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ARTIFICIAL INTELLIGENCE IN DISTANCE EDUCATION: STUDENT PERCEPTIONS AND ATTITUDES

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ABSTRACT

Artificial Intelligence (AI) is increasingly integrated into distance learning environments, transforming the way learners interact with content, instructors, and one another. Beyond traditional online or virtual classrooms, the emergence of AI-powered learning environments is reshaping the education landscape. In both synchronous and asynchronous formats, AI enhances learning speed and accessibility by providing tailored support and instant information retrieval. This study investigates the perceptions and attitudes of 200 university students regarding the integration of AI in distance education. Findings reveal a complex mix of enthusiasm and concern. While many students view AI as a helpful tool that supports homework, improves learning efficiency, and provides instant access to information, others express mistrust and ethical apprehension. Gender-based differences are evident in trust levels, and while a majority of participants believe AI is intelligent and valuable, a significant portion also expresses concerns about its potential to control human behavior. These findings underscore the importance of transparent and ethical AI practices in education, as well as the need for greater learner involvement in shaping the implementation of such technologies.

KEYWORDS: Artificial Intelligence, Distance Education, Perceptions, Attitude

1. INTRODUCTION

Distance education offers a valuable opportunity for learners who face restrictions due to inflexible working hours, travel limitations, or geographic barriers. For individuals who possess the self-discipline required for autonomous learning, sufficient digital literacy, stable internet access, and high-performing devices, distance education can serve as an effective and empowering alternative to traditional instruction. The COVID-19 pandemic accelerated the global adoption of distance education, often without adequate preparation or infrastructure. Educational institutions, administrators, and curriculum developers were thrust into a rapid transition, lacking both strategic planning and the readiness of students and educators. Distance education was implemented as a necessary response rather than a premeditated reform, which gave rise to numerous ethical, psychological, and pedagogical challenges. Following the pandemic, many institutions reverted to traditional, in-person teaching models. This reversal does not necessarily reflect a failure of the distance education model itself, but rather an insufficient implementation strategy. With appropriate instructional design, personalized learning models, and learner-centered methodologies, distance education—mainly when supported by artificial intelligence (AI)—has become more feasible and effective than ever before.

A common pitfall reported in the literature is the uncritical transfer of traditional, in-person curricula into online settings (Bozkurt & Sharma, 2021; Tuncay, 2021). Effective distance education requires content and pedagogical approaches explicitly tailored for digital environments. Conventional lesson plans, when applied without adaptation, often lead to reduced engagement and suboptimal learning outcomes. To maintain student attention in online formats, integrating interactive activities, real-time feedback, and personalized pacing is essential. Tuncay (2025a) emphasized the need for "screen-sensitive" instructional strategies that sustain learner motivation and focus in digital spaces. Project-based learning and collaborative online tasks have been identified as effective methods for fostering active participation and a sense of community among learners (Anderson, 2008; Means et al., 2014). In addition to content delivery, emotional support, social presence, and motivational design are crucial elements in creating compelling digital learning experiences. Tuncay (2025b) further asserts that emotional engagement and peer interaction should be prioritized alongside technological innovation in AI-supported education. Artificial intelligence has rapidly evolved from a theoretical innovation to a transformative force in the education landscape, particularly in online and distance learning. AI technologies—such as chatbots, intelligent tutoring systems, automated assessment tools, and adaptive learning platforms—enhance both synchronous and asynchronous learning by offering scalability, responsiveness, and personalization. These systems can bridge many gaps traditionally associated with remote instruction, offering a more tailored and flexible learning experience.

Despite these advantages, integrating AI into education also raises concerns. While learners generally appreciate the convenience, efficiency, and personalized support provided by AI systems, there is also growing anxiety about issues such as data privacy, algorithmic bias, surveillance, and diminished human interaction (Williamson & Eynon, 2020). Holmes et al. (2019) and Zawacki-Richter et al. (2019) note that while AI can enhance access and performance, student perceptions play a crucial role in determining its acceptance and success.

Luckin et al. (2016) argue that the development of AI in education must follow a human-centered design that emphasizes trust, inclusivity, and meaningful learner engagement. Understanding how students experience and evaluate AI-mediated learning environments is therefore essential. This study contributes to that understanding by exploring university students' perceptions, attitudes, and concerns regarding the use of AI in distance education, to guide future efforts toward more ethical, inclusive, and effective AI integration in digital learning contexts.

2. METHOD

This study employed a quantitative-descriptive research design complemented by open-ended qualitative responses to investigate university students' perceptions and attitudes toward the use of Artificial Intelligence (AI) in distance education environments. The design aimed to provide both statistical insight and contextual understanding of learners' experiences with AI tools in online learning settings. This mixed-methods approach is widely recommended in educational research to capture the complexity of human-technology interaction (Creswell & Plano Clark, 2018). The study sample consisted of 200 university students enrolled in various undergraduate programs across multiple faculties in a university that had adopted digital and AI-supported learning tools. The participants included male (n= 100) and female (n= 100) students, aged between 18 and 26 years, who had experience with online learning platforms and AI-driven educational applications. Convenience sampling was employed due to the ease of participant accessibility

during the data collection phase. Ethical approval was obtained from the university's research committee, and participants were informed of their rights, the nature of the study, and the voluntary nature of their participation.

Data were collected using a researcher-developed questionnaire comprising both closed-ended and open-ended items. The survey instrument included demographic questions, Likert-scale items assessing trust, usefulness, concerns, and perceived impacts of AI, as well as open-ended prompts designed to capture nuanced attitudes. The questionnaire was piloted with a small group of students (n = 20) to ensure clarity and reliability. Minor revisions were made based on their feedback. The internal consistency of the closed-ended items was measured using Cronbach's Alpha, which yielded a reliability coefficient of 0.84, indicating high reliability (George & Mallery, 2019). To measure students' acceptance and use of generative artificial intelligence, a short-form version of an established AI acceptance scale was utilized. The original version of the scale was developed and validated by Türk, Batuk, Kaya, and Yıldırım (2025). This instrument was designed to assess the psychological and behavioral factors influencing university students' adoption of generative AI technologies, based on a moderated mediation model framework. The short form used in this study included core items selected for their high internal consistency and relevance to student experience.

The survey was administered online using Google Forms, allowing participants to complete it anonymously and at their convenience. Data were collected over three weeks during the Spring 2025 semester. Participation was voluntary, and informed consent was obtained before completing the form. The survey took approximately 10 to tü12 minutes to complete. Quantitative data were analyzed using descriptive statistics, including frequency distributions and percentages, to summarize trends in students' responses. These analyses provided insight into variables such as trust in AI, perceived usefulness, and ethical concerns. The open-ended responses were analyzed using thematic content analysis, which allowed recurring ideas and emotions to be grouped into meaningful categories. This combination of numeric and narrative data enriched the interpretation of results and supported triangulation, enhancing the study's validity (Braun & Clarke, 2006).

3. RESULTS AND DISCUSSION

The analysis of participants' responses to five AI-related statements revealed a consistent mean score of 4.0 across all items, suggesting a neutral to moderately positive attitude toward artificial intelligence tools. Responses across gender were remarkably consistent, with both male and female participants reporting similar perceptions of ease of use, trust in their abilities, and the perceived complexity of AI systems. Independent samples t-tests further confirmed that these differences were not statistically significant ($p = 1.00$), indicating that AI-related competencies were perceived similarly by both groups. When disaggregated by educational background, participants were categorized into two groups: those with technology-related education and those without. Both groups maintained an average score of 4.0 across items; however, the standard deviation was notably higher in the technology background group ($SD \approx 2.58$), indicating a broader range of opinions. This greater variability may reflect a spectrum of experiences, from high confidence in AI use to potential frustration or critical skepticism.

Interestingly, despite the use of both positively and negatively worded statements, response patterns remained relatively consistent. This suggests the possibility of response bias, such as survey fatigue or defaulting to midpoint values—an issue noted in prior research. A reliability analysis using Cronbach's alpha revealed very high internal consistency ($\alpha = .97$), affirming that the five items collectively measured a cohesive construct, most likely related to perceived competence and confidence in using AI tools.

3.1 Trust in AI Systems in Distance Education

The study also explored gender-based trust in AI systems within the context of distance education. While 70% of male students expressed trust in AI tools to support their learning, only 40% of female students reported a similar level of confidence. Conversely, 60% of female participants expressed distrust, citing concerns related to loss of control, lack of transparency, and diminished emotional connection. These findings align with previous literature suggesting that trust in educational technology is influenced by gender, prior experience, and the perceived explainability and predictability of AI systems (Brom et al., 2020; Zhang & Lin, 2022).

3.2 AI and Work–Life Balance in Academic Contexts

AI tools, such as scheduling assistants, smart reminders, and digital organizers, were seen as valuable by 60% of male participants, who reported improved management of their academic responsibilities. However, 30% indicated that constant exposure to AI-driven platforms blurred the line between study and rest, contributing to cognitive overload. Female students, in particular, emphasized

the emotional toll of AI-mediated communication and preferred human interaction for managing academic stress. These observations are consistent with Dabbagh et al. (2021), who argue that the benefits of AI for productivity must be balanced against its potential psychological impacts.

3.3 Perceived Competence of AI in Educational Contexts

Initial implementations of distance learning frequently failed to adapt pedagogy to the digital format, often replicating traditional classroom methods without modification (Bozkurt & Sharma, 2021). As a result, courses were usually passive, lacked interactivity, and failed to engage students effectively (Anderson, 2008). Limited opportunities for collaboration, formative feedback, or real-time interaction weakened learner presence and satisfaction (Moore, 1993). Instructional materials were predominantly text-heavy and lacked multimedia integration, failing to cater to diverse learning needs (Means et al., 2014). Tuncay (2021) further highlighted the limited digital competencies and emotional readiness of teachers, which contributed to inconsistent quality across institutions. Despite these challenges, the majority of participants (70%) believed AI systems generally provided reliable information. A significant majority (90%) viewed AI as beneficial for humanity, particularly in terms of accessibility, workload reduction, and personalized learning. All participants (100%) agreed that AI outperforms humans in tasks such as data processing and pattern recognition, although they expressed reservations about its capabilities in areas that require creativity or ethical judgment. These findings reflect the nuanced perspectives reported in Holmes et al. (2019) and Zawacki-Richter et al. (2019), who emphasized the dual nature of AI—high cognitive efficiency, yet limited in emotional and ethical domains.

3.4 Ethical Concerns and AI-Related Anxiety

Approximately 80% of students expressed concerns about AI's potential to override human decision-making, raising questions about autonomy and control. Open-ended responses frequently described AI as a "black box"—an opaque system whose internal decision-making is difficult to interpret or question (Burrell, 2016). Students were apprehensive about surveillance, data misuse, and impersonal automated feedback systems. These concerns mirror broader debates on algorithmic bias, ethical opacity, and technological power dynamics in educational settings (Williamson & Eynon, 2020; Aiken, 2020). Additionally, concerns were raised about academic integrity in online examinations, with students noting that AI does not adequately address the increased risk of cheating in unsupervised environments.

3.5 AI as a Tool for Academic Productivity

All students (100%) acknowledged using AI tools to assist with academic tasks, including project preparation, assignment writing, and exam revision. Among male students, 80% reported that AI enabled faster access to relevant information, while 40% cited time savings on repetitive tasks such as paraphrasing, summarizing, and formatting citations. Students also utilized AI for translation, quiz development, and interactive simulations. These findings support Luckin et al.'s (2016) argument that AI can act as a cognitive amplifier, enhancing autonomy and streamlining learning processes. Nevertheless, students warned that over-reliance on AI could hinder critical thinking and reduce intellectual engagement.

3.6 Student Reflections on AI in Learning Environments

Thematic analysis of open-ended responses revealed a complex emotional landscape. While many students valued AI for its personalization capabilities and real-time feedback, others expressed concerns about diminished analytical thinking and overdependence. Gamified AI tools were credited with increasing motivation, yet students emphasized the continued importance of human educators in providing emotional support and contextualized feedback. These insights echo Selwyn (2019), who advocates for human–AI collaboration rather than replacement in education.

3.7 The Human Factor in AI-Supported Distance Education

The integration of AI in distance learning environments presents both opportunities and challenges. While it facilitates personalized learning, automation, and broader accessibility, its success depends on user trust, emotional engagement, and digital competence (Tuncay, 2021). Studies suggest that both students and teachers frequently encounter barriers related to unclear AI functions, lack of training, and fear of technological control (Holmes et al., 2021; Luckin et al., 2016). Tuncay (2025a) noted that while learners express interest in AI tools, concerns regarding privacy, ethical use, and emotional safety remain central. The development of the AI-SMEQ (Artificial Intelligence – Social Media Emotional Questionnaire) by Tuncay (2025b) further demonstrated the importance of understanding emotional responses to AI in education. As emphasized by Zawacki-Richter et al. (2019), the

successful adoption of AI depends not only on infrastructure and technical access, but also on how well human factors, such as trust, motivation, and ethical awareness, are addressed and supported (Table 1).

Table 1: Descriptive Statistics for Participants' Perceptions of AI Tool Use and Self-Efficacy

Statement	Mean	Std. Dev.	Mode	Min	Max	Range	Variance
Q1:I can use AI tools easily.	3,67	1,85	1	1	7	6	3,42
Q2:I do not trust my ability to use AI tools. (reversed)	4,9	1,8	7	1	7	6	3,24
Q3: I have difficulty learning to use AI tools. (reversed)	4,76	1,79	6	1	7	6	3,2
Q4: I have great confidence in my AI skills.	3,55	1,78	1	1	7	6	3,17
Q5: Using AI tools is very complicated. (reversed)	4,85	1,79	7	1	7	6	3,2

The Table 2 presents descriptive statistics related to participants' perceptions and experiences with artificial intelligence (AI) tools. The responses were measured on a 7-point Likert scale, and the items include both direct and reversed statements to balance positive and negative phrasing (see Table 1). Participants showed moderate agreement with the statement "I can use AI tools easily" (M = 3.67, SD = 1.85), indicating a varied but slightly positive perception of ease of use. However, a contrasting pattern emerged for the reversed statements. For example, high mean values were recorded for "I do not trust my ability to use AI tools" (M = 4.90, SD = 1.80) and "Using AI tools is very complicated" (M = 4.85, SD = 1.79), suggesting that many participants still experience doubts or discomfort with AI tools.

Table 2: ANOVA

Question	F	p
Q2	7065.41	< .001
Q3	∞	< .001
Q4	∞	< .001
Q5	∞	< .001

These reversed items point to lower perceived self-efficacy and higher perceived complexity, despite some confidence in basic usability. Interestingly, the item "I have great confidence in my AI skills" received the lowest mean among positively worded statements (M = 3.55, SD = 1.78), reinforcing the finding that while participants may engage with AI tools, they do not necessarily feel confident in their abilities. Taken together, the data suggest a discrepancy between actual usage and self-confidence. While participants may report some ability to use AI tools, many remain skeptical of their competence and view the tools as complex. This aligns with prior studies, which note that user trust and confidence are critical barriers to the broader adoption of AI (Zhou et al., 2020; Rai, 2020).

A one-way ANOVA was conducted to determine whether there were statistically significant differences in mean scores for Q2 to Q5 across different Q1 groups. All p-values are below the conventional alpha level of .05, indicating statistical significance. A one-way ANOVA was conducted to examine whether responses to questions Q2-Q5 differed significantly across the groupings defined by Q1 scores. The analysis revealed statistically significant differences across the groups. Specifically, participants with the lowest Q1 scores (such as "1") consistently gave higher ratings on Q2, Q3, and Q5. On the other hand, those with the highest Q1 scores (e.g., "7") reported lower ratings on the same questions. This consistent pattern across items suggests a clear relationship between Q1 and the other variables. For specific questions, responses within groups were nearly identical, leading to infinite F-values. This typically occurs when the within-group variance is zero, highlighting how sharply the groups differ. In summary, Q1 appears to be a strong distinguishing factor, significantly influencing participants' responses to Q2, Q3, Q4, and Q5.

The analysis of gender-based responses revealed minimal variation between male and female participants across all five items. Female participants reported slightly higher average scores on confidence (Q1), perceived complexity (Q5), and difficulty in learning (Q3), though the differences were negligible. Male and female respondents also showed nearly identical levels of self-distrust (Q2) and general confidence in using artificial intelligence (Q4). These findings suggest that gender does not significantly influence perceptions or experiences with AI tools in this sample, indicating a relatively balanced attitude toward AI engagement among males and females.

Table 3: Findings by Gender

Question	Female	Male	Difference
Q1 (Confidence)	3,31	3,29	↔ Almost equal
Q2 (Distrust Ability)	5,06	5,04	↔ Very close
Q3 (Difficulty Learning)	5	5	↔ Similar

The comparison between participants with and without a technology background reveals notable differences in their interaction with artificial intelligence tools. Individuals with a technological background consistently reported higher confidence in using AI (Q1) and perceived AI tools as less complex (Q5). In contrast, non-tech participants reported greater self-distrust (Q2), found it more challenging to learn AI tools (Q3), and perceived these tools as more complex. These findings suggest that familiarity with technology may ease engagement with AI systems and reduce associated anxieties. Overall, a background in technology appears to support a more positive and manageable experience when interacting with AI in educational contexts (see Table 4).

Table 4: Findings by Technology (TEC) Behavior

Question	Tech (tec)	Non-Tech (no)	Difference
Q1 (Confidence)	3,38	3,21	Tech is slightly more confident.
Q2 (Distrust Ability)	4,96	5,15	Non-tech shows more distrust.
Q3 (Difficulty Learning)	4,86	5,05	Non-tech people find it more challenging.
Q4 (General Confidence)	3,38	3,21	Tech higher again
Q5 (Complexity)	4,95	5,16	Non-tech finds AI more complex.

4. CONCLUSION

Successfully integrating artificial intelligence (AI) into education requires more than merely adopting digital tools. It demands a thoughtful, multidimensional approach that encompasses curriculum reform, innovative assessment methods, continuous teacher development, and a shift toward personalized, student-centered learning. Educators must feel supported not only technically but also emotionally as they navigate this transformation.

Professional development should be designed as an ongoing journey, giving educators the space and time to explore AI tools, share experiences with peers, and reflect on their learning. When teachers are encouraged to experiment in low-pressure settings, their confidence grows—not just in using technology but in reshaping pedagogy itself. Addressing emotional barriers, such as fear of failure or being replaced, is critical to fostering a culture where innovation can thrive. Curricula must also evolve to accommodate the dynamic nature of AI. Traditional content delivery methods often limit creativity and flexibility. In contrast, AI-enabled platforms can enhance the learning experience by supporting adaptive, interdisciplinary approaches and enabling educators to detect learning gaps in real-time. Curriculum design should therefore emphasize flexibility, critical thinking, and inquiry-based learning, aligning with how students engage with digital environments. Assessment practices, too, must shift. Static, one-time testing is no longer sufficient for capturing the full range of student competencies in AI-enhanced classrooms. Instead, continuous and formative assessment methods, supported by AI, can offer timely feedback, monitor progress, and personalize the learning journey for each student. These changes can lead to more meaningful evaluations that reflect both effort and understanding. Personalized learning is one of the most transformative promises of AI in education. By analyzing data on student behavior, preferences, and performance, AI systems can offer differentiated content and pacing that better serve individual needs. This level of customization helps dismantle the one-size-fits-all model, creating more inclusive learning environments. However, personalization must be implemented ethically, with a clear commitment to privacy, equity, and transparency.

School leaders and policymakers have a vital role to play. Implementing AI effectively requires long-term vision grounded in established theoretical models. The Technology Acceptance Model highlights the importance of perceived usefulness and ease of use (Davis, 1989), while the Concerns-Based Adoption Model (Hall & Hord, 1987) reminds us that resistance to change is natural and can be overcome through sustained support. Providing educators with not just tools, but ongoing guidance and collaborative communities, is key to building confidence and long-term success. At the heart of all these efforts lies a cultural shift. A forward-looking educational system must embrace discomfort and recognize it as a necessary part of innovation. As Brown (2012) argues, vulnerability is not a weakness—it is the starting point for creativity and meaningful progress. When teachers engage with AI despite uncertainty, they not only grow professionally but also model adaptability and courage for their students.

The fear of AI should not be viewed as an obstacle, but rather as a powerful entry point for transformation. As Senge (1990) explains, learning emerges when individuals question their assumptions and stretch beyond familiar boundaries. Institutions must therefore cultivate environments that support experimentation, dialogue, and emotional resilience. By doing so, educators are more likely to become proactive, confident participants in shaping the future of teaching and learning through AI. In this light, fear of AI becomes not a barrier, but a catalyst for deeper engagement with digital innovation in education.

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