and capacity-building initiatives in response to technological transformations, thereby facilitating a more sustainable path for educational development. Accordingly, the following sections present the theoretical framework and review of literature, followed by the research methodology and findings concluding with the discussion and conclusions.

Literature Review

Attitudes toward AI

The concept of attitude was first introduced in the 1930s by Allport as the "central concept of social psychology". In the following decades, researchers sought to clarify the structure of attitudes. Fishbein and Ajzen (1975) incorporated attitudes into behavioral models through the Theory of Reasoned Action (TRA). Ajzen (1991) further extended this perspective in the Theory of Planned Behavior (TPB). Ajzen (1991) identified attitude as one of the three primary determinants of behavioral intention and emphasized that a positive attitude increases the likelihood of performing a behavior. Within this framework, attitude is considered as the result of individuals' beliefs about

the consequences of a behavior and their positive or negative evaluations of those consequences.

Within the TPB, attitudes are conceptualized as one of the primary determinants of behavioral intention, which in turn shapes the actual behavior (Ajzen, 1991). Research on attitudes toward technology suggested two main approaches to attitude modeling. The first approach focuses on analytical models of attitude. The one-dimensional model conceptualizes attitude along a simple positive–negative continuum, whereas the two-dimensional model allows for the simultaneous coexistence of positive and negative emotions and is considered more effective in explaining attitudes toward emerging technologies (Cacioppo et al., 1997). In addition, the functional theory of attitudes views attitudes as tools that serve the individuals' psychological and social needs, identifying four core functions ofutilitarian, knowledge, value-expressiveness, and ego-defensiveness (Katz, 1960; Smith et al., 1956). Furthermore, Bem's self-perception theory (1972) posited that individuals may infer their attitudes not solely from internal beliefs but also from observable behaviors and practical experiences, including repeated interactions with technology (Bem, 1972). Similarly, the Elaboration Likelihood Model suggested that attitude change may occur through either a central route (deep, systematic processing) or a peripheral route (superficial and unstable cues), both of which are relevant to technology acceptance processes (Petty & Cacioppo, 1986).

In the second approach, attitude is treated as a key variable in the formation of behavioral intention. The TRA identifies attitude and subjective norms as predictors of behavioral intention but does not adequately address environmental and contextual constraints (Fishbein & Ajzen, 1975). The TPB addresses this limitation by introducing perceived behavioral control, demonstrating that a positive attitude is a necessary but insufficient condition for actual behavior to occur (Ajzen, 1991). Building on these foundations, the Technology Acceptance Model (TAM) and its extensions emphasize the roles of perceived usefulness and perceived ease of use in shaping attitudes and intentions to use technology (Davis, 1989). Likewise, the Unified Theory of Acceptance and Use of Technology (UTAUT) highlights the importance of organizational, social, and infrastructural factors in translating positive attitudes into actual usage behavior (Kulkarni et al., 2024; Venkatesh et al., 2003). Collectively, these theoretical perspectives indicate that attitudes toward technology-including AI—are multidimensional and dynamic constructs that cannot be adequately explained without considering their cognitive, affective, behavioral, and contextual dimensions (Allport, 1935; Katz, 1960; Smith et al., 1956).

The ABC Model and the Multidimensional Analysis of Attitudes

The ABC model was first introduced by Eagly and Chaiken (1993) and provides a comprehensive framework for examining the multidimensional nature of attitudes. This model conceptualizes attitude as a construct composed of three interrelated components—affective, behavioral, and cognitive. From this perspective, attitudes represent a condensed reflection of an individual's readiness to respond to various

aspects of the world—including objects, activities, or ideas—along a continuum ranging from acceptance to rejection (Eagly & Chaiken, 1993).

In studies of attitudes toward technology, particularly in relation to emerging technologies like AI, using comprehensive and multidimensional analytical models is essential. The ABC model, by simultaneously addressing cognitive, affective, and behavioral dimensions, enables a more nuanced and accurate analysis of attitudes. Within this framework, the cognitive component refers to individuals' beliefs, perceptions, and knowledge; the affective component reflects positive or negative feelings and emotions toward the target object; and the behavioral component denotes an individual's tendency or readiness to engage in action. This integrative approach has rendered the ABC model a valuable tool for analyzing the "attitude–behavior gap" and for examining the role of social and affective factors in technology adoption processes (Eagly & Chaiken, 1993).

From this standpoint, attitudes toward AI, as an emerging phenomenon, are not confined to purely rational or cognitive evaluations. Rather, they are the product of a complex interaction among beliefs, emotions, affective responses, and behavioral tendencies, all of which must be considered holistically in empirical analyses. By offering such an integrative lens, the ABC model facilitates a more comprehensive understanding of the complexity inherent in attitudes toward AI.

Notably, a growing body of research has supported the applicability of the ABC model in educational settings (McChesney et al., 2025; Neysani et al., 2023). Findings from these studies indicated that even when individuals hold positive cognitive beliefs about technology, the presence of negative affective or behavioral barriers may constrain its adoption. Consequently, the ABC model is particularly well suited for analyzing the academics' actual behaviors in accepting or resisting technologies like AI, as their attitudes may be shaped by negative affective responses or behavioral constraints despite favorable cognitive evaluations. Accordingly, the ABC model offers a comprehensive and flexible framework capable of simultaneously and coherently capturing all dimensions influencing attitudes toward AI and other emerging technologies.

AI in Education

AI is currently widely applied across various sectors of society. However, with regard to its direct impact on teaching and learning processes, despite considerable promises, tangible practical achievements have so far remained relatively limited. Zuboff (2019) provided a comprehensive overview of different domains in which AI has been applied within higher education and identified the primary areas on which researchers have focused. She highlighted four key applications of AI in education and learning: profiling and prediction, intelligent tutoring systems, educational assessment and evaluation, and adaptive and personalized learning systems.

Using AI in education has a long history, dating back to the early stages of the technology's development, when researchers first became interested in its potential for supporting learning. The first significant step in this direction occurred in the 1960s with the emergence of Computer-Assisted Instruction (CAI). Systems such as PLATO and

the LOGO programming language sought to structure learning through practice and repetition while functioning alongside human teachers.

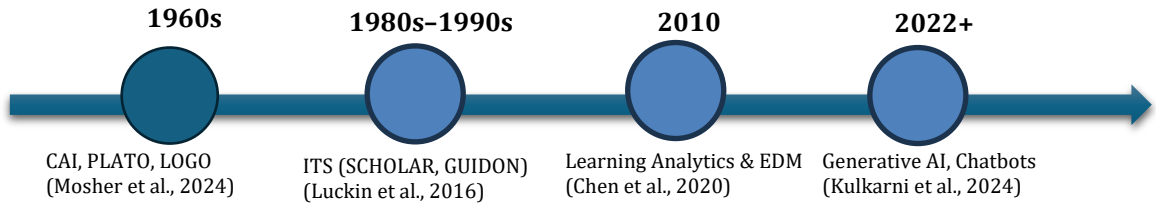
During the 1980s and 1990s, a new generation of systems known as Intelligent Tutoring Systems (ITS) was introduced. These systems employed learner knowledge modeling and error diagnosis to adapt learning pathways to individual needs. Projects such as SCHOLAR and GUIDON represent prominent examples from this period (Luckin et al., 2016).

The 2010s can be characterized as the era of learning analytics and educational data mining. In this phase, researchers increasingly relied on behavioral data collected from online learning platforms to identify learning patterns and predict student performance (Chen et al., 2020).

More recently, the emergence of large language models and generative AI technologies—like ChatGPT—has marked a new phase of transformation. These tools not only contribute to the generation of educational content and the design of interactive learning activities but also enable students to access real-time support and engage in more self-directed learning experiences (Kulkarni et al., 2024).

Overall, the trajectory of AI in education has evolved from linear drill-and-practice software to intelligent systems and, most recently, to large language models. This progression has facilitated the introduction of concepts such as personalized learning, large-scale educational data analytics, and interactive instruction, thereby providing a robust theoretical foundation for understanding the academics' attitudes toward AI technologies in educational contexts.

Figure 1.
The Evolution of AI in Education



(Source: The Researcher's Findings)

Background of Research

In recent years, AI in academic contexts has emerged as one of the most challenging yet compelling areas of research. Scholars worldwide have sought to understand the implications of introducing intelligent technologies into universities for both teaching and research. Luckin et al. (2016) emphasized that the success of AI tools in education largely depends on the acceptance and attitudes of teachers and faculty. They argued that even the most advanced technologies cannot achieve educational effectiveness without active engagement and positive attitudes from educators (Luckin et al., 2016). Following this initial work, numerous studies have explored the opportunities, advantages, disadvantages, and challenges of using AI in education (e.g., Ghimire et al., 2024; Halachev, 2023; Kulkarni et al., 2024; Qian, 2025; Wang et al., 2024). Most of these

studies focused primarily on educational applications. However, only a limited number explicitly examined the attitudes of academics (see Ghimire et al., 2024; Halachev, 2023; Kulkarni et al., 2024; Ng et al., 2025; Omar et al., 2024).

In a study conducted by Ghimire et al. (2024), the faculty attitudes and acceptance of generative AI tools were investigated, highlighting that positive attitudes and sufficient awareness are prerequisites for effective adoption of AI technologies in higher education. Similarly, Qian (2025) demonstrated that the benefits of AI in education include enhanced research capabilities through rapid access to data and scholarly resources, personalized learning tailored to individual student needs, and improved accessibility and inclusivity for students with diverse abilities and requirements.

This body of literature underscored the dual nature of AI in higher education, offering substantial opportunities while presenting critical challenges that necessitate careful consideration, particularly in relation to faculty attitudes and acceptance.

Saki et al. (2025) examined the perspectives of university faculty on AI-enhanced education, reporting that faculty generally held positive attitudes toward AI, while also noting certain concerns. Their findings emphasized that the success of AI technologies is contingent upon active engagement and positive attitudes from instructors. Najafi and Rasouli (2023) investigated the advantages, threats, and challenges of AI adoption in higher education.

A review of the literature indicated that although research on AI in academic and research environments in Iran has accelerated in recent years, most studies have focused on technical and practical aspects, such as tool functionality, algorithm efficiency, and instructional applications (Omar, 2024; Wang et al., 2024). Few studies have examined the academics' attitudes toward AI, and those that did typically employ general technology acceptance models (e.g., TAM), focusing primarily on variables such as perceived ease of use, perceived usefulness, and behavioral intention (Ghimire et al., 2024). In contrast, cultural, ethical, identity-related, and epistemic dimensions of faculty attitudes—which may critically influence the acceptance or resistance to AI—have received limited attention. Moreover, Iranian research has predominantly addressed specific educational applications of AI, such as the use of ChatGPT or automated assessment systems, while overlooking broader faculty perspectives on the opportunities and threats posed by AI in higher education. This gap is particularly significant given that recent developments in generative AI are challenging traditional boundaries of education and even redefining the roles of instructors and researchers.

Methodology

Design

The present study employed a qualitative research design with a deductive content analysis strategy. A qualitative approach and deductive content analysis were chosen because the study aimed to gain an in-depth understanding of the academics' attitudes and to extract shared meanings from their responses regarding the opportunities and challenges of AI in higher education research.

Following the ABC model framework for examining the attitudes, a deductive content analysis was conducted. Deductive analysis is theory- or model-driven, moving from the general to the specific. In this approach, pre-established analytical categories derived from theory are applied to the text, linking them to the data. The qualitative coding process involves systematically assigning controlled categories to segments of the text (Mayring, 2000). Qualitative content analysis focuses on understanding meaning and interpreting text rather than merely counting elements (Krippendorff, 2013). The researcher examines topics, themes, concepts, and hidden patterns in the data while considering the cultural, social, or educational context (Mayring, 2015). Qualitative content analysis can be inductive or deductive; in deductive analysis, codes and categories are predefined, usually based on theoretical frameworks, models, or prior findings and the data are then examined and matched against this framework (Gläser-Zikuda et al., 2020; Mayring, 2015).

Population, Sample, and Sampling Method

The study population comprised faculty members and postgraduate students. Postgraduate students were selected because they had greater needs for learning, academic presentations, and research activities. Therefore, they were more likely to seek and use AI tools. The University of Tehran, as the leading and most prestigious higher education institution in the country, was selected as a representative of the broader academic community. The university hosts a wide range of disciplines, faculty, and students, providing internal demographic and academic diversity.

Given that humanities in Iran are generally less digitalized and technologically integrated compared to engineering and medical fields, attitudes and responses in this domain may differ and warrant focused examination. Most existing AI research has concentrated on technical, engineering, and medical fields, so selecting humanities disciplines introduces an interdisciplinary and innovative perspective. Accordingly, the study population consisted of faculty and graduate students in the humanities and behavioral sciences at the University of Tehran who had experience using AI tools and systems in educational activities. Participants were selected through purposive and convenience sampling based on the following criteria: willingness to participate, prior experience or familiarity with AI tools in teaching, and availability for an interview.

The sample size was determined by theoretical saturation, meaning interviews continued until no new information emerged. In total, 48 interviews were conducted (22 with faculty members and 26 with students). Saturation was reached by the 19th interview for faculty and the 22nd interview for students.

Table 1.
The Characteristics of the Interviewees

Row	Faculty/Professors			Students		
	Experience in Using AI	Teaching Experience	Field of Study/Specialty	Experience in Using AI	Degree Level	Field of Study
1	2 years	10 years	Management	2 years	Master's degree	Management
2	2 years	4 years	Theology	2 years	PhD	Management
3	1 year	23 years	Management	2 years	PhD	Law
4	2 years	14 years	Psychology	1 year	PhD	Sociology
5	1 year	3 years	Management	1 year	Master's degree	Psychology
6	2 years	15 years	Management	2 years	Postdoctoral	Management
7	2 years	14 years	Law	Less than 2 years	Master's degree	Management
8	1.5 years	16 years	Philosophy	1 year	PhD	Counseling
9	2 years	10 years	Management	2 years	Master's degree	Psychology
10	2 years	7 years	Educational Sciences	2 years	Master's degree	Psychology
11	1 year	12 years	Sociology	1.5 years	Master's degree	Law
12	6–7 months	11 years	Psychology	2 years	Master's degree	Management
13	2 years	6 years	History	1 year	PhD	Philosophy
14	2 years	4 years	Management	2 years	PhD	Management
15	2 years	5 years	Educational Sciences	2 years	Master's degree	Management
16	1 year	7 years	Management	1 year	Master's degree	Law
17	2 years	14 years	Law	2 years	PhD	Theology
18	1 year	9 years	Law	1 year	Master's degree	Philosophy
19	2 years	10 years	Management	2 years	Master's degree	Management
20	7 months	4 years	Persian Language	2 years	PhD	Law
21	1 year	5 years	Management	1 year	PhD	Counseling
22	2 years	8 years	Philosophy	2 years	Master's degree	Management
23	-	-	-	1 year	PhD	Management
24	-	-	-	a few months	PhD	Psychology
25	-	-	-	10 months	PhD	Philosophy
26	-	-	-	1 year	Master's degree	Law

(Source: The Researcher's Findings)

Research Instrument

The data collection instrument was a semi-structured interview guide, designed based on the ABC model of attitude. The interview protocol consisted of questions covering the cognitive, affective, and behavioral dimensions, allowing for an in-depth examination of the participants' attitudes toward the opportunities and challenges of AI in education.

The interview questions were carefully formulated with reference to the main research question. The participants were asked to respond to the questions, and depending on their answers, follow-up and probing questions were posed to gain a more comprehensive understanding of their experiences and perspectives. Interviews were conducted between March and June 2025, either in person or via social media platforms. Prior to the interviews, the research objectives and how the data would be used were explained, and verbal informed consent was obtained from all participants.

Data Analysis

Since this study aimed to examine the academics' attitudes regarding the opportunities and challenges of AI in education, deductive content analysis was conducted following the steps outlined by Mayring (2015). In the first step, data were collected through the interviews. The texts were transcribed, organized, and segmented. The unit of analysis included words, phrases, or sentences indicating an opportunity or threat.

In the second step, categories and codes were defined based on the theoretical framework and previous literature, and coding rules were established. The core principle was that for each deductive category, explicit definitions, examples, and coding rules were provided to clearly determine under what conditions a text segment could be assigned to that category. These definitions were compiled into a coding manual (Mayring, 2000).

Depending on the study objectives, deductive content analysis can use either a structured or unstructured coding framework (Kyngäs & Vanhanen, 1999). Since the ABC model was applied in this study, a structured approach was employed, with categories defined according to the cognitive, affective, and behavioral dimensions, as detailed in the coding table.

Table 2.
The Coding Manual (Translation & Structured Format)

Coding Rules	Example	Category Definition	Category Name (Dimension)
Any perception, belief, or thought of the student (or faculty) regarding the use of AI in education, if positive, is considered an opportunity; if negative, a challenge. The presence of any of these features is sufficient.	Positive aspect: *"I think using AI increases work speed".* Negative aspect: *"AI creates dependency and reduces critical thinking".*	Refers to beliefs, perceptions, and thoughts that an individual associates with a phenomenon, including mental processes of understanding and interpreting information.	Cognitive Dimension of Attitude
Any emotion or feeling, including fear, interest, concern, anxiety, etc., expressed by the student (or faculty) regarding the use of AI in education, if positive, is considered an opportunity; if negative, a challenge. The presence of any of these features in the interview text is sufficient.	Positive aspect: *"Fast and efficient content generation".* Negative aspect: *"Dependence on AI for content creation".*	Refers to emotional or affective reactions that an individual has toward an object, person, topic, or situation. This includes feelings such as liking, disliking, love, hate, worry, anxiety, fear, etc.	Affective Dimension of Attitude
Any behavior, action, behavioral intention, or decision regarding the use of AI in education by the individual, or expression/repetition of such behavior, if positive, is considered an opportunity; if negative, a challenge. The presence of any of these features in the interview text is sufficient.	Positive aspect: *"I use AI because it enables continuous learning".* Negative aspect: *"I am cautious in using it because I don't know if it is ethical".*	Refers to how an individual acts or behaves toward an object, person, topic, or situation based on his/her attitude, or behavioral intention. Indicators include direct action, behavioral tendency, choice and decision-making, avoidance, social expression of behavior, and repetition of behavior.	Behavioral Dimension of Attitude

(Source: The Researcher's Findings)

In the third step, a sample of the data was coded. In this phase, because the interviewees differentiated between educational settings (e.g., in-person classes, online classes, etc.) during the interviews, the activity contexts were treated as subcategories. In the fourth step, text segments were assigned to the predefined categories, and it was examined whether all data could fit into these categories or if a new category was needed. In the fifth step, validity and reliability were assessed. To evaluate the coding validity, the member checking method was employed. Six student interview transcripts and six faculty interview transcripts were shared with the participants after coding. They were asked to comment on the identified opportunities and challenges and verify whether the extracted codes accurately reflected their intended meanings, which confirmed the validity of the research. Textual examples were also provided for each category of code.

The reliability was assessed using a two-coder approach and by calculating Cohen's kappa coefficient, which measures the agreement between two coders beyond chance. Values near 1 indicate high agreement, while values near 0 indicate agreement comparable to chance. The inter-coder agreement table is presented below.

Table 3.
The Intercoder Agreement

	Coder 2: Yes	Coder 2: No	Total
Coder 1: Yes	18	3	21
Coder 1: No	2	16	18
Total	20	19	39

(Source: The Researcher's Findings)

The Cohen's kappa coefficient was 0.74, significant at the 99% confidence level, indicating substantial agreement between the coders (Landis & Koch, 1977). Finally, the category structure was finalized, and relevant textual examples were included for each category.

Findings

In this stage, the researcher tried to extract the main themes and codes of each meaningful sentence from the interview transcripts. The basis for naming or labeling the participants' sentences was the selection of words appropriate to the content of the sentences or the explicit statements of the participants. The unit of analysis here was considered a sentence or phrase (several meaningful words) that was neither too large as to create ambiguity nor too small as to be meaningless. It is worth noting that manifest content analysis was used in the study. An important point was that participants sometimes referred to the activity context in which the teaching took place and distinguished it. This led the analysis to consider another level, namely the educational activity context. Therefore, the subcategories were created according to the activity context. Furthermore, due to the overlap of some initial codes or their semantic similarity, these codes (opportunities or threats) were converted into final codes (deleted or merged).

Table 4.
The Identified Opportunities and Challenges in Different Categories According to Students' Perspectives

Category	Subcategory	Identified Opportunities and Challenges		Code Source	Related Studies
Cognitive Dimension	In-person class	Opportunities	Enhancing understanding of the course concepts with intelligent tools	P6, P3, P2, P8	Tlili et al. (2023); Baig & Yadegaridehkordi (2024)
			Increasing the learning speed	P16, P13, P2, P18, P9	Kasneci et al. (2023); Baig & Yadegaridehkordi (2024)
			Providing quick feedback	P6, P13, P12, P8	Crompton & Burke (2024)
			Access to supplementary resources instantly	P6, P9, P22, P8, P21	Tlili et al. (2023)
		Challenges	Overreliance on AI	P6, P3, P2, P1, P11, P22, P27	Lo (2023); Kasneci et al. (2023)
			Reduction of critical thinking	P1, P3, P2, P8, P6	Crompton & Burke (2024)
			Decrease in independent problem-solving skills	P6, P14, P2, P8, P25	Tlili et al. (2023); Adiguzel et al. (2023)
	Course exercises and assignments	Opportunities	Better understanding of the course concepts with AI	P6, P3, P2, P18, P24	Lo (2023); Islam & Islam (2024)
			Providing step-by-step solutions for problem-solving	P4, P12, P2, P8, P23, P22, P14	Kasneci et al. (2023); Baig & Yadegaridehkordi (2024)
			Quick feedback to correct mistakes	P12, P3, P2, P8, P23, P24, P17	Fuller (2024); Crompton & Burke (2024)
		Challenges	Overreliance on AI	P6, P7, P8, P18, P22, P21, P3	Kasneci et al. (2023); Dwivedi et al. (2023)
			Reduction in creativity and problem-solving skills	P6, P13, P7, P8, P11, P21, P20	Adiguzel, Kaya, & Cansu (2023); Dwivedi et al. (2023)
			Possibility of receiving incorrect answers	P6, P3, P2, P7, P8, P20	Adiguzel et al. (2023); Tlili et al. (2023)
	Online learning	Opportunities	Flexibility and easy access to content	P6, P3, P12, P8, P19	Kasneci et al. (2023); Crompton & Burke (2024)
			Self-directed learning and tracking progress	P9, P3, P2, P4, P17	Kasneci et al. (2023)
			Enhancement of personal learning skills	P6, P14, P2, P8, P16, P17, P26	Cotton et al. (2023)
			Time management and planning with AI	P16, P3, P2, P8, P15	Lo (2023); Baig & Yadegaridehkordi (2024)
		Challenges	Unreliable content	P1, P3, P2, P8	Tlili et al. (2023); Kasneci et al. (2023)
			Complexity of tools and confusion	P6, P12, P2, P8, P11	Grassini (2023); Dwivedi et al. (2023)

Category	Subcategory	Identified Opportunities and Challenges		Code Source	Related Studies
Affective Dimension	All activity contexts	Opportunities	Increased motivation and learning excitement	P6, P3, P9, P8, P12	Adiguzel et al. (2023); Dwivedi et al. (2023)
			Satisfaction from quick and easy access to information	P6, P5, P2, P8	Baig & Yadegaridehkordi (2024); Tlili et al. (2023)
			Sense of progress and greater achievement	P6, P3, P12, P18	Crompton & Burke (2024); Baig & Yadegaridehkordi (2024)
		Challenges	Anxiety and stress from using new tools	P6, P1, P2	Baig & Yadegaridehkordi (2024)
			Reduced sense of control and independence in learning	P6, P3, P6, P8	Crompton & Burke (2024)
			Fear of decreased human and interpersonal skills	P6, P3, P7, P8, P15, P8, P8, P10	Kasneci et al. (2023); Dwivedi et al. (2023)
Behavioral Dimension	In-person class	Opportunities	Using AI for active class interaction	P10	Adiguzel et al. (2023); Tlili et al. (2023)
			Using AI to improve learning in class	P10, P23, P2, P18	Kasneci et al. (2023); Crompton & Burke (2024)
		Challenges	Reduced independence in classroom learning	P6, P3, P2, P8, P26, P11	Kasneci et al. (2023)
			Dependence on tools for learning	P1, P13, P11, P8, P26, P20	Cotton et al. (2023)
	Assignments	Opportunities	Completing assignments and correcting mistakes	P6, P1, P2, P8, P24, P13, P7	Lo (2023); Baig & Yadegaridehkordi (2024)
			Receiving more exercises and assignments	P10, P9	Tlili et al. (2023); Kasneci et al. (2023)
		Challenges	Reduced problem-solving ability	P6, P13, P5, P8, P22, P26	Grassini (2023); Dwivedi et al. (2023)
			Reduced interaction with professors and classmates	P9, P10, P11, P18, P26, P25	Adiguzel et al. (2023); Dwivedi et al. (2023)
	Online learning	Opportunities	Using AI to manage time and resources in online learning	P16, P13, P21, P8	Baig & Yadegaridehkordi (2024); Tlili et al. (2023)
			Enhancing digital literacy	P3, P12, P18, P26, P24	Crompton & Burke (2024); Baig & Yadegaridehkordi (2024)
			Using AI dashboards to track progress	P6, P13, P2, P8, P26, P10, P9	Baig & Yadegaridehkordi (2024)
		Challenges	Complexity of AI tools	P6, P13, P2, P8, P24, P20, P26	Crompton & Burke (2024)
			Reduced ability for independent learning in non-presential environments	P1, P3, P7	Kasneci et al. (2023); Dwivedi et al. (2023)

(Source: The Researcher's Findings)

Table 5.
The Identified Opportunities and Challenges in Different Categories According to Faculty Members' Perspectives

Category	Subcategory	Identified Opportunities and Challenges		Code Source	
Cognitive Dimension	In-person class	Opportunities	Improving the quality of education	I1, I3, I22, I18, I7	Zawacki-Richter et al. (2019); Kasneci et al. (2023)
			Increasing creativity in teaching	I2, I3, I21, I18, I5, I8	Dwivedi et al. (2023); Tlili et al. (2023)
			Creating conditions for deeper learning	I4, I13, I20, I17, I3, I5	Chiu et al. (2023); Lo (2023)
		Challenges	Superficiality of the teaching content	I2, I3, I19, I14, I12, I7	Kasneci et al. (2023); Farrokhnia et al. (2024)
			Content errors	I4, I6, I22, I17	Ji et al. (2023); Kasneci et al. (2023)
			Weakening the faculty's analytical skills	I2, I16, I8, I9	Lo (2023); Cotton et al. (2023)
	Online learning	Opportunities	Personalized learning	I9, I10, I11, I15, I21	Dwivedi et al. (2023); Kasneci et al. (2023)
			Improving the quality of educational content	I7, I14, I15, I22, I17	Bond et al. (2024); Zawacki-Richter et al. (2019)
			Possibility of interactive learning	I11, I13, I22, I10, I8	Bond et al. (2024); Chiu et al. (2023)
			Possibility of enriching the class content	I6, I10, I11	Chiu et al. (2023); UNESCO (2023)
		Challenges	Reduced depth of learning	I7, I3, I16, I19, I20, I22	Bond et al. (2024); UNESCO (2023)
			Content errors	I6, I3, I2	Zawacki-Richter et al. (2019); Kasneci et al. (2023)
			Weakening faculty teaching skills	I5, I1, I3, I10, I18, I7	Kasneci et al. (2023); Tlili et al. (2023)
Affective Dimension	All activity contexts	Opportunities	Increasing the faculty's motivation to provide engaging and interactive content	I1, I3, I22, I18, I7	Dwivedi et al. (2023); Farrokhnia et al. (2024)
			Enhancing satisfaction from positive impacts on student learning	I4, I7, I16, I18, I21	Chen et al. (2020); Zawacki-Richter et al. (2019)
			Creating confidence and assurance in class management with technological support	I1, I2, I3, I8, I13, I14, I15	Chiu et al. (2023); Lo (2023)
			Enhancing excitement for continuous learning through educational innovations	I2, I3, I14, I20	Bond et al. (2024); UNESCO (2023)

Category	Subcategory	Identified Opportunities and Challenges		Code Source	
			Reducing anxiety from simultaneously managing multiple educational activities	I9, I11, I16, I18, I7	Zawacki-Richter et al. (2019); Kasneci et al. (2023)
		Challenges	Feeling threatened by the reduction of faculty's role in class	I1, I5, I20, I18, I11, I4, I21, I18, I22	Zawacki-Richter et al. (2019); Joksimović et al. (2023)
			Anxiety from facing new technologies and learning novel tools	I1, I3, I22, I18, I7	Chiu et al. (2023); Bond et al. (2024)
			Reduced sense of control over teaching process and student interaction	I11, I15, I17, I19, I20	Kasneci et al. (2023); Farrokhnia et al. (2024)
			Concern about damage to scientific status compared to AI performance	I5, I14, I17, I18, I1, I2, I21	Dwivedi et al. (2023); UNESCO (2023)
Behavioral Dimension	Conducting classes	Opportunities	Willingness to implement innovative teaching methods	I1, I3, I20	Zawacki-Richter et al. (2019); Joksimović et al. (2023)
			Creating conditions for continuous learning for faculty	I7, I8	Dwivedi et al. (2023); UNESCO (2023)
		Challenges	Resistance to changing the teaching methods	I12, I14, I20	Chiu et al. (2023); Bond et al. (2024)
			Reduced active faculty's presence in class	I7, I3, I22, I18, I7, I19, I6	o direct study was found.
			Weak AI infrastructure in Iran	I4, I7, I17, I18, I21, I22	Chiu et al. (2023); UNESCO (2023)
	Educational content production	Opportunities	Designing innovative and multimedia content	I8, I9, I17	Kasneci et al. (2023); Tlili et al. (2023)
			Fast and efficient content production	I7, I13, I14, I15	Dwivedi et al. (2023); Farrokhnia et al. (2024)
			Possibility of keeping educational content up to date	I15, I19, I20, I21, I22	Chen et al. (2020); Zawacki-Richter et al. (2019)
		Challenges	Resistance to changing the traditional content production methods	I1, I6, I3, I16, I20, I22	Bond et al. (2024); Chiu et al. (2023)
			Sense of lack of ownership over content	I2, I9, I10	Dwivedi et al. (2023); UNESCO (2023)
			Possibility of producing incorrect content	I1, I23, I4, I5, I7, I10, I11, I17, I18, I20	Ji et al. (2023); Alkaissi & McFarlane (2023)
			Dependence on AI for content production	I3, I5, I6, I7, I8, I9, I11, I20, I21, I22	Cotton et al. (2023); Kasneci et al. (2023)

(Source: The Researcher's Findings)

Description of Identified Opportunities and Challenges

Next, the identified opportunities and challenges are explained separately.

The Students' Attitudes toward Opportunities and Challenges of Using AI in Education

In the cognitive dimension, based on the perspectives, 11 opportunities and 8 challenges were identified regarding the use of AI in education, which can be differentiated across three activity contexts: in-person classes, assignments and exercises, and online learning.

In in-person classes, the main opportunities included improving understanding of the course concepts, increasing the learning speed, quick access to supplementary resources, and providing immediate feedback. Students believed that AI tools, by personalizing learning, providing step-by-step explanations, and simpler examples, facilitate the learning of complex concepts and accelerate the learning process. One participant stated: "…Now with ChatGPT and many other tools, I learn quickly". (P2)

Additionally, quick and easy access to supplementary resources at the moment was considered an important advantage: "…It is easier and faster to reach the supplementary resources… this feature is more prominent in in-person classes". (P9)

On the other hand, the main challenges included over-reliance on AI, reduced critical thinking, and weakening of independent problem-solving skills. Students believed that dependency on AI could lead to passive learning: "…It creates a lot of dependency and takes away problem-solving skills from a person". (P1)

Regarding assignments, opportunities such as better understanding of the concepts, step-by-step solutions, and receiving immediate feedback were identified. Students noted that AI, by providing stepwise solutions and instant error correction, fosters more active learning: "…Before the professor's assessment, we can evaluate our work… it provides step-by-step solutions". (P12)

However, challenges such as over-reliance, reduced creativity, and the possibility of receiving incorrect answers were also raised. Some participants pointed to potential errors in AI outputs: "…It may provide incomplete solutions… it will reduce creativity and problem-solving ability". (P7)

In online learning, opportunities included temporal and spatial flexibility, self-directed learning, progress tracking, and strengthening personal learning skills. Students believed that AI enables constant access to content and better management of the learning path: "…The student can access the course content anytime and anywhere". (P3)

In contrast, challenges in online learning included unreliable or incorrect content and the complexity of AI tools. Some students mentioned lack of direct instructor supervision and confusion in using the tools: "…Not being sure of the accuracy and validity of the content… this problem is more evident…". (P3)

In the affective dimension, based on the students' perspectives, 3 opportunities and 3 challenges were identified regarding the use of AI in education. Based on the analysis of interview texts, in the affective dimension of students' attitudes toward AI, no clear differentiation was observed across different educational contexts. Overall,

opportunities and challenges were presented generally, independent of the type of learning environment.

Regarding opportunities, students referred to increased motivation and excitement for learning, satisfaction from quick and easy access to information, and enhanced sense of personal progress and achievement. From their perspective, AI, by enabling immediate Q & A, explaining difficult concepts through examples and intelligent simulations, makes the learning experience more engaging and interactive, and is especially motivating for students tired of traditional methods. Additionally, constant access to educational resources reduces the learning anxiety and increases the psychological comfort. One participant stated: "…Learning anxiety decreases and it strengthens the sense of personal achievement". (P5)

In contrast, in the challenges dimension, anxiety and stress from using new technologies, reduced sense of control and independence in learning, and concern about weakening human interactions and communication skills were raised. Some students identified unfamiliarity with AI tools as a source of stress and fear of mistakes, which can affect their focus and psychological comfort and lead to a kind of "technology anxiety".

Furthermore, reduced sense of control over the learning path and dependence on AI outputs were highlighted as factors undermining the learners' self-efficacy and independence. In this regard, one student stated: "…It raises the concern that the professor's role will be diminished… and I lose the opportunity for human interaction and learning social skills". (P8)

Overall, the findings indicated that although AI can affectively enhance motivation, satisfaction, and psychological comfort in learning, uncontrolled use may lead to emotional insecurity, "technology anxiety", and a reduced sense of autonomy and human interaction in the learning process.

In the behavioral dimension, based on the students' perspectives, 7 opportunities and 6 challenges were identified regarding the use of AI in education. In the behavioral dimension, which refers to intention, decision, and execution of educational behaviors, three activity contexts were identified based on the interview texts: in-person classes, assignments, and online learning.

In in-person classes, the opportunities included more active student engagement and improved learning in class, while the challenges included reduced independence and dependency on tools. Students believed that using AI could increase confidence for participation and interaction: "…It improves interaction… it enhances learning". (P10)

At the same time, concerns about behavioral dependence on the tools were also raised:

"…It makes a person dependent on the tool… one must be cautious". (P3)

In the context of assignments, the opportunities included error correction and receiving tailored exercises, while the challenges included reduced problem-solving ability and decreased interaction with instructors and classmates. Some students reported using AI practically to correct their assignments: "…It identifies and corrects errors… I use it". (P8)

In contrast, over-reliance on AI was highlighted as a factor that could reduce initiative, creativity, and collective interaction.

In online learning, opportunities such as time and resource management, progress tracking, and enhancement of digital literacy were identified, while challenges included tool complexity and reduced independent learning. One participant stated: "…Time and resource management can also be done easily". (P13)

Overall, the findings indicated that AI in the behavioral dimension can enhance participation and improve learning performance, but excessive use may lead to behavioral dependency and reduced learner autonomy.

The Faculty Members' Attitudes toward Opportunities and Challenges of AI in Education

In the cognitive dimension, according to faculty members, 7 opportunities and 6 challenges of using AI in education were identified which can be categorized into two contexts: in-person classes and online learning.

In in-person classes, the opportunities included enhancing the teaching quality, increasing creativity in instruction, and fostering deeper learning. Faculty believed that AI, by providing rapid access to up-to-date resources and diversifying teaching methods, could make face-to-face education more effective: "…It helps enhance the quality of education… this is very important in in-person classes". (I1) "…A good opportunity for monotonous in-person teaching". (I9)

In contrast, challenges such as superficiality of content, content errors, and weakening of analytical skills for both instructors and students were noted: "…Over-reliance… can reduce the instructor's analytical ability". (P2)

In online learning, opportunities included personalized instruction, improved quality and richness of educational content, and more interactive learning. Faculty highlighted the role of AI in producing diverse and structured content: "…It makes teaching and learning more interactive". (I11)

However, challenges such as reduced depth of learning, content errors, and weakening of teaching skills were also reported: "…It may provide incorrect or incomplete information… this reduces the credibility of education". (I14) "…Reduced teaching skills may occur if used continuously". (I5)

Overall, the findings indicated that AI in the cognitive dimension can enhance the teaching quality and creativity, but excessive use may lead to superficial learning and weaken analytical and teaching skills.

In the affective dimension, according to faculty members, 5 opportunities and 4 challenges of AI use in education were identified. The interview texts showed no clear differentiation across educational contexts.

In terms of opportunities, faculty noted increased motivation and creativity in teaching, enhanced affective satisfaction from impacting student learning, strengthened confidence in classroom management, increased excitement for continuous learning, and reduced anxiety from managing multiple teaching activities simultaneously. AI tools, by reducing workload and enabling the design of interactive activities, provide faculty with a greater sense of control and calm: "…Their motivation for learning and

professional growth increases… excitement for continuous learning is enhanced". (I16)

In contrast, challenges included feeling threatened by a potential reduction in the instructor's role, anxiety from learning new technologies, reduced sense of control over the teaching process, and concerns about diminishing the academic status. Some faculty members expressed worries about the partial replacement of their instructional role and the stress of adapting to new tools: "…Their guiding and mentoring role may be diminished… causing psychological stress". (I1) "…Quickly learning to use new tools… can create psychological pressure". (I11) "…It may make faculty doubt their academic position and feel concerned". (I14)

Overall, the findings indicated that AI in the affective dimension can enhance the faculty's motivation, satisfaction, and psychological comfort, but in the absence of proper support and training, it may lead to anxiety, affective insecurity, and concerns about professional standing.

In the behavioral dimension, based on the students' perspectives, 5 opportunities and 7 challenges were identified in the use of AI in education. In the behavioral dimension, based on the interview texts, two educational contexts including classroom instruction and educational content production were identified. Opportunities and challenges of AI use were extracted for each.

In classroom instruction, opportunities included a willingness to implement innovative teaching methods and creating conditions for continuous learning for faculty. Faculty noted that AI encourages them to update their teaching knowledge and skills: "…I use it so that this behavior demonstrates continuous learning and professional development in class". (I7)

In contrast, challenges included resistance to changing classroom teaching methods and reduced active presence of instructors in class, as some faculty preferred traditional methods or were concerned about a diminished guiding role.

In educational content production, opportunities included designing innovative and multimedia content, producing content quickly and efficiently, and keeping educational materials up to date: "…They produce content in more engaging formats such as videos and simulations". (I8) "…The ability to keep educational content up-to-date… has increased the faculty's willingness". (I15)

On the other hand, challenges included resistance to changing traditional content production methods, feeling a lack of ownership over the content, potential content errors, and dependency on AI: "…They are unwilling to change behavior… this resistance is a challenge". (I16) "…Creates a sense of lack of ownership over the content". (I9)

Overall, the findings indicated that AI in the behavioral dimension can enhance the faculty's willingness for innovation, continuous learning, and dynamic content production, but behavioral resistance and professional concerns may reduce acceptance and practical use.

Discussion and Conclusion

This study aimed to examine the attitudes and experiences of faculty members and students regarding the use of AI tools in the teaching and learning process.

The findings revealed that increased learning speed was considered as one of the most important and frequently mentioned opportunities in the cognitive dimension by both faculty and students. Analysis of the interviews indicated that, according to students, using AI tools allows them to reach answers more quickly, correct their mistakes, and feel less time-related lag. Faculty also noted that this feature can free up teaching time and allow them to focus on more analytical topics. Therefore, it can be concluded that learning speed represents a valuable capacity for enhancing the quality of education.

However, the same findings showed that one of the most frequently mentioned challenges in the cognitive dimension is reduced critical thinking and superficial learning. Many participants explained that under such conditions, students engage less in questioning and analysis and rely more on ready-made answers. This suggests that the very factor that accelerates learning, if not properly managed, may reduce the depth of learning. International research in the field of education generally confirms this concern. For example, Zhai et al. (2024) reported that over-reliance on AI-generated ready-made answers can reduce the motivation for independent analysis and weaken problem-solving ability. Similarly, Chen et al. (2020), in their systematic review, emphasized that learning data analysis and AI tools, if used without proper instructional design, can lead to superficial decision-making and the weakening of analytical skills.

The findings of this study indicated that opportunities created in the affective dimension, such as increased motivation and satisfaction, were repeated across all educational contexts (in-person classes, online learning, and even assignments) and overlapped between faculty and students. However, what was noteworthy was the significant difference in how faculty expressed affective challenges across different contexts. In in-person classes, the faculty members were concerned about a reduction in their role and being compared to AI performance. They emphasized that if students receive accurate and immediate responses from AI, the academic authority of the instructor might be diminished, and direct interaction may decrease. In contrast, students in the same context expressed greater concern about reduced human interaction and the loss of social and communication skills. In other words, while the instructors' concern centers on maintaining their position and instructional authority, the students' concern focuses on preserving the quality of human interaction and learning.

Furthermore, the findings of this study indicated that the use of AI tools also influenced the behavioral dimension of the students' and instructors' attitudes in in-person classes. Students became more actively engaged in class discussions, asked more questions, and volunteered to answer. From the instructors' perspective, the increased student participation prompted them to redesign the classroom structure, reducing one-way lectures and emphasizing interactive activities such as group problem-solving and collective discussions. These findings are consistent with the study by Pahi et al. (2024), who reported that combining teaching assistants with generative AI tools increased

student participation, facilitated rapid identification of conceptual problems, and enabled more precise feedback. This has made the classroom environment more dynamic; however, it also introduces challenges. The use of AI has led some students to reduce personal effort in problem-solving and rely more on ready-made answers. Instructors consider this trend concerning, as it can diminish their active role and reduce opportunities for independent learning. Therefore, it is recommended that instructional design should reinforce interaction while preventing complete dependency.

Overall, the findings indicated that both instructors and students believe that using AI accelerates and smooths the learning process while providing immediate feedback. Students can solve exercises in real time using tools like chatbots, and for instructors, preparing educational examples and correcting assignments has become easier with these tools. This finding demonstrated that the perceived usefulness plays a significant role in fostering a positive attitude. The present result aligns with the study by Kulkarni et al. (2024), which explained that generative language models accelerate learning by providing rapid responses.

This study also showed that a positive attitude alone is not sufficient, and the lack of infrastructure and digital skills constitutes the main barrier to actual AI use. This finding is consistent with the Theory of Planned Behavior (Ajzen, 1991), which emphasizes that perceived behavioral control is a prerequisite for converting attitude into behavior.

Many instructors and students in the interviews expressed uncertainty regarding the reliability of AI outputs and were concerned that students might use this data without critical evaluation. To prevent this problem, as Roozbahani (2025) suggested, a hybrid approach can be employed. This finding underscored the importance of training in source credibility assessment. Chen et al. (2020) also emphasized the necessity of validating learning data, and Halaweh (2023) warned that language models may generate fabricated content, highlighting that data screening should be an integral part of research methodology.

The results showed that continuous use of AI can weaken problem-solving skills and critical thinking. This finding is consistent with the study by Najafi and Rasouli (2023), which indicated that overreliance in technology threatens students' independent thinking and suggested that instructional design should strengthen students' analysis and inquiry skills.

Using AI, like any other emerging technology, comes with both challenges and opportunities, and managing these challenges while leveraging the opportunities can help optimize its use. It can also be argued that in today's digital world, avoiding technology is not feasible. Identifying challenges and opportunities is a crucial step toward its proper utilization. The findings demonstrated that it is possible to distinguish between "assistive or supportive" use and "inappropriate" use of AI, which can serve as a basis for designing ethical guidelines in universities.

The report further recommends that countries develop educational programs and empower human resources. In this regard, Halaweh (2023) showed that even when

attitudes toward AI are positive, the lack of formal training, limited resources, and a sense of unpreparedness can lead to hesitation and resistance to practical use of technology. The importance of these two sources for the present study lies in highlighting that, in addition to assessing the attitudes, structural and educational barriers must also be identified to obtain a more comprehensive understanding of faculty and student acceptance or resistance.

In the field of education, AI still remains a "sleeping giant". It appears that the "disruptive" applications of AI in teaching and learning are unlikely to emerge naturally from mainstream higher education (Akinwalere & Ivanov, 2022). Examining the presented AI models raises a fundamental question: should technology aim to replace teachers and instructors through automation, or should it be utilized to empower both teachers and learners? Even if AI achieves remarkable success in reducing the costs of teaching and learning, the question arises as to what the human cost of such a transformation would be.

Ultimately, AI is undoubtedly a field that drives innovation and, through this, enhances the competitiveness of countries. Nations will continue to compete in this rapidly evolving and rich domain; however, at least in the field of education, there is also space for collaboration, which is grounded in knowledge sharing. The need for more information about how countries are advancing in this realm is uncertain and constantly changing—an issue that can strengthen dialogues and highlight the importance of adopting comprehensive approaches to AI in education.

The present study was conducted based on the ABC model using qualitative content analysis. Accordingly, using a predetermined analytical framework may have resulted in some emerging themes outside the core dimensions of the model being less evident, although efforts were made to mitigate this limitation by identifying and incorporating relevant subcategories. In addition, the qualitative and cross-sectional nature of the study limits the statistical generalizability of the findings and the ability to examine changes in participants' attitudes and experiences over time. The limited scope of the sample, as well as the rapid evolution of the capabilities and applications of AI, represents another limitation of the present study. Therefore, the findings should be interpreted in light of the context and time in which the study was conducted. Future research is recommended to employ larger and more diverse samples, longitudinal and comparative designs, and quantitative methods to test the findings of the present study. In addition, inductive qualitative approaches may help identify the emerging dimensions and themes that may not have been captured within the ABC model.

The findings of the present study have several important implications for higher education policy and management. First, the coexistence of opportunities and challenges associated with AI across cognitive, affective, and behavioral dimensions highlights the need for a balanced approach to university-level policymaking, whereby AI is used as a complementary tool for learning and research rather than as a substitute for human capabilities and interactions.

Second, the findings underscore the need to develop clear ethical and operational

frameworks governing the use of AI in educational and research activities. Issues such as transparency in AI use, academic originality, intellectual property, privacy, and accountability for AI-generated content require explicit regulation and clarification at the university level.

Third, the findings highlight the need to develop AI literacy. The ability to assess the validity of AI-generated outputs, identify errors and fabricated information, recognize the limitations of AI tools, and critically evaluate AI-generated content should be incorporated into capacity-building programs for faculty members and students.

Fourth, concerns regarding superficial learning, reduced critical thinking, and dependence on ready-made answers point to the need to reconsider instructional design and assessment practices. Greater emphasis on reasoning, analysis, problem-solving, creativity, and the ability to defend ideas may help prevent AI from substituting for the learning process itself.

Fifth, the findings underscore the importance of maintaining and strengthening human interaction throughout the educational process. From this perspective, the integration of AI should support feedback, participation, and interactive learning, while also facilitating a shift in the instructor's role from merely transmitting information toward facilitating and guiding the learning process.

Finally, differences in the perceptions and concerns of faculty members and students, together with the continuous evolution of AI capabilities, highlight the need for group-specific forms of support and mechanisms for the continuous monitoring and revision of relevant policies and guidelines.

Regarding the cognitive dimension, faculty members should critically evaluate and verify AI-generated content before incorporating it into teaching and educational content production, particularly in light of the reported concerns about inaccurate content, superficial learning, and weakened analytical and teaching skills. AI should be employed to enrich learning, personalize instruction, and support content development while preserving faculty members' analytical judgment and pedagogical expertise. Regarding the affective dimension, universities should provide sustained support to address faculty members' anxiety about emerging AI technologies, reduced perceived control over the teaching process, and concerns about changes in their academic and instructional roles. Such support should strengthen faculty members' confidence in using AI while emphasizing the continuing importance of faculty expertise and meaningful faculty–student interaction. Regarding the behavioral dimension, faculty members should integrate AI selectively into classroom teaching, interactive learning, and educational content production while maintaining active involvement in the teaching process. AI can be used to support innovative and multimedia content development and to update educational materials. However, faculty members should retain responsibility for validating AI-generated content and making final instructional decisions.

Regarding the cognitive dimension, students should critically evaluate AI-generated information and verify its accuracy through reliable academic sources, particularly given the reported concerns about unreliable content, overreliance on AI, and reduced critical

thinking and problem-solving abilities. AI should therefore function as a supplementary cognitive tool rather than a substitute for independent reasoning and academic judgment**.** In the affective dimension, universities should provide guidance and support to help students manage anxiety and stress associated with emerging AI technologies while maintaining their sense of control and independence in learning. Such support should strengthen students' confidence in using AI without encouraging excessive dependence and should reinforce the value of meaningful interaction with faculty members and peers. Finally, in the behavioral dimension, students should use AI purposefully in classroom learning, assignments, and online learning, particularly for clarifying concepts, obtaining feedback, managing learning activities, and monitoring progress. At the same time, students should retain responsibility for substantive reasoning, problem-solving, and academic work, while maintaining active interaction with faculty members and classmates.

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