AIlessphobia in Education among University Students: Prevalence and Associations with Deep and Surface Learning Approaches

OPEN PRAXIS

RESEARCH ARTICLES

INTERNATIONAL COUNCIL FOR OPEN AND DISTANCE EDUCATION

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ABSTRACT

The rapid integration of generative artificial intelligence (GenAI) tools into higher education has created new learning affordances, but it may also relate to AIlessphobia in education, defined as anxiety and a lack of academic confidence experienced when AI support is unavailable. This cross-sectional correlational research study examined university students' AIlessphobia in education and its relations with deep and surface learning approaches (and their subdimensions). Data were collected in the spring semester of 2025–2026 from 550 undergraduates at Trakya University using convenience sampling through an online survey; analyses were conducted with 467 students who reported using at least one AI tool. Participants completed the AIlessphobia in Education Scale (AILPES) and the Revised Two-Factor Study Process Questionnaire (R-SPQ-2F). The mean AIlessphobia in education score was 2.30; subscale means were 2.01 for Academic Self-Efficacy Anxiety and 2.67 for Lack of Academic Confidence Without AI. Pearson correlations indicated positive relations between AIlessphobia in education and both deep and surface learning approaches. In stepwise regression, surface motivation (a subdimension of the surface learning approach) showed the strongest standardized relation with AIlessphobia in education, and deep strategy (a subdimension of the deep learning approach) accounted for additional variance, with the final model explaining 11.1% of the variance. Overall, learning-approach dimensions, particularly surface-oriented motivation and deep strategic engagement, were related with AIlessphobia in education, highlighting the importance of supporting metacognitive regulation and balanced, responsible AI use in higher education.

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KEYWORDS:

Artificial intelligence; AIlessphobia; education; phobia; learning approaches; academic anxiety; university students; educational context; AI dependence; educational technology

TO CITE THIS ARTICLE:

Gezgin, D. M., Nurlu, O., Arapoğlu, Ç., & Demirelli, M. M. (2026). AIlessphobia in Education among University Students: Prevalence and Associations with Deep and Surface Learning Approaches. *Open Praxis*, *18*(3), pp. 428–440. DOI: https://doi.org/10.55982/openpraxis.18.3.1142

INTRODUCTION

Learning is a multifaceted process that leads to relatively permanent changes in an individual's behaviour and in the ways, they think, feel, and act; it has both affective and cognitive dimensions (Bransford et al., 2000; Singh et al., 2020). The teaching-learning process is considered a phenomenon that continues throughout an individual's entire life and exhibits continuity (Prakash et al., 2019). While the teaching methods and approaches adopted by educators are among the key factors determining the effectiveness of the learning process (Wijngaards-de Meij & Merx, 2018), the success of this process is also closely related to how the learner perceives and processes information. In this context, learning approaches are defined as dynamic structures shaped by instructional design and environmental variables rather than the learner's personality traits, which determine the form of the learner's participation in the learning process (Alias et al., 2025). In this structure, examined through the deep and surface learning approaches (Marton & Saljo, 1976), it is reported that students who adopt the deep learning approach focus on understanding fundamental principles, learning with intrinsic motivation, and integrating their existing knowledge with new concepts (Chan, 2003; Howie & Bagnall, 2013). In contrast, it is noted that students who adopt a surface learning approach tend to focus on memorisation strategies aimed at exam success rather than analysing information and require more external regulation (Ramsden, 2003). In addition to this dual classification, the strategic learning approach is considered an orientation with the primary motivation of academic success and the goal of achieving the highest possible grade (Ballantine et al., 2018; Entwistle et al., 2000). To the extent that it achieves high performance, this approach can include both surface and deep learning strategies (Hasnor et al., 2013), with deep learning often emerging as a by-product of academic success rather than the primary goal. Students who adopt a strategic approach are defined as individuals who carefully monitor assessment criteria, manage time and resources effectively, and have regular study habits (Entwistle & Peterson, 2004).

LITERATURE REVIEW

The learning approaches adopted by students are closely related to the ultimate goals of higher education. Developing university students' problem-solving and critical thinking skills (Dinsmore & Alexander, 2012), strengthening their lifelong learning orientation, and encouraging them in this direction are particularly important for higher education, especially in terms of the deep learning approach (Biggs & Tang, 2007; Dolmans et al., 2016).The role of technology in achieving these gains has become increasingly apparent over time. Technology can be defined as a set of tools that can create change in the way work is done or enable existing tasks to be performed more quickly and efficiently (Selwyn, 2021). The continuous use of technology can save time (Aloubade, 2022) and provide convenience for both students and educators in terms of adaptability to materials and needs (Maxwell, 2016). Technology offers educators diversity in terms of lessons, attendance, exam and grade tracking, and learning management systems, while also offering students free access at different times, access to online educational videos, and new opportunities that support self-learning (Aloubade, 2022). For example, it has been reported that e-books have a moderate effect on language learning compared to printed materials and support student success with their interactive features (Listanto et al., 2025). Furthermore, a meta-analysis has shown that generative artificial intelligence may have a small positive effect on students' learning goals; however, this effect may vary depending on variables such as the field of knowledge, intervention duration, and education level (Zhu et al., 2025).

Technology-Enhanced Learning refers to the strategic use of technology to achieve pedagogical objectives. In this context, the design of digital learning environments plays a decisive role in learners' cognitive load management (Xie, 2021), while the proliferation of internet-based reading and writing technologies in academic and social spheres has increasingly shifted learning processes to digital environments (Cifuentes et al., 2011; Liccardi et al., 2007). It is emphasised that the integration of digital technology into educational environments has the potential to transform learning outcomes; in particular, statistically significant and positive relationships can be found between deep learning and learning outcomes (Wu, 2024). Furthermore, it has been shown that deep learning can be further supported in hybrid applications where digital technology is used in conjunction with online or face-to-face environments (Wu, 2024).

However, students may not always find online tools effective, depending on their individual learning styles and preferences (Balakrishnan & Lay, 2016). It has been reported that students who develop a high level of dependence on teacher-centred learning processes may tend to consume the content superficially rather than internalising online platforms as a space for in-depth learning (Camarero et al., 2012). Similarly, it is stated that when digital interaction tools such as online discussion forums are not pedagogically structured correctly, student contributions may lack critical analysis and be limited to a simple transfer of information (Aderibigbe, 2021; Garrison et al., 2000).

The integration of artificial intelligence (AI) technologies into educational processes, particularly through generative AI (GenAI) tools and their functions such as learning enhancement, data analysis, content generation, and programme code development, has ushered in a new era in learning paradigms (Bozkurt, 2023; Chiu, 2024; Qin & Zhang, 2025; Yavuz et al., 2025). It has been reported that AI-based educational applications support students' self-regulated learning skills by offering personalised feedback mechanisms, thereby accelerating and enhancing deep learning (Jaldemark et al., 2025). It is noted that GenAI tools such as ChatGPT can enrich critical thinking and learning experiences by providing instant feedback and personalised support (Alemdag, 2025; Younas et al., 2025). In this context, tools such as ChatGPT and Gemini, which are widely used by students, are considered chat-based software that interacts with users using natural language (Karri & Kumar, 2020; Sağlam & Kalanlar, 2025). It has been reported that these tools can support motivation by offering personalised learning support and facilitating brainstorming and discussion processes; they can also enrich the learning experience by making access to information more practical (Gezgin, 2024; Schei et al., 2024). At the same time, recent studies have suggested that students may also use AI tools for speed, efficiency, and task completion under academic pressure, indicating that AI-supported learning may serve both supportive and performance-oriented functions (Ait Baha et al., 2024). However, multidisciplinary studies emphasise that AI should not be treated solely as a technical solution; it requires a comprehensive research agenda integrated with teaching and learning theories (Jaldemark et al., 2025). Similarly, Rasul et al. (2023) emphasised that the educational use of AI should be evaluated not only in terms of efficiency, but also in relation to process-oriented learning, assessment practices, and the preservation of meaningful student engagement. In summary, these tools are considered modern approaches that can support student performance and participation when used within appropriate pedagogical frameworks (Sawyer, 2022).

On the other hand, the comfort zone offered by AI may also carry the risk of developing excessive trust in technology and excessive dependence on technology among students (Jaldemark et al., 2025; Qin & Zhang, 2025). Indeed, the literature emphasises that the widespread and intensive use of digital technologies such as the internet and smartphones can be associated with various problematic patterns over time. In this context, the fear of being away from one's mobile phone is addressed by the concept of nomophobia (King et al., 2013), while the fear of not being able to access the internet or being without internet is addressed by the concept of netlessphobia (Kanbay et al., 2022). The fact that these technologies can fulfil functions such as 'feeling safe,' 'staying connected,' 'accessing information,' and 'feeling comfortable' for individuals can strengthen psychological attachment to these tools over time. This function-based psychological attachment is also consistent with earlier technology-related anxiety frameworks, which suggest that the emotional meanings attributed to digital tools may intensify discomfort when access is interrupted (Yıldırım & Kişioğlu, 2018). A similar dynamic has brought a new phenomenon to the fore with the widespread use of artificial intelligence technologies that facilitate life in both daily and academic contexts (Gezgin & Kurtça, 2025). In this context, the phenomenon of AIlessphobia in education, defined by panic, anxiety, and feelings of deprivation when AI tools are inaccessible in an educational setting, has been proposed in the literature (Gezgin & Kurtça, 2025). In literature, AIlessphobia in education is defined as the irrational fear, intense anxiety, and lack of academic self-confidence experienced when academic tasks cannot be performed without the support of artificial intelligence language models in educational processes (Gezgin & Kurtça, 2025).

This fear and the possible mechanism behind the feeling of 'AI deprivation' can be explained through the functional meaning students attribute to AI tools and the role these tools play in cognitive processes. The intensive and repetitive use of AI technologies in academic tasks may, over time, increase the search for external cognitive support; which is particularly associated with a risk of weakened effective use of cognitive skills such as problem solving, creative thinking, and critical analysis in students who use GenAI in every academic task (Gezgin & Kurtça, 2025; Zhai et al., 2024). Furthermore, Sağlam and Kalanlar (2025) emphasised that over-reliance on AI in fields involving direct human life applications, such as nursing, could create a risk framework leading to incorrect clinical decision-making and problems in patient care; in terms of educational processes, they stressed the need for serious research into AIlessphobia in the context of increasing surface tendencies in learning efforts. A study conducted by Gezgin (2025) with engineering students using AI tools in computer programming tasks also discussed that the learning process may become less 'productive' under certain conditions and may pose a risk of weakening the development of programming skills in the long term. Likewise, Özbay (2026) reported that academic self-efficacy, as a component associated with the deep learning approach, may be related to AIlessphobia in education; however, due to the cross-sectional nature of that study, it remained unclear whether this relationship reflected an adaptive or risk-enhancing student experience.

On the other hand, AI tools may reduce cognitive load and provide rapid access to ready information (Zhu et al., 2025). In this respect, they may facilitate the learning process, particularly for students who adopt a surface learning approach and require greater external regulation, while also serving as a personalised academic assistant for students who adopt a deep learning approach (Younas et al., 2025). However, among university students with high surface learning motivation, the rapid-response and ready-output features of AI may reinforce a more product-oriented and speed-centred approach to academic tasks. This may risk pushing the fundamental components of learning, such as comprehension, questioning, and deep processing, into the background. Nevertheless, stronger interpretations regarding whether learning approaches shift from deep to surface learning over time require longitudinal evidence. In addition, recent cross-cultural psychometric evidence from the Chinese version of the AIlessphobia in Education Scale (AILPES) suggests that AIlessphobia in education can be assessed reliably across different higher-education contexts (Xu et al., 2026). This finding indicates that AIlessphobia in education is not merely a context-specific issue but an emerging construct with broader academic relevance.

Considering the existing literature, AI tools appear to have the potential to both support and undermine learning processes, depending on the learner's orientation toward academic tasks. This makes deep and surface learning approaches a particularly relevant context for examining AIlessphobia in education. Understanding whether AIlessphobia in education is more closely associated with deep learning or surface learning is important, because such knowledge may help clarify whether students' reliance on AI reflects an adaptive form of academic support, a compensatory strategy, or a potential educational risk. Furthermore, although AIlessphobia in education is gaining broader scholarly attention, empirical research examining its relationship with learning approaches remains limited.

In this context, which learning approach (deep or surface) exhibits stronger relationships with AIlessphobia in education remains an insufficiently clarified research problem. Therefore, the aim of this study is to examine the relationship between the learning approaches adopted by university students and AIlessphobia in education. In this regard, the following research questions were addressed:

1. What is the level of AIlessphobia in education among university students?
2. Is there a relationship between AIlessphobia in education and learning approaches among university students?
3. Do learning approaches predict the levels of AIlessphobia in education among university students?

METHOD

This study employed a cross-sectional correlational research design to examine the relationships among variables without manipulation and to determine the degree and direction of associations among naturally occurring phenomena (Fraenkel et al., 2012). In this design, variables were measured as they existed at a single point in time, and cause-and-effect relationships were not inferred.

PARTICIPANTS

During the spring semester of 2025–2026, the study sample consisted of 550 undergraduate students from different faculties at Trakya University. The participants were selected using a convenience sampling method, based on accessibility and voluntary participation. The study excluded 83 participants who did not use any AI tools. Therefore, the study sample contains 467 university students. Participants ranged in age from 18 to 29 years (M = 21.88), including 298 females (63.8%) and 169 males (36.2%). Additionally, all students in the study stated that they had used any chatbot at least once. Demographic properties of the students were given in Table 1.

Table 1 Demographic characteristics of university students.

	N	%
Gender		
Female	298	63.8
Male	169	36.2
Year of study		
First year	33	7.1
Second year	56	12.0
Third year	199	42.6
Fourth year	179	38.3
Frequency of Chatbot Use		
Daily	67	14.3
Several times a week	174	37.3
Weekly	103	22.1
Once or twice a month	123	26.3
Chatbot Name		
ChatGPT	436	93.8
DeepSeek	3	0.6
Gemini	13	2.8
Others	15	2.8
Total	467	100.0

DATA COLLECTION TOOLS

Demographic information form, AIlessphobia in education scale and learning approaches scale were used in this study.

Demographic information

The demographic information form contains information about gender, age, year of study, GPA, frequency of chatbot use, and name of the chatbot used.

The AIlessphobia in Education Scale (AILPES)

The AILPES was developed by Gezgin and Kurtça (2025). The scale includes 18 Likert-type items, ranging from 1 (strongly disagree) to 5 (strongly agree). An example item from the scale is "I feel stronger academically with an AI-based language model". The scale has two subdimensions: Academic Self-efficacy Anxiety (10 items: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10) and Lack of Academic Confidence without AI (8 items: 11, 12, 13, 14, 15, 16, 17, 18). The total explained variance is 56.23%. The confirmatory factor analysis (CFA) indicates that the model fit indices are remarkable (χ^2/df = 2.25, CFI = .99, TLI = .99, NFI = .98, IFI = .99, SRMR = .049, RMSEA = .050, CI: 0.042–0.057). The scale shows high reliability: for the Academic Self-Efficacy Anxiety subscale, Cronbach's Alpha ranges from 0.925 to 0.935 and McDonald's Omega from 0.923 to 0.929; for the Lack of Academic Confidence without AI subscale, Alpha ranges from 0.847 to 0.877 and Omega from 0.850 to 0.879; and for the overall scale, Alpha ranges from 0.925 to 0.941 and Omega from 0.923 to 0.942. In this study, the Cronbach's alpha value for the entire scale was found to be .92, with Academic Self-Efficacy Anxiety subscale at .92 and Lack of Academic Confidence without AI subscale at .85.

The Revised Approaches to Learning Scale

The Revised Two-Factor Study Process Questionnaire (R-SPQ-2F; Biggs et al., 2001), originally developed by Biggs (1987) and subsequently revised by Biggs et al. (2001), was adapted into Turkish by Bati et al. (2010). An example item from the scale is "I find that at times studying gives me a feeling of deep personal satisfaction". The approaches to learning scale comprises two subdimensions: the deep learning approach (10 items: 1, 2, 5, 6, 9, 10, 13, 14, 17, 18) and the surface learning approach (10 items: 3, 4, 7, 8, 11, 12, 15, 16, 19, 20), along with two sub-dimensions that include two sub-determinants of these dimensions. The deep learning approach dimension comprises deep motivation (5 items: 1, 5, 9, 13, 17) and deep strategy (5 items: 2, 6, 10, 14, 18), whereas the surface learning approach encompasses surface motivation (5 items: 3, 7, 11, 15, 19) and surface strategy (5 items: 4, 8, 12, 16, 20) subscales. The Cronbach's alpha internal consistency coefficients for this study were .77 for the deep learning approach, .73 for the surface learning approach.

DATA COLLECTION AND ANALYSIS

In this study, participants were informed of the research's objective before its initiation, and data was collected voluntarily. The data collection was conducted through a Google-based survey created by the researchers and distributed to university students. The data collected was analysed via SPSS 27.0. Descriptive statistics, including minimum, maximum, mean, standard deviation, skewness, and kurtosis values, were calculated to summarize the characteristics of the study variables. Normality assumptions were evaluated based on skewness and kurtosis values, which were considered acceptable within the range of ±1.96 for large samples (Tabachnick et al., 2007). Following the descriptive analyses, bivariate associations among the study variables were examined using Pearson's correlation coefficients (r). The resulting correlation matrix was visualized as a heatmap using the Seaborn library in Python to facilitate interpretation of the direction and magnitude of the correlations. Finally, stepwise multiple regression analysis was performed to determine the significant predictors of AIlessphobia in education and to identify the relative contribution of independent variables to the explained variance. The statistical significance level was set at .05 for all analyses.

FINDINGS

Table 2 presents the descriptive statistics for the study variables. The mean scores were 2.30 for AIlessphobia in education and 2.01 for academic self-efficacy anxiety, whereas the mean score for lack of academic confidence without AI was 2.67. For learning approaches, the average scores were 3.12 for deep learning and 3.15 for surface learning. The subdimensions yielded mean values of 2.89 for deep motivation, 3.09 for deep strategy, 2.72 for surface motivation, and 3.04 for surface strategy. Standard deviations indicated adequate variability across all measures. Given that these scales do not provide established cut-off points, the results are reported descriptively without categorical labels. Skewness and kurtosis values for all variables fell within ±1, suggesting approximate normality; therefore, parametric statistical procedures were considered appropriate.

Table 2 Descriptive statistics.

SCALES	MIN	MAX	MEAN	STD. DEV.	SKEWNESS	KURTOSIS
AIlessphobia in education	1.00	4.39	2.30	.734	.261	–.598
Academic self-efficacy anxiety	1.00	4.30	2.01	.819	.550	–.751
Lack of academic confidence without AI	1.00	5.00	2.67	.864	.058	–.467
Deep learning approach	1.40	4.70	3.12	.599	.045	.135
Deep motivation	1.40	4.40	2.89	.531	.091	–.062
Deep strategy	1.20	5.00	3.09	.666	.040	.129
Surface learning approach	1.20	4.80	3.15	.635	–.033	.082
Surface motivation	1.00	4.60	2.72	.681	.053	–.087
Surface strategy	1.40	4.60	3.04	.606	–.068	–.026

The correlation matrix of the variables is presented in Figure 1. Pearson correlation analysis was conducted to examine the correlations among AIlessphobia in education and learning approach variables. AIlessphobia in education showed weak but statistically significant positive correlations with Deep Learning ($r = .116$, $p < .05$), Surface Learning ($r = .299$, $p < .01$), Deep Motivation ($r = .102$, $p < .05$), Deep Strategy ($r = .112$, $p < .05$), Surface Motivation ($r = .297$, $p < .01$), and Surface Strategy ($r = .230$, $p < .01$). A correlation coefficient ranging from 0 to 0.29 is considered low, correlations between 0.30 and 0.69 are considered moderate, and correlations between 0.70 and 1.00 are considered strong (Warner, 2008). Although the correlation coefficients in the present study fall within the low range according to Warner's (2008) criteria, their proximity to the .30 threshold suggests that the association between surface learning and AIlessphobia in education may be interpreted as being at the low-to-moderate boundary. The correlation matrix suggests that AIlessphobia in education demonstrates statistically significant relationships with both deep and surface learning approaches.

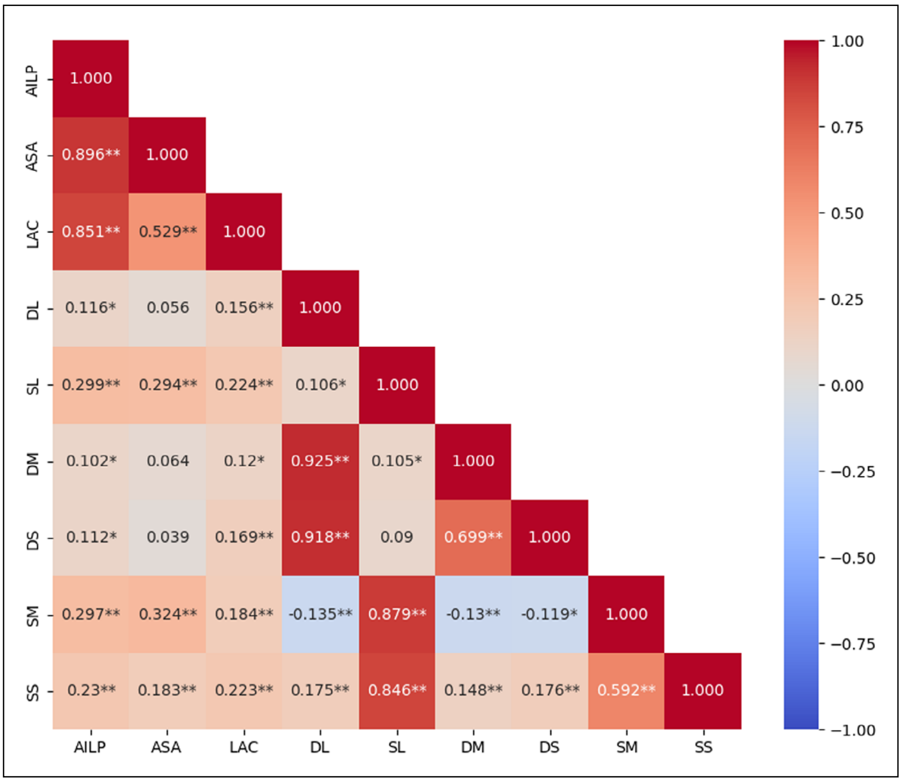

Figure 1 Correlation matrix.

Notes. AILP: AIlessphobia in education; ASA: Academic self-efficacy anxiety; LAC: Lack of academic confidence without AI; DL: Deep learning; SL: Surface learning; DM: Deep motivation; DS: Deep strategy; SM: Surface motivation; SS: Surface strategy. ** Indicates $p < .01$ and * Indicates $p < .05$.

STEPWISE REGRESSION ANALYSIS

The results of the stepwise regression analysis examining the predictors of AIlessphobia in education are presented in Table 3. In the first step, surface motivation was entered the model as a significant predictor. Surface motivation was found to positively and significantly predict AIlessphobia in education ($\beta = .297$, $t = 6.717$, $p < .001$). In the second step, deep strategy was added to the model and emerged as a statistically significant predictor ($\beta = .150$, $t = 3.396$, $p = .001$). In this final model, surface motivation remained the strongest predictor ($\beta = .315$, $t = 7.148$, $p < .001$), indicating that higher levels of surface motivation and deep strategy are associated with higher levels of AIlessphobia in education.

Table 3 Results of Stepwise Regression Analysis.

MODEL	VARIABLE	B	STANDARD ERROR	β	t	p	PART r	PARTIAL r	VIF
1	Constant	1.429	.134		10.673	.000			
	Surface motivation	.320	.048	.297	6.717	.000	.297	.297	1.000
2	Constant	.831	.220		3.767	.000			
	Surface motivation	.340	.047	.315	7.148	.000	.313	.315	1.014
	Deep strategy	.173	.051	.150	3.396	.001	.149	.156	1.014

The overall fit and explanatory power of the regression models are shown in Table 4. The first model explained 8.8% of the variance in AIlessphobia in education (R^2 = .088), and the model was statistically significant, F (1, 465) = 45.117, p < .001. The inclusion of deep strategy in the second model resulted in a significant increase in explained variance (ΔR^2 = .022, F change = 11.536, p = .001), raising the total explained variance to 11.1% (R^2 = .111; Adjusted R^2 = .107). The Durbin–Watson value (1.840) indicated that the assumption of independence of errors was met. Before executing the regression analysis, multicollinearity had been determined by Variance Inflation Factor (VIF) values. The analysis revealed that all VIF values were well below the threshold of 5, indicating that multicollinearity does not pose a threat to the validity of the regression model (Hair et al., 2011).

Table 4 Model Summary of Stepwise Regression Analysis.

MODEL	R	R^2	ADJUSTED R^2	R^2 CHANGE	F CHANGE	df1	df2	p	DURBIN-WATSON
1	.297	.088	.086	.088	45.117	1	465	.000	
2	.333	.111	.107	.022	11.536	1	464	.001	1.840

DISCUSSION

This study aimed to examine university students' levels of AIlessphobia in education and investigate the relationship between this phenomenon and their learning approaches. The findings show that the participants' average AIlessphobia in education score was 2.30, with academic self-efficacy anxiety at 2.01 and academic confidence deficiency without artificial intelligence language model support at 2.67 in terms of sub-dimensions. When the subscale averages of the AIlessphobia in education scale are evaluated together, it is seen that students exhibit a pattern of being more prone to experiencing academic confidence deficiency without AI support. Supporting the findings of this study, a similar finding was reported in a study conducted by Gezgin (2025) with 133 students studying at the faculty of engineering. These findings can be interpreted in line with findings that AI applications facilitate learning processes by providing personalised support (Jaldemark et al., 2025) and suggest that they can play a functional facilitating role for students by saving time (Aloubade, 2022). Furthermore, the fact that students use these tools not only as an auxiliary resource but sometimes as an external memory to externalise their cognitive processes can be associated with reduced cognitive load and cognitive externalisation strategies (Zhu et al., 2025). In contrast, the perceived lack of academic confidence in the absence of AI presents a pattern that may be conceptually parallel to technology-based anxieties such as nomophobia and netlessphobia. The finding that feelings of anxiety and unease experienced in the absence of the internet or smartphones can increase the orientation towards digital tools (Yıldırım & Kişioğlu, 2018) suggests that a similar mechanism could be discussed in the use of AI in an educational context. In the literature, this situation is addressed in the context of irrational beliefs and anxieties that students will not be able to continue their academic tasks without AI support (Gezgin & Kurtça, 2025). However, whether this experience is more of a situational response or a more persistent tendency should be empirically tested in the future, considering different types of anxiety and their relationship with personality.

The findings obtained within the scope of the second question of the study indicate that AIlessphobia in education is significantly and positively related to both deep learning (r = .116) and surface learning (r = .299) approaches. These relationships appear to be explainable when evaluated within the framework of studies on technology acceptance and learning approaches. The approach that the learner's motivation to use the tool can remain relatively consistent even if the nature of the tool changes may be functional in interpreting this finding (Balakrishnan & Lay, 2016; Camarero et al., 2012). Previous studies have emphasised that digital tools can serve different learning processes in different ways (Cifuentes et al., 2011). Similarly, today, AI can serve as an intellectual assistant in the process of discovering and understanding concepts for students who adopt a deep learning approach (Wu, 2024), while it can be used as a pragmatic tool for completing faster tasks and with less effort from a superficial learning perspective (Gezgin, 2024). Within this framework, the level of interaction established by both approaches with AI tools can be observed alongside the anxiety and lack of confidence felt in the absence of AI. However, the higher level of association with surface learning indicates that the ease of access to ready-made information may correspond more strongly with surface strategies (Gezgin, 2024). Furthermore, a study conducted by Özbay (2026) reported a positive relationship between academic self-efficacy and AIlessphobia in education, and this pattern was discussed in terms of how high-performance expectations could increase AI usage. When these results are considered together, the relationship between self-efficacy and performance expectations with AI usage and AIlessphobia in education should be examined in greater detail, considering differences in contextual and learning approaches.

The stepwise regression analysis conducted within the scope of the third question of the study reveals a noteworthy finding regarding the variables predicting AIlessphobia in education. The findings indicate that surface motivation, one of the sub-dimensions of the surface learning approach, and deep strategy, one of the sub-dimensions of the deep learning approach, are significant predictors of AIlessphobia in education. However, the exclusion of deep motivation, which represents the intrinsic desire to learn, from the regression model suggests that AIlessphobia in education may be more closely related to performance pressure, task completion, and efficiency-focused reasons. The relatively stronger predictive value of surface motivation is consistent with interpretations that students may use AI tools in some situations as a means to complete tasks quickly rather than to deepen learning (Rasul et al., 2023). On the other hand, the positive predictive factor of deep strategy indicates that the phenomenon should not be considered solely in terms of convenience. For strategic learners, AI use can provide time management and efficiency (Ait Baha et al., 2024). Furthermore, Zhang et al. (2024) reported that students with high AI literacy and academic self-confidence can develop more positive attitudes towards AI and may experience anxiety when access is unavailable. This finding also strengthens the possibility that performance anxiety and high expectation levels may be associated with AIlessphobia in education. However, how AI usage is positioned in the context of academic competition and ethical boundaries should be further discussed, considering institutional assessment practices and contextual factors (Ballantine et al., 2018).

CONCLUSION AND SUGGESTIONS

In summary, this study is one of the exploratory studies that empirically addresses the phenomenon of AIlessphobia in education, which is a relatively new topic in the literature, alongside learning approaches. The results show that the integration of AI technologies in education is not merely a matter of tool usage but rather a pedagogical phenomenon related to the learner's approach to the learning process. A prominent aspect of the findings is that AIlessphobia in education is particularly associated with surface motivation and deep strategy. However, the findings should not be interpreted as indicating that university students are likely to switch from deep learning to surface learning. As the current study is cross-sectional, it is not possible to draw conclusions about possible changes in learning approaches over time. However, the fact that surface motivation, a sub-dimension of the surface learning approach, is more strongly related to AIlessphobia in education points to a possibility that needs to be carefully considered from a pedagogical perspective. When combined with time pressure and a performance-oriented assessment climate, the rapid response and ready output features of AI tools may reinforce the tendency to quickly complete and move on from academic tasks, particularly among students with high surface motivation. Such reinforcement may increase the risk of the dimensions of learning—meaning-making, questioning, and deep processing—being relegated to the background. Therefore, in instructional design and assessment processes, it is important to strengthen process-oriented practices that make visible not only the final product but also the reasoning, rationalization, and original contributions university students demonstrate during the learning process. As generative AI rapidly reshapes the landscape of teaching and learning, both educators and learners need to develop a deep and critical understanding of these technologies and their pedagogical implications (Bozkurt, 2024). In this context, an important agenda for educators and policymakers is to strengthen process-oriented and authentic assessment approaches that support students' self-regulated learning skills (Ifelebuegu, 2023; Rasul et al., 2023). Furthermore, the relationship between performance-oriented variables such as academic stress, academic anxiety, and exam anxiety and AIlessphobia in education should be specifically addressed in future studies, as it may provide a framework that better explains students' motivations for using AI.

LIMITATIONS

This study has certain limitations. Firstly, as the research is based on a cross-sectional and correlational design, the relationships between variables should not be interpreted causally. Secondly, the data is self-reported; this may increase the likelihood of common method bias and social desirability effects. Thirdly, the fact that the sample was collected from a single university and that the vast majority of participants used a specific tool, particularly ChatGPT, may limit the generalisability of the findings to different institutions and different AI tools. Fourthly, since convenience sampling was dependent on accessibility and voluntary response rather than random selection, it may have created selection bias. The sample may have been overrepresented by students interested in or conversant with AI techniques, reducing its representativeness and generalizability. Finally, as AIlessphobia in education is a relatively new phenomenon, confirmatory studies with different samples, evidence of criterion validity, and, if possible, longitudinal designs are needed for the theoretical framework and nomological network of the concept to be fully established. Future research could test the temporal dynamics of anxiety and lack of confidence that emerge when AI access is restricted, using longitudinal and experimental designs; it could also examine the mediating or moderating roles of variables such as academic stress, exam anxiety, AI literacy, and self-regulation.

DATA ACCESSIBILITY STATEMENT

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

SUSTAINABLE DEVELOPMENT GOALS (SDGs)

This study is linked to the following SDG: Quality Education (SDG 4), by addressing how AI-related learning constraints (AIlessphobia in education) may relate to students' learning approaches in higher education.

ETHICS AND CONSENT

Ethical approval was obtained from the Trakya University Social and Human Sciences Research Ethics Committee (decision no. 05/19; meeting date: 07 May 2025; reference no. E-29563864-050.99-842996).

FUNDING INFORMATION

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

COMPETING INTERESTS

The authors have no competing interests to declare.

AUTHOR CONTRIBUTIONS (CRediT)

Deniz Mertkan Gezgin: Conceptualization, Investigation, Methodology, Project administration, Writing – original draft, Writing – review & editing. Onur Nurlu: Data curation, Formal Analysis, Visualization, Writing – original draft, Writing – review & editing. Çiğdem Arapoğlu Validation, Writing – original draft, Writing – review & editing. Mehmet Murat Demirelli: Validation, Writing – original draft, Writing – review & editing. All authors have read and agreed to the published version of the manuscript.

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TO CITE THIS ARTICLE:
Gezgin, D. M., Nurlu, O., Arapoğlu, Ç., & Demirelli, M. M. (2026). AIlessphobia in Education among University Students: Prevalence and Associations with Deep and Surface Learning Approaches. *Open Praxis*, *18*(3), pp. 428–440. DOI: https://doi.org/10.55982/openpraxis.18.3.1142

Submitted: 26 January 2026
Accepted: 29 March 2026
Published: 04 August 2026