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# A Questionnaire of Artificial Intelligence Use Motives: A Contribution to Investigating the Connection between AI and Motivation

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# A Questionnaire of Artificial Intelligence Use Motives: A Contribution to Investigating the Connection between AI and Motivation

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## Abstract

This study introduces the Questionnaire of AI Use Motives (QAIUM), an instrument designed to measure motivation levels in individuals using artificial intelligence (AI) applications. Building on a theoretical framework that emphasizes motivation over dispositions and defines motivation as expectancy/value, the QAIUM aims to fill a research gap in understanding the motivational factors that govern AI application use. Previous studies have often overlooked this human aspect, focusing instead on technological facets while failing to provide a robust theoretical foundation for measuring motivation. The QAIUM, administered to 1068 university students across various degree programs, was evaluated for its factorial structure, reliability, discriminatory capacity, and correlation with the General Attitudes to Artificial Intelligence Scale (GAAIS). The results demonstrate that the QAIUM aligns with the Eccles and Wigfield motivation model, boasts good reliability levels, discriminatory capacity, and a significant correlation with GAAIS, confirming its validation and reliability. Hence, the QAIUM provides an effective tool for investigating motivational factors affecting AI application utilization in academic instruction and intervention.

## Introduction

In the continuously evolving and advancing field of technology, artificial intelligence (AI) has a transformative impact on our interaction with information and services (Gökçearslan et al., 2024). In an era where AI possesses cognitive capabilities, including learning, reasoning, and autonomous decision-making, understanding how individuals form preferences for AI applications has become increasingly crucial. This is a time when AI, with its ability to make autonomous decisions and contribute actively to our daily lives, is becoming an integral component. It has become important to comprehend how individuals shape their preferences for AI applications. According to Karaman and Göksu (2024), the integration of AI and chatbots in particular brings about a paradigm shift in educational tools, introducing a diverse array of transformative applications. In the realm of education in various forms, including personalized learning platforms designed to enhance students' educational experiences, automated assessment systems that assist educators in evaluating student progress, and facial recognition systems that yield valuable insights into learners' behaviors. Notably, this multifaceted incorporation of AI in education underscores its capacity to revolutionize traditional teaching methods and enhance the overall learning ecosystem

(Mabuan, 2024).

Artificial intelligence (AI) can be succinctly defined as a branch of computer science that focuses on simulating intelligent behavior in computers, aiming to mimic and ideally enhance human behavior (Naqvi, 2020). While it exerts a significant influence in the fields of science, engineering, and technology, it also makes its presence felt in education through machine learning systems and algorithmic advancements (Naqvi, 2020). Although thoughts about AI may not be at the forefront of our daily considerations, it consistently influences various aspects of our lives as we routinely interact with AI applications. Whether searching the internet, reviewing emails, scheduling a medical appointment, seeking driving directions, or receiving recommendations for movies and music, we engage with AI applications, benefiting from their assistance in different facets of our daily experiences.

AI has become a prominent presence in academia and education, leveraging technology as a substantial and advantageous component (Giray et al., 2024). With the use of leveraging effect of AI applications like ChatGPT, creation of tailored personalized learning environments for individual students becomes achievable which enables them to navigate and structure the course content in alignment with their specific academic tasks (Karaman & Göksu, 2024). Personalized learning systems designed to enhance students' learning experiences, automated assessment systems aiding teachers in evaluating students' knowledge, and facial recognition systems offering insights into learners' behaviors can be viewed as various algorithmic applications of artificial intelligence in education, all aimed at improving students' learning experiences (Remian, 2019).

As the use of artificial intelligence in the field of education rapidly expands, there is a growing curiosity about how students approach the adoption of this innovative technology and what motivates them in this context (Gansser & Reich, 2021; Hmoud et al., 2024). An effective perspective regarding what motivates individuals in this regard is the Expectancy-Value Theory. According to expectancy-value theorists, there are two basic sources that feed motivational beliefs: expectancy and value (Figure 1). Individuals' choices, persistence, and performance can be explained by their beliefs about how well they will perform in an activity and the value they attribute to that activity (Atkinson, 1957; Eccles et al., 1983; Wigfield, 1994; Wigfield & Eccles, 1992). This theory, originally developed to study math performance (Eccles et al., 1983), suggests that an individual's values and expectations directly shape their choices related to achievement, their performance, their level of effort, and their persistence (Wigfield & Eccles, 2000). Widely applied in educational psychology, the Expectancy-Value Theory provides insights into understanding individuals' achievement-oriented motivations, offering a cognitive and emotional understanding of the processes underlying students' preferences, effort expenditures, and persistency in academic pursuits (Wigfield & Eccles, 2000).

According to the Expectancy-Value Theory, both expectations and task values directly impact achievement choices, as well as performance, effort, and persistence (Wigfield & Eccles, 2000). This theory assumes that task-specific beliefs, such as beliefs about ability, the perceived difficulty of tasks, and an individual's goals, self-schemas, and affective memories, influence expectations and values. These social cognitive variables, in turn, are shaped by an individual's perception of their previous experiences and various socialization influences (Wigfield & Eccles, 1992). Eccles et al. (1983) defined achievement expectations as beliefs about how well individuals will do on upcoming tasks. While ability beliefs are defined as the individual's perception of their current competence at a given activity, achievement expectations focus on the future (Wigfield & Eccles, 2000).

According to the Expectancy-Value Theory, two critical factors determining students' motivation, academic performance, and activity choices are achievement expectations and task values (Rosenzweig et al., 2019). In this context, developing a motivation scale for the use of artificial intelligence within the framework of Expectancy-Value Theory would involve examining the task value dimensions, consisting of four fundamental sub-dimensions: attainment, utility value, intrinsic value, and cost (Valenzuela et al., 2011). Each of these four subdimensions contribute to shaping an individual's motivational disposition toward a task.

Attainment Value represents the perceived significance of task completion, given its consonance with an individual's identity, thereby accentuating tasks deemed instrumental to their self-concept (Eccles & Wigfield, 2002). Utility Value, on the other hand, delineates the alignment of a task with an individual's prospective goals, serving as an evaluative measure of the task's relevance and instrumental utility in the attainment of long-term objectives (Barron & Hulleman, 2015). Intrinsic Interest Value captures the inherent gratification or interest derived by an individual from task engagement, propelled by the extent of enjoyment and curiosity elicited by the task (Ryan & Deci, 2000).

Lastly, Cost encapsulates the potential detriments associated with task engagement, including the required effort, potential for failure, or the opportunity cost incurred as a result of time diversion from other activities (Barron & Hulleman, 2015). In the specific context of artificial intelligence, a profound understanding of these subdimensions provides a solid foundation for identifying the motivational factors that drive the utilization of artificial intelligence applications. By collectively encompassing these subdimensions, a comprehensive understanding emerges of the multifaceted influences that guide an individual's decision to initiate and sustain engagement in a given task.

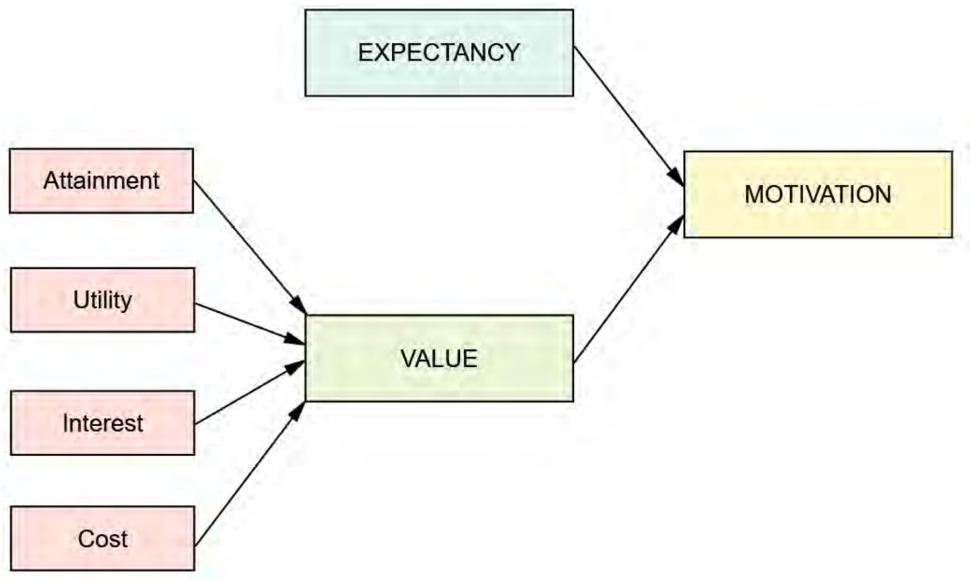


Figure. 1. The Motivational Model of Eccles and Wigfield, 2002 (simplified)

Guided by the situated expectancy–value theory, Wang et al. (2023) investigate the role of supportive environments and expectancy–value beliefs in fostering university students' intentions to learn AI. Their findings underscore the critical influence of supportive environments and positive expectancy–value beliefs on students' motivation to engage with AI technologies. Complementarily, Chiu et al. (2023) explore the impact of teacher support on students' motivation to learn with AI-based chatbots. By employing self-determination theory, the researchers examine how teacher support moderates the effects of student expertise on intrinsic motivation and competence in AI learning. This study highlights the necessity of considering both teacher support and student expertise when designing effective AI interventions in educational contexts.

Additionally, Salas-Pilco & Yang (2022) and Zawacki-Richter et al. (2019) emphasize the importance of understanding motivational factors alongside AI curriculum and technical aspects. They assert that learning environments and motivational beliefs significantly shape students' intentions to learn about new technologies. By identifying critical factors that promote or inhibit students' intentions to learn AI, these studies aim to provide valuable insights for higher education institutions to inform effective interventions, enhancing students' motivation and engagement in AI education. These studies collectively underscore the multidimensional nature of motivational influences in AI education and advocate for comprehensive approaches to enhancing students' motivation and engagement.

While existing studies propose that generative AI has the potential to enhance student motivation in specific teaching settings (Khasawneh & Jadallah Abed Khasawneh, 2023; Yilmaz & Yilmaz, 2023), a critical gap in the literature exists regarding the underlying motives behind the utilization of artificial intelligence. Addressing this gap, Baek and Kim (2023) employed the 'uses and gratifications (U&G) theory' (Choi & Drumwright, 2021) to investigate user motivations for integrating ChatGPT, thereby introducing a scale to gauge how AI, particularly ChatGPT, satisfies user needs. An alternative perspective presented by Ahmed et al. (2022) unveiled that educators deem factors such as concern for others' opinions, acquisition of academic incentives, and an intrinsic desire to succeed as pivotal for motivation in utilizing AI within educational settings. Despite a multitude of studies exploring the impact of AI on motivation, there remains a conspicuous absence of a theoretically grounded framework to comprehend the motivational factors propelling individuals to engage with AI. The development of an instrument becomes imperative to discern the factors and levels of motivation associated with AI use, thereby elucidating the intricate connection between AI and motivation.

This study seeks to undertake an in-depth investigation into the motivational factors and levels exhibited by students in their utilization of artificial intelligence (AI), thereby establishing correlations with their broader attitudes towards AI. To achieve these objectives, a scale rooted in the theoretical framework of expectancy-value theory has been purposefully devised for this research endeavor. The primary aim of this scale is to unveil invaluable insights regarding the motivational determinants that impel individuals to engage with AI. Moreover, in order to examine the interplay between motivation and attitudes concerning the use of AI, the researchers have opted to employ the General Attitudes to Artificial Intelligence Scale (GAAIS), as conceptualized by Schepman and Rodway (2020). By leveraging this scale, the study endeavors to scrutinize the associations between individuals' motivations for utilizing AI and their comprehensive attitudes toward this technological domain.

Within the confines of this study, the principal objective revolves around substantiating the validity of the Questionnaire of AI Use Motives (QAIUM) and establishing meaningful correlations between its outcomes and the General Attitudes to Artificial Intelligence Scale (GAAIS). The attainment of this objective is poised to contribute to the existing corpus of knowledge surrounding the motivational factors and levels pertinent to AI employment. In addition, the study aims to undertake a comprehensive exploration of the psychometric properties inherent in the developed questionnaire. This exploration is of paramount importance as it substantiates the questionnaire's validity and reliability, thereby paving the way for subsequent investigations into the motivational factors and levels associated with AI utilization.

## Method

### Participants

In this research, participants were selected using the convenient sampling method. A total of 1068 university students from various cities in Turkey participated in the study. The participants were selected from seven different faculties: The Faculty of Arts and Sciences, the Faculty of Engineering, the Faculty of Economics and Administrative Sciences, the Faculty of Education, the Faculty of Fine Arts, the Faculty of Communication, and the Faculty of Sports Sciences.

Participation in the research was based on voluntariness, and participants were provided with the opportunity to respond to the online survey through Google Forms. 58.6% of the students (n=626) were female, while 41.4% (n=442) were male. The average age of the students was 22.93 (SD= 5.46, Range=17 to 54). The proportion of first-year students was 24.2% (n=258), second-year students was 29% (n=310), third-year students was 21.4% (n=229), and fourth-year students was 25.4% (n=271). 65.2% of the participants (n=696) indicated that they actively use artificial intelligence applications (ChatGPT, Bing, etc.).

### Instruments

*The Questionnaire of AI Use Motives (QAIUM)*

A motivation survey for using artificial intelligence applications was developed within the framework of the Expectancy-Value Theory to identify motivational factors driving the use of artificial intelligence applications. According to the Expectancy-Value Theory, motivation has two fundamental dimensions: expectancy and task value. The task value dimension consists of four sub-dimensions: attainment, utility, interest, and cost. These dimensions are ranked as attainment, utility, interest, and cost.

During the scale development, a literature review was initially conducted, and items suitable for each dimension were written. In the process of creating the item pool, inspiration was drawn from scales developed based on the Expectancy-Value Theory in different fields (Eccles & Wigfield, 1995; Valenzuela et al., 2011). The item pool consisted of 30 items, with 6 items for each dimension. The questionnaire was rated on a 5-point Likert scale (1= completely false through 5= completely true).

*General Attitudes to Artificial Intelligence Scale (GAAIS)*

The General Attitudes to Artificial Intelligence Scale (GAAIS) was used to measure convergent validity. The scale was developed by Schepman and Rodway in 2020 and adapted for the Turkish context by Kaya et al. (2024). It evaluates people's general attitudes towards AI and consists of 20 items - 12 Positive GAAIS items and 8 Negative GAAIS items. A five-point Likert-type scale rates each item (1=strongly disagree through 5=strongly agree). Good internal consistency reliability is reported for the scale, with alpha=0.82 for Positive GAAIS and alpha=0.84 for Negative GAAIS (Kaya et al., 2024).

*Procedures*

In this study, the validity analyses of the scale were conducted in terms of content and appearance validity. Experts selected to assess the scope and face validity of the questionnaire consisted of three academics who had completed their doctorates in psychology, measurement-evaluation, and language fields. These experts thoroughly examined the dimensions and items of the questionnaire, suggesting the removal of similar items and the modification of some expressions to evaluate the scope and face validity. Considering the expert recommendations, all corrections were made, and some items were excluded from the questionnaire. As a result of these adjustments, a total of 20 items were included in the questionnaire, with 4 items for each dimension. The distribution of questionnaire items by dimensions is shown in Table 1.

In the next step, the structural validity of the questionnaire was tested. In this regard, exploratory factor analysis (EFA) was initially conducted, followed by confirmatory factor analysis (CFA). The data of 524 students were used for EFA, and for CFA, the data of 544 students were utilized. Principal Axis Factoring, one of the factor extraction methods, was employed during EFA. This method is among the most commonly used methods in social sciences (Warner, 2012). Considering the interrelated factor structures, oblique rotation methods are recommended (Field, 2005). Since it was assumed that the dimensions of the questionnaire were correlated, the Promax (kappa=4) oblique rotation method was used.

CFA was employed to examine the congruence of the five-factor model of the questionnaire with the available data. Model fit was assessed using various indices, including $\chi^2$/df, standardized root mean residual (SRMR), root mean square error of approximation (RMSEA), comparative fit index (CFI), and Tucker-Lewis index (TLI) (Hu & Bentler, 1999). Convergent and discriminant validity were examined by calculating composite reliability (CR), average variance extracted (AVE), maximum shared variance (MSV), and maximum reliability (MaxR(H)).

Additionally, alpha coefficients were computed to assess the internal consistency reliability of the measurement instrument. Criterion validity was evaluated to determine the extent to which the questionnaire serves its purpose. In this regard, the QAIUM and the General Attitudes to Artificial Intelligence Scale were concurrently administered, and the relationships between the scores obtained from the two tests were analyzed. SPSS 25.0 and AMOS 24.0 statistical software packages were used for the analyses.

Table 1. Items of the Questionnaire of AI Use Motives (QAIUM)

| | |
|---|---|
| | **Expectancy** |
| It1 | I can learn the skills that enable effective use of artificial intelligence applications. |
| It2 | My general knowledge about artificial intelligence is more than sufficient compared to many. |
| It3 | I am better than most of my peers in effectively using artificial intelligence applications. |
| It4 | My potential to effectively use artificial intelligence applications surpasses many people in my surroundings. |
| | **Task value** |
| | *Attainment* |
| It5 | The ability to effectively use artificial intelligence is important to me. |
| It6 | Learning and implementing innovations in artificial intelligence applications are a priority for me. |
| It7 | It is important for me to stay updated on developments related to artificial intelligence. |
| It8 | I attach great importance to strengthening my skills in using artificial intelligence applications. |
| | *Utility value* |
| It9 | Artificial intelligence applications will assist me in becoming a proficient professional. |
| It10 | Artificial intelligence enhances my overall efficiency, making my life more effective. |
| It11 | In daily life, artificial intelligence helps me streamline my tasks. |
| It12 | Artificial Intelligence, benefits me in various subjects and courses. |
| | *Intrinsic/interest value* |
| It13 | I take pleasure in using artificial intelligence applications. |
| It14 | I enjoy experiences related to artificial intelligence. |
| It15 | Following developments in artificial intelligence is an interesting activity for me. |
| It16 | Developing my skills in using artificial intelligence is a delightful learning process for me. |
| | *Cost* |
| It17 | Investing time and effort to learn artificial intelligence applications is worthwhile for me. |
| It18 | Learning artificial intelligence applications is an easy task for me. |
| It19 | I am inclined to sacrifice time from other activities to learn artificial intelligence applications. |
| It20 | I am not hesitant to invest a considerable amount of time and effort to enhance my skills related to artificial intelligence. |

## Results

The adequacy of the sample was assessed by calculating the Kaiser-Meyer-Olkin (KMO) value, and the suitability of the data for factor analysis was examined using Bartlett's Sphericity test. The KMO value was calculated as .96, and the result of the Bartlett test showed a significant chi-square value ($\chi^2$=10291.85, p<.001). These results indicated that the data were suitable for Exploratory Factor Analysis (Watkins, 2018). The Principal Axis Factoring method was employed with a five-factor solution, and a promax rotation was conducted. The obtained results are presented in Table 2.

Table 2. Factor Loadings of 5-Factor QAIUM Items Rotated According to the Promax Method

| Items | | Factor | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| | ***Utility value*** | | | | | |
| It12 | Artificial Intelligence, benefits me in various subjects and courses. | .94 | | | | |
| It11 | In daily life, artificial intelligence helps me streamline my tasks. | .84 | | | | |
| It10 | Artificial intelligence enhances my overall efficiency, making my life more effective. | .81 | | | | |
| It9 | Artificial intelligence applications will assist me in becoming a proficient professional. | .62 | | | | |
| | ***Expectancy*** | | | | | |
| It3 | I am better than most of my peers in effectively using artificial intelligence applications. | | .93 | | | |
| It2 | My general knowledge about artificial intelligence is more than sufficient compared to many. | | .87 | | | |
| It4 | My potential to effectively use artificial intelligence applications surpasses many people in my surroundings. | | .80 | | | |
| It1 | I can learn the skills that enable effective use of artificial intelligence applications. | .30 | .55 | | | |
| | ***Attainment*** | | | | | |
| It7 | It is important for me to stay updated on developments related to artificial intelligence. | | | .83 | | |
| It6 | Learning and implementing innovations in artificial intelligence applications are a priority for me. | | | .79 | | |
| It8 | I attach great importance to strengthening my skills in using artificial intelligence applications. | | | .62 | | |
| It5 | The ability to effectively use artificial intelligence is important to me. | .30 | | .52 | | |
| | ***Intrinsic/interest value*** | | | | | |
| It14 | I enjoy experiences related to artificial intelligence. | .31 | | | .76 | |
| It15 | Following developments in artificial intelligence is an interesting activity for me. | | | | .76 | |
| It13 | I take pleasure in using artificial intelligence applications. | .33 | | | .67 | |
| It16 | Developing my skills in using artificial intelligence is a delightful learning process for me. | | | | .60 | |
| | ***Cost*** | | | | | |
| It19 | I am inclined to sacrifice time from other activities to learn artificial intelligence applications. | | | | | .91 |
| It20 | I am not hesitant to invest a considerable amount of time and effort to enhance my skills related to artificial intelligence. | | | | | .76 |
| It18 | Learning artificial intelligence applications is an easy task for me. | | .30 | | | .55 |
| It17 | Investing time and effort to learn artificial intelligence applications is worthwhile for me. | | | | | .52 |
| | *Eigenvalue* | *12.63* | *2.29* | *1.92* | *1.69* | *1.16* |
| | *% of Variance* | *53.14* | *9.64* | *8.08* | *7.11* | *4.88* |

Examining Table 2, it is understood that QAIUM items are grouped under five factors, as anticipated. The factor loadings of the items in the questionnaire range from 0.52 to 0.94. The five-factor structure resulting from factor analysis explained 82.85% of the total variance. The high proportion of explained variance indicates that the items have a high level of representational power.

**Confirmatory Factor Analysis Results**

Confirmatory factor analysis was conducted to assess the compatibility of the questionnaire's five-factor structure with the data. The adequacy of the model fit for QAIUM was demonstrated in Table 3, with the following results: $\chi^2$(DF=150) = 459.40, $\chi^2$/DF = 3.663, p<.001, SRMR= .038, RMSEA= .070, GFI= .901, AGFI= .862, CFI= .962, NFI= .949, IFI= .962, and TLI= .952. The five-factor model showed a good fit with the data (Hu & Bentler, 1999). Standardized regression weights for the measurement model can be found in Figure 1, with each standardized factor loading being statistically significant at the 0.001 level.

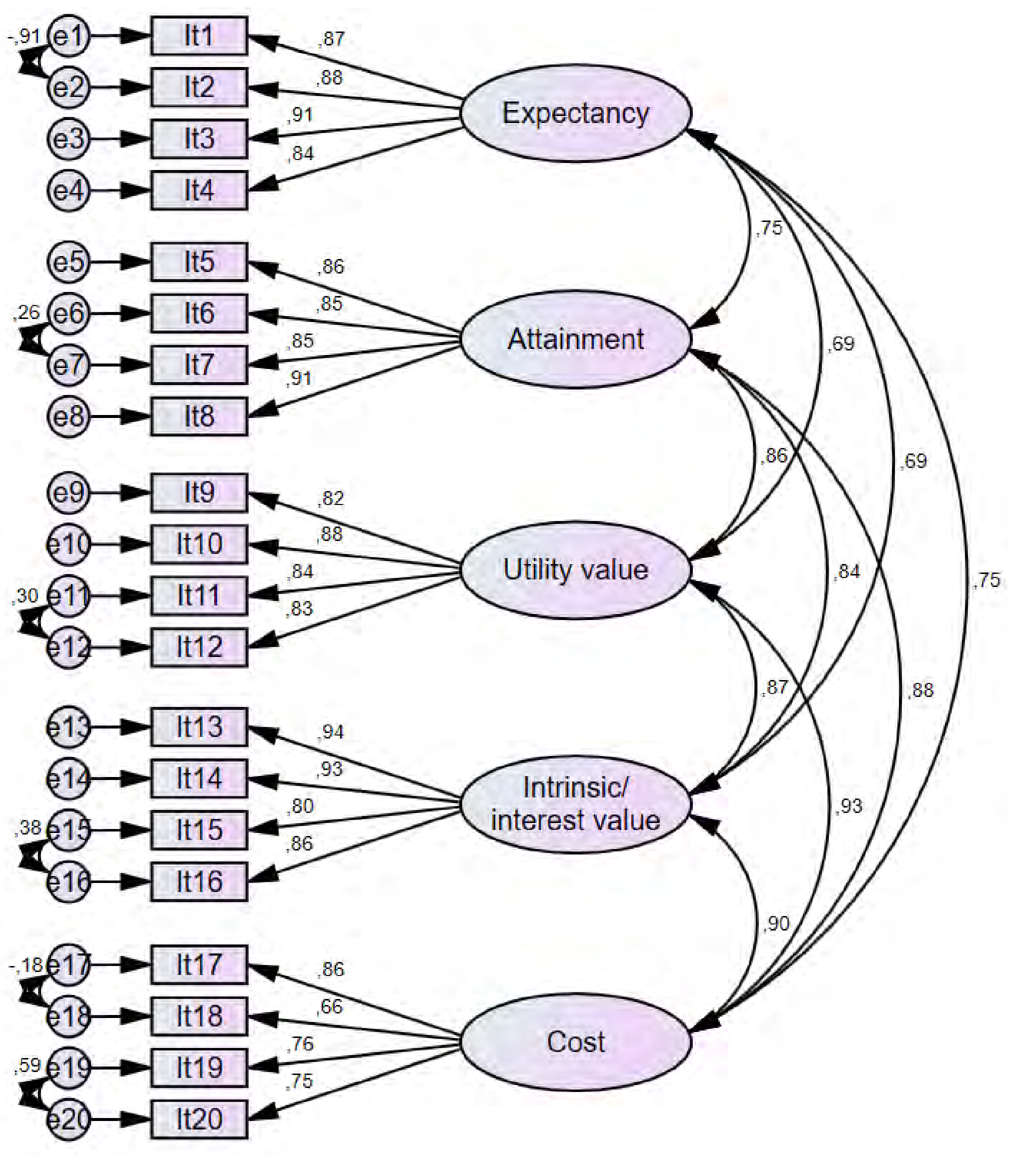


Figure 1. The Measurement Model

Table 3. Model Fit Indices

| Fit Indices | QAIUM | Reference Values |
|---|---|---|
| GFI | .901 | ≥.90 |
| AGFI | .862 | ≥.80 |
| NFI | .949 | ≥.90 |
| IFI | .962 | ≥.90 |
| TLI | .952 | ≥.90 |
| CFI | .962 | ≥.90 |
| SRMR | .038 | ≤ .08 |
| RMSEA | .070 | ≤ .08 |

QAIUM= The Questionnaire of AI Use Motives

**Discriminant and Convergent Validity**

The internal reliability, convergent validity, and discriminant validity of the questionnaire were tested using composite reliability (CR), average variance extracted (AVE), and MaxR(H) (maximum reliability). The results indicated that all CR and alpha values exceeded the threshold of .70, and MaxR(H) exceeded the threshold of .80, indicating satisfactory internal reliability (Yurt, 2023). Furthermore, the AVE > .50 and CR > AVE conditions were met, meaning that convergent validity was achieved (Hair et al., 2013). As evidence of discriminant validity, most of the square root of AVE values were greater than correlations between constructs. Also, Hu and Bentler (1999) argued that MaxR(H) > CR indicated that discriminant validity was met. Therefore, the results demonstrated that both discriminant and convergent validity were achieved (Table 4).

Table 4. Convergent and Discriminant Validity

| | Construct | α | CR | AVE | MaxR(H) | 1. | 2. | 3. | 4. | 5. |
|---|---|---|---|---|---|---|---|---|---|---|
| 1. | Expectancy | .881 | .929 | .767 | .933 | .876 | | | | |
| 2. | Attainment | .923 | .924 | .751 | .927 | .747*** | .867 | | | |
| 3. | Utility value | .915 | .910 | .716 | .912 | .686*** | .860*** | .846 | | |
| 4. | Intrinsic/ interest value | .935 | .933 | .778 | .948 | .694*** | .837*** | .868*** | .882 | |
| 5. | Cost | .865 | .844 | .578 | .862 | .754*** | .885*** | .926*** | .902*** | .760 |

***p<.001

**Criterion Validity**

Criterion validity was tested by correlation analysis between the Questionnaire of AI Use Motives (QAIUM) and the General Attitudes to Artificial Intelligence Scale (GAAIS). The results obtained are shown in Table 5. The correlations between QAIUM and GAAIS components were statistically significant. The results indicate that individuals scoring higher in QAIUM may have positive and negative attitudes toward artificial intelligence.

Table 5. Pearson Correlation Coefficients

| Variables | Positive GAAI | Negative GAAI |
|---|---|---|
| Expectancy | .562** | .237** |
| Attainment | .623** | .211** |
| Utility value | .685** | .178** |
| Intrinsic/ interest value | .696** | .153** |
| Cost | .662** | .200** |

**p< .01, N=544, GAAI= General Attitudes to Artificial Intelligence

## Discussion

This study aimed to develop a questionnaire (QAIUM) that determines the motivations of university students to use artificial intelligence applications based on the Expectancy-Value Theory. A total of 1068 university students from various cities in Turkey participated in the study. Exploratory and confirmatory factor analysis was applied to test the construct validity of the questionnaire. Additionally, the questionnaire's reliability, convergent, discriminant, and criterion validities were examined.

The findings of the exploratory factor analysis (EFA) provide evidence for the structural integrity and reliability of the developed the Questionnaire of AI Use Motives (Watkins, 2018). The robust Kaiser-Meyer-Olkin (KMO) value of 0.96 and the significant result of the Bartlett's Sphericity test ($\chi2$=10291.85, p<.001) indicate that the data is suitable for factor analysis. The EFA revealed a comprehensive five-factor structure in the questionnaire, namely utility value, expectancy, attainment, intrinsic/interest value, and cost. The factor loadings ranged from 0.52 to 0.94, indicating excellent representation of the items. This five-factor structure accounted for an impressive 82.85% of the total variance, suggesting a high level of representativeness. These findings align with previous studies that have utilized exploratory factor analysis to examine motivational factors in various domains (Wong & Law, 2002; Kim & Mueller, 1978; Knekta, Runyon, & Eddy, 2019; Dabbagh et al., 2023).

Confirmatory factor analysis (CFA) further supports the validity and reliability of the QAIUM. All model fit indices, including $\chi2$/DF, SRMR, RMSEA, GFI, AGFI, CFI, NFI, IFI, and TLI, met or exceeded widely accepted thresholds (Hayashi et al., 2011; Hu & Bentler, 1999). Also, the significant standardized regression weights indicate that the proposed five-factor model adequately represents the observed data. This finding supports the notion that the factor structure of QAIUM is consistent with the underlying construct of AI use motives. The alignment between the hypothesized model and the observed data provides strong evidence for the validity and reliability of the questionnaire. The confirmatory factor analysis results demonstrate that the factor structure of QAIUM aligns consistently with the observed data, as indicated by the satisfactory fit indices and significant standardized regression weights.

In terms of reliability and validity assessments, the questionnaire demonstrated commendable internal reliability, convergent validity, and discriminant validity. High internal consistency was indicated by Composite Reliability (CR) values surpassing the 0.70 threshold (Yurt, 2023). Convergent validity was confirmed by Average Variance Extracted (AVE) values exceeding 0.50 (Hair et al., 2013). Additionally, the CR > AVE condition was met, further supporting convergent validity. Discriminant validity was robustly established through the square root of AVE values surpassing inter-construct correlations and MaxR(H) > CR (Hair et al., 2013; Hu & Bentler, 1999). Finally, criterion validity analysis uncovered statistically significant correlations between QAIUM and the General Attitudes to Artificial Intelligence Scale (GAAIS), implying that higher QAIUM scores may indicate individuals exhibiting both positive and negative attitudes toward artificial intelligence.

This study, rooted in the Expectancy-Value Theory, contributes fundamentally to understanding the motivational sources associated with artificial intelligence (AI) usage. Aligned with contemporary AI in education research, the study accentuates the crucial need for exploring motivational dimensions linked to AI utilization. Chiu et al.'s exploration of the intricate relationship between student motivation, intrinsic motivation, and competence in AI-based chatbot learning sheds crucial light (Chiu et al., 2023). Their findings emphasize the interplay of motivational factors and the pivotal role of external support, particularly from teachers, alongside student expertise. The predictions of the expectancy-value model have also found confirmation in the context of artificial intelligence, demonstrating the ongoing development of the theory in this direction. Moreover, various studies have highlighted the evident potential of AI systems to significantly enhance the quality and effectiveness of student learning, particularly in higher educational contexts (Luckin & Cukurova, 2019). However, Shank et al.'s insight into user unease or discomfort when generative AI technology exceeds expectations raises relevant considerations that need to be addressed (Shank et al., 2019). Privacy concerns are another important factor to consider, especially for systems like ChatGPT that rely on extensive data for improved task performance (Paul et al., 2023). It is crucial to strike a balance between the benefits of AI and ethical considerations, particularly in educational settings. In AI-based learning environments, teacher support emerges as a critical determinant in shaping student motivation (Chiu et al., 2023). The active involvement of educators significantly influences student motivation, emphasizing the collaborative nature necessary for effective integration of AI in education. Furthermore, applying the Expectancy-Value Theory, as demonstrated in Green's exploration of teachers' motivational strategies, provides an additional layer of understanding regarding the intricate interplay of motivations in educational settings (Green, 2002). Investigating how teachers' approaches align with this theoretical framework yields valuable insights into the motivational dynamics shaping the AI-assisted learning landscape.

## Recommendations, Future Research, and Limitations

Looking ahead, it is crucial to acknowledge the adaptability of AI motivational scales to different societal groups. This adaptability not only facilitates inclusive research but also opens avenues for diverse applications of AI technology. By incorporating a range of perspectives, researchers can gain a more comprehensive understanding of the motivations behind AI use across different contexts and populations. This inclusivity ensures that AI technologies are developed and implemented in a manner that considers the needs and interests of all individuals, promoting equitable access to AI benefits.

Longitudinal studies tracking changes in AI motivations offer valuable insights into the evolving relationship between individuals and AI technologies. These studies can identify trends, patterns, and potential challenges associated with the integration of AI into daily life. Examining how motivations for using AI evolve over time sheds light on the broader societal impact of AI, including its effects on education, healthcare, and the workplace. Such studies help in navigating the potential benefits and risks associated with widespread AI adoption.

Comprehensive investigations into the effective use of AI are crucial for informing educational practices and policies. As AI continues to permeate various facets of society, understanding how to harness its potential for more widespread and effective utilization becomes paramount. Research examining the factors influencing successful AI implementation, identifying barriers and challenges, and exploring best practices can guide educational institutions and policymakers in making informed decisions about integrating AI into teaching and learning environments.

The study's exclusive focus on university students limits the generalizability of findings beyond this demographic. To address this limitation, future research should broaden the participant base to include diverse demographic groups across educational levels, age groups, and socio-economic backgrounds. Exploring various settings and contexts would contribute to a more nuanced understanding of the relationship between AI use and motivation, ultimately bolstering the relevance of the research across different populations and settings.

The cross-sectional design of the study impedes the investigation of motivational changes over time, hindering the identification of temporal patterns and dynamics in the relationship between AI use and motivation. To overcome this limitation, future research should embrace a longitudinal approach, employing a comprehensive tracking mechanism across multiple time points. Additionally, expanding methodological approaches, such as employing mixed-methods and alternative data sources, would fortify methodological robustness, enhancing the credibility and transferability of study outcomes across varied populations and contexts.

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## Appendix A. Questionnaire of Artificial Intelligence Use Motives (English Form)

| No | Expectancy |
|---|---|
| 1. | I can learn the skills that enable effective use of artificial intelligence applications. |
| 2. | My general knowledge about artificial intelligence is more than sufficient compared to many. |
| 3. | I am better than most of my peers in effectively using artificial intelligence applications. |
| 4. | My potential to effectively use artificial intelligence applications surpasses many people in my surroundings. |
| | **Task value** |
| | *Attainment* |
| 5. | The ability to effectively use artificial intelligence is important to me. |
| 6. | Learning and implementing innovations in artificial intelligence applications are a priority for me. |
| 7. | It is important for me to stay updated on developments related to artificial intelligence. |
| 8. | I attach great importance to strengthening my skills in using artificial intelligence applications. |
| | *Utility value* |
| 9. | Artificial intelligence applications will assist me in becoming a proficient professional. |
| 10. | Artificial intelligence enhances my overall efficiency, making my life more effective. |
| 11. | In daily life, artificial intelligence helps me streamline my tasks. |
| 12. | Artificial Intelligence, benefits me in various subjects and courses. |
| | *Intrinsic/interest value* |
| 13. | I take pleasure in using artificial intelligence applications. |
| 14. | I enjoy experiences related to artificial intelligence. |
| 15. | Following developments in artificial intelligence is an interesting activity for me. |
| 16. | Developing my skills in using artificial intelligence is a delightful learning process for me. |
| | *Cost* |
| 17. | Investing time and effort to learn artificial intelligence applications is worthwhile for me. |
| 18. | Learning artificial intelligence applications is an easy task for me. |
| 19. | I am inclined to sacrifice time from other activities to learn artificial intelligence applications. |
| 20. | I am not hesitant to invest a considerable amount of time and effort to enhance my skills related to artificial intelligence. |

*Note: 5-point Likert (1 = Completely false, 5 = Completely true).*

## Appendix B. Yapay Zeka Kullanımına Yönelik Motivasyon Anketi (Turkish Form)

| No | Yeterlik Beklentisi |
|---|---|
| 1. | Yapay zekâ uygulamalarını etkili kullanmayı sağlayan becerileri öğrenebilirim. |
| 2. | Yapay zekâ hakkında genel bilgi seviyem, birçok kişiye göre daha yeterlidir. |
| 3. | Yapay zekâ uygulamalarını etkili kullanma konusunda, akranlarımın çoğundan daha iyiyim. |
| 4. | Yapay zekâ uygulamalarını etkili kullanma konusundaki potansiyelim çevremdeki birçok kişiyi aşabilir. |
| | **Değer** |
| | *Yarar-Önem* |
| 5. | Yapay zekâ uygulamalarını etkin bir şekilde kullanabilme becerisi benim için önemlidir. |
| 6. | Yapay zekâ uygulamalarındaki yenilikleri öğrenmek ve uygulamak, benim için öncelikli bir konudur. |
| 7. | Yapay zekâ ile ilgili gelişmeleri takip etmek benim için önemlidir. |
| 8. | Yapay zekâ uygulamalarını kullanma becerilerimi güçlendirmeye büyük bir önem veririm. |
| | *Fayda* |
| 9. | Yapay zekâ uygulamaları, iyi bir profesyonel olmama yardım edecektir. |
| 10. | Yapay zekâ, genel verimliliğimi artırarak hayatımı daha etkili kılar. |
| 11. | Günlük hayatta yapay zekâ, işlerimi kolaylaştırmama yardımcı olur. |
| 12. | Yapay zekâ, çeşitli konularda ve derslerde bana fayda sağlar. |
| | *İçsel değer* |
| 13. | Yapay zekâ uygulamalarını kullanmaktan zevk alırım. |
| 14. | Yapay zekâ ile ilgili deneyimlerimden keyif alırım. |
| 15. | Yapay zekâ gelişmelerini takip etmek benim için ilginç bir aktivitedir. |
| 16. | Yapay zekâyı kullanma becerilerimi geliştirmek benim için keyifli bir öğrenme sürecidir. |
| | *Maliyet* |
| 17. | Yapay zekâ uygulamalarını öğrenmek zaman ve çaba harcamaya değer. |
| 18. | Yapay zekâ uygulamalarını öğrenmek kolay bir iştir. |
| 19. | Yapay zekâ uygulamalarını öğrenmek için başka şeylere ayıracağım zamandan fedakârlık yapma eğiliminde olurum. |
| 20. | Yapay zekâ ile ilgili becerilerimi geliştirmek için oldukça fazla zaman ve çaba harcamaktan çekinmem. |

*Not: 5'li Likert (1=Tamamen yanlış 5=Tamamen doğru).*