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From Bytes to Attitudes: Unpacking Students' Cognitive, Affective, and Behavioral Responses to AI

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ABSTRACT

This study aims to explore secondary and high school students' attitudes towards artificial intelligence (AI) in affective, behavioural, and cognitive dimensions and to analyse the relationships between these attitudes using multilevel and structural equation modeling. The study was conducted with quantitative data obtained from 702 students and 8 English as a Foreign Language teachers. Multilevel models were constructed considering students' gender, grade level, previous use of AI, and teacher-related classroom effects. The findings demonstrated that students who had previously used AI exhibited more positive attitudes in all attitude dimensions. In addition, cognitive attitudes significantly predicted affective attitudes, affective attitudes significantly predicted behavioural attitudes, and affective attitudes played a partial mediating role in this relationship. Although the teacher effect was limited, it provided a significant contribution to the model. These results reveal that students' attitudes towards AI are influenced not only by individual but also by contextual factors, and emphasize that strategic planning for AI integration in educational environments needs to be designed by considering multilevel structures.

1 INTRODUCTION

Artificial intelligence (AI) is a discipline that models human cognition and focuses on the design of intelligent systems that can perform processes such as learning, reasoning and decision-making (Coppin, 2004; Russell & Norvig, 2021). Alan Turing's question "Can machines think?" is considered one of the theoretical cornerstones in this field (Turing, 1950, p. 433). Over time, this concept has evolved to include not only systems that perform specific tasks, but also those that can improve themselves by learning from their experiences (Schank, 1987). Schank (1987) defines AI as a discipline that enables programs to acquire the ability to improve themselves over time by learning from their own experiences. Similarly, Coppin (2004) refers to AI as systems that attempt to solve complex problems by imitating the intelligent behaviour of humans and animals. In this perspective, AI stands out as a technology that performs human-like functions such as learning, analysing and decision-making, generates solutions based on data from its environment, and can adapt itself over time (Derinalp & Ozyurt, 2024; İşler & Kılıç, 2021). With the rapid expansion of generative AI technologies such as ChatGPT, especially in recent years, AI has not only been limited to technical fields such as engineering and data science, but has also started to be employed effectively in social sciences such as education (Derinalp, 2024; Holmes et al., 2022). This transformation has further increased the importance of research on the role of AI in learning environments.

Artificial intelligence systems in education are actively used in numerous fields such as adaptive learning environments, intelligent tutoring systems, automatic feedback mechanisms, student performance prediction systems, and natural language processing-supported applications (Chen et al., 2020; Kamalov et al., 2023). Recently, generative AI technologies have gained prominence in foreign language teaching and learning processes given their ability to improve writing skills, increase language input, and provide instant and personalised feedback to name a few (Baskara et al., 2024; Xin, 2024; Zaim et al., 2024). In this regard, it can be asserted that AI has become not only a tool but also almost an indispensable part of the learning environment.

As the impact of AI in education is increasing, the perceptions and attitudes of students, the largest and most directly affected component of the education system, towards this technology become even more important. The prominent theoretical models of technology acceptance posit that attitudes play a decisive role in individuals' intentions to adopt a technology. Davis's (1989) Technology Acceptance Model (TAM), for example, suggests that individuals' intention to use a technology is determined by two basic variables: perceived usefulness and perceived ease of use. Similarly, in the Unified Theory of Acceptance and Use of Technology (UTAUT) model, although there is no direct attitude variable, constructs such as performance expectancy and effort expectancy are accepted as important indicators reflecting individuals' perceptions and attitudes towards technology and it is emphasized that they are strongly related to the intention to use technology (Venkatesh et al., 2003). Hence, considering these theoretical approaches, it becomes clear that individuals' attitudes towards technology play a critical role in the adoption process of the technology in question.

Attitude is a multidimensional structure that includes an individual's beliefs, emotions, and behavioural tendencies towards a particular object or situation (Eagly & Chaiken, 2007). The three-component model, as widely accepted in the social psychology literature, conceptualises attitude in three main dimensions: cognitive (beliefs and knowledge), affective (emotions and appraisals), and behavioural (intentions and dispositions) (Eagly & Chaiken, 1993; Rosenberg & Hovland, 1960). Theoretically, it is postulated that these components are not only independent of each other, but also function within an interactional and sequential process (Derinalp & Halife, 2025; Derinalp & Ozyurt, 2024).

Along these lines, Bandura's (1986) social cognitive theory suggests that individuals' cognitive evaluations shaped by environmental and personal experiences are reinforced through emotional reactions, which in turn transform into behavioural orientations. Likewise, the technological pedagogical content knowledge (TPACK) model developed in the context of pedagogical integration of educational technologies (Mishra & Koehler, 2006) emphasises the attitudinal impact of individuals' cognitive awareness of technology on pedagogical practices. Teo's (2009) studies based on technology acceptance models also show that individuals' perceived usefulness and ease of use significantly affect behavioural intention through attitude. Hence, it might be argued that students' cognitive attitudes towards artificial intelligence (e.g. finding it useful, understanding) shape affective reactions (e.g. satisfaction or anxiety) towards this technology, and affective attitudes affect behavioural orientations (e.g. intention to use, propensity to use) both directly and through mediation.

Several studies in the literature, indeed, reveal that individuals' cognitive attitudes significantly affect their affective reactions, and that these affective attitudes are determinant on behavioural tendencies. For example, Cidral et al. (2018) found that university students' cognitive perceptions of distance education technologies are reflected in their learning behaviours through affective responses. Similarly, in their structural equation modelling study with 595 university students in the Peruvian context, Acosta-Enriquez et al. (2024) revealed that cognitive attitudes strongly predicted affective attitudes and both cognitive and affective attitudes had significant effects on behavioural attitudes. Another study conducted with 57 high school students in Newcastle, England, examined students' perceptions of the use of AI for academic purposes (Charles & Charles, 2024). Students reported that AI enhanced their learning process, rendering it more effective and motivating. These findings suggest that students' perception of AI as useful (cognitive attitude) leads to positive emotional reactions, which in turn increase their behavioural intentions to use AI.

In the Turkish context, in turn, technology and AI attitude research has addressed students' attitudes towards digital tools from various perspectives. For instance, Çakır and Solak's (2015) study revealed that Turkish EFL students have generally positive attitudes towards technology and that these attitudes have significant effects on academic achievement. In particular, it was emphasised that anxiety towards e-learning (affective dimension) negatively affected achievement, whereas cognitive elements such as perceived ease of use and self-efficacy positively affected students' behavioural tendencies and thus their achievement. These findings suggest that students' affective approaches towards technology may indirectly affect their technology use behaviours, while cognitive perceptions may directly shape these behaviours. In a more recent study, Korkmaz and Akbıyık (2024) examined EFL students' attitudes towards AI and found that the participants generally had a moderate attitude towards the use of AI. In Kara's (2024) study, which was conducted in a discipline other than EFL, it was observed that AI-supported teaching increased student attitudes and course outcomes. Although these studies are very valuable, it is important to note that educational settings are hierarchical structures in which not only individual but also contextual variables are effective. Students study in classes connected to specific teachers and teacher-level differences can indirectly affect students' attitudes towards technology (Tondeur et al., 2017). Therefore, it may not be sufficient to focus only on the student level to make sense of individual attitudes; multilevel analyses that also take into account teacher-related classroom effects are recommended (Snijders & Bosker, 2012). Also, most of the studies focusing on AI and attitude in Turkey are in the form of scale development (Aktay et al., 2024) or adaptations (Köse et al, 2025; Turgut & Kunuroglu, 2025; Satıcı et al., 2025) and it can be concluded that empirical studies testing the theoretical models are limited in number.

In order to fill this gap, the current study examines students' attitudes towards AI at both individual (gender, grade level, AI use) and contextual (teacher-related grade level) levels and then analyses the relationships between these attitude components with structural equation modelling (SEM). In this direction, the following research questions were sought to be answered:

RQ1. To what extent are students' cognitive, affective and behavioural attitudes towards AI predicted by individual (gender, grade level, and AI use) and contextual (teacher level) variables?

RQ2. Do students' cognitive attitudes towards AI significantly predict their affective attitudes?

RQ3. Do students' affective attitudes affect their behavioural attitudes directly and/or indirectly through cognitive attitudes?

The structural model tested based on these questions is grounded on the following hypotheses:

H1. Students' cognitive attitudes towards artificial intelligence significantly predict their affective attitudes.

H2. Students' affective attitudes significantly predict their behavioural attitudes.

H3. Cognitive attitudes affect behavioural attitudes indirectly through affective attitudes.

2 METHODS

2.1 Research Model

This research is a quantitative study that aims to explain students' attitudes towards AI on the basis of individual and contextual variables and to examine the structural relationships between these attitudes. Accordingly, the study was designed within the framework of relational survey model and multilevel linear modeling (MLM) and structural equation modeling (SEM) techniques were used together in the analysis process.

The research model was designed in two phases in accordance with the hierarchical nature of the data structure. At the first level, the relationships between students' individual characteristics (gender, grade level, and use of AI) and their attitudes towards AI were analyzed. However, the fact that the students were in certain classes under certain teachers created a nested structure that may cause a violation of the independence assumption between observations. Since students under the same teacher are exposed to similar pedagogical approaches, classroom atmosphere, and teaching conditions, the likelihood of correlations between their responses increases (Hox et al., 2017; Raudenbush & Bryk, 2002).

In such nested data structures, it is statistically necessary to distinguish between individual-level (student) variance and contextual-level (teacher) variance. Since classical regression analyses cannot perform this separation, they may produce inadequate and erroneous results, especially when the assumption of independence between observations is not valid (Snijders & Bosker, 2012). The method proposed to overcome this problem is multilevel linear modeling (MLM). MLM allows for independent estimation of multilevel sources of variance by including fixed effects (namely gender, grade level, AI use) and random effects (namely teacher-level variance) simultaneously in the model.

In this study, the teacher factor was added to the model as a random intercept at the second level. Thus, systematic differences that may be observed in the attitude scores of the student group belonging to each teacher were controlled by the model. Multilevel modeling is considered one of the most appropriate approaches in educational research in terms of both methodological validity and statistical precision when students are connected to higher-level groups such as teachers, grades, or schools (Hox et al., 2017; Raudenbush & Bryk, 2002; Snijders & Bosker, 2012).

The second phase of the study examined the structural relationships between students' attitudes towards AI. In this direction, a sequential model in which cognitive attitudes predict affective attitudes and affective attitudes predict behavioural attitudes was tested using structural equation modeling (SEM). The construction of the model is based on the cognitive-affective-behavioral sequence that is widely accepted in attitude theories (Eagly & Chaiken, 1993; Rosenberg & Hovland, 1960) and structural frameworks widely used in attitude towards technology research (Mishra & Koehler, 2006; Teo, 2009). In this framework, it is accepted that cognitive awareness transforms into affective acceptance and affective acceptance translates into behavioural intention. In the model tested in the study, both direct and indirect effects were taken into account, thus, it was aimed to explain the relationships between the components of students' attitudes towards AI.

2.2 Data Collection Tool

In this study, 'Student Attitudes Toward Artificial Intelligence' (SATAI) scale developed by Suh and Ahn (2022) and adapted into Turkish by Derinalp and Ozyurt (2024) was used. As a result of the validity and reliability studies of the original form of the scale, a three sub-dimensional (behavioural, affective, and cognitive) structure was obtained; Cronbach's alpha values were reported as .96 (behavioural), .92 (affective) and .90 (cognitive) respectively.

In the adaptation study, the linguistic validity of the scale was ensured by translation- back translation method; linguistic, conceptual and cultural equivalence were meticulously examined. Turkish and English forms were administered to students in two different school levels (secondary and high school) and the correlation coefficient between the total scores obtained was found to be .827 and .820 respectively. This result shows that the scale has significant equivalence between the two languages. Confirmatory factor analysis results confirm the three-factor structure of the scale and show that the model fits the data well; furthermore, internal consistency coefficients reveal that the scale has a high level of reliability.

The scale consists of two main parts. The first part includes demographic information such as students' grade levels and whether they have used AI before. The second part consists of a total of 26 items measuring students' attitudes towards AI. These items are grouped into three sub-dimensions: cognitive (items 1-4), affective (items 5-14), and behavioural (items 15-26). The scale is structured with a 5-point Likert-type rating system ranging from 'Strongly agree' to 'Strongly disagree'.

2.3 Participants

The data were collected from a total of 702 secondary and high school students who were reached through eight different teachers working in different provinces of Turkey. The students had a wide range of grade levels from 5th to 12th grade. The data set is organised in such a way that each student is connected to only one teacher. In this regard, the data structure is nested in a hierarchical structure and analyses were performed in accordance with this structure.

2.4 Ethical Considerations

The ethical approval required within the scope of this research was obtained from Gaziantep University's ethics committee. Informed consent was obtained from the individuals who participated in the study, stating that they voluntarily participated in the study and agreed to the use of data. In order to protect the privacy of the participants and the confidentiality of their personal data, the teachers were assigned numerical codes such as 101, 102, and so on. This practice was carried out to ensure that identities remain anonymous in the data analysis process and to maintain adherence to ethical principles.

2.5 Data Analysis

The data analysis process was performed using the R programming language (version 4.4.1). The analyses were carried out in three main stages. Firstly, the demographic characteristics of the students and teacher-based data on grade level, gender and AI use were analysed through descriptive statistics and cross tabulations (See Table 1).

Table 1
Cross-Tabulation of Students' Demographic Characteristics by Teacher (N = 702)

Teacher	*Gender*	*Grade 5*		*Grade 6*		*Grade 7*		*Grade 8*		*Grade 9*		*Grade 10*		*Grade 11*		*Grade 12*		*Total*
		NU	U	NU	U	NU	U	NU	U	NU	U	NU	U	NU	U	NU	U	
101 (n=80)	Female									5	3			12	4	16	3	43
	Male									6	6			9	7	6	3	37
102 (n=66)	Female	1		8		1	5	1	5		1		2	2	14	1	9	50
	Male	3	1	2			1		4						1		4	16
103 (n=73)	Female									3	6	1	2	7	6	5	11	41
	Male									3	4	1	3	1	2	7	11	32
104 (n=192)	Female	5	4	26	23	18	15	8	6		2	1	5	1			3	117
	Male	5	3	11	13	15	11	3	3		3		2		4	1	1	75
105 (n=57)	Female									3	3	1		19	23	3	4	56
	Male													1				1
106 (n=117)	Female	1		16	19	14	4	5	2									61
	Male			21	13	12	5	2	3									56
107 (n=58)	Female	2	4	2	1	1		8	5			1		5	5			34
	Male	2	1	2		2	2	11	4									24
108 (n=59)	Female			1	1	14	19											35
	Male					13	11											24
	Total	19	13	89	70	90	73	38	32	20	28	5	14	57	66	39	49	702

U: Used *NU: Not Used*

A total of eight teachers participated in the study. It was determined that two of these teachers worked at both secondary and high school levels. In addition, when Table 1 is analysed, it is seen that the number of students who stated that they had experienced AI technologies before was 370; on the other hand, the number of students who had never used these technologies was 332. This distribution shows that approximately half of the students have had direct interaction with AI and creates a presumption that their attitudes may differ in line with this experience.

Multilevel linear models were constructed to predict cognitive, affective, and behavioural attitudes. These models were constructed separately using the lmer() function; in each model, gender, grade level, and AI use were defined as fixed effects, and teacher was defined as a random effect (See Table 2). Finally, within the scope of structural equation modelling (SEM), a sequential structure extending from cognitive attitudes to affective attitudes and then to behavioural attitudes was tested. In this analysis, lavaan package was used, direct, indirect, and total effects were calculated and the results were visualised with path diagrams (See Table 3, Figure 3).

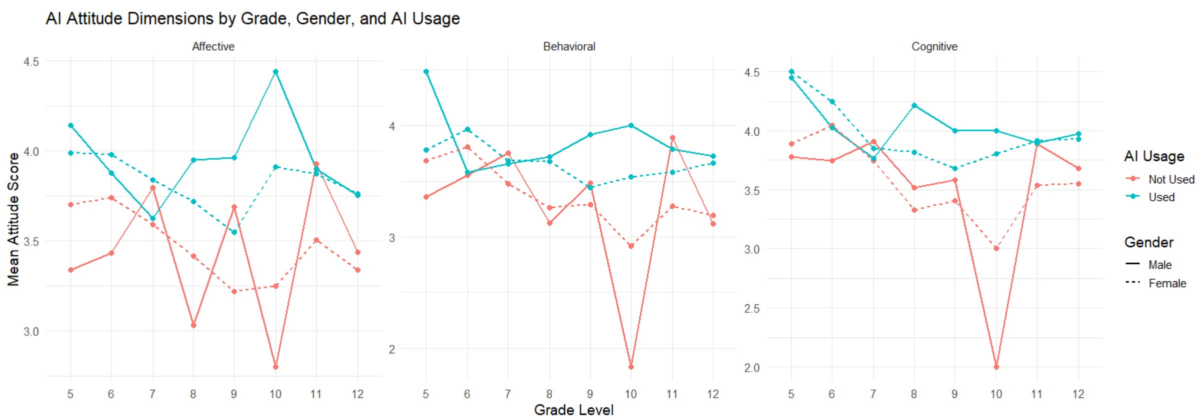
3 RESULTS AND DISCUSSION

3.1 Results

3.1.1 RQ1. Predictors of Attitudes towards AI

Within the scope of this research question, the extent to which students' affective, behavioural, and cognitive attitudes towards AI can be predicted by individual (gender, grade level, AI use) and contextual (teacher-related classroom setting) variables was analysed by multilevel linear modelling (MLM). Figure 1 comparatively illustrates the mean affective, behavioural and cognitive attitudes of the students according to gender, grade level and AI use.

Figure 1
The Distribution of Students' Mean Affective, Behavioural and Cognitive Attitudes towards AI by Gender, Grade Level and AI Use



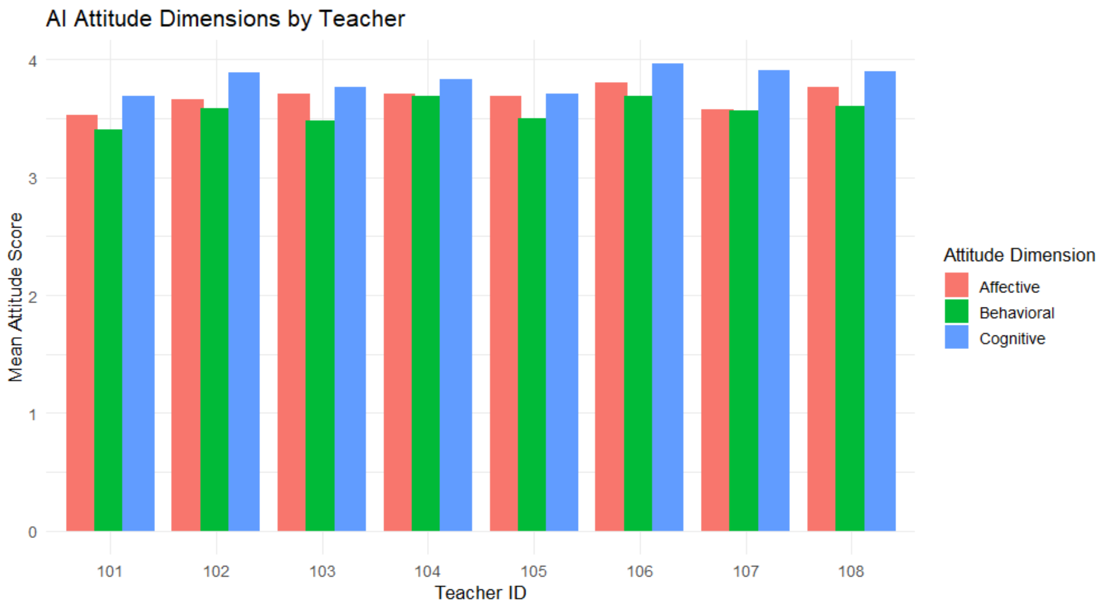
The multilevel model results found that students' attitudes towards AI vary significantly in affective, behavioural and cognitive dimensions depending on different individual and contextual variables. First, in the affective attitude dimension, students' previous use of AI technologies stood out as a significant and strong predictor. It is revealed that the use of AI positively affected this attitude ($\beta = 0.311$, $p < .001$). On the other hand, gender and grade level variables had no significant effect on affective attitude. This finding indicates that students' positive or negative affective evaluations towards AI are shaped more by individual experience.

Regarding the behavioural attitude dimension, the strongest predictor was again the use of AI ($\beta = 0.266$, $p < .001$). That is, students who have previously experienced AI tools have more intention to use this technology. In terms of grade level, 8th and 12th grade students showed some significant differences; students at these levels exhibited higher behavioural tendencies than the reference category. It was also found that the gender variable did not create a significant difference in the behavioural dimension.

Lastly, the findings of the cognitive attitude dimension revealed a similar pattern. Students who had used AI before had more positive appraisals in beliefs and perceptions towards AI ($\beta = 0.288$, $p < .001$). In addition, 5th, 6th, and 11th grade students reported significantly higher cognitive attitude scores than the reference category of 10th grade. This finding reveals that there are differences in students' cognitive attitudes according to grade level. In this dimension, the effect of gender was not significant either.

In this study, it was aimed to examine students' affective, behavioural, and cognitive attitudes towards AI not only in terms of individual variables but also at the teacher level. In the figure below, without ignoring the teacher factor, the average scores of the students affiliated with each teacher in the three attitude dimensions towards AI are calculated and visualized comparatively in Figure 2 below.

Figure 2
Mean Scores of Affective, Behavioural, and Cognitive Attitude Dimensions by Teacher



In order to reveal how students' attitudes towards AI vary at the teacher level, the mean scores of the attitude dimensions were calculated according to the teacher groups. Descriptive findings revealed that the mean scores of the students in the affective attitude dimension varied between 3.53 and 3.80 depending on the teacher. The highest affective mean was observed in the group of Teacher 106 (3.80) and the lowest in the group of Teacher 101 (3.53). In the behavioural attitudinal dimension, the averages varied between 3.40 and 3.69, and the students of Teachers 104 and 106 had the highest attitude level in this dimension (3.69). In the cognitive attitude dimension, the mean scores varied between 3.69 and 3.97 among the teacher groups; the highest mean cognitive attitude was observed in the students of Teacher 106 (3.97).

However, despite these differences, it is important to note that multilevel linear modeling (MLM) analyses revealed that the variance at the teacher level was quite low. Especially in the cognitive and affective dimensions, the random effect variance of the teacher was estimated as 0.00046 and 0.0004, respectively, while in the behavioural dimension, this variance was negligible at 0.0000.

3.1.2 RQ2. The Predictive Role of Cognitive Attitudes in Students' Affective Attitudes towards AI

In the model created within the scope of structural equation modeling, it was tested whether students' cognitive attitudes significantly predicted affective attitudes. The results of the analysis conducted through structural equation modeling (SEM) revealed that students' cognitive attitudes significantly and strongly predicted their affective attitudes. According to the findings, the effect of cognitive attitudes on affective attitudes was statistically significant ($\beta = 0.596$, $p < .001$). Hence, it can be said that this finding supports Hypothesis 1 and suggests that students' level of knowledge and beliefs about AI plays an important role in determining their affective reactions towards this technology.

The statistics on the fit of the model are also found to be very high. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) were both calculated as 1.000, indicating that the model provided an excellent fit. In addition, the Root Mean Square Error Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR) values were calculated as 0.000, respectively, indicating that the model was in perfect fit with the data. Moreover, the model explained approximately 35% of the variance in affective attitude ($R^2 = 0.355$), which indicates a highly significant level of explanatory power.

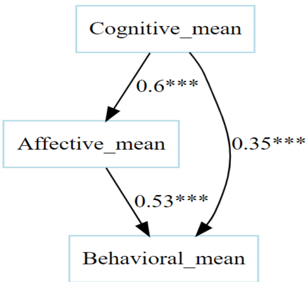
3.1.3 RQ3. Testing the Mediating Role of Affective Attitudes

In this study, the relationships between cognitive, affective and behavioural dimensions of attitudes towards AI were examined not only in terms of direct effects but also in terms of the mediating role of affective attitudes. In this regard, in the structure established within the scope of structural equation modeling, it was observed that students' cognitive attitudes towards AI significantly predicted affective attitudes ($\beta = 0.596$, $p < .001$). Affective attitudes also significantly predicted behavioural attitudes ($\beta = 0.528$, $p < .001$), which supports hypothesis 2.

Hypothesis 3 (H3), in turn, tests whether students' affective attitudes play a mediating role in the relationship between cognitive attitudes and behavioural attitudes. The mediation analysis conducted in this regard revealed that the indirect effect of cognitive attitudes on behavioural attitudes was statistically significant (indirect effect = 0.281, $p < .001$). At the same time, the direct effect of cognitive attitudes on behavioural attitudes was also significant ($\beta = 0.350$, $p < .001$). This result reveals that affective attitudes play a partial mediation role as a mediating variable. According to the model, the total effect of cognitive attitudes on behavioural attitudes was calculated as 0.594 ($p < .001$). These findings indicate that H3 is statistically supported and reveal that students' behavioural orientations towards AI develop depending on both direct cognitive evaluations and emotional reactions shaped by these evaluations. The related structural model is visualized in Figure 3 below.

Figure 3

The Mediating Role of Affective Attitude between Cognitive and Behavioural Attitudes



When the criteria for the fit of the model are examined, the values obtained show that the model fits the data quite well. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) were both found to be 1.00. Similarly, the Root Mean Square Error of Approximation (RMSEA) value was 0.000 and the Standardized Root Mean Square Residual (SRMR) value was 0.000. These results suggest that the tested model is in a near perfect fit with the observed data.

4 Discussion

This study aimed to examine how secondary and high school students' affective, behavioural, and cognitive attitudes towards AI are related to individual and contextual variables and the structural relationships between these attitudes. Multilevel modeling results revealed that AI usage, and grade level significantly predicted attitudes, while gender was not effective. According to the results of structural equation modeling, cognitive attitudes significantly predicted affective attitudes, and affective attitudes had both direct and mediated effects on behavioural attitudes.

One of the findings of this study was that exposure to or direct experience of using AI positively influenced students' attitudes towards AI, which is an expected finding. This finding is consistent with previous studies. For example, Katsantonis and Katsantonis (2024) found that students' future frequency of AI use was significantly related to attitude components. In Fošner's (2024) study, the majority of students reported using AI tools frequently and this use was reported to be associated with positive attitudes. Similarly, Dobrovská et al. (2024) reported that the majority of students used AI tools for information processing and comprehension and that this experience facilitated their adoption of the technology. These findings are in line with the arguments that experience is a determinant of attitudes in technology acceptance models (Davis, 1989; Venkatesh et al., 2003).

In the current study, gender did not show a significant difference in students' cognitive, affective and behavioral attitudes towards AI. This finding is in line with the studies conducted by Katsantonis and Katsantonis (2024) and Dobrovská et al. (2024). However, Ofosu-Ampong's (2023) study with higher education students in Ghana reported that gender was a significant predictor of the use of AI-based tools and male students demonstrated more positive and innovative tendencies towards these technologies. This contradiction in the literature may be due to contextual differences. It is worth noting that Ofosu-Ampong's study was conducted in a cultural setting where gender norms are more dominant, whereas other studies conducted in the European context have observed a narrower gender-based digital divide. This might suggest that attitudes towards AI are shaped not only by individual but also by socio-cultural factors.

The findings reveal that 5th, 6th and 11th grade students have higher cognitive attitudes towards AI compared to 10th grade students. However, this difference does not exhibit a linear increase according to grade level; on the contrary, it shows a complex pattern shaped by students' developmental characteristics, motivation levels and experiences in the educational context. At this point, Çakır and Çelik's (2020) study at the high school level showed that 12th grade students' levels of self-directed learning with technology were significantly higher than 11th grade students. This suggests that upper grade students develop more functional and purposeful attitudes towards technology. On the other hand, 10th graders' lower cognitive attitudes may be a reflection of the pedagogical conditions or lack of guidance specific to this grade level. In this context, it can be said that grade level differences should be addressed based not only on the student but also on contextual factors.

Another finding of this study is that although the teacher variable explained only a low level of variance in students' affective, behavioural, and cognitive attitudes towards AI, it contributed significantly to the model. This finding suggests that teacher influences, although limited, play a role that should not be ignored. Likewise, the results of this study are in line with the findings of the comprehensive study conducted by Ardies et al. (2015), which examined teacher influence on students' attitudes towards technology using a multilevel approach. While Ardies et al. (2015) found that teachers' attitudes and level of technology integration can influence students' perceptions of technology, the significant variance contribution observed at the teacher level in the present study indicates the existence of this indirect effect.

The structural equation modeling results obtained in this study revealed that students' cognitive attitudes towards AI significantly predicted their affective attitudes and this relationship was supported by a strong structural fit. This finding is in line with the study conducted by Torres et al. (2024), which concluded that students' finding AI useful and understandable increased their affective engagement. This is in line with the concept of perceived usefulness proposed by Davis (1989) within the Technology Acceptance Model (TAM). Indeed, individuals' cognitive evaluations of the extent to which they find a technology useful and meaningful determine whether they develop positive or negative emotional reactions towards the technology in question. Similarly, Acosta-Enriquez et al. (2024) also reported that the cognitive dimension was positively related to affective attitudes. This suggests that similar relationships can be observed in different sample groups and contexts.

The predictive effect of affective attitudes on behavioural attitudes was also found significant in this study. This finding is in line with the results reported by Otermans, Roberts and Baines (2025) that students' affective dispositions increase their tendency to use AI technologies in the educational context. These findings show that students' affective attitudes shape their behavioural attitudes towards technological tools. They also indicate that affective attitudes can play a critical mediating role in the process of adoption of educational technologies. Therefore, it can be argued that affective attitudes are not only a temporary reaction but also a functional determinant in structuring technological behaviours in learning environments.

4.1 Implications for Theory, Practice, and Policy

The findings of this study reinforce the theoretical framework of the multidimensional nature (cognitive, affective and behavioural) of attitudes towards AI. In particular, affective attitudes are both influenced by cognitive attitudes and partially mediate behavioural attitudes, indicating the importance of integrating social psychology-based attitude models such as Eagly and Chaiken (1993) and technology acceptance models such as Davis (1989; Venkatesh et al., 2003) in a holistic manner. Moreover, examining this construct with multilevel analyses (MLM) reveals that individual attitudes cannot be considered independent of the classroom or teacher context, necessitating the integration of contextual variables into theoretical models.

In terms of practical implications, this study suggests that to increase the adoption of AI tools in education, different components of student attitudes should be focused on simultaneously. The finding that increasing knowledge of the usefulness and functionality of AI, especially at the cognitive level, can lead to an increase in affective acceptance and behavioural dispositions, suggests that conscious AI awareness and pedagogical integration needs to be promoted in educational programs. Moreover, the finding that the differences between teachers were significant despite the low variance contribution suggests that developing digital pedagogical competencies in teacher education can positively affect student attitudes.

The findings of this study provide several recommendations for policy makers to improve AI literacy, especially at the secondary and high school level. First, to bridge the gap between awareness of the use of AI tools and pedagogical practice, it is suggested to include content at the curricular level that includes cognitive, affective and behavioural objectives related to AI. Secondly, holistic support mechanisms such as teacher development programs, student support platforms are needed to reduce inequalities in technological integration across schools and teachers.

4.2 Limitations and Suggestions for Further Studies

This study has some limitations. First of all, the study was conducted with a cross-sectional design; therefore, the relationships between variables should not be interpreted at the causality level. To overcome this limitation, longitudinal designs are recommended for future studies. In addition, the measurement tools used in the study were based on students' self-reports, which may lead to social desirability bias and the risk of not accurately reflecting actual attitudes. Therefore, mixed-method designs supported by behavioural data such as observation or usage records could be preferred in future research. Furthermore, the teacher factor was only included in the model as a random effect in the multilevel analysis; however, teachers' pedagogical competencies, technological integration practices, and belief systems were not explored in qualitative depth. It is important to examine these factors in detail in future research to gain a more comprehensive understanding of the influence of teachers on the formation of students' attitudes. Finally, in this study, AI technologies were treated as a holistic concept and different AI applications such as ChatGPT, intelligent assessment systems, adaptive learning software were not differentiated. In future studies, the effects of these different technologies on students' attitude components could be analysed separately.

5 CONCLUSIONS

This study reported significant insights by examining secondary and high school students' affective, behavioural, and cognitive attitudes towards AI using multilevel and structural equation modeling approaches. The results of the study revealed that students who had previously experienced AI had more positive attitudes in all dimensions. In addition, it was determined that cognitive attitudes significantly predicted affective attitudes, affective attitudes significantly predicted behavioural attitudes, and affective attitudes partially mediated this relationship. The findings draw attention to the interactional nature of attitude components in understanding the adoption of AI technologies in education and emphasize the importance of considering both individual and contextual variables.

6 STATEMENTS AND DECLARATIONS

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7 REFERENCES

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