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Can Artificial Intelligence Give a Hand to Open and Distributed Learning? A Probe into the State of Undergraduate Students' Academic Emotions and Test Anxiety in Learning via ChatGPT

Sha Gao
Zhejiang Industry & Trade Vocational College, Wenzhou 325003, China

Abstract

Artificial Intelligence (AI), as an innovation in technology, has greatly affected human life. AI applications such as ChatGPT have been used in different fields, particularly education. However, the use of AI applications to enhance undergraduate students' academic emotions and test anxiety has not been appropriately investigated. This study addresses the effects of undergraduate students' test anxiety and academic emotions. A total of 160 undergraduate students majoring in different fields of study were selected through convenience sampling and divided into control and experimental groups. Both groups received test anxiety and academic emotions scales at the onset of the treatment. The students assigned to the experimental group were trained to use ChatGPT and monitored for learning and doing their assignments outside the classroom during the semester. The two groups received the scales at the end of the semester, which lasted 16 weeks. Independent samples *t*-tests were used for analyzing the data. Results revealed that using AI-empowered applications significantly reduced the students' test anxiety and negative academic emotions but enhanced their positive academic emotions. Students can use ChatGPT as an auxiliary instrument to overcome their negative emotions and enhance their educational attainment. Findings affect teachers, educational technologists, educational psychologists, and students.

Keywords: AI-empowered applications, undergraduate students, academic emotions, test anxiety

Introduction

Distance learning has rapidly expanded in a short period due to the power of the Internet and high-speed communication. This expansion has been fueled by the shift to using smartphones, virtual reality, and augmented reality as tools for advancing blended learning structures (Clark, 2020). Virtual education, a paradigm of distance learning, has reached significant development levels nationally and internationally. The Ministry of National Education in Colombia defines virtual education as a teaching method that overcomes spatial and temporal constraints (Ngah et al., 2022).

According to this model, scientific activity is related to the teacher and involves the student. Virtual education transfers information in virtual classrooms and continuously supports the production and reproduction of information, contributing to knowledge generation (Dhir et al., 2017). Virtual education can be said to refer to a method of education where the teacher and student are separated from each other in terms of time, place, or both, unlike traditional methods presented in face-to-face classrooms, laboratories, etc. (Roa et al., 2022]).

Virtual learning generally refers to education in a learning environment where the teacher and student are separated by time, place, or both. The content of these courses is transmitted through information technology programs, multimedia resources, the Internet, video conferences, and so on (Dung, 2020). According to Garrison et al. (2003), virtual education occurs over a network via an Internet environment within a formal structure; a set of multimedia technologies is used in its creation. Johnson et al. (2023) stated that virtual education employs network technology to design, select, manage, and expand education. Khan (2003) viewed virtual learning as an innovative approach that uses Web facilities to provide education remotely. Virtual learning is not just about delivering educational content; it focuses on the learning process and knowledge generation, making use of information technology and computers to create learning experiences (Horton, 2006).

In the context of open and distributed learning (ODL), the proliferation of virtual education platforms and technologies has reshaped the landscape of education so that it transcends traditional boundaries of time and space (Blake, 2009). ODL, characterized by its flexibility and accessibility, has become increasingly synonymous with virtual education, offering learners opportunities to engage with educational content remotely (Rumble, 1989). Leveraging advancements in information and communication technologies, ODL environments enable students to access resources, interact with instructors, and collaborate with peers regardless of geographical constraints (Fleming & Hiple, 2004). As such, the integration of artificial intelligence (AI) into these platforms holds immense potential to further enhance the efficacy and inclusivity of ODL experiences.

The expansion of virtual space has had extensive effects on human life. Nowadays, one distressing factor for students is exam anxiety, a common phenomenon in schools (Yazdani & Asadi, 2022). Piroozmanesh and Imanipour (2018) described *anxiety* as a widespread, unpleasant, and ambiguous feeling of fear and apprehension with an unknown origin that puts individuals in a state of agitation and stress in related circumstances. It includes uncertainty, indecision, and physiological arousal, affecting individuals' mental well-being (Salmalian et al., 2020).

Exam anxiety is considered a significant inhibitory factor in successful assessment and learning for students, imposing substantial costs on societies (King et al., 1991; Lufi & Awwad, 2013). Moreover, it is one of the most prominent psychological issues among students, consistently emphasized by various theorists and researchers. Exam anxiety has been studied extensively since the early 20th century and has always been a severe issue in the field of education. Exam anxiety is a psychological reaction to an evaluative situation that leaves individuals doubtful and reduces their coping abilities in that situation (Basaknezhad et al., 2013). It results from cognitive and physiological responses triggered in testing situations or similar evaluative conditions (Ghafourian et al., 2020).

The second area that national technology, particularly distance learning, might affect is academic emotions. As a critical determinant of university students' access to social and economic opportunities, students' academic achievement depends on many cognitive, affective, and educational variables. Therefore, identifying the main factors that promote and correlate with academic achievement is necessary (Hayat et al., 2018). Different factors affect students' performance in educational contexts (Yavorsky, 2017), including academic emotions related to motivational, cognitive, physiological, and behavioral processes (Pekrun et al., 2011). Pekrun's (2006) control-value theory provides researchers with a comprehensive framework to study the impacts of different emotions that students experience in academic contexts. This theory assumes that expectancy-value theories of transactional approaches, attributional theories, and performance models affect students' emotions and achievement. Different emotions, particularly academic emotions, are also believed to be associated with students' academic outcomes (Talib & Sansgiry, 2012). Yu and Dong (2010) maintained that students' academic emotions affect their academic achievements, manifested while doing daily homework, learning in classrooms, and taking exams. Researchers have classified academic emotions in different ways. However, the most commonly used typology of academic emotions reveals that positive and negative emotions are either activating or deactivating; that is, there are positive/negative activating emotions and positive/negative deactivating emotions.

This study holds significance in contributing to the existing body of knowledge by shedding light on the specific relationship between AI-empowered technology educational applications (apps) and undergraduate students' academic emotions and test anxiety. The findings of this research have practical implications for educators, app developers, and policymakers in shaping the future of AI in education. A comprehensive understanding of how these technologies impact students' emotional well-being can guide the development of better tailored and more effective educational tools. Additionally, insights from this study can inform strategies to create a supportive learning environment, ultimately enhancing the overall educational experience for undergraduate students. Although undergraduate students' test anxiety and academic emotions have been studied in different ways, the effect of AI-empowered educational applications on undergraduate Chinese students' test anxiety and academic emotions has not been well explored. To fill in the gap, the following research questions were raised:

1. Does undergraduate students' use of AI-empowered educational applications significantly affect their test anxiety?

2. Does undergraduate students' use of AI-empowered educational applications significantly affect their academic emotions?

Literature Review

Open and Distributed Learning

ODL constitutes a multifaceted educational paradigm characterized by its use of technology to extend learning opportunities beyond traditional classroom confines. Central to ODL is the concept of "openness," advocating for unrestricted access to educational resources and materials (Bates, 2015). This approach aims to democratize education by removing barriers such as geographical, temporal, and socioeconomic constraints, thereby fostering inclusivity and equity in learning (Bates, 1997).

In ODL, the theoretical framework of distributed learning plays a pivotal role. Distributed learning emphasizes the dispersion of learning activities across various modalities, platforms, and contexts (Siemens, 2005). It recognizes the dynamic interplay between formal and informal learning environments, acknowledging that learning occurs not only within structured educational settings but also through interactions with peers and mentors and through real-world experiences (Anderson, 2016). By embracing the principles of distributed learning, ODL endeavors to create interconnected learning ecosystems that facilitate seamless navigation between different learning environments and modalities, promoting lifelong learning and adaptability in the digital age (Bozkurt et al., 2015).

AI and Higher Education

Twenty-first-century higher education is rapidly changing due to globalization, technological advancements, and student demographics (Dieguez et al., 2021). Online learning platforms have become widely accessible, enabling universities to offer fully online courses and degree programs, expanding access to education, and providing flexibility in learning (Neumann & Baumann, 2021). The growing diversity of the educational field, with students from various backgrounds, highlights the significance of global citizenship and intercultural understanding. Universities play a significant role in promoting innovation and research as technological advancements speed up (Amornkitpinyo et al., 2021), encouraging industry–academia cooperation and focusing on commercialization and entrepreneurship. The emphasis is shifting toward skills-based learning patterns for practical, career-focused skills, as evidenced by recent recruitment trends favoring graduates with particular skills (Koçak et al., 2021).

To enhance the quality of higher education, the industry is exploring various strategies to meet stakeholders' requirements (Khan et al., 2022). AI integration is one particularly hopeful solution (Chedrawi et al., 2019). As technology advances, AI in education has enormous potential to change the teaching and learning environment (Bahado-Singh et al., 2019). AI is significantly improving the quality of higher education in several ways (Ali & Choi, 2020). AI-powered learning strategies evaluate students' performance, pinpoint their advantages and disadvantages and offer individualized learning experiences. With the help of these strategies, students can acquire knowledge and produce more valuable results in the real world (Aldosari, 2020).

Chatbots, virtual assistants, and adaptive learning systems are examples of AI-based technologies that provide immersive and exciting learning environments while enabling students to actively investigate complicated ideas (Chaudhry et al., 2023; Pradana et al., 2023). AI helps with assessment and feedback in grading assignments, tracking student participation, giving quicker and more accurate feedback, and freeing up teachers' time for other teaching responsibilities (Essien et al., 2020). AI chatbots provide quick, individualized support by evaluating student data to identify individuals who may be at risk of academic failure and enabling early interventions for academic success. Various AI apps and platforms, including Bit.ai, Mendeley, Turnitin, elink.io, and Coursera are tools that support higher education research by analyzing large datasets, generating insights, and identifying patterns challenging for human researchers to detect (Wenge, 2021). We expect even more cutting-edge AI applications to emerge in education due to continued technological advancement, giving students individualized, engaging, and productive learning experiences (Li et al., 2021).

The exciting development of AI dramatically improves both the effectiveness and engagement of instructors in postsecondary education. Adopting AI helps educators free up time for more meaningful activities by automating administrative duties like tracking attendance and grading assignments (Bisen et al., 2021). Additionally, AI allows educators to pinpoint areas in which they can grow by offering individualized opportunities for professional development (Minkevics & Kampars, 2021). Solutions are needed for enduring problems in modern higher education, such as limited inclusivity and unequal access (Odhiambo, 2016). Traditional teaching methods hinder active participation and critical thinking skills (Kistyanto et al., 2022). The inability of traditional assessment techniques to capture thorough understanding makes using AI necessary. AI algorithms analyze individual learning patterns, tailor coursework, and predict at-risk students, enabling timely interventions (Rudolph et al., 2023). Content delivery is revolutionized by AI-driven systems that adjust to students' learning styles, pace, and knowledge gaps.

Adopting AI in higher education empowers the system by addressing challenges and enhancing the quality of education. Ongoing research aims to understand faculty members' awareness of AI's applicability and impact on learning experiences, work engagement, and productivity in higher education. This research provides insights for institutional policymakers to facilitate the adoption of new technologies and overcome specific challenges. Despite the increasing integration of technology and AI in education, there is a notable gap in understanding how AI-powered educational apps specifically influence the academic emotions and test anxiety of undergraduate students. While various studies have explored the general impact of technology on education and student emotions, focused research on the unique effects of AI-powered educational apps is needed. Understanding the dynamics between these technologies and students' emotional experiences can provide valuable insights into the efficacy of AI app in promoting positive emotions and reducing test anxiety.

Studies on Academic Emotions

Lei and Cui (2016) defined *academic emotions* as "students' emotional experiences related to the academic processes of teaching and learning, including enjoyment, hopelessness, boredom, anxiety, anger, and pride" (p. 1541). Based on arousal and enjoyment concepts, academic emotions have been divided into three categories: positive low arousal, negative low arousal, and negative high arousal (Artino & Jones, 2012). It is also argued that achievement emotions include prospective emotions, such as fear of failure, and retrospective emotions, such as shame, which learners experience after they receive feedback on their achievements (Pekrun et al., 2017).

Academic accomplishment serves as a commonly employed criterion for evaluating the effectiveness of educational systems, teachers, schools, and the success or failure of students. Consequently, scholars in this field have conducted empirical investigations to explore the causal link between students' academic emotions and academic achievements, as evidenced by a body of practical studies (Cocoradă, 2016; Kim & Hodges, 2012). However, the findings from these studies have been inconsistent. In general, positive emotions are anticipated to forecast favorable outcomes in academic settings, including high grades and commendable performance in both local and large-scale educational assessments (Villavicencio & Bernardo, 2013). Conversely, it is hypothesized that negative emotions will correlate with adverse consequences, such as lower grades and compromised performance in classroom activities and standardized examinations (Shen et al., 2023; Villavicencio, 2011).

Results of the meta-analysis undertaken by Lei and Cui (2016) showed support for Dong and Yu's (2010) Chinese version of the Academic Emotions Questionnaire, which was employed to evaluate the academic emotions of adolescents. Academic emotions have been linked to various variables, including cognitive activity, learning motivation, and strategies. Lei and Cui's (2016) meta-analysis revealed positive correlations between positive high arousal, positive low arousal, and academic achievement and negative correlations between negative high arousal, negative low arousal, and academic achievement. The study suggested that factors such as a student's age, regional location, and gender could moderate the effects of epistemic cognition on academic achievement.

Positive correlations have been shown between positive high arousal, positive low arousal, and academic achievement and negative correlations between negative high arousal, negative low arousal, and academic achievement.

Currently, scholars, both domestically and internationally, are directing their attention toward analyzing academic emotions in distance learners, resulting in noteworthy research outcomes (Pekrun, 2006). Cerniglia et al (2021) delved into the impact of screen time on emotion regulation and student performance. The study involved over 400 children over 4 years of age, examining their use of smartphones and tablets. The research analyzed the correlation between these behaviors, emotions, and academic performance, concurrently evaluating students' abilities and academic achievements. Similarly, Schlesier et al (2019) investigated the influence of early childhood emotions on academic preparation and social-emotional issues. Emotion regulation, the process of managing emotional arousal and expression, is crucial in determining children's adaptation to the school environment.

Moreover, Chen and Li (2012) integrated connectionist learning theory to devise an innovative distance education model. This model introduced educational content aligned with emotional education objectives and implemented the Mu class teaching mode, establishing a distance learning community and humanized network courses to address emotional shortcomings in the distance education process. Ensuring effectiveness, Pekrun et al. (2017) developed a hybrid virtual reality intelligent classroom system, incorporating television broadcasting and interactive space technology, to create a networked teaching environment. Teachers used diverse media, including video, audio, and text, to foster engagement and enhance communication between educators and students during the network teaching phase.

Artino and Jones (2012) introduced an emotion recognition algorithm based on facial expression scale-invariant feature transformation. This algorithm captures the facial expressions of distance learners, employing Scale Invariant Feature Transform (SIFT) feature extraction and expression recognition to address emotional gaps in the learning phase of distance education. Simultaneously, Turner and Schallert (2001) developed a learner emotion prediction model for an intelligent learning environment using a fuzzy cognitive map. This model facilitates extracting and predicting distance learners' emotional states, allowing real-time adjustments to the teaching approach based on anticipated emotions. Wang and Che (2005) contributed to the field by introducing the Distance Learner Emotion Self-Assessment scale, defining essential emotion variables, and establishing a distance learner emotion early warning model.

Drawing inspiration from the valuable contributions of the scholars mentioned earlier, Zembylas and McGlynn (2012) examined the academic emotions experienced by adults in online education. This investigation involved analyzing diverse influencing factors and exploring an environmental factor model within the online learning community, specifically focusing on academic emotional tendencies.

Building upon the insights derived from these scholars, our objective was to delve into the academic emotions of distance learners. To do this, we analyzed online learning behavior data to uncover meaningful findings in this domain.

Methodology

Sampling and Procedure

A cohort of 180 undergraduate students from y Zhejiang Industry & Trade Vocational College in China was randomly chosen during the second semester of 2023. The students' majors ranged from engineering and humanities to social sciences and law. The primary goals at the study's outset were to assess test anxiety and academic emotions. Following that, 80 students were randomly selected to participate in a 4-hour workshop covering the use of an AI-powered app (ChatGPT) in education. The participants ranged in age from 20 to 30, with a mean age of 24 (SD = 3.12). Interestingly, 25% of the students were over 27, 25% were between the ages of 22 and 27, and 50% were between 20 and 22. Over 16 weeks, this intervention group was closely observed via weekly Skype sessions to record and monitor their interactions with ChatGPT. Additionally, they were instructed to work on their homework and assignments using ChatGPT. The remaining 100 pupils were in the control group and did not receive special assistance. Scales measuring test anxiety and academic emotions were given to all 180 participants 2 weeks before the term final exams; 160 completed questionnaires were returned at the end of the study, resulting in a large dataset that could be analyzed. Statistical tests such as t-tests were used to identify significant differences between the control group and the experimental group receiving AI training. It is acknowledged that all ethical requirements were met, guaranteeing that the study complied with regulations about informed consent, confidentiality, and withdrawal rights.

Instruments

The researcher used the Westside Test Anxiety Scale, created by O'Driscoll and McAleese (2023), containing 10 items, to measure test anxiety. Participants chose answers using a 5-point Likert-type scale, with scores ranging from 1 to 5. The internal consistency of this scale was robust, with a Cronbach's alpha of 0.856, a mean of 32.5, and a standard deviation of 3.25. Pekrun (2006) developed and validated the Academic Emotion Questionnaires (AEQ) to assess academic emotions. The AEQ, which consists of 75 statements and 8 different emotions, was scored using a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree). These feelings had both positive and negative aspects. Among the positive feelings were joy (9 items), hope (5 items), and pride (8 items). Anger (10 points), boredom (11 points), shame (11 points), fear (11 points), and hopelessness (10 points) were the negative emotions. The eight categories of academic emotion in the current study had Cronbach's alpha coefficients ranging from 0.82 to 0.89, suggesting a high degree of internal consistency.

Data Analysis

Data were analyzed in different ways. First, descriptive statistics were estimated, including means and standard deviations for all pretests and the posttest. Then, the groups' scores on all variables were submitted to different independent samples *t*-tests. Moreover, Cohen's *d* for each *t*-test was calculated to determine the effect size for the treatment.

Results

Research Question 1

The first research question investigated the effect of AI-empowered educational applications on undergraduate students' test anxiety. The results of independent samples *t*-tests showed that the groups' mean scores on the test anxiety at the onset of the study were not statistically significant. Still, they had different test anxiety at the end of the semester. Results are presented in Table 1.

Table 1

Groups' Test Anxiety Before and After Treatment

Test group		Descriptive statistics		*t*-test			
		M	*SD*	*t*	*df*	*p*	Effect size
Pretest	Control group	32.5	3.25	1.29	158	.52	0.079
	Experimental group	32.23	3.56				
Posttest	Control group	31.26	2.89	16.26	158	.001	1.24
	Experimental group	27.25	3.5				

As seen in Table 1, the difference between the control group (M = 32.5, SD = 3.25) and experimental group (M = 32.23, SD = 3.56) on the pretest was not statistically significant (t = 1.29, df = 158, p = .52, d = 0.079). This suggests that at the onset of the study, the two groups had comparable levels of test anxiety. However, in contrast, the posttest results revealed a notable distinction between the control group (M = 31.26, SD = 2.89) and the experimental group (M = 27.25, SD = 3.5). The t-test for the posttest demonstrated a highly significant difference between the groups (t = 16.26, df = 158, p < .001, d = 1.24), indicating that the experimental intervention had a substantial impact on reducing test anxiety in the experimental group compared with the control group.

Research Question 2

The group's scores on the academic emotions test administered before and after the treatment are presented as follows.

As shown in Table 2, the mean scores of the control and experimental groups' scores on all academic emotions are similar. The results of independent sample t-tests verified that the differences between the groups' scores on all emotions were not statistically significant (p > .05).

Table 2

Groups' Academic Emotions Scores Before Treatment

Emotion group		Descriptive statistics		*t*-test			
		M	*SD*	*t*	*df*	*p*	Effect size
Enjoyment	Control group	3.71	0.60	1.29	158	.52	0.079
	Experimental group	3.62	0.56				
Hope	Control group	3.50	0.45	0.96	158	.46	0.054
	Experimental group	3.48	0.46				
Pride	Control group	3.30	0.62	0.83	158	.33	0.063
	Experimental group	3.33	0.58				
Anger	Control group	2.50	0.40	0.87	158	.29	0.058
	Experimental group	2.53	0.39				
Anxiety	Control group	2.60	0.54	1.12	158	.16	0.061
	Experimental group	2.63	0.53				
Hopelessness	Control group	2.56	0.46	1.23	158	.42	0.042
	Experimental group	2.60	0.39				
Shame	Control group	2.80	0.42	1.32	158	.36	0.08
	Experimental group	2.78	0.52				
Boredom	Control group	2.62	0.40	0.98	158	.41	0.06
	Experimental group	2.58	0.38				

In addition, the groups' scores on the academic emotions administered after the treatment were compared through independent samples t-tests. Results are presented in Table 3.

Table 3

Groups' Academic Emotions Scores After Treatment

Emotion group		Descriptive statistics		***t*-test**			
		M	*SD*	*t*	*df*	*p*	Effect size
Enjoyment	Control group	3.61	0.50	1.29	158	.001	1.53
	Experimental group	4.25	0.32				
Hope	Control group	3.60	0.40	0.96	158	.001	1.69
	Experimental group	4.20	0.30				
Pride	Control group	3.33	0.52	0.83	158	.001	1.87
	Experimental group	4.10	0.26				
Anger	Control group	2.50	0.44	0.87	158	.001	1.24
	Experimental group	1.78	0.56				
Anxiety	Control group	2.40	0.63	1.12	158	.001	1.36
	Experimental group	1.80	0.53				
Hopelessness	Control group	2.43	0.46	1.23	158	.001	1.40
	Experimental group	1.80	0.39				
Shame	Control group	2.60	0.42	1.32	158	.001	1.60
	Experimental group	2.00	0.52				
Boredom	Control group	2.52	0.40	0.98	158	.001	1.57
	Experimental group	21.90	0.38				

As seen in Table 3, the difference between the control group (M = 3.61, SD = 0.50) and the experimental group (M = 4.25, SD = 0.32) in enjoyment is statistically significant (t = 1.29, df = 158, p = .001, d = 1.53). Implementing the AI-empowered application had a substantial positive impact on the level of enjoyment experienced by the experimental group. Likewise, for hope, the observed difference between the control group (M = 3.60, SD =0.40) and the experimental group (M = 4.20, SD = 0.30) was statistically significant (t = 0.96, df = 158, p = .001, d = 1.69), underscoring the substantial improvement in hope facilitated by the AI-empowered application. A noteworthy difference was found in pride between the control group (M = 3.33, SD = 0.52) and the experimental group (M = 4.10, SD = 0.26) that was statistically significant (t = 0.83, df = 158, p = .001, d = 1.87), signifying the considerable enhancement in pride resulting from the experimental treatment. Moreover, the differences in anger (t = 0.87, df = 158, p = .001, d = 1.24), anxiety (t = 1.12, df = 158, p = .001, d = 1.36), hopelessness (t = 1.23, df = 158, p = .001, d = 1.40), shame (t = 1.32, df = 158, p = .001, d = 1.60), and boredom (t = 0.98, df = 158, p = .001, d = 1.57) all highlight statistically significant reductions in emotional states for the experimental group compared with the control group.

Discussion and Conclusion

The results indicate a significant reduction in test anxiety among undergraduate students after using an AI-powered educational app. At the start of the study, the first analysis revealed no statistically significant differences in test anxiety scores between the experimental and control groups. By the end of the semester, though, there was a noticeable difference in the two groups' test anxiety levels, with the experimental group reporting significantly lower test anxiety than the control group. This observed decrease in test anxiety among the experimental group aligns with existing research highlighting the potential benefits of incorporating AI and technology in educational settings. Kim and Hodges (2012) investigated the effects of an emotional control treatment on academic emotions, motivation, and achievement in an online mathematics course, emphasizing the interconnectedness of emotions and learning outcomes. Similarly, Ghafourian et al. (2020) used brain signal analysis to assess exam anxiety in healthy individuals, providing insight into possible physiological components of anxiety.

According to a review of the literature on AI in education found in several sources, including Picard and Healey's (1997) groundbreaking work on affective computing, technology can be used to personalize learning, adjust to the needs of each student, and improve overall engagement—all of which may help lower anxiety. Additionally, Wang et al. (2015) investigated how students' emotional experiences in computer-based learning environments are influenced by their cognitive-affective states, offering insights into how technology shapes students' learning experiences.

Another study by D'Mello and Graesser (2012) on the dynamics of affective states during complex learning lends credence to the idea that technology—including AI—can significantly impact how students feel about themselves. Furthermore, Calvo and D'Mello (2010) provided an interdisciplinary viewpoint on affect detection, which is pertinent when talking about how AI affects students' emotional states in learning environments.

Conversely, it is imperative to recognize that the present investigation may not be in direct accordance with all cited sources. Some references might not specifically address AI interventions, instead concentrating on other facets of technology in education or the study of emotions. Additionally, since the field is developing, more recent sources—like the instructional technology research of Moreno and Mayer (2005)—may present differing viewpoints regarding the efficacy of AI applications in lowering test anxiety.

The study's findings also show that AI-powered educational apps have a complex effect on students' emotional experiences, affecting positive and negative academic emotions. According to the findings, positive academic emotions including hope, pride, and enjoyment have significantly improved, and negative academic emotions like anxiety, shame, helplessness, anger, and boredom have decreased considerably. These outcomes align with existing research that underscores the potential of technology, including AI, to positively influence students' emotional states in educational settings.

Kim and Hodges (2012) underscored the interplay between emotions and learning outcomes by investigating the impact of an emotion control intervention on academic emotions, motivation, and achievement in an online mathematics course. Similarly, Ghafourian et al. (2020) advanced our understanding of emotional experiences in academic contexts through their analysis of exam anxiety via brain signals, revealing potential physiological components of anxiety.

As articulated by Picard and Healey (1997), the literature on affective computing provides a theoretical framework for understanding how technology can detect and respond to human emotions. This framework emphasizes the importance of considering affective dimensions in the learning process and can inform discussions on AI in education. Additionally, Baker et al. (2010) examined cognitive-affective states during interactions with computer-based learning environments, offering insights into how technology influences students' emotional experiences during the learning process. D'Mello and Graesser (2012) further supported the notion that technology, including AI, can significantly affect students' self-perceptions through their study on the dynamics of affective states during complex learning.

Calvo and D'Mello's (2010) review article provided an interdisciplinary perspective on affect detection, highlighting the relevance of technology in understanding and addressing emotional states in educational settings. The overarching goal of fostering a positive and supportive learning environment aligns with the observed reduction in negative academic emotions such as anxiety, shame, helplessness, anger, and boredom.

The literature reviewed, including the study by Pekrun (2006) on the control-value theory of achievement emotions, emphasizes the importance of addressing negative emotions to enhance overall academic performance and well-being.

The findings of this study resonate strongly with the principles of ODL, which seeks to employ technology to extend learning opportunities beyond traditional classroom boundaries, thereby democratizing education and promoting inclusivity and equity (Bates, 2015). The observed reduction in test anxiety among undergraduate students using AI-powered educational apps aligns with the essence of ODL, as it demonstrates how technology can remove barriers such as geographical, temporal, and socioeconomic constraints, making learning more accessible and accommodating diverse learner needs. Furthermore, the study's emphasis on the dynamic interplay between formal and informal learning environments and the promotion of lifelong learning and adaptability through distributed learning principles mirrors the approach taken in implementing AI-powered interventions to enhance students' emotional experiences and learning outcomes. Thus, the study's findings underscore the transformative potential of ODL paradigms facilitated by technology in promoting positive educational experiences and outcomes.

The implications of this study hold significant value for language teachers, developers of educational materials, and policymakers alike. For language teachers, the findings emphasize the potential of AI-powered educational applications in mitigating test anxiety and fostering positive academic emotions among undergraduate students. Integrating such technologies into language-learning environments can create more supportive and engaging settings conducive to enhanced learning outcomes. Materials developers can leverage these findings to design and adapt educational materials that incorporate AI-driven interventions, catering to diverse learner needs and promoting a more inclusive and effective learning experience. Policymakers can use this research to inform decisions regarding the integration of technology in education and the allocation of resources to support the development and implementation of AI-powered educational tools. By recognizing the benefits demonstrated in this study, language teachers, materials developers, and policymakers can collaborate to harness the potential of AI in education, ultimately improving the quality and accessibility of language-learning experiences.

To conclude, the results of this study align with the broader body of research indicating the possibility for AI-driven educational interventions to positively impact students' emotional experiences, particularly in terms of lowering exam anxiety. Nonetheless, it is critical to consider each study's unique characteristics, approaches, and settings in addition to recent developments in this dynamic field of study. Future studies should examine the complex implications of AI in the classroom and how it affects students' emotional health. Further investigation into the complex impacts of AI in education and its capacity to promote a healthy emotional environment is also necessary to improve learning outcomes and student well-being.

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