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# Development of the Artificial Intelligence Perception and Attitude Scale (AIPAS): Validity and Reliability Study

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#### **Abstract**

Given the increasing integration of artificial intelligence (AI) into daily life, understanding public perception and attitudes towards these technologies is crucial. This research introduces the 'Artificial Intelligence Perception and Attitude Scale' (AIPAS), developed to comprehensively assess individuals' perceptions and attitudes towards AI technologies. The instrument evaluates four distinct yet interconnected sub-dimensions: Positive Perception (evaluating optimistic views and perceived benefits), Negative Perception (assessing concerns and anxieties), Generative Media Use (gauging interaction with AI in creative media generation), and Chatbot Interaction (focusing on experiences with conversational AI). Validation and reliability testing involved 1,600 participants from Türkiye. Exploratory Factor Analysis revealed a clear four-factor structure with 24 items, accounting for 73.59% of the total variance. Confirmatory Factor Analysis affirmed this structure, yielding strong fit indices (x²/sd = 1.54, RMSEA = .07, CFI = .97, TLI = .97). The scale's overall internal consistency, measured by Cronbach's alpha, was excellent at .93, with sub-dimension alphas ranging robustly between .90 and .96. These findings demonstrate that AIPAS is a reliable and valid tool, offering a nuanced instrument for examining the multifaceted nature of AI-related perceptions and attitudes, particularly within the Turkish context, and providing a valuable resource for future research and policy-making.

**Keywords:** Artificial intelligence, AI perception, AI attitude, scale development, AI Chatbots, generative AI, AI media tools

# Yapay Zekâ Algı ve Tutum Ölçeğinin Geliştirilmesi: Geçerlilik ve Güvenilirlik Çalışması Öz

Yapay zekânın günlük hayata artan entegrasyonu göz önüne alındığında, bu teknolojilere yönelik toplumsal algı ve tutumların anlaşılması büyük önem taşımaktadır. Bu çalışmanın amacı, bireylerin yapay zekâ teknolojilerine yönelik algı ve tutumlarını kapsamlı bir şekilde ölçmek için "Yapay Zekâ Algı ve Tutum Ölçeği"ni (YAZAT) geliştirmektir. Ölçek, birbiriyle ilişkili ancak ayrı dört alt boyutu değerlendirmektedir: Olumlu Algı (iyimser görüşleri ve algılanan faydaları değerlendiren), Olumsuz Algı (endişeleri ve kaygıları ölçen), Üretken Medya Kullanımı (yaratıcı medya üretiminde yapay zekâ ile etkileşimi belirleyen) ve Sohbet Robotu Etkileşimi (sohbet tabanlı yapay zekâ deneyimlerine odaklanan). Geçerlilik ve güvenilirlik analizleri, Türkiye'den 1600 katılımcıyla gerçekleştirilmiştir. Açımlayıcı Faktör Analizi, 24 madde ve dört faktörden oluşan net bir yapının toplam varyansın %73,59'unu açıkladığını ortaya koymuştur. Doğrulayıcı Faktör Analizi bu yapıyı doğrulamış ve güçlü uyum indeksleri sunmuştur (x²/sd = 1.54, RMSEA= .07, CFI= .97, TLI= .97). Ölçeğin Cronbach alfa ile ölçülen genel iç tutarlılığı .93 ile mükemmel düzeydedir; alt boyut alfa katsayıları ise .90 ile .96 arasında güçlü bir aralıkta değişmektedir. Bulgular, YAZAT'ın, özellikle Türkiye bağlamında yapay zekâ ile ilgili algı ve tutumların çok yönlü doğasını incelemek için incelikli bir araç sunan ve gelecekteki araştırmalar ile politika oluşturma süreçleri için değerli bir kaynak teşkil eden geçerli ve güvenilir bir ölçek olduğunu göstermektedir.

**Anahtar Kelimeler:** Yapay zekâ, algı, tutum, ölçek geliştirme, yapay zekâ sohbet robotu, üretken yapay zekâ, medya araçları

# INTRODUCTION

The proliferation of artificial intelligence (AI), particularly with the recent surge of accessible generative AI tools like large language models and image generators, has begun to profoundly reshape daily life and professional practices across the globe. AI is no longer a futuristic concept but an increasingly integrated technology influencing diverse domains such as education, healthcare, finance, and transportation at an unprecedented scale. While AI's transformative potential is vast, this rapid integration has simultaneously brought to the forefront significant concerns surrounding employment displacement, data privacy, algorithmic bias, and complex ethical dilemmas. Navigating this evolving landscape requires a deep understanding of how the public perceives and emotionally responds to these technologies. Public acceptance and efficient, responsible utilization of AI depend heavily on individuals' perceptions and attitudes. Understanding these perceptions and attitudes is not merely an academic exercise; it is fundamental to guiding the societal integration of AI, fostering responsible innovation, and mitigating potential negative consequences. This critical need has led to a growing emphasis on the development of robust psychometric scales designed to measure these multifaceted perspectives. Such scales not only shed light on the factors influencing users' acceptance and use of AI but also provide invaluable insights into its broader ethical and societal implications (Dinler, 2024; Schepman & Rodway, 2020; Ma & Chen, 2024).

The theoretical underpinnings for understanding technology adoption, and by extension AI adoption, are well-established in models such as the Technology Acceptance Model (TAM; Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003). These models emphasise the pivotal role of perceptions in the uptake of novel technologies. The Technology Acceptance Model, for instance, posits that perceived usefulness and perceived ease of use are the predominant factors affecting technology acceptance intention (Davis, 1989). Perceived usefulness refers to the degree to which an individual believes that using a particular system would enhance their job performance, while perceived ease of use is the degree to which an individual believes that using a particular system would be free of effort. A similar argument is made by the Unified Technology Acceptance and Use Model, which posits that technology use behaviour is influenced by performance expectancy (similar to perceived usefulness), effort expectancy (similar to perceived ease of use), social influence (the degree to which an individual perceives that important others believe they should use the new system), and facilitating conditions (an individual's belief about the availability of organizational and technical infrastructure to support use of the system) (Venkatesh et al., 2003). These models provide a valuable lens through which to examine the factors influencing individuals' willingness to engage with AI technologies.

In the context of AI, educators' and students' perceptions and attitudes towards AI will play a critical role in determining whether this technology will be successfully integrated in education. When teachers perceive the potential benefits of AI, such as personalising learning processes, reducing assessment burden, and monitoring student performance, they are more likely to use and integrate AI-powered educational tools or intelligent educational robots into their lessons (Dinler, 2024; Holmes, 2019; Luckin & Holmes, 2016). Similarly, students' positive perceptions of AI can increase their motivation to learn, engagement in class, and academic achievement (Zawacki-Richter et al., 2019).

It is acknowledged that the conceptual boundaries between perception (as cognitive appraisal and understanding) and attitude (as affective and evaluative response) can sometimes be blurred in practice, particularly when individuals form overall impressions of complex and evolving technologies like artificial intelligence (AI). The very concept of 'attitude' has been described as perhaps the most distinctive and indispensable in social psychology (Allport, 1935), often defined as a mental and neural state of readiness, organized through experience, that exerts a directive influence on responses (Allport, 1935). As noted by researchers in various fields (Singh et al., 2023), both cognitive understanding (akin to what Allport might term a 'mental attitude' or 'cortical set') and affective evaluations are critical in shaping responses to AI. The 'Artificial Intelligence Perception and Attitude Scale' (AIPAS) is thus titled to reflect its aim to capture this broader spectrum of individuals' cognitive and affective engagement with AI.

Operationally within this scale, the sub-dimensions termed 'Positive Perception' and 'Negative Perception' are designed to assess individuals' overarching positive or negative evaluations, feelings, and stance towards AI. These dimensions, tapping into core components often associated with 'attitude' in psychological literature (Eagly & Chaiken, 1993; Schepman & Rodway, 2020), can be seen as reflecting the "affect for or against a psychological object" aspect that Allport (1935) discusses, fundamentally informed by individuals' cognitive appraisals and beliefs about AI's nature and impact. The subsequent sub-dimensions, 'Generative Media Use' and 'Chatbot Interaction,' then focus on more specific attitudinal and behavioral dispositions related to the engagement with

particular AI applications, reflecting how these general evaluative stances (attitudes, in Allport's sense of 'readiness for response') translate into tendencies for interaction with these tools.

While the AIPAS aims to operationalize these constructs distinctly, empirically, existing research shows that complex and sometimes even contradictory perceptions of AI exist. Alongside the potential benefits of AI, negative perceptions such as job loss, ethical concerns, data privacy concerns, algorithmic bias, and reduced human interaction are also prevalent (Holmes et al., 2022; Tarafdar et al., 2023). These negative perceptions may hinder the widespread adoption and effective use of AI technologies in education and other sectors.

Consequently, there is a pressing need for robust instruments that can accurately measure the diverse perceptions and attitudes towards AI. While some scales address general AI literacy (Laupichler et al., 2023; Ma & Chen, 2024) or AI anxiety (Wang & Wang, 2022; Schiavo et al., 2024), a comprehensive scale that specifically captures both positive and negative perceptions alongside emerging use patterns related to generative media and chatbots is less common, particularly one validated with a large and diverse sample. These instruments should encompass various sub-dimensions, including positive and negative perceptions, and specific usage behaviors like interaction with generative AI tools and conversational agents, providing valuable data for educators, researchers, and policymakers.

In the process of developing scales to measure the perception of artificial intelligence, it is of great importance to conduct validity and reliability analyses meticulously. In order to ensure the structural validity of the scales, researchers frequently employ methods such as Confirmatory Factor Analysis (CFA). In addition, they utilise reliability tests, including internal consistency analysis, to ensure that the scale consistently measures results between individuals (Laupichler et al., 2023). For instance, Ma and Chen (2024) developed the "Artificial Intelligence Literacy Scale (AILS-CCS)" with the aim of measuring individuals' knowledge levels of artificial intelligence. The researchers conducted extensive analyses in order to test the scale's construct validity and reliability.

In the literature, perception and attitude scales towards artificial intelligence generally aim to cover individuals' knowledge level, operational competence, ethical evaluations and emotional attitudes. For example, Sindermann et al. (2022) examined the relationship between individuals' level of trust in artificial intelligence and their tendency to use this technology and emphasised that these scales play a critical role in understanding positive or negative perceptions towards the technology. Laupichler et al. (2023), on the other hand, aimed to address both technical and ethical dimensions in a balanced way in their scale focusing on artificial intelligence literacy.

The rapid development of artificial intelligence technologies and their widespread use in social areas have increased individuals' concerns about these technologies. This situation has brought along the need for scale development studies to measure artificial intelligence anxiety. In particular, issues such as the impact of technology on the labour force, privacy violations and ethical problems cause individuals to increase their anxiety levels (Zhang & Dafoe, 2019). Scales designed to measure AI anxiety often assess how individuals perceive potential risks and uncertainties, and how these perceptions influence their adoption of AI technologies.

Existing scales for measuring AI anxiety typically adopt a multi-dimensional approach, encompassing emotional, cognitive, and behavioral responses. For example, Wang & Wang (2022) developed a scale to measure fear and uncertainty associated with AI technologies, finding a correlation between ethical decision-making and anxiety levels. Similarly, Schiavo et al. (2024) created a scale emphasizing the negative impact of AI-induced anxiety on technology acceptance. These studies highlight the importance of incorporating the anxiety dimension in research exploring perceptions and attitudes towards AI.

Studies focusing on AI anxiety are crucial for understanding the potential downsides of these technological advancements. However, an excessive focus on anxiety could lead to an overly deterministic view of AI's impact. Therefore, a balanced approach in measuring AI anxiety is essential to objectively evaluate both the potential benefits and risks (Zhang & Dafoe, 2019; Wang & Wang, 2022). This balanced perspective can help individuals make informed decisions about AI.

The inclusion of both positive and negative statements is critical in scales assessing attitudes towards AI. Research suggests that negative statements can exhibit different psychometric properties and influence scale reliability (Krägeloh et al., 2025). Therefore, the careful placement of positive and negative items in scale development is crucial for ensuring valid and reliable results.

In developing the AIPAS, I drew upon established technology acceptance and usage models, namely TAM and UTAUT. Consequently, the AIPAS was designed to measure: (a) overall positive and negative evaluations of AI, aligning with TAM's 'perceived usefulness' and UTAUT's 'performance expectancy'; and (b) behavioral

dispositions towards specific AI applications, namely Generative Media Use and Chatbot Interaction, which correspond to 'effort expectancy' and 'facilitating conditions' within the UTAUT framework. Additionally, the multidimensional structure of AIPAS acknowledges the concerns highlighted in the AI anxiety literature (Wang & Wang, 2022; Zhang & Dafoe, 2019).

Recent years have witnessed an escalation in research endeavours concerning artificial intelligence, encompassing both the public's perception of the subject and their attendant attitudes. In particular, the emergence of generative AI models such as ChatGPT has brought a new dimension to research in this field. For example, Wakunuma and Eke (2024) revealed that ChatGPT has a transformative potential in areas such as education, agriculture and health, but these technologies also carry significant risks in terms of prejudices, protection of cultural diversity and ethical concerns. The authors emphasise the importance of governance approaches in the use of ChatGPT (Wakunuma & Eke, 2024). Another study, conducted by Monib, Qazi & Mahmud. (2025), examined the impact of ChatGPT on university students' learning processes and showed that the perceived usefulness of the model is high, but concerns remain about its long-term reliability and ethical use. Moreover, Amankwah-Amoah et al. (2024) explored the impact of generative AI models on creative industries, emphasising the prospective adverse consequences of such technologies on the labour market and the facilitation of creative procedures. These recent developments highlight the dynamic nature of AI and the continuous need to understand public engagement with specific AI applications like generative tools and chatbots.

In this study, "perception" and "attitude" towards AI are considered as complementary but distinct constructs, both of which are crucial for understanding human-AI interaction and the societal adoption of AI technologies, a distinction also recognized in domain-specific AI adoption research (Singh et al., 2023). Perception, in the context of AI, refers to how individuals understand, interpret, and mentally represent AI technologies. This encompasses their awareness and beliefs about AI's capabilities, limitations, potential benefits, and associated risks (Ma & Chen, 2024). This cognitive component aligns with notions of AI literacy and understanding AI principles, which Choi et al. (2024) found to be related to ethical consciousness. More specifically, perception involves the cognitive processing of information about AI, leading to an individual's subjective reality and comprehension concerning these technologies. For instance, an individual's perception might include beliefs about AI's potential to enhance productivity or, conversely, concerns about algorithmic bias. Indeed, Fakhri et al. (2025) conceptualize "AI Perception Dynamics" as a key mediating factor influencing societal impact and behavioral responses to AI, underscoring the active and evolving nature of these cognitive appraisals.

Attitude, on the other hand, represents a more evaluative stance, referring to individuals' overall affective reactions, feelings, and predispositions towards AI (Schepman & Rodway, 2020). As highlighted by Choi et al. (2024), attitudes towards AI significantly influence learners' interactions with AI. Similarly, Singh et al. (2023) investigated attitudes among dental professionals, acknowledging that a positive or negative disposition towards AI can shape its acceptance and integration into practice. Attitudes are often built upon underlying perceptions; for example, someone who perceives AI as highly beneficial and easy to use (a cognitive-perceptual assessment) is likely to develop a positive attitude (an affective-evaluative response) and exhibit a greater willingness to engage with AI tools. This relationship is well-supported by established models of technology acceptance, where perceptions of usefulness and ease of use (cognitive components) are consistently identified as key antecedents of attitude and subsequent behavioral intention (Davis, 1989; Venkatesh et al., 2003).

Perceptions and attitudes towards AI are thus deeply intertwined and can be reciprocally influential. An accurate and informed perception of AI's capabilities, coupled with a clear understanding of its potential benefits, is likely to foster a more positive attitude and increase an individual's willingness to use AI technologies. Conversely, a predominantly negative attitude, perhaps fueled by misperceptions, lack of understanding, or anxieties about risks, might lead an individual to overestimate AI's threats or underestimate its potential advantages. The dynamic interplay between how AI is perceived and the attitudes subsequently formed suggests that a comprehensive measurement approach should address both constructs. Given this complex relationship, a thorough assessment incorporating both perception-related cognitions and attitude-related evaluations is essential for a holistic understanding of AI's impact on individuals and society. The AIPAS scale I developed contributes to this understanding by employing a multi-dimensional structure. This structure is designed to address not only the cognitive-perceptual aspects (e.g., through items related to understanding AI's nature and expected outcomes) and the affective-evaluative components (e.g., through items reflecting positive or negative feelings and overall stance towards AI), but also individuals' behavioral engagement with specific, contemporary AI applications like generative media and chatbots.

Therefore, this study focuses on developing the "Artificial Intelligence Perception and Attitude Scale" (AIPAS) to provide a more comprehensive measurement of individuals' perceptions and attitudes towards AI, specifically including dimensions related to generative media use and chatbot interactions, which are increasingly prevalent. By incorporating established methodological approaches from the literature and addressing the aforementioned gaps, the scale I developed aims to be a valuable tool for understanding AI's social acceptance and individual-level effects. The study's findings are expected to contribute significantly to both academic research and practical applications related to AI.

The primary objective of this research is to address the current gap in validated instruments for measuring AI-related perceptions and attitudes in a multifaceted way. The AIPAS offers a multi-dimensional perspective, covering both general perceptions and specific use-case interactions, which will significantly enhance the field. The scale will enable researchers and policymakers to better understand public reactions to AI technologies, foresee potential risks, and make informed decisions regarding the development and implementation of these technologies. The AIPAS has the potential to become a valuable resource for assessing AI's impact across various domains, such as education, healthcare, business, and daily life.

# **METHOD**

#### Research Design

This study employed a quantitative survey design to develop and validate the Artificial Intelligence Perception and Attitude Scale (AIPAS). The survey model constitutes one of several forms of quantitative research method, the aim of which is to gather data on a given subject or sample over a defined time period in order to describe this information, or examine the relationships between variables (Karasar, 2005). This study aimed to develop a psychometrically sound scale to measure both perceptions and attitudes toward artificial intelligence in a multidimensional manner.

#### 2.1. Participants

The AIPAS development process involved a rigorous methodology. A comprehensive scale development process was followed for the validity and reliability analyses of AIPAS. This multi-stage process ensured both content and construct validity. Firstly, the current literature focusing on the perception and attitude towards artificial intelligence was reviewed and the leading scales in the field were analysed. I initiated this by conducting an extensive review of existing literature on AI perceptions, attitudes, established technology acceptance theories (e.g., TAM, UTAUT), AI literacy, and AI anxiety. This comprehensive review, complemented by an analysis of prominent scales in related fields, served as the foundation for item generation. This review served as the basis for determining the scope of AIPAS and creating an item pool of initially 60 statements designed to capture a wide array of AI perception and attitude facets, including the then-emerging and increasingly relevant aspects of generative AI applications and chatbot interactions. Subsequently, four experts in the fields of education, psychology, and technology were consulted to evaluate this initial item pool, leading to a refined set of 50 items. Expert opinions played an important role in ensuring the content validity and linguistic appropriateness of the scale items. These experts meticulously evaluated each item based on its direct relevance to the intended constructs, the overall structural design, inclusiveness, comprehensibility, and linguistic appropriateness. Acting upon their collective feedback, I implemented several substantive modifications as detailed in the "Creation of the Scale Form" section, leading to the 50-item draft.

The 50-item draft version of the AIPAS, developed through the initial item generation and expert review process described in section 2.2, was administered to a large sample of 1600 participants. This sample provided the opportunity to evaluate the psychometric properties of these initial items and subsequently refine the scale. The data obtained from these 1600 participants were analysed in a two-stage process for scale validation. In the first stage, data from a randomly selected sub-sample of 855 participants were used for Exploratory Factor Analysis (EFA) to identify the underlying factor structure and reduce the item pool. Following the EFA, which resulted in a 24-item structure, Confirmatory Factor Analysis (CFA) was conducted on the remaining independent sub-sample of 745 participants to confirm this refined structure. The scale's internal consistency (Cronbach's alpha) for the final 24-item version was then evaluated using data from the second sub-sample (n=745) on which the CFA was performed.

The study sample consisted of 1600 participants. Demographic characteristics revealed that 75.4% of the participants were female (n = 1206) and 24.6% were male (n = 394). The largest age group was 21-25 (n = 581, 36.3%), followed by 18-20 (n = 459, 28.7%). Smaller proportions of participants were in the age groups of 26-30

(n = 164, 10.3%), 31-40 (n = 96.6%), and 40 and above (n = 200, 12.5%). Regarding education, the majority were high school graduates (n = 1021, 63.8%), followed by university graduates (n = 504, 31.5%), primary school graduates (n = 61, 3.8%), and postgraduates (n = 14, 0.9%). This demographic profile indicates a predominantly young sample with a high school education. Table 1 provides detailed demographic information.

**Table 1.** Demographic information of the participants

Theme	Code	f	%
C1	Male	394	24.6
Gender	Woman	1206	75.4
	18-20	459	28.7
	21-25	581	36.3
Age	26-30	164	10.3
	31-40	96	6
	40 and above	200	12.5
	Primary education	61	3.8
Education	High School	1021	63.8
Status	University	504	31.5
	Postgraduate	14	0.9
Total		1600	100

The participants in this study, by virtue of being recruited through online channels and engaging with an online survey instrument, can be characterized as possessing the digital literacy skills requisite for such participation. All participants were literate and were regular users of digital devices such as computers, tablets, or smartphones, indicating a general familiarity with the digital environment where AI technologies are increasingly encountered. While specific metrics on the frequency or type of individual AI tool usage were not the primary focus of data collection for this scale development study, and therefore participants' AI experience levels were not experimentally controlled or used as a stratification variable, the participants' active engagement in the digital sphere implies a baseline level of interaction with, or at least awareness of, various online services and applications, many of which now incorporate AI features. The broad nature of the recruitment aimed to capture a wide spectrum of naturally occurring perceptions and attitudes towards AI within the Turkish context among individuals who are active in the digital world. This approach acknowledges that attitudes towards emerging technologies like AI are not solely formed by direct, hands-on experience but are also shaped by a myriad of indirect exposures, public discourse, and media representations, making the assessment of attitudes relevant even among those with limited direct usage. The demographic diversity in age and education, albeit skewed towards younger and high-school educated individuals, provides a valuable initial foundation for understanding AI perceptions within this digitally engaged population. Future research could certainly delve deeper into specific AI usage patterns across more narrowly defined user segments.

# 2.2. Creation of the Scale Form

The initial step in scale development involved a thorough literature review to identify relevant statements for measuring perceptions and attitudes towards AI. As a result of the scanning, a scale draft was prepared with a total of 60 original statements about artificial intelligence. The draft scale was shared with 4 faculty members working in the fields of computer teaching, guidance and psychological counselling, preschool teaching, Turkish language and literature and they were asked to evaluate the suitability of the draft items to the field, structural design, inclusiveness, comprehensibility and fluency. In accordance with the expert feedback received, enhancements were made with regard to grammar, semantic integrity and the extent to which the construct under measurement was reflected. Considering the opinions and suggestions of the field experts, some statements were made into two separate items, and some items were corrected to increase comprehensibility (Lawshe, 1975). For example, an item such as "Artificial intelligence technologies are complex" was transformed into two separate items as "It is difficult for me to understand artificial intelligence technologies" and "It is difficult for me to use

artificial intelligence technologies" in line with expert opinions. In addition, it was suggested that the word "for the benefit of" in the item "Artificial intelligence should be used for the benefit of humanity" be replaced with the word "for the benefit of" to make it clearer and more understandable. Furthermore, the wording of several items was modified and reorganised to provide a clearer representation of positive and negative perceptions. For example, the item "Artificial intelligence will take away our jobs" has been changed to "Artificial intelligence may cause some professions to disappear over time" to give a more specific meaning. The statement "Artificial intelligence is fun" (item 5 in the initial pool) was edited accordingly. Expert feedback highlighted that the use of "artificial intelligence" as a general subject was not optimally compatible with a predicate such as "fun," potentially leading to ambiguous interpretations by participants and thereby threatening the item's clarity and its ability to consistently measure the intended underlying construct. It was reasoned that such ambiguity could weaken the item's psychometric performance (e.g., its contribution to a clear factor structure or its internal consistency with other items measuring similar affective responses). Therefore, to enhance its conceptual clarity and potential for robust measurement, it was deemed more appropriate to use expressions focusing on specific manifestations of AI, such as "artificial intelligence applications" or "artificial intelligence tools," when assessing affective responses like "fun. As a result of the corrections made, a 50-item "Artificial Intelligence Perception and Attitude Scale Draft Form" based on a 7-point Likert-type rating was formed (Appendix 1).

#### 2.3. Collection of Data

Data collection was conducted online after obtaining necessary ethical approvals from the Kilis 7 Aralık University Scientific Research and Publication Ethics Committee (Document No. 2024/14-E.66754, dated 28.11.2024). The questionnaire form was transferred to the online environment via Google Forms and comprised of two sections. The first section contained information regarding the purpose of the study, voluntary participation in the study, and the confidentiality of the data. Informed consent was implicitly obtained by participants proceeding to complete the questionnaire. The second part consisted of questions about demographic information and a draft scale form. The online survey form was shared with approximately 1900 people through Whatsapp groups between March 2024 and April 2024, and after a 6-week data collection period, responses were screened for completeness and irregularities. Incomplete or clearly erroneous submissions were removed, leaving a total of 1600 volunteer participants (Appendix 2). The recruitment through diverse WhatsApp groups suggests a sample drawn from the general population with access to and familiarity with online technologies, facilitating the collection of data from individuals actively participating in the digital sphere.

#### 2.4. Data Analysis

Prior to analysis, the data from 1600 participants who completed the 50-item Artificial Intelligence Perception and Attitude Scale draft form were randomly split into two datasets: one with 855 participants for Exploratory Factor Analysis (EFA) and the other with 745 participants for Confirmatory Factor Analysis (CFA). This split-sample approach was used for cross-validation, mitigating the risk of inflated construct validity in a single sample and enhancing the generalizability of findings. The EFA was conducted on the first dataset to determine the scale's structure, while the CFA was conducted on the second dataset to confirm the structure identified in the EFA. The sample size met the recommendations of Tavşancıl and Keser (2002) for scale development. EFA was performed using principal component analysis as the extraction method and Oblimin rotation, as inter-factor correlations were anticipated. CFA was conducted using specialized analysis software Mplus.

Before factor analysis, the dataset's suitability for the EFA sample (n=855) was assessed using the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity. Multivariate outliers were also checked using Mahalanobis distance. A KMO value above 0.90 and a statistically significant Bartlett's test (p < .05) indicate suitability for factor analysis (Tabachnick & Fidell, 2015). The 50-item draft scale was then subjected to EFA, employing the eigenvalue criterion (greater than 1) and the scree plot to determine the number of factors. Based on these criteria, a four-factor structure was identified. Factor loadings above 0.40 were considered significant, and a minimum difference of 0.10 between factor loadings (no overlap) was required. Items not meeting these criteria (36 items) were removed. The resulting 24-item scale was then subjected to CFA to test the four-factor structure. The CFA results indicated a good model fit ( $\chi^2$ /sd= 1.54, RMSEA= 0.07, CFI= 0.97, and TLI= 0.97). Modification indices were examined, and correlations were allowed between specific items based on high modification index values and theoretical justification. Specifically, correlations were allowed between item 4 and item 5 (Positive Perception), between item 14, 15, and 17 (Negative Perception), and between item 17 and 18 (Negative Perception). Item 14 was also found to correlate with both positive and negative perception factors,

suggesting multiple interpretations. Consequently, the relationship of item 14 with the negative perception factor was reversed. These modifications improved the model fit.

The AIPAS scale's construct validity and reliability were assessed using statistical software. Construct validity was analyzed using EFA (with principal component analysis and Oblimin rotation) and CFA. The Oblimin rotation method was chosen due to the potential for correlations between factors. Oblique rotation methods like Oblimin are preferred when inter-factor correlations are expected (Tabachnick & Fidell, 2015). Model fit in CFA was evaluated using fit indices such as chi-square ( $\chi^2$ ), RMSEA, CFI, TLI, and WRMR (Weighted Root Mean Square Residual, as the WLSMV estimator was used given the ordinal nature of Likert-scale data). Acceptable fit index values are typically 0.90-1.00 for CFI and TLI (Bentler & Bonnet, 1980; Tucker & Lewis, 1973) and 0.03-0.08 for RMSEA (with values  $\leq$  .05 indicating good fit) and SRMR (Hooper et al., 2008). Generally accepted cutoff values for good fit are: RMSEA  $\leq$  0.08, CFI  $\geq$  0.95, TLI  $\geq$  0.95, and SRMR  $\leq$  0.08 (Hu & Bentler, 1999; Brown, 2015). For WRMR, values around 1.0 or less generally suggest good model fit. Internal consistency reliability was assessed using Cronbach's alpha coefficients, calculated on the data from the CFA sub-sample (n=745).

#### **Research Ethics**

The data for the study were collected online after the necessary permissions had been obtained from the Kilis 7 Aralık University Scientific Research and Publication Ethics Committee, with the document number 2024/14-E.66754 and approval date 28.11.2024.

#### **FINDINGS**

# 3.1. Construct Validity

#### 3.1.1. Findings Related to Exploratory Factor Analysis

To assess the AIPAS's construct validity, the data from 1600 participants were randomly divided into two datasets: one with 855 participants for EFA and another with 745 for CFA. This split-sample approach allows for cross-validation, enhancing the generalizability of findings. Before conducting EFA, the data for the 855 participants were examined for missing values and outliers. Outliers, which are extreme values outside the typical distribution of variables, can influence analysis results (Tabachnick & Fidell, 2014). Outliers were identified and removed using standardized z-scores, with values |z| > 3.29 considered outliers (Tabachnick & Fidell, 2014).

The Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity were used to determine the data's suitability for factor analysis. A KMO value of 0.941 and a significant Bartlett's test ( $\chi^2 = 19028.027$ , df = 276, p < .001) indicated the data were appropriate for factor analysis (Hair et al., 2010). These results demonstrate both a sufficient sample size and significant inter-item correlations, confirming the data's suitability for factor analysis.

The EFA revealed a four-factor structure for the AIPAS: Positive Perception, Negative Perception, Generative Media Use, and Chatbot Interaction. A direct oblimin rotation was applied, and each item exhibited high loadings on its intended factor. The Positive Perception factor, comprising 11 items, reflects positive beliefs and expectations about AI. These items include statements such as: "Artificial intelligence makes life easier" (item 1), "I think artificial intelligence will be effective in the future" (item 2), "Artificial intelligence makes my life easier" (item 3), "An AI-powered device can make life easier" (item 4), "Artificial intelligence is fun" (item 5), "I find artificial intelligence useful" (item 6), "I am curious about artificial intelligence" (item 7), "Artificial intelligence designs a good future for people" (item 8), "Artificial intelligence is useful in art" (item 9), "I know what artificial intelligence is" (item 10), and "With artificial intelligence, all information is easily accessible" (item 11). The Negative Perception factor, consisting of 8 items, captures concerns and anxieties about AI. These items include: "Artificial intelligence will bring the end of humanity" (item 12), "I am afraid of artificial intelligence" (item 13), "Artificial intelligence will ruin people's lives" (item 14), "Artificial intelligence will take over the world" (item 15), "Artificial intelligence is harmful for humanity" (item 16), "Artificial intelligence should be banned" (item 17), "Artificial intelligence is unnecessary" (item 18), and "Artificial intelligence is dangerous" (item 19). The Generative Media Use factor (3 items) measures the frequency of using AI-based tools for generative media creation. Finally, the Chatbot Interaction factor (2 items) assesses the frequency of interacting with AI chatbots. The items are: "AI chatbot applications (chatgpt, deepseek, grok etc.) are installed on my phone" (item 23) and "I frequently ask questions to AI chatbots" (item 24).

Principal component analysis revealed four components with eigenvalues greater than one, explaining 46.90%, 63%, 70.20%, and 75.17% of the variance, respectively. These findings align with the desirable criteria for EFA in scale development (Büyüköztürk, 2005), where item loadings should exceed .40, and the difference between loadings for the same item should be at least .10. Following EFA, scale validity procedures were

implemented, beginning with the calculation of sub-dimensions. The analysis confirmed a four-factor structure for the scale, illustrated in Figure 1.

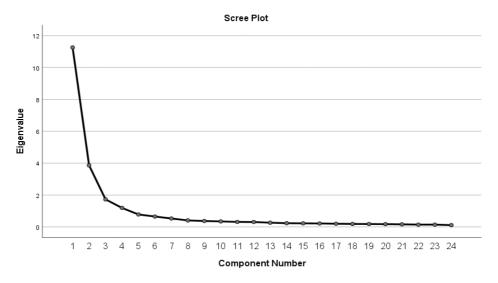


Figure 1. Scree Plot Graphic

Figure 1 presents the scree plot, which visually depicts the eigenvalues for each factor. The inflection point on the graph is around the fourth factor, suggesting a four-factor structure, corroborated by the eigenvalues greater than 1 up to the fourth factor. Beyond the fourth factor, eigenvalues fall below 1 and plateau, further supporting the four-factor solution. For clarity, the eigenvalues for each factor are: Factor 1 (11.25), Factor 2 (3.86), Factor 3 (1.72), and Factor 4 (1.19).

The Slope Accumulation graph also indicated a four-factor solution, as it plateaued after the fourth factor. Following EFA and two rounds of CFA on the initial 60-item draft, 24 items were retained, reflecting the four sub-dimensions identified, in accordance with the criteria outlined by Büyüköztürk (2005). Thirty-six items were removed due to low factor loadings (below 0.40) or overlapping loadings. (A detailed list of removed items and justifications can be provided as a supplementary document). Table 2 displays the item factor loadings for the retained items.

**Table 2.** Item Factor Loadings of Artificial Intelligence Perception and Attitude Scale

	Positive Perception	Negative Perception	Generative Media Use	Chatbot Interaction
m1	.90	.29	.31	.28
m2	.88	.28	.26	.29
m3	.87	.31	.41	.33
m4	.86	.28	.30	.33
m5	.85	.30	.39	.34
m6	.85	.29	.40	.35
m7	.84	.27	.37	.34
m8	.83	.27	.38	.33
m9	.82	.31	.38	.31
m10	.77	.36	.43	.24
m11	.76	.27	.20	.33
m12	.33	.86	.21	.17
m13	.21	.85	.35	.23
m14	.35	.84	.20	.14
m15	.27	.83	.35	.28
m16	.39	.80	.20	.22
m17	.11	.78	.43	.32
m18	.16	.78	.39	.34
m19	.44	.74	.13	.23
m20	.50	.41	.91	.41
m21	.52	.36	.90	.39
m22	.56	.37	.88	.40
m23	.33	.25	.31	.95
m24	.41	.25	.34	.94

Table 2 presents the factor loadings for each of the 24 retained items on the four identified factors (Positive Perception, Negative Perception, Generative Media Use, and Chatbot Interaction). All items show strong loadings (.74 to .95) on their respective factors and weak loadings (.11 to .56) on other factors, indicating good discriminant

**Table 3.** Distribution of Item Factor Loadings of Artificial Intelligence Perception and Attitude Scale According to Sub-dimensions

Components	First Eigenvalues			Extraction Sums of Squared Loadings	1		Rotation Sums of Squared Loadings
	Total	Variance Percentage	Cumulative Percentage		Variance Percentage	Rotation Sums of Square Impositions	Total
Positive Perception	11.25	46.90	46.90	11.25	46.90	46.90	9.73
Negative Perception	3.86	16.10	63.00	3.86	16.10	63.00	6.87
Generative Media Use	1.72	7.20	70.20	1.72	7.20	70.20	4.8
Chatbot Interaction	1.19	4.97	75.17	1.19	4.97	75.17	3.96
5	.78	3.25	78.43				
6	.65	2.71	81.15				
7	.52	2.20	83.35				
8	.40	1.70	85.05				
9	.37	1.551	86.60				
10	.34	1:439	88.04				
11	.31	1.31	89.35				
12	.30	1.29	90.64				
13	.26	1.10	91.75				
14	.23	.96	92.72				
15	.22	.93	93.65				
16	.21	.89	94.55				
17	.20	.83	95.39				
18	.18	.77	96.16				
19	.18	.75	96.92				
20	.17	.72	97.65				
21	.16	.67	98.32				
22	.14	.60	98.92				
23	.14	.60	99.52				
24	.11	.47	100				

Table 3 displays the variance explained by each factor, the cumulative variance percentage, and the eigenvalues. The Positive Perception factor accounts for 46.90% of the variance (eigenvalue = 11.25). The Negative Perception factor explains 16.10% (eigenvalue = 3.86). The Generative Media Use factor explains 7.20% (eigenvalue = 1.72). The Chatbot Interaction factor explains 4.97% (eigenvalue = 1.19). Together, these four factors explain 75.17% of the total variance, indicating that the scale effectively captures a substantial portion of the variance in AI perception and attitudes. (Positive Perception: This factor reflects positive beliefs and expectations toward AI. Negative Perception: This factor reflects concerns and fears about AI. Generative Media Use: This factor reflects the use of AI tools for generative media production. Chatbot Interaction: This factor reflects interaction with AI chatbots (e.g., Deepseek, ChatGPT, Grok).

As shown in Table 3, the scale demonstrates a strong ability to differentiate between the four factors, with factor loadings ranging from 0.74 to 0.95 and eigenvalues between 1.19 and 11.25. These findings align with the scree plot in Figure 1.

# 3.1.2. Findings Related to Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis was conducted to further validate the four-factor structure of the AIPAS. A first-order CFA was performed on the second dataset (n=745) to examine the factor loadings and relationships between the dimensions.

A first-level CFA (confirmatory factor analysis) was conducted on the second data set (n=745) to verify the four-factor scale structure obtained as a result of the principal component analysis. The factor levels of the sub-dimensions and of the items obtained after the CFA procedure are presented in Figure 2 on a sub-dimension basis.



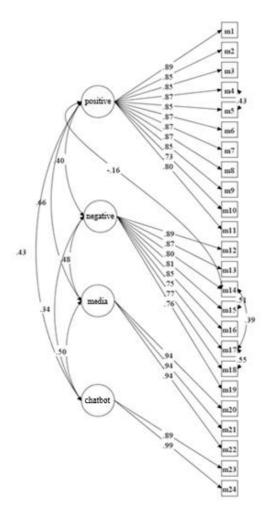
Figure 2. Diagram representation of the first CFA procedure

In order to determine the construct validity of the AIPAS Scale that was developed within the framework of this study, a CFA was carried out. In the first step, the scale underwent a first-order CFA, analysing the factor loads of the items in the scale and the relationships between them.

Figure 2 displays the standardized regression coefficients (factor loadings) and inter-factor correlations from the first-order CFA. The model includes four latent variables representing the four factors (Positive Perception, Negative Perception, Generative Media Use, and Chatbot Interaction) and the observed variables (items) associated with each factor. The factor loadings represent the strength of the relationship between each item and its corresponding factor, while the inter-factor correlations show the relationships between the factors. All factor loadings were statistically significant (p < .001).

The model did not fit the data perfectly according to the fit indices in the first CFA analysis. and required some modifications, especially since the RMSEA value (0.107) was above the acceptable limit of 0.08. In order to improve the model fit, modification indices were examined and correlation between parameters with high modification indices was allowed. The correlation between item 4 ("An AI-supported device can make life easier") and item 5 ("Artificial intelligence is fun") in the positive perception subscale (MI=45.21), between item 14 ("Artificial intelligence will ruin people's lives") and item 15 ("Artificial intelligence will take over the world") in the negative perception subscale (MI=41.88) and item 17 ("Artificial intelligence should be banned") (MI=38.52), as well as between item 17 and item 18 ("Artificial intelligence is unnecessary") (MI=35.76). Finally, the item "artificial intelligence will take over the world" (item 15) in the negative perception sub-dimension was reversely linked to the positive perception sub-dimension because it was also perceived as positive, and CFA analysis was performed again. These modifications show that the error variances of the items are correlated and item 15 ("Artificial intelligence will take over the world") reflects both positive and negative perceptions. For example, while some participants interpreted the statement "Artificial intelligence will take over the world" as meaning that

artificial intelligence will destroy humanity, some participants may have interpreted it as meaning that artificial intelligence will solve the problems in the world and benefit humanity.



**Figure 3.** Diagram representation of the second CFA procedure

Figure 3 displays the standardized regression coefficients and factor correlations for the revised CFA model. The modifications resulted in improved model fit indices (see Table 4). As shown in the figure, correlations were permitted between items 4 and 5, 14, 15, and 17, and 17 and 18. Additionally, item 14 was allowed to correlate with the Positive Perception factor, and its relationship with the Negative Perception factor was reversed. All factor loadings remained statistically significant (p < .001).

The second CFA analysis, incorporating the modifications, particularly the dual loading of item 14 and the correlation between items 14 and 17, significantly improved model fit. This suggests that these adjustments better reflect the scale's factor structure and the relationships between items.

Table 4. Model Fit Indices of CFA 1st and 2nd Analyses

CFA Analysis	$\chi^2$ (sd)	RMSEA	CFI	TLI	WRMR
DFA 1	2359.98	.107	.954	.948	2.077
DFA 2	1261.67	.076	.978	.974	1.377

Table 4 compares the fit indices from the initial and revised CFA models. The initial model's fit indices were outside acceptable ranges ( $\chi^2/\text{sd}=5.07$ , RMSEA=0.107, CFI=0.954, TLI=0.948, WRMR= 2.077). However, the revised model demonstrated acceptable fit indices ( $\chi^2/\text{sd}=1.54$ , RMSEA= 0.076, CFI= 0.978, TLI= 0.974, WRMR= 1.377), indicating a substantial improvement in model fit. The  $\chi^2/\text{sd}$  value (1.54) suggests a good fit to the data, the RMSEA value (0.076) indicates an acceptable level of approximate error, and the CFI (0.978) and

TLI (0.974) values indicate a strong comparative fit. The WRMR value (1.377), being close to 1, further supports the good model fit.

The scale's fit indices ( $\chi^2/\text{sd} = 1.54$ , RMSEA = 0.07, CFI = 0.97, and TLI = 0.97) align with the acceptable criteria for good model fit reported in the literature:  $\chi^2/\text{sd} < 5$ , RMSEA  $\leq 0.08$ , CFI > 0.90, and TLI > 0.90 (Byrne, 2011; Fife-Schaw, 2000; Hair et al., 2010; Kline, 2023; Rigdon, 1996; Tabachnick & Fidell, 2015).

Table 5. Sub-dimensions correlation matrix

	Positive Perception	Negative Perception	Generative Media Use	Chatbot Interaction
Positive Perception	1	.32*	.35*	.33*
Negative Perception	.32*	1	.31	.26*
Generative Media Use	.35*	.31*	1	.34*
Chatbot Interaction	.33*	.26*	.34*	1

p<0.01 \*, p<0.001 \*\*

Table 5 presents the correlations between the four sub-dimensions of the scale. All correlations are positive and statistically significant (p < .05 or p < .01), indicating moderate relationships between the sub-dimensions. This suggests that while the sub-dimensions are related, they measure distinct but related constructs. These findings demonstrate that the AIPAS sub-dimensions, while inter-correlated, capture unique aspects of AI perceptions and attitudes. The moderate correlations indicate conceptual overlap but also distinct contributions of each sub-dimension.

When the relationships between the sub-dimensions of the AIPAS scale were analysed, it was observed that there were positive and significant correlations. The Positive Perception dimension correlated with Negative Perception at the level of r=,32, with Generative Media Use at the level of r=,35 and with Chatbot Interaction at the level of r=,33. Similarly, the Negative Perception dimension showed significant relationships with Generative Media Use at the level of r=,31 and with Chatbot Interaction at the level of r=,26. The Generative Media Use dimension showed a positive relationship with the Chatbot Interaction dimension at the level of r=,34. These results show that the sub-dimensions of the scale are significantly related to each other and that the different dimensions work as interrelated but independent structures. The fact that the correlation coefficients are generally at a moderate level also reveals that the different dimensions of the scale offer clear conceptual distinctions but are complementary to each other to some extent. These findings contribute to the construct validity of the scale and show that the sub-dimensions offer a holistic perspective on the construct measured.

These findings show that the sub-dimensions of the scale form a whole that conceptually differentiates from each other but handles perceptions and attitudes towards artificial intelligence in a multidimensional structure. In particular, the significant relationship of the Positive Perception dimension with both Generative Media Use and Chatbot Interaction dimensions reveals that positive perceptions are an important factor in individuals' interaction with AI tools. On the other hand, the fact that the Negative Perception dimension presents weaker correlation values suggests that this dimension may have a more independent structure than other factors. Table 5 presents the correlation matrix for the sub-dimensions of the scale.

#### 3.2. Reliability Analysis

After completing the CFA process and confirming the factor structure with the second sub-sample (n=745), Cronbach's Alpha was determined for the scale's subdimensions and the scale's reliability coefficient was determined based on this same sub-sample. The Cronbach's Alpha internal consistency coefficient was used to analyse the evidence of the reliability of the scale. For this purpose, the Cronbach's alpha coefficient of internal consistency was calculated for the scale as a whole and for each of its sub-dimensions using the data from the CFA sample (n=745).

Cronbach's alpha internal consistency coefficient was calculated as .96 for the whole scale (AIPAS Scale in Table 6), .96 for the "Positive Perception" factor, .92 for the "Negative Perception" factor, .94 for the "Generative Media Use" factor and .90 for the "Chatbot Interaction" factor, all based on the CFA sample (n=745).

Table 6. Reliability coefficients for Artificial Intelligence Perception and Attitude Scale Subscales

Sub Dimension	Cronbach's Alpha	Standardised Cronbach's Alpha	Article Number	Average	Standard Deviation
Positive Perception	.96	.96	11	4.40	1.87
Negative Perception	.92	.92	8	3.22	1.83
Generative Media Use	.94	.94	3	3.38	1.99
Chatbot Interaction	.90	.90	2	3.06	2.12
AIPAS Scale	.96		24		

Table 6 presents Cronbach's alpha coefficients, the number of items, means, and standard deviations for the AIPAS subscales and the overall scale. The overall Cronbach's alpha for the scale was .96, indicating excellent internal consistency. The sub-dimensions also demonstrated high internal consistency: Positive Perception (.96), Negative Perception (.92), Generative Media Use (.94), and Chatbot Interaction (.90). These values indicate that the scale and its sub-dimensions are highly reliable. The mean scores suggest that participants generally hold positive perceptions towards AI (M = 4.40 for Positive Perception), while the standard deviations highlight the variability in responses, particularly for Positive Perception (SD = 1.87) and Negative Perception (SD = 1.83).

Cronbach's Alpha coefficients are based on the CFA sample (n=745). Cronbach's alpha internal consistency coefficient was calculated as .96 for the whole scale, .96 for the "positive perception" factor, .92 for the "negative perception" factor, .94 for the "generative media use" factor and .90 for the "chatbot interaction" factor. These high Cronbach's alpha values demonstrate the scale's strong internal consistency and reliability (Byrne, 2013; Fife-Schaw, 2000; Kline, 2023; Özdamar, 2011; Tabachnick & Fidell, 2015).

## **DISCUSSION & CONCLUSION**

The EFA and CFA results confirmed the four-factor structure of the AIPAS, demonstrating a good fit to the data. The four sub-dimensions—Positive Perception, Negative Perception, Generative Media Use, and Chatbot Interaction—capture the multifaceted nature of individuals' engagement with AI. This structure deliberately encompasses both perceptual (cognitive and belief-based) and attitudinal (affective and evaluative) components, recognizing their distinct yet interrelated roles in shaping human responses to technology (Davis, 1989; Schepman & Rodway, 2020). This structure is not arbitrary but rather finds grounding in established theoretical frameworks concerning technology acceptance and human-computer interaction, as well as the emerging body of literature specifically addressing responses to artificial intelligence.

The 'Positive Perception' and 'Negative Perception' sub-dimensions of the AIPAS primarily tap into the attitudinal domain, reflecting individuals' overall positive or negative evaluations, feelings, and stance towards AI, which are informed by their underlying perceptions. For example, items reflecting beliefs about AI making life easier or being harmful for humanity (which are perceptual elements) contribute to an overall positive or negative attitude. This distinction is important, as studies like Choi et al. (2024) demonstrate that interventions can lead to changes in both ethical awareness (a perceptual/cognitive construct) and attitudes towards AI, highlighting that these are related yet separable outcomes.

The 'Generative Media Use' and 'Chatbot Interaction' sub-dimensions, while reflecting behavioral tendencies, are also intrinsically linked to both perceptions (e.g., perceived usefulness and ease of use of these specific tools) and attitudes (e.g., general feelings towards engaging with such AI applications). An individual's perception of the utility of AI for media creation or information retrieval via chatbots, combined with their general attitude towards AI, will likely influence their usage patterns. Thus, the AIPAS aims to provide a holistic measure by not only assessing general perceptions and attitudes but also by grounding these in the context of interaction with tangible AI applications, which is an increasingly important aspect of understanding the human-AI relationship in the contemporary technological landscape.

The Positive Perception sub-dimension, which focuses on the perceived benefits and potential of AI, directly aligns with core constructs from prominent technology acceptance theories. Specifically, it resonates strongly with the 'perceived usefulness' component of the Technology Acceptance Model (TAM) (Davis, 1989) and the 'performance expectancy' component of the Unified Theory of Acceptance and Use of Technology

(UTAUT) (Venkatesh et al., 2003). My findings corroborate the central tenet of these models: a positive perception regarding the utility and potential benefits of AI is a crucial determinant in its acceptance and intended use.

Conversely, the Negative Perception sub-dimension, addressing concerns and anxieties related to AI, connects with the growing body of research on 'AI anxiety' (Wang & Wang, 2022; Zhang & Dafoe, 2019; Schiavo et al., 2024). This dimension encapsulates apprehensions about job displacement, privacy erosion, and potential loss of human control, which the literature identifies as significant barriers to AI adoption. The identification of this distinct factor underscores the importance of addressing these user concerns to foster trust and facilitate responsible AI integration.

The Generative Media Use sub-dimension, measuring the frequency and habits of using AI-powered tools for creative media generation, can be understood through the lens of UTAUT's 'effort expectancy' and 'facilitating conditions'. The perceived ease of using these tools (effort expectancy) and the availability of resources and support for their use (facilitating conditions) likely influence individuals' engagement with them. Furthermore, this dimension reflects the rapidly evolving landscape of AI applications where users are not just consumers but also creators using AI, a phenomenon that requires specific attention in perception and attitude research.

Similarly, the Chatbot Interaction sub-dimension, which assesses the frequency of using conversational AI systems like ChatGPT, also relates to 'effort expectancy' and 'perceived usefulness' from TAM/UTAUT. The conversational nature of these tools potentially lowers the effort required for interaction, while their ability to provide information and perform tasks relates to their usefulness. This dimension is particularly unique and timely, as it specifically examines attitudes towards these increasingly prevalent dialogue-based AI systems, an area that is rapidly expanding and contributing novel interaction paradigms to the broader field of human-AI interaction.

While the sub-dimensions 'Positive Perception' and 'Negative Perception' use the term 'perception,' the items within them primarily capture evaluative and affective responses, which align closely with established definitions of 'attitude,' such as a "tendency to act toward or against some environmental factor" (Bogardus, 1931, as cited in Allport, 1935) or more broadly, a "mental and neural state of readiness, organized through experience, exerting a directive or dynamic influence" (Allport, 1935). The scale's overall title 'Perception and Attitude Scale' was chosen to reflect the broad aim of capturing both the cognitive understandings (perceptions) that Allport (1935) traced back to concepts like 'mental attitudes' or 'cortical set,' which underpin these evaluations, and the overall evaluative stances (attitudes) themselves, as well as attitudes towards specific AI uses. This study's operationalization considers these general positive and negative evaluations as broad 'perceptions' or initial framings of AI, which then inform more specific attitudes towards use – the 'readiness for response' – as measured in the 'Generative Media Use' and 'Chatbot Interaction' dimensions.

A pertinent question arises regarding the meaningfulness of measuring attitudes towards AI among individuals who may lack extensive direct experience with sophisticated AI tools. It is important to recognize that "experience" with AI is not a monolithic concept confined to active, technical usage. In an era where AI is increasingly pervasive, individuals form perceptions and attitudes through diverse channels beyond direct interaction. These include media portrayals of AI, news reports, social discussions, and even ambient exposure to AI-driven features in everyday digital tools (e.g., recommendation systems, search algorithms, virtual assistants). Consequently, individuals, even those without self-identified "experience" in using specific AI applications like generative media tools or advanced chatbots, develop a set of beliefs, feelings, and behavioral intentions towards AI based on this broader informational and socio-cultural context (Zhang & Dafoe, 2019).

The AIPAS was designed to capture this spectrum of perceptions and attitudes within a general, digitally-engaged population, not exclusively among expert users. Measuring the attitudes of those with limited direct experience is crucial for several reasons. Firstly, these attitudes can significantly influence their future willingness to adopt or engage with AI technologies. Secondly, public opinion, shaped by both experienced and less experienced individuals, plays a vital role in the societal acceptance and ethical governance of AI. Understanding the nascent or developing attitudes of those less directly familiar with AI can provide early insights into potential concerns, misconceptions, or areas where public education and transparent communication are needed. Therefore, assessing these attitudes, regardless of the depth of direct technical experience, provides a more holistic understanding of AI's societal footprint and the factors that will shape its trajectory.

Collectively, the four-factor structure of the AIPAS I developed reflects the multidimensional nature of AI perception as suggested by existing literature (Mulgan, 2016; Russell & Norvig, 2016), but it extends this by integrating both general affective and cognitive evaluations (Positive and Negative Perceptions) with behavioral

tendencies towards specific, contemporary AI applications (Generative Media Use and Chatbot Interaction). This integrated approach, grounded in established technology acceptance models and responsive to current AI trends, allows for a more nuanced understanding than examining these facets in isolation. People tend to think that AI has both positive and negative aspects. While some believe that AI will make life easier, create new opportunities, and change the future for the better, others worry that it may lead to job loss, privacy violations, and even loss of control of humanity (Mulgan, 2016; Russell & Norvig, 2016). The AIPAS provides a structured way to quantify these varied perspectives. The findings that positive perception towards artificial intelligence is linked to usage intentions (as suggested by its correlation with the use-related sub-dimensions) further reinforce the propositions of TAM and UTAUT. The fact that negative perceptions also emerge as a strong, distinct factor highlights the critical need to address AI anxiety and ethical concerns, as emphasized in the AI anxiety literature.

The correlations between the sub-dimensions of the AIPAS support this complex perception structure. A moderate correlation (r = 0.321) was found between Positive Perception and Negative Perception sub-dimensions. This finding shows that positive and negative perceptions towards artificial intelligence are not mutually exclusive and that a person can have both positive and negative thoughts about artificial intelligence.

The Positive Perception sub-dimension also shows significant correlations with Generative Media Use and Chatbot Interaction sub-dimensions. This finding suggests that a positive perspective towards AI is associated with more use of AI-based tools. Similarly, the Generative Media Use sub-dimension is also significantly correlated with the Chatbot Interaction sub-dimension. This suggests that the use of different AI tools is interrelated and that individuals' attitudes towards AI technologies in general affect their tendency to use these tools.

The loading of item 14 ("Artificial intelligence will take over the world") on both Positive Perception and Negative Perception factors shows that this statement can be interpreted in different ways by different people. This necessitated the modification of item 14 ("Artificial intelligence will take over the world") in the CFA analysis. Some participants may have interpreted this statement from a dystopian perspective that artificial intelligence will surpass human intelligence and take control. Others may have interpreted it from a utopian perspective that AI will play an important role in solving global problems and creating a better world. This situation shows that perceptions towards artificial intelligence are open to individual differences and interpretations. For example, while a participant responded "Strongly Agree" to the statement "Artificial intelligence will take over the world", he/she may believe that artificial intelligence will make the world a better place. Another participant, while answering "Strongly Agree" to the same statement, may be worried that artificial intelligence will bring the end of humanity. Therefore, the statement "Artificial intelligence will take over the world" is an item that can reflect both positive and negative perceptions. Therefore, the relationship of this item with the Negative Perception factor was reversed and the model fit was improved.

The findings of the study significantly overlap with other studies in the literature. For example, while Ma & Chen (2024) aim to measure it, knowledge level of individuals about artificial intelligence, AIPAS covers perceptions and attitudes as well as knowledge level. While Laupichler et al.'s (2023) study addresses both technical and ethical dimensions of AI literacy, the AIPAS examines attitudes towards the use of AI tools as well as ethical perceptions. While the findings of Sindermann et al. (2022) show that there is a relationship between trust in AI and propensity to use it, AIPAS analyses this relationship separately for different types of AI (Generative Media Use and Chatbot Interaction).

The scale can be used to examine the effects of artificial intelligence in different sectors (such as education, health, business world) and to increase social awareness about artificial intelligence. It can also be a useful tool in formulating policies for the ethical and responsible development of AI technologies. AIPAS is a valuable tool for understanding how individuals view and react to this technology in the rapidly evolving world of artificial intelligence. Further development and widespread use of the scale will help us better understand the societal impacts of AI and ensure that AI technologies are developed in a way that benefits humanity.

This study provided empirical evidence for the validity and reliability of the AIPAS. The scale is a multidisciplinary instrument consisting of 24 items with four subscales: Positive Perception, Negative Perception, Generative Media Use and Chatbot Interaction. However, in order to contextualise these findings, some limitations need to be considered. Firstly, the scale was developed and tested in Türkiye, thus, its generalisability across culturally and demographically diverse groups is limited. This suggests that the validity and reliability analyses should be repeated by applying the scale in different cultures and demographic groups. In the future, cross-cultural adaptation and validation studies should be conducted to increase the use of the scale in different contexts. Secondly, participants' interactions with AI were measured through self-report. This may lead to results that are open to response bias. For example, participants may have given responses that do not reflect their true thoughts

about artificial intelligence with the concern of social favorability. In the future, it is possible to overcome this limitation by collecting behavioural data of individuals who actively use AI. Thirdly, in this study, validity analyses between the AIPAS and other reliable AI perception and attitude measures were not conducted. This limits the full assessment of the convergent and divergent validity of the scale.

It can be concluded that AIPAS is a valid and reliable tool for measuring people's perception and attitude towards AI. The four sub-dimensions of the scale (Positive Perception, Negative Perception, Generative Media Use, and Chatbot Interaction) reflect the multidimensional structure of the perception of artificial intelligence. The significant correlation between Positive Perception and Negative Perception dimensions shows that individuals may have both positive and negative thoughts about artificial intelligence. The significant correlations of the Positive Perception dimension with the Generative Media Use and Chatbot Interaction dimensions reveal that positive perceptions towards artificial intelligence are related to the use of these technologies. The significant correlation between the dimensions of Generative Media Use and Chatbot Interaction shows that the use of different artificial intelligence tools is related to each other.

Artificial intelligence significantly affects individuals' daily lives and has lasting effects on perceptions, attitudes and behaviours. AIPAS is a valid and reliable measurement tool developed to explore these dimensions in depth and provide a broad perspective in areas such as education, media and ethical use of AI. Its sub-dimensions provide important information to understand various aspects of individuals in relation to AI, which offers a great opportunity to study the effects of AI, especially in areas such as education and media. In particular, the Chatbot Interaction sub-dimension adds an important innovative dimension to understand individuals' interactions with speech-based artificial intelligence systems.

The AIPAS can be utilized in various sectors (e.g., education, healthcare, business) to understand the impact of AI and raise social awareness about its implications. The scale is valuable for understanding public reaction to and interaction with AI in this rapidly evolving technological landscape, aiding in the development of ethical and responsible AI policies and practices.

The present study offers empirical evidence for the validity and reliability of the AIPAS, showcasing its strength as a multidisciplinary measure of AI perceptions and attitudes with four distinct subscales. However, some limitations should be considered. The study's Turkish context might limit the generalizability of the findings to other cultures and demographics. Future cross-cultural validation studies are needed. The reliance on self-report measures might introduce response bias, a limitation that can be addressed in future research through the inclusion of behavioral measures. Finally, future research should investigate the convergent and discriminant validity of the AIPAS by comparing it with other established AI perception and attitude scales.

In conclusion, the AIPAS is a valid and reliable tool for measuring perceptions and attitudes towards AI. Its four sub-dimensions (Positive Perception, Negative Perception, Generative Media Use, and Chatbot Interaction) offer a nuanced perspective on this complex construct. The correlations between sub-dimensions highlight the intricate interplay between positive and negative perceptions and AI tool usage. The inclusion of the Chatbot Interaction sub-dimension offers a unique contribution to the literature by addressing attitudes towards conversational AI systems.

The AIPAS holds promise for informing the development of AI-related policies, practices, and educational interventions. It can be used to gauge perceptions and attitudes across different demographics and professional settings, contributing to a better understanding of AI's societal impact. Specifically, the scale can be used to understand how educators and students perceive AI, inform ethical guidelines for media professionals using AI tools, and track evolving attitudes towards new AI technologies like ChatGPT.

#### Limitations

This study has several limitations that should be acknowledged. Firstly, the sample was drawn from a single country, Türkiye, which may limit the generalizability of the findings to other cultural contexts. Secondly, the demographic profile of the participants, while large, was skewed towards younger individuals with at least a high school education. Additionally, this study did not systematically control for or measure the specific levels of prior AI experience among participants. While the scale aims to capture general perceptions and attitudes across a broad digitally engaged population, future research could benefit from examining how varying degrees of AI experience might influence responses on the AIPAS

#### **Statements of Publication Ethics**

This study followed all ethical principles of the publication process. Kilis 7 Aralık University ethical committee has approved under protocol number 2024/14-E.66754 on November 28, 2024.

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# **APPENDIX**

Appendix 1. Artificial Intelligence Perception and Attitude Scale (AIPAS)

The list below contains items related to artificial intelligence. Please tick them by thinking about your perceptions, ideas and attitudes towards the use of artificial intelligence.  Please tick '1' if you strongly disagree, '2' if you disagree, '3' if you partially disagree, '4' if you have no opinion, '5' if you partially agree, '6' if you agree and '7' if you strongly agree.	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
1- Artificial intelligence makes life easier.	1	2	3	4	5	6	7
2- I believe artificial intelligence will have a significant impact in the future.	1	2	3	4	5	6	7
3- Artificial intelligence makes my life easier.	1	2	3	4	5	6	7
4- AI-powered devices can make life easier.	1	2	3	4	5	6	7
5- Artificial intelligence is fun.	1	2	3	4	5	6	7
6- I find artificial intelligence useful.	1	2	3	4	5	6	7
7- I am curious about artificial intelligence.	1	2	3	4	5	6	7
8- Artificial intelligence contributes to a better future for humanity.	1	2	3	4	5	6	7
9- Artificial intelligence is valuable for artistic creation.	1	2	3	4	5	6	7
10- I know what artificial intelligence is.	1	2	3	4	5	6	7
11- Artificial intelligence makes information easily accessible.	1	2	3	4	5	6	7
12- Artificial intelligence will bring the end of humanity.	1	2	3	4	5	6	7
13- I am afraid of artificial intelligence.	1	2	3	4	5	6	7
14- Artificial intelligence will negatively affect people's lives.	1	2	3	4	5	6	7
15- Artificial intelligence will take over the world.	1	2	3	4	5	6	7
16- Artificial intelligence is harmful for humanity.	1	2	3	4	5	6	7
17- Artificial intelligence should be banned.	1	2	3	4	5	6	7
18- Artificial intelligence is unnecessary.	1	2	3	4	5	6	7
19- Artificial intelligence is dangerous.	1	2	3	4	5	6	7
20- I use AI-supported video production tools.	1	2	3	4	5	6	7
21- I use AI-supported audio production tools.	1	2	3	4	5	6	7
22- I use AI-supported visual generation tools.	1	2	3	4	5	6	7
23- AI chatbot applications (chatgpt, deepseek, grok etc.) are installed on my phone.	1	2	3	4	5	6	7
24- I frequently ask questions to AI chatbots.	1	2	3	4	5	6	7

**Appendix 2.** Turkish Version of Artificial Intelligence Perception and Attitude Scale (Yapay Zekâ Algısı ve Tutum Ölçeği - YAZAT-24)

Aşağıdaki listede yapay zekâ ile ilgili maddeler yer almaktadır. Lütfen yapay zekâya dair algı, fikir ve kullanma tutumlarınızı düşünerek işaretleyiniz.  Okuduğunuz maddedeki yargıya; "Kesinlikle katılmıyorsanız" ise 1'i, "Katılmıyorsanız" ise 2'yi, "Kısmen katılmıyorsanız" ise 3'ü, "Fikrim yoksa" ise 4'ü, "Kısmen katılıyorsanız" ise 5'i, "Katılıyorsanız" ise 6'yı ve "Kesinlikle katılıyorsanız" ise 7'yi işaretleyiniz.	Kesinlikle Katılmıyorum	Katılmıyorum	Kısmen Katılmıyorum	Fikrim Yok	Kısmen Katılıyorum	Katılıyorum	Kesinlikle Katılıyorum
<ol> <li>Yapay zekâ hayatı kolaylaştırır.</li> </ol>	1	2	3	4	5	6	7
2. Yapay zekânın gelecekte etkili olacağını düşünürüm.	1	2	3	4	5	6	7
3. Yapay zekâ benim hayatımı kolaylaştırır.	1	2	3	4	5	6	7
4. Yapay zekâ destekli bir cihaz hayatı kolaylaştırabilir.	1	2	3	4	5	6	7
5. Yapay zekâ eğlencelidir.	1	2	3	4	5	6	7
6. Yapay zekâyı faydalı bulurum.	1	2	3	4	5	6	7
7. Yapay zekâyı merak ederim.	1	2	3	4	5	6	7
8. Yapay zekâ insanlar için iyi bir gelecek tasarlar.	1	2	3	4	5	6	7
9. Yapay zekâ sanat konusunda yararlıdır.	1	2	3	4	5	6	7
10. Yapay zekânın ne olduğunu bilirim.	1	2	3	4	5	6	7
11. Yapay zekâ ile her bilgiye kolayca ulaşılır.	1	2	3	4	5	6	7
12. Yapay zekâ insanlığın sonunu getirecektir.	1	2	3	4	5	6	7
13. Yapay zekâdan korkarım.	1	2	3	4	5	6	7
14. Yapay zekâ insanların hayatını mahvedecektir.	1	2	3	4	5	6	7
15. Yapay zekâ dünyayı ele geçirecektir.	1	2	3	4	5	6	7
16. Yapay zekâ insanlık için zararlıdır.	1	2	3	4	5	6	7
17. Yapay zekâ yasaklanmalıdır.	1	2	3	4	5	6	7
18. Yapay zekâ gereksizdir.	1	2	3	4	5	6	7
19. Yapay zekâ tehlikelidir.	1	2	3	4	5	6	7
20. Yapay zekâ destekli video üretme araçlarını kullanırım.	1	2	3	4	5	6	7
21. Yapay zekâ destekli şarkı, müzik vb. ses üretme araçlarını kullanırım.	1	2	3	4	5	6	7
22. Yapay zekâ destekli resim, afiş vb. görsel üretme araçlarını kullanırım.	1	2	3	4	5	6	7
23. Yapay zekâ sohbet robotu uygulaması (chatgpt, deepseek, grok vb.) telefonumda yüklüdür.	1	2	3	4	5	6	7
24. Yapay zekâ sohbet robotlarına aklıma takılan soruları sorarım.	1	2	3	4	5	6	7