

Turkish Adaptation of the AI Motivation Scale (AIMS): A Self-Determination Theory Approach

Şahin Gökçeşlan ¹, Hatice Yıldız Durak ², Nebi Yılmaz ^{3*}

¹ Hacettepe University, Institute of Informatics, Türkiye,  0000-0003-3532-4251

² Necmettin Erbakan University, Eregli Education Faculty, Türkiye,  0000-0002-5689-1805

³ Hacettepe University, Institute of Informatics, Türkiye,  0000-0002-0591-4667

* Corresponding author: Nebi Yılmaz (nebi.yilmaz@hacettepe.edu.tr)

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Abstract

The rapid integration of artificial intelligence (AI) into higher education has underscored the need to better understand students' motivation to learn with AI. Motivation is a key determinant of students' engagement and effective use of AI-supported learning environments; however, there is a scarcity of validated instruments grounded in robust motivational theory and adapted to different cultural contexts. Recently, the Artificial Intelligence Motivation Scale (AIMS), based on Self-Determination Theory, was developed to assess university students' motivation to learn with AI across five dimensions: intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation. The present study aims to adapt the AIMS into Turkish and to examine its validity and reliability among Turkish university students. The study sample consisted of 221 undergraduate and graduate students from 10 universities in Türkiye. Following a translation and back-translation procedure, the Turkish version of the AIMS was administered online. The factorial structure of the scale was examined using first- and second-order confirmatory factor analyses, and internal consistency was assessed using Cronbach's alpha coefficients. The results supported the original five-factor structure and demonstrated acceptable model fit and satisfactory reliability coefficients. The second-order analysis provided partial support for a higher-order AI motivation construct. Overall, the findings indicate that the Turkish version of the AIMS is a valid and reliable instrument for assessing university students' motivation to learn with AI in the Turkish education context.

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Introduction

Artificial intelligence (AI) has become one of the key technologies transforming teaching and learning processes in higher education. AI-based technologies such as intelligent tutoring systems, generative AI tools, adaptive learning platforms, and automated feedback systems are increasingly integrated into university learning environments (Chiu et al., 2023a and Crompton et al., 2023). AI-powered chatbots and AI-enhanced learning environments are gaining traction due to their capacity to facilitate interactive learning experiences. These environments harness the power of artificial intelligence, promising to transform the educational landscape (Gökçeşlan et al., 2025). This rapid transformation has made it a critical research priority to understand students' motivation to learn with AI.

Motivation is a fundamental factor that determines the extent to which students engage with learning technologies, the effort they invest in the learning process, and the quality of the learning outcomes they achieve (Ryan et al., 2020). A substantial body of research in educational psychology has demonstrated strong associations between motivation, student engagement, and academic achievement (Ryan et al., 2000; Bureau et al., 2022). However, because motivation is a context-specific construct (Bureau et al., 2022), motivational measures developed for traditional learning environments may not adequately represent motivation in AI-supported learning contexts (Gökçeşlan et al., 2024).

Self-Determination Theory (SDT) offers a robust theoretical framework for understanding motivation based on different levels of internalization (Ryan et al., 2000; Ryan et al., 2020). SDT classifies motivation into intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation, emphasizing that more autonomous forms of motivation are associated with more adaptive learning outcomes (Vansteenkiste et al., 2009). Despite this, much of the research on AI-supported learning has focused primarily on intrinsic motivation or perceived usefulness, while controlled forms of motivation and amotivation have received limited attention (Esiyok et al., 2025; Lai et al., 2023; Xia et al., 2022).

To address this theoretical and measurement gap, Li et al. (2025) developed the Artificial Intelligence Motivation Scale (AIMS), grounded in Self-Determination Theory. The AIMS conceptualizes university students' motivation to learn with AI across five dimensions and has demonstrated strong psychometric properties through comprehensive validity and reliability analyses. Moreover, the findings revealed that motivation mediates the relationship between supportive learning environments and student engagement. Nevertheless, given that motivation is influenced by cultural and contextual factors (King et al., 2019), the applicability of the AIMS across different cultural contexts requires empirical validation. Scale adaptation studies play a crucial role in ensuring conceptual equivalence and measurement validity across cultures (Hambleton et al., 2005). Although the use of AI in Turkish higher education has increased rapidly, there is currently no Turkish measurement instrument that comprehensively and theoretically assesses university students' motivation to learn with AI. This limitation represents a significant gap for both research and educational practice. Therefore, the aim of the present study is to adapt the Artificial Intelligence Motivation Scale (AIMS) developed by Li et al. (2025) into Turkish and to examine its validity and reliability within a sample of Turkish university students. To this end, the factor structure

of the scale was tested using confirmatory factor analyses, and its reliability and construct validity were evaluated. The study is expected to provide a valid and reliable measurement tool for investigating motivation in AI-supported learning contexts within the Turkish higher education system.

The remainder of this paper is organized as follows. The next section presents the method of the study, including information about the participants, the data collection tool, and the data collection process. This is followed by the findings section, in which the results of the confirmatory factor analyses and reliability analyses are reported. The discussion section interprets the findings in relation to the relevant literature, and finally, the conclusions and recommendations section summarizes the main results and offers implications for future research and practice.

Method

Participants

221 students from 10 different universities in Turkey participated in the study. The average age of the participants was determined to be 24.78, with ages ranging from 18 to 54. Participants were invited via online platforms (email and online survey platforms) from different faculties and departments at different universities in Turkey and were informed that the scale was designed to assess their motivation toward artificial intelligence. When examining the academic levels of the participants, it was found that 173 students were undergraduate (78.2%) and 48 students (21.8%) were graduate (master's and doctoral) level.

Data Collection Tool

The Artificial Intelligence Motivation Scale (AIMS), developed by Li et al. (2025), consists of five dimensions and 20 items and was developed to assess university students' motivation to learn with artificial intelligence. The factors are listed as “Intrinsic Motivation,” “Identified Regulation,” “Introjected Regulation,” “External Regulation,” and “Amotivation.” The scale is answered using a 7-point Likert-type rating scale (ranging from “Strongly Disagree (1)” to “Strongly Agree (7)”). During the scale development process, both item-level analyses and confirmatory factor analyses (CFA) were conducted, and the goodness-of-fit indices were found to be acceptable.

Data Collection Process

The necessary permissions for using the scale were first obtained from the developer via email. The scale, consisting of 5 factors and 20 items, was translated into Turkish by a team of two field and language experts. To ensure the accuracy and conceptual equivalence of the translation, the scale was retranslated into English by an independent language expert, and the semantic consistency of the statements in both languages was evaluated. Following the translation process, preliminary interviews were conducted with a group of five undergraduate students to test the scale's comprehensibility, and feedback on the items was collected. After making the necessary adjustments based on this feedback, the scale was converted into an online survey format and made available to students.

Findings

The Artificial Intelligence Motivation Scale consists of a total of 5 factors and 20 items. First-order confirmatory factor analysis (CFA) was applied to these items. To evaluate the model fit based on the CFA results, the χ^2/df ratio, RMSEA, SRMR, CFI, NFI, NNFI, and IFI fit indices were examined. The values obtained from the analysis [$\chi^2=423.97$, $df=160$, $\chi^2/df=2.65$, $p<.001$), RMSEA=0.087, SRMR=0.084, CFI=0.96, NFI=0.93, SRMR=0.084, CFI=0.96, NFI=0.93, NNFI=0.95, IFI=0.96] indicate that the model showed an acceptable level of fit. The fact that the chi-square value is below 5 when divided by the degrees of freedom indicates that the model shows a statistically significant fit. Furthermore, the fact that the SRMR value is within acceptable limits supports the validity of the model. The RMSEA is close to the recommended 0.08 threshold for acceptable fit. This indicates that the model's fit is borderline. CFI, NNFI, and IFI values around or above 0.95 provide strong fit indicators. The standardized factor loadings obtained from the first-order DFA range from 0.65 to 0.95. All items in the scale were found to have meaningful loadings on the relevant factors. Furthermore, t values ranged from 10.05 to 18.59 and were found to be significant for all items. These findings indicate that each item in the scale makes a statistically significant contribution to representing the relevant factor. In conclusion, the confirmatory factor analysis findings reveal that the scale has acceptable fit values and that its construct validity is ensured. The DFA standardized values and t-value diagrams of the scale are presented in Figure 1 and Figure 2, respectively.

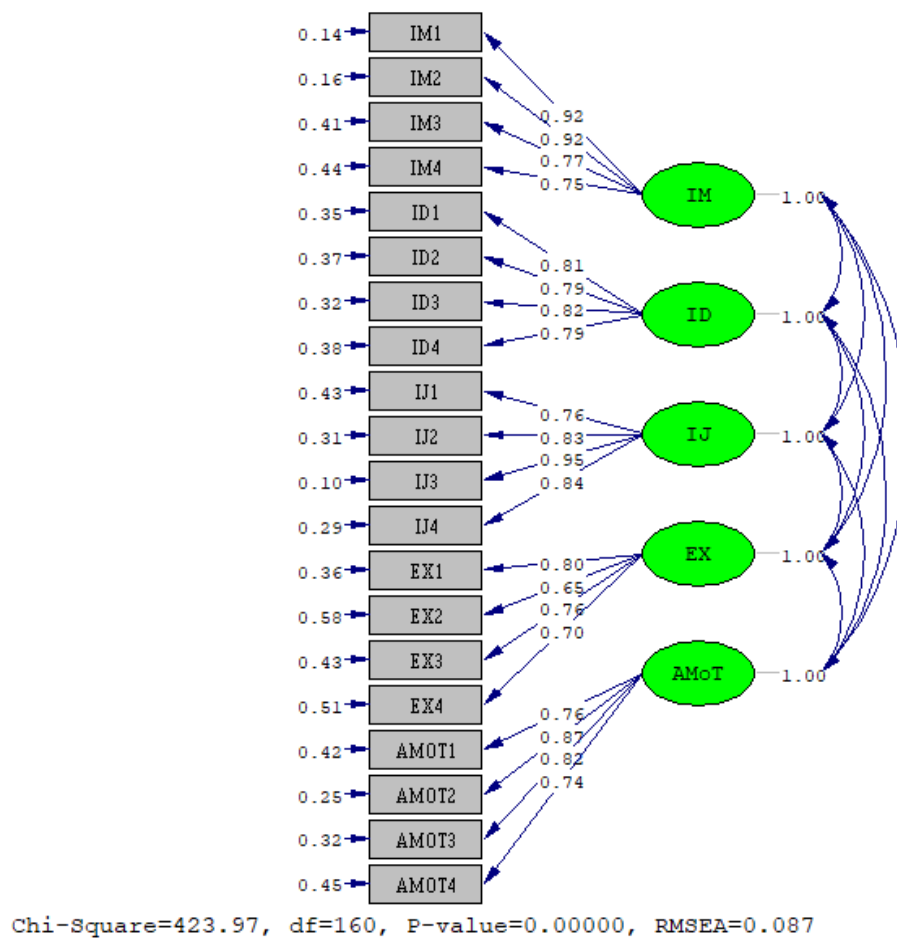


Figure 1. First-level DFA - Standardized Values

A second-order confirmatory factor analysis (CFA) was applied to the scale to identify artificial intelligence motivation as a high-level latent variable for students. The fit indices obtained from the analysis were calculated as [$\chi^2=541.37$, $df=147$, $\chi^2/df=3.68$, $p<.001$, $RMSEA=0.110$]. Although these values do not indicate an excellent fit, particularly because the RMSEA is above 0.08, they indicate that the model has an acceptable level of fit (MacCallum et al., 1991). When examining the path coefficients and t values between the first-order factors and the latent variable of artificial intelligence motivation in the second-order DFA, the strongest relationship was found between “Internal Regulation” (ID) ($\beta=0.98$, $t=11.04$, $R^2=0.97$) and “Intrinsic Motivation” (IM) ($\beta=0.84$, $t=9.79$, $R^2=0.70$) factors. In contrast, the relationship between the “Internal Judgment” (IJ) factor and artificial intelligence motivation was found to be weak ($\beta=0.11$, $t=1.52$, $R^2=0.013$) and statistically insignificant. On the other hand, the relationships established with the “External Motivation” (EX) ($\beta=0.25$, $t=3.07$, $R^2=0.061$) and “Amotivation” (AMoT) ($\beta=0.47$, $t=5.95$, $R^2=0.22$) factors are meaningful and have low and medium levels of explanatory power.

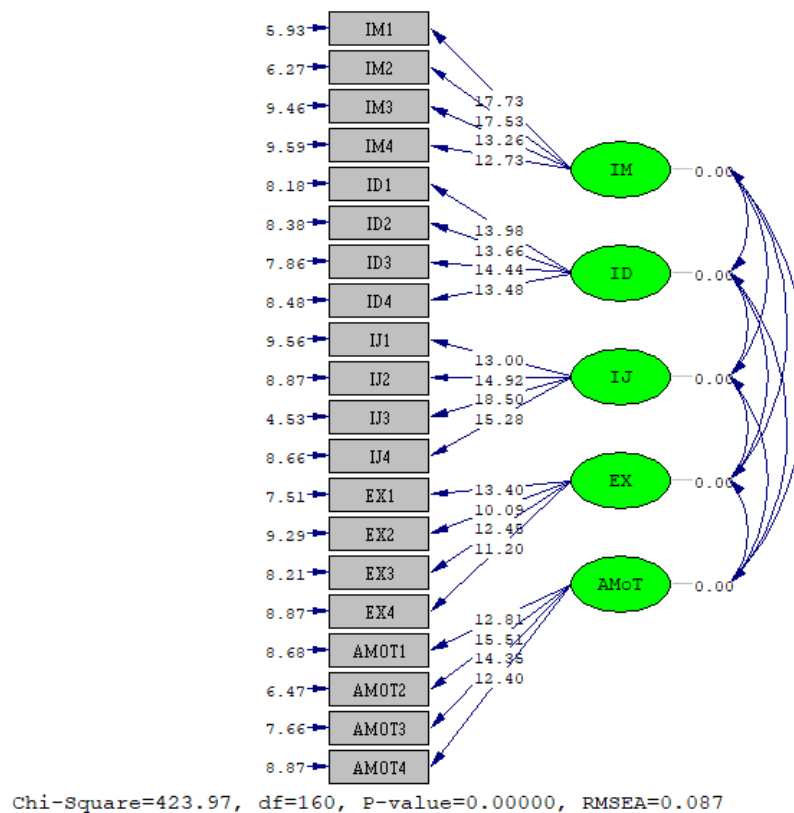


Figure 2. First-level DFA - t Values

When examining the variances explained (R^2) in the first-level factors, it was determined that the highest explanation rates occurred in the Identified Regulation (0.97) and Intrinsic Motivation (0.70) factors. In contrast, it was observed that the introjected regulation (0.013) factor was not explained by the second-level latent variable. Although the direct relationship between the IJ dimension and AIMoT in the structural model was not statistically significant, this dimension was not removed from the scale. This decision is based on several reasons. First, the fact that all items belonging to the IJ dimension exhibit high and statistically significant factor loadings indicates that this dimension represents a robust and reliable structure in terms of the measurement model. According to

expert opinions, IJ may be a more context-sensitive and situational form of regulation based on the individual's perception of the importance of tasks in a specific context. It was decided not to remove this structure as it may be sensitive to sampling due to being a transitional and time-sensitive form of regulation. In conclusion, the second-level DFA findings reveal that the artificial intelligence motivation latent variable generally supports the factor structure of the scale, but the model has partial limitations, particularly in the “introjected regulation” dimension, due to its low explanatory power. The standardized path coefficients, t-values, and explanatory ratios (R^2) of the relevant model are presented in detail in Figure 3.

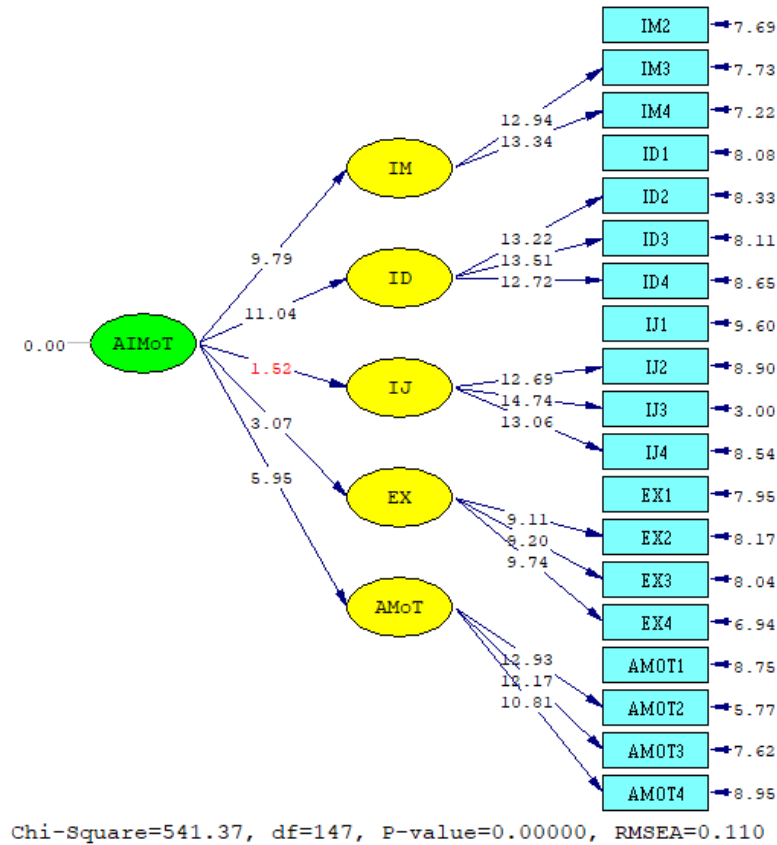


Figure 3. Second-level DFA Diagram - t Values

The reliability coefficient of the scale was found to be Cronbach's α value of 0.866. This value indicates that the scale has high reliability. Table 1 shows the reliability coefficients of the scale based on factors.

Table 1. Artificial Intelligence Motivation Scale Reliability Findings

Dimensions	Number of Items	Cronbach α
Intrinsic Motivation	4	0.901
Identified Regulation	4	0.879
Internal Judgment	4	0.902
External Regulation	4	0.815
Amotivation	4	0.875
Total	20	0.866

Conclusions

This study aimed to adapt the Artificial Intelligence Motivation Scale (AIMS), developed by Li and colleagues (Li et al., 2025) based on Self-Determination Theory (SDT), into Turkish and examine its psychometric properties. The findings confirm that the five-factor structure of the scale (Intrinsic Motivation, Identified Regulation, Internal Judgment, External Regulation, Amotivation) is also valid for the sample of Turkish university students. First-order DFA results paralleled the findings of the original study and provided information about the cross-cultural validity of the scale. The high internal consistency coefficients of the scale indicate that the instrument can measure students' motivational profile structure. Second-order DFA results revealed that the “Internal Judgment” dimension was distinct from the general artificial intelligence motivation superstructure. The findings of this study indicate that “Identified Regulation” (perceived benefit) and “Intrinsic Motivation” (interest/enjoyment) are the factors with the highest explanatory power in students' use of artificial intelligence.

This research determined that the Turkish version of the Artificial Intelligence Motivation Scale (AIMS) is a valid and reliable tool for measuring university students' motivational orientations in AI-supported learning processes. From a broader perspective, this research fills an important gap in the Turkish higher education context by providing a validated measurement tool that can support both empirical research and evidence-based educational practices. The scale's five-factor structure was preserved and high internal consistency coefficients were achieved. The scale can be used to determine students' motivation profiles and offer personalized learning paths. In conclusion, the Turkish version of AIMS is a psychometrically suitable measurement tool that can be used in research and educational applications aimed at understanding AI-based learning processes in the context of higher education in Turkey. In future research, faculty members can use AIMS to diagnose students' motivational profiles and design AI-supported learning activities that promote autonomous motivation. The identification of students exhibiting low intrinsic or identified motivation enables instructors to implement autonomy-supportive strategies, such as the design of meaningful tasks, the provision of choice, and the utilization of AI applications that are focused on relevance. Longitudinal designs may be particularly valuable for understanding how students' motivation toward AI evolves over time. In order to develop effective guidelines and policies for AI integration in higher education, policy makers and institutional leaders must consider the motivational factors involved.

Statements and Declarations

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Appendix A. Survey Items

IM	IM1	Yapay zeka ile öğrenmekten çok keyif alıyorum	I enjoy learning with AI very much*
	IM2	Yapay zeka ile öğrenmek benim için eğlenceli	Learning with AI is fun for me*
	IM3	Yapay zeka ile öğrenmekten memnun hissediyorum	I feel satisfied through learning with AI+
	IM4	Yapay zeka ile bilgiyi keşfetmek benim için büyüleyici	Exploring knowledge with AI is fascinating to me+
ID	ID1	Yapay zeka ile öğrenmek etkinliğimi artırabilir^	Learning with AI could enhance my effectiveness^
	ID2	Yapay zeka ile öğrenmek akademik performansım için önemli^	Learning with AI is important for my academic performance^
		Yapay zeka ile öğrenmek gelecekteki kariyerim için önemli+	Learning with AI is important for my future career+
	ID4	Yapay zeka ile öğrenmek, gelecekteki zorluklarla başa çıkmama yardımcı olmak açısından önemli+	Learning with AI is important in helping me deal with future challenges+
IJ*	IJ1	Yapay zeka ile öğrenmezsem kendimi suçlu hissedeceğim+	I will feel guilty if I don't learn with AI+
	IJ2	Yapay zeka ile öğrenme zorunluluğu hissediyorum çünkü başkaları benden bunu bekliyor+	I feel a sense of obligation to learn with AI because others expect it of me+
	IJ3	Yapay zeka ile öğrenemezsem utanacağım+	I will feel ashamed if I cannot learn with AI+
	IJ4	Başkaları yapay zeka ile öğrenmekten aciz olduğumu düşünürse utanç duyacağım+	I will feel ashamed if others think I am incapable of learning with AI+
EX	EX1	AI# ile öğrenmekten başka seçeneğim yok	I have no other choice but to learn with AI#
	EX2	Yapay zeka ile öğrenme kurallardan biridir#	Learning with AI is one of the rules#
	EX3	AI# ile öğrenmezsem başım belaya girecek	I will get in trouble if I don't learn with AI#
	EX4	Yapay zeka ile öğrenmem gerekiyor+	I'm required to learn with AI+
AM	AM1	Yapay zeka ile öğrenmek anlamsızdır+	Learning with AI is meaningless+
	AM2	Neden yapay zeka ile öğrenmem gerektiğini anlayamıyorum+	I cannot see why I need to learn with AI+
	AM3	Yapay zeka ile öğrenmekten ne elde edeceğimi bilmiyorum	I don't know what I am getting out of learning with AI+
	AM4	Yapay zeka ile öğrenmek zaman kaybıdır	Learning with AI is a waste of my time+

*The IJ dimension was removed from the scale.