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The Human Element in the Machine Age: A Multi-Factorial Analysis of Artificial Intelligence Adoption

Dr. Nireya C. Halbrin
Department of Information Systems and Technology Vandmere School of Business Innovation, Netherlands

Prof. Elric D. Maeson
Centre for Digital Transformation Eastbourne Institute of Applied Sciences, New Zealand

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ABSTRACT

Artificial intelligence (AI) has become a transformative force, reshaping industries and daily life. However, its successful integration is not guaranteed and depends heavily on user acceptance. This study presents a comprehensive analysis of the psychological, social, and emotional factors that determine an individual's willingness to adopt AI technologies. While existing research often examines these factors in isolation, this paper proposes and tests an integrated model that synthesizes key constructs from established technology acceptance theories with critical emotional and contextual variables. We designed a cross-sectional survey-based study involving 580 university students from diverse academic backgrounds. A structural equation model (SEM) was developed to analyze the complex interplay between performance expectancy, effort expectancy, social influence, hedonic motivation, perceived risk, AI anxiety, and trust, as they collectively influence the behavioral intention to use AI. The results reveal that performance expectancy and hedonic motivation are the most significant direct predictors of adoption intention. Social influence and trust act as crucial mediating variables, channeling the effects of other predictors. Notably, AI anxiety emerged as a powerful negative predictor, capable of overriding a user's perception of the technology's utility. The model demonstrated a strong fit, explaining a substantial portion of the variance in AI adoption intention. These findings underscore that user acceptance is a multifaceted phenomenon, driven by a combination of utilitarian calculations, emotional responses, and social pressures. This research provides a nuanced framework for developers, educators, and policymakers, offering actionable insights for designing human-centered AI systems that foster trust and mitigate user apprehension, thereby facilitating more effective and ethical technological integration.

Keywords: Artificial Intelligence, Technology Acceptance, Human-AI Interaction, Structural Equation Modeling, User Psychology, AI Anxiety, Trust in AI

1. Introduction

1.1 Broad Background and Historical Context

Artificial intelligence (AI), once a concept confined to science fiction, has evolved into one of the most disruptive and pervasive technologies of the 21st century [21]. Its capacity to analyze vast datasets, identify patterns, automate complex processes, and simulate human-like cognitive functions has catalyzed innovation across nearly every sector of the global economy and society [1, 3]. From optimizing supply chains in manufacturing [19] and personalizing consumer experiences in e-commerce [2] to revolutionizing diagnostic processes in healthcare [15] and transforming pedagogical approaches in education [11], the applications of AI are both diverse and profound [4]. This technological revolution is driven by advancements in sub-fields such as machine learning, natural language processing, computer vision, and robotics, which empower machines to perform tasks that traditionally required human intelligence [23].

The impact of AI extends beyond mere automation. These technologies are increasingly integrated into the fabric of human decision-making, offering personalized recommendations, translating languages in real-time, and even acting as digital companions or assistants [24, 26]. In organizational contexts, leaders face mounting pressure to adopt AI to maintain a competitive edge, enhance efficiency, and improve service delivery [6]. However, this imperative is often met with significant hurdles, including the complexity of integrating new systems and overcoming user resistance to change [7]. The integration of AI does not merely alter organizational workflows; it fundamentally redefines roles, reshapes human-technology interaction, and introduces new ethical considerations for producers and consumers alike [35].

In specialized domains, the stakes are particularly high. Within university education, AI is positioned as a pivotal tool for research and the training of future professionals, yet its adoption is often hindered by institutional inertia and a lack of understanding of the factors that predict student and educator engagement [9, 13]. Similarly, in healthcare, while AI promises to augment human capabilities in diagnostics and treatment planning on an unprecedented scale [15], its successful implementation is contingent on overcoming the limited understanding of healthcare professionals' perceptions and needs [16]. The willingness of practitioners to trust and utilize AI-assisted systems remains a critical and under-explored variable [17]. Even in manufacturing, where the benefits of efficiency and productivity are clear, the organizational acceptance of AI is ultimately determined by the attitudes and willingness of the employees who must interact with these systems daily [18]. As AI devices become more autonomous and socially present [25], understanding the human response to them is no longer a secondary consideration but a primary determinant of their ultimate success and societal value.

1.2 Critical Literature Review

The study of technology acceptance has a rich history, with foundational models providing robust frameworks for understanding user behavior. Theories such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2) have identified core constructs like perceived usefulness (or performance expectancy) and perceived ease of use (or effort expectancy) as primary drivers of adoption. In the context of AI, numerous studies have validated the role of these utilitarian expectations. Research consistently shows that when users believe an AI system will help them attain gains in job performance or daily tasks, their intention to use it increases significantly [39, 45]. This holds true across various domains, including healthcare, where professionals' intention to use AI for diagnosis is positively correlated with its expected performance and ease of use [17, 40], and in corporate settings, where performance expectancy is a vital predictor for the adoption of AI in human resources and financial services [41, 42, 43].

However, the findings are not always uniform, particularly concerning effort expectancy. While some studies confirm its importance [45], others report it as a non-significant factor in professional environments [41, 43], suggesting its influence may be context-dependent or moderated by other variables such as user skill or the mandatory nature of the technology's use. This inconsistency points to the need for models that move beyond purely utilitarian calculations.

Recognizing these limitations, researchers have increasingly incorporated social and contextual factors into their analyses. Social influence—the degree to which an individual perceives that important others believe they should use a new system—has emerged as a powerful predictor [49]. In collaborative environments like hospitals or corporations, the opinions and behaviors of peers and superiors can significantly shape an individual's willingness to adopt new AI tools [17, 51]. Social influence can positively affect adoption intention for technologies ranging from AI-powered job application systems to generative AI tools like ChatGPT [53, 54, 56]. Yet, here too, the evidence is not entirely consistent, with some research finding no direct effect of social influence on AI acceptance, suggesting its impact may be mediated by other factors or vary across different cultural and organizational settings [43].

Other contextual factors have also garnered attention. Hedonic motivation, defined as the fun or pleasure derived from using a technology, is a strong determinant of intention, particularly for consumer-facing AI like personal assistants or gamified applications [57, 58, 60]. Anthropomorphism, or the attribution of human-like characteristics to AI, can foster social connection and positive attitudes, thereby increasing performance expectations and driving adoption [74, 75]. Conversely, perceived risk—encompassing concerns about privacy, security, and performance reliability—acts as a significant barrier [89, 91]. These risks can diminish trust and reduce willingness to use AI, with perceptions varying based on user context, such as urban versus rural environments [88], or individual differences like gender [90].

More recently, the affective dimension of human-AI interaction has become a critical area of investigation. The integration of AI into high-stakes decision-making and daily routines can evoke powerful emotional responses that significantly influence acceptance or rejection [32]. AI anxiety, characterized by apprehension or fear regarding one's ability to use or interact with AI, has been consistently identified as a major impediment to adoption [98, 100]. This anxiety can negatively impact user attitudes and behavioral intentions across educational and professional settings [101, 102, 104]. Stress is another relevant emotion; while AI can alleviate workload, it can also introduce new pressures, leading to job-related stress if not implemented with adequate support [108, 109, 110]. On the other side of the emotional spectrum is trust, a cornerstone of successful human-AI collaboration [96, 111]. Trust in an AI's reliability, integrity, and capabilities is often a direct antecedent of adoption intention [40, 113], yet it is a fragile construct, easily undermined by perceived risks or poor performance [112]. Some studies, however, have found that trust is not always a significant predictor, indicating a complex and context-dependent relationship [114].

1.3 Research Gap

The existing literature provides compelling evidence that AI adoption is influenced by a confluence of user expectations, contextual factors, and emotional responses. However, a significant gap remains in our understanding of how these factors interact within a single, unified framework. Much of the research tends to examine these determinants in a fragmented manner, focusing on a limited subset of variables or specific contexts, which can lead to conflicting findings and limit the generalizability of results. For instance, the inconsistent effects of effort expectancy and social influence suggest the presence of unexamined mediators or moderators. Similarly, while trust and anxiety are recognized as important, their interplay with cognitive evaluations like performance expectancy and contextual factors like hedonic motivation is less understood.

There is a pressing need for more holistic, multidimensional models that can simultaneously account for the rational, social, and emotional dimensions of AI acceptance. Few studies have attempted to integrate constructs from classical acceptance models (e.g., UTAUT2) with crucial emotional variables (e.g., AI anxiety) and nuanced contextual factors (e.g., perceived risk, hedonic motivation) in a comprehensive structural model. Understanding these complex interactions is essential for developing a more complete and accurate theory of human-AI interaction and for designing technologies that are not only powerful but also readily and ethically adopted by their intended users.

1.4 Objectives and Hypotheses

This study aims to address the identified research gap by developing and empirically testing an integrated model of AI acceptance. Our primary objective is to investigate the simultaneous influence of cognitive, social, and affective factors on an individual's behavioral intention to use AI devices. We seek to clarify the direct and indirect relationships between these constructs and to provide a more comprehensive explanation of the user acceptance process.

Based on the critical literature review, we propose the following hypotheses:

- **H1: Performance Expectancy** will have a significant positive effect on the behavioral intention to use AI.
- **H2: Effort Expectancy** will have a significant positive effect on the behavioral intention to use AI.
- **H3: Social Influence** will have a significant positive effect on the behavioral intention to use AI.
- **H4: Hedonic Motivation** will have a significant positive effect on the behavioral intention to use AI.
- **H5: Perceived Risk** will have a significant negative effect on Trust in AI.
- **H6: AI Anxiety** will have a significant negative effect on the behavioral intention to use AI.
- **H7: Trust in AI** will have a significant positive effect on the behavioral intention to use AI.
- **H8: Trust in AI** will mediate the relationship between Perceived Risk and behavioral intention to use AI.

By testing these hypotheses within a single structural equation model, this research will contribute to a more nuanced and integrated understanding of the determinants of AI adoption, setting the stage for the development of AI systems that better align with human needs and values.

2. Methods

2.1 Research Design

This study employed a quantitative, cross-sectional research design to investigate the factors influencing the acceptance of AI devices. The core of our methodology was the development and administration of a structured online survey. This approach was chosen for its ability to efficiently collect data from a large and diverse sample, allowing for the statistical analysis of relationships between multiple variables simultaneously. The primary analytical strategy was Structural Equation Modeling (SEM), a powerful statistical technique that is ideal for testing complex theoretical models. SEM allows for the examination of both direct and indirect (mediating) effects among a set of observed and latent variables, making it perfectly suited to test the integrated model of AI acceptance proposed in this study. The research was conducted in a non-experimental setting, capturing a snapshot of participants' perceptions, attitudes, and intentions at a single point in time. All procedures were designed to ensure participant anonymity and adherence to ethical research standards, including obtaining informed consent prior to data collection.

2.2 Participants / Sample

The target population for this study was university students. This demographic was selected for several reasons: (1) university students are generally early adopters of new technologies; (2) they are increasingly exposed to various AI applications for educational and personal purposes, from generative AI tools for research to AI-driven learning platforms [12, 14, 48]; and (3) they represent a diverse group of future professionals who will soon be integrating AI into their respective fields.

Participants were recruited from a large, multidisciplinary public university in a major metropolitan area. An open invitation to participate in an online survey was distributed via official university email lists and social media channels associated with various student organizations. To encourage participation, a small incentive was offered in the form of a prize draw for one of ten gift cards. The initial data collection yielded 624 responses. After data cleaning, which involved removing incomplete surveys (missing >10% of data) and identifying and eliminating patterned responses (e.g., selecting the same answer for all questions), a final sample of N = 580 usable responses was retained for analysis.

The final sample consisted of 319 individuals identifying as female (55.0%), 255 identifying as male (44.0%), and 6 identifying as non-binary or other (1.0%). The age of participants ranged from 18 to 34, with a mean age of 21.6 years (SD = 2.8). The sample was academically diverse, with participants from a wide range of faculties: STEM (Science, Technology, Engineering, and Mathematics) fields (38%), Social Sciences and Humanities (35%), Business and Economics (20%), and Health Sciences (7%). The majority of participants (72%) were undergraduate students, while the remaining 28% were pursuing postgraduate degrees. This demographic diversity within the student population enhances the generalizability of the findings within this context and allows for potential exploratory analyses across different academic disciplines.

2.3 Materials and Apparatus

The primary instrument for data collection was a self-administered online questionnaire created using the Qualtrics survey platform. The questionnaire was structured into three sections.

Section 1: Demographics and AI Usage. This section collected basic demographic information, including age, gender, and academic field of study. It also included questions about participants' general familiarity with and frequency of use of AI-powered devices and services (e.g., virtual assistants, recommendation algorithms, generative AI).

Section 2: Measurement of Latent Constructs. This core section of the survey consisted of multiple items designed to measure the latent variables in our proposed research model. All constructs were measured using established, validated scales from prior research in technology acceptance and information systems, adapted slightly to fit the context of general AI devices. A 7-point Likert scale, ranging from 1 (Strongly Disagree) to 7 (Strongly Agree), was used for all items to ensure consistency and to capture a sufficient degree of variance in responses. The constructs and their corresponding source inspirations are as follows:

- **Performance Expectancy (PE):** 4 items adapted from the UTAUT literature, assessing the degree to which an individual believes that using AI will help them attain gains in performance (e.g., "Using AI devices improves my productivity") [39].

- **Effort Expectancy (EE):** 4 items adapted from UTAUT, measuring the perceived ease associated with the use of AI (e.g., "My interaction with AI devices is clear and understandable") [43].

- **Social Influence (SI):** 3 items adapted from studies on social influence in technology adoption, gauging the impact of one's social environment (e.g., "People who are important to me think that I should use AI devices") [49, 54].

- **Hedonic Motivation (HM):** 3 items adapted from research on user motivation, measuring the perceived enjoyment or pleasure derived from using AI (e.g., "Using AI devices is fun") [57, 58].

- **Perceived Risk (PR):** 4 items adapted from studies on consumer risk perception, assessing concerns related to privacy, security, and potential negative outcomes (e.g., "I am concerned that my personal data is not secure when using AI") [88, 91].

- **AI Anxiety (ANX):** 4 items adapted from scales measuring technology anxiety, focusing on feelings of apprehension and fear when dealing with AI (e.g., "I feel apprehensive about using AI") [98, 105].

- **Trust in AI (TR):** 4 items adapted from research on trust in automated systems, measuring the belief in an AI's reliability and integrity (e.g., "I trust that AI devices will perform as they are supposed to") [96, 113].

- **Behavioral Intention to Use (BI):** 3 items adapted from standard technology acceptance models, assessing the likelihood of future use (e.g., "I intend to continue using AI devices in the future") [14].

The survey was pilot tested with a group of 20 students who were not part of the final sample. Feedback from the pilot test was used to refine the wording of several items for clarity and to ensure the overall flow and timing of the questionnaire were appropriate.

2.4 Data Collection Procedure

The data collection was conducted over a six-week period. An email containing a brief description of the study's purpose and a link to the online survey was sent to all registered students via the university's administrative office. The same invitation was posted on the official social media pages of the student union and major departmental student societies. The initial page of the survey provided a detailed information sheet explaining the voluntary nature of participation, the estimated time to complete the survey (approximately 15-20 minutes), the measures taken to ensure data anonymity and confidentiality, and the details of the prize draw incentive. Participants were required to provide digital informed consent by ticking a checkbox before they could proceed to the questionnaire. IP address tracking was used to prevent duplicate submissions from the same device. Data was collected and stored securely on the Qualtrics server, accessible only to the research team. At the end of the six-week period, the survey was closed, and the collected data was exported for analysis.

2.5 Data Analysis

The data analysis was conducted using a two-stage process utilizing IBM SPSS Statistics (Version 28) and IBM SPSS AMOS (Version 28).

Stage 1: Preliminary Analysis. The first stage involved data screening, cleaning, and preliminary analysis using SPSS. Descriptive statistics (means, standard deviations, frequencies) were calculated for all demographic variables and the main study constructs. To assess the internal consistency and reliability of the measurement scales, Cronbach's alpha was calculated for each of the latent variables. An alpha coefficient of 0.70 or higher was considered the threshold for acceptable reliability. Pearson correlation analysis was then conducted to examine the bivariate relationships between all the latent constructs in the model, providing an initial check of the hypothesized associations.

Stage 2: Structural Equation Modeling (SEM). The second and primary stage of analysis involved using AMOS to test the proposed structural model. This was done following the two-step approach recommended for SEM. First, a **Confirmatory Factor Analysis (CFA)** was performed to establish the measurement model's validity. The CFA assessed how well the observed variables (the survey items) represented the underlying latent constructs. This step involved evaluating the model's goodness-of-fit and examining factor loadings, convergent validity (Average Variance Extracted - AVE), and discriminant validity (comparing the square root of AVE with inter-construct correlations).

Second, after confirming the validity of the measurement model, the **structural model** was tested. This involved specifying the hypothesized directional paths between the latent constructs (as outlined in H1-H8) and assessing the overall fit of this theoretical model to the empirical data. Several goodness-of-fit indices were used to evaluate the model, including: the Chi-square/degrees of freedom ratio ($\chi 2/df$), the Goodness-of-Fit Index (GFI), the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), and the Root Mean Square Error of Approximation (RMSEA). Commonly accepted thresholds for a good model fit (e.g., CFI/TLI > 0.90, RMSEA < 0.08) were used as benchmarks. Once an acceptable model fit was established, the standardized path coefficients (β) and their statistical significance (p-values) were examined to test each of the individual hypotheses. Finally, the bootstrapping procedure in AMOS (using 5,000 samples) was used to test the significance of the mediating effect proposed in H8.

3. Results

3.1 Preliminary Analyses

Before proceeding to the main analysis, the dataset ($N = 580$) was screened for missing values and outliers; no significant issues were found. Preliminary analyses were conducted, which included calculating descriptive statistics, examining a Pearson correlation matrix, and assessing reliability coefficients (Cronbach's alpha) for all latent constructs. The mean scores indicated that, on average, participants held moderately positive views regarding Performance Expectancy ($M = 5.21$, $SD = 1.15$) and Hedonic Motivation ($M = 4.98$, $SD = 1.34$). Effort Expectancy also scored relatively high ($M = 5.35$, $SD = 1.09$), suggesting participants generally found AI easy to use. Trust in AI was more neutral ($M = 4.15$, $SD = 1.28$), while Perceived Risk ($M = 4.55$, $SD = 1.41$) and AI Anxiety ($M = 3.89$, $SD = 1.55$) showed a moderate level of concern. Finally, Behavioral Intention to use AI was positive ($M = 5.12$, $SD = 1.30$). All measurement scales demonstrated excellent internal consistency, with Cronbach's alpha coefficients ranging from 0.85 to 0.94, well above the recommended 0.70 threshold, confirming the reliability of the constructs. The Pearson correlation analysis revealed significant relationships among the variables in the directions expected. Behavioral Intention was strongly and positively correlated with Performance Expectancy ($r = .68$, $p < .001$), Hedonic Motivation ($r = .62$, $p < .001$), Social Influence ($r = .45$, $p < .001$), and Trust ($r = .58$, $p < .001$). It was negatively correlated with AI Anxiety ($r = -.49$, $p < .001$) and Perceived Risk ($r = -.38$, $p < .001$). Trust was strongly negatively correlated with Perceived Risk ($r = -.65$, $p < .001$). These initial findings provide strong preliminary support for the hypothesized relationships within the proposed model.

3.2 Main Findings

Measurement Model (CFA)

A Confirmatory Factor Analysis (CFA) was conducted on the eight latent constructs to assess the validity of the measurement model. The initial model showed an adequate fit to the data. After minor modifications based on modification indices (allowing for the covariance of two error terms within the same construct), the final measurement model demonstrated a good fit: $\chi2(348) = 752.4$, $p < .001$; $\chi2/df = 2.16$; CFI = 0.96; TLI = 0.95; GFI = 0.92; RMSEA = 0.045. All standardized factor loadings for the items on their respective latent constructs were significant ($p < .001$) and ranged from 0.71 to 0.92, exceeding the recommended value of 0.70.

Convergent validity was confirmed, as the Average Variance Extracted (AVE) for each construct was above the 0.50 threshold (ranging from 0.63 to 0.81). Discriminant validity was also established, as the square root of the AVE for each construct was greater than its correlation with any other construct in the model. These results confirm that the measurement model was reliable and valid, providing a solid foundation for testing the structural model.

Structural Model

The proposed structural model was tested using AMOS. The model provided a good fit to the data, as indicated by the goodness-of-fit indices: $\chi2(354) = 815.7$, $p < .001$; $\chi2/df = 2.30$; CFI = 0.95; TLI = 0.94; GFI = 0.91; RMSEA = 0.048. The model accounted for 67% of the variance (R2 = 0.67) in Behavioral Intention to use AI and 45% of the variance (R2 = 0.45) in Trust, indicating substantial explanatory power.

The standardized path coefficients for the hypothesized relationships were then examined to test the hypotheses. The results are as follows:

- **H1: Performance Expectancy -> Behavioral Intention:** The path was positive and highly significant ($\beta = 0.41$, $p < .001$). **H1 was supported.**

- **H2: Effort Expectancy -> Behavioral Intention:** The path was not statistically significant ($\beta = 0.05$, $p = .210$). **H2 was not supported.**

- **H3: Social Influence -> Behavioral Intention:** The path was positive and significant ($\beta = 0.14$, $p < .01$). **H3 was supported.**

- **H4: Hedonic Motivation -> Behavioral Intention:** The path was positive and highly significant ($\beta = 0.25$, $p < .001$). **H4 was supported.**

- **H5: Perceived Risk -> Trust:** The path was negative and highly significant ($\beta = -0.67$, $p < .001$). **H5 was supported.**

- **H6: AI Anxiety -> Behavioral Intention:** The path was negative and significant ($\beta = -0.18$, $p < .001$). **H6 was supported.**

- **H7: Trust -> Behavioral Intention:** The path was positive and significant ($\beta = 0.19$, $p < .001$). **H7 was supported.**

Mediation Analysis

To test **H8**, the mediating role of Trust between Perceived Risk and Behavioral Intention, the bootstrapping procedure in AMOS was used with 5,000 resamples. The results revealed a significant indirect effect of Perceived Risk on Behavioral Intention via Trust (indirect effect $\beta = -0.13$; 95% CI [-0.19, -0.08]). Since the indirect effect was significant and its confidence interval did not include zero, **H8 was supported.** This indicates that while Perceived Risk does not have a direct significant path to Behavioral Intention in the final model, it exerts its influence indirectly by significantly reducing users' Trust in AI, which in turn lowers their intention to use it.

In summary, all hypotheses except for H2 (the direct effect of Effort Expectancy) were supported by the data. The strongest predictors of Behavioral Intention were Performance Expectancy, followed by Hedonic Motivation. AI Anxiety, Trust, and Social Influence also emerged as significant, albeit weaker, predictors.

3.3 Exploratory Findings

Given the diverse academic backgrounds of the participants, a post-hoc exploratory analysis was conducted to examine potential differences between students in STEM fields (N = 220) and those in Social Sciences and Humanities (SSH) (N = 203). A multi-group SEM analysis was performed to test for invariant paths between the two groups.

The analysis revealed one key difference: the path from **Hedonic Motivation** to **Behavioral Intention** was significantly stronger for the SSH group ($\beta = 0.33$, $p < .001$) compared to the STEM group ($\beta = 0.16$, $p < .01$). This suggests that while enjoyment is a factor for all students, it plays a much more prominent role in driving AI adoption among those in non-technical fields.

Conversely, the path from **Performance Expectancy** to **Behavioral Intention** was slightly stronger for the STEM group ($\beta = 0.45$, $p < .001$) than for the SSH group ($\beta = 0.38$, $p < .001$), although this difference was not statistically significant. This finding hints that students in technical fields may be slightly more driven by the utilitarian and productivity benefits of AI.

No other significant differences were found in the structural paths between the groups, including the negative impact of AI Anxiety and the role of Trust. This suggests that the core mechanisms of risk perception, trust formation, and anxiety operate similarly across students, regardless of their primary field of study. These exploratory results indicate that while the fundamental model of AI acceptance is robust, the relative importance of specific drivers like hedonic versus utilitarian motivations may vary depending on the user's background and orientation toward technology.

4. Discussion

4.1 Interpretation

This study set out to develop and test an integrated model of AI acceptance, combining cognitive, social, and affective factors. The results of our structural equation model provide a nuanced and compelling picture of the drivers behind a user's intention to adopt AI technologies. Our model demonstrated strong explanatory power, accounting for 67% of the variance in behavioral intention, which suggests that the selected constructs work in concert to form a comprehensive framework for understanding AI adoption.

The most powerful predictor of behavioral intention was **Performance Expectancy**, underscoring the fundamentally utilitarian nature of technology adoption. This finding (supporting H1) aligns with decades of research in the field and confirms that, above all, users are motivated to adopt AI if they believe it will enhance their productivity, effectiveness, and overall performance [39, 45]. In a world of rapidly evolving technologies, the perceived practical value remains the cornerstone of acceptance.

Interestingly, **Effort Expectancy** did not have a significant direct effect on behavioral intention, leading to the rejection of H2. This result, while seemingly counterintuitive, is consistent with several recent studies in professional and organizational contexts [41, 43]. It does not imply that ease of use is unimportant. Rather, it suggests that its influence may be indirect, perhaps by shaping initial perceptions of performance expectancy, or that for a digitally native population like university students, a baseline level of usability is already assumed. In the presence of strong drivers like performance benefits and hedonic value, the marginal effect of ease of use diminishes.

Our findings highlight the significant role of non-utilitarian factors. **Hedonic Motivation** emerged as the second-strongest predictor of adoption (supporting H4), indicating that the enjoyment, fun, and intrinsic pleasure derived from interacting with AI are powerful motivators [57, 61]. This is particularly crucial as AI becomes more integrated into creative, social, and personal domains. Furthermore, our exploratory analysis suggested this factor was even more potent for students in non-STEM fields, implying that as AI expands to new user bases, its affective and experiential qualities will become increasingly critical for widespread adoption.

The affective dimension was further emphasized by the significant negative impact of **AI Anxiety** (supporting H6). Even when a user recognizes the benefits of an AI tool, feelings of apprehension and fear can act as a powerful deterrent [98, 101]. This emotional barrier operates independently of cognitive evaluations of utility, highlighting the need for designs and implementations that actively work to mitigate user anxiety through transparency, user control, and support.

The social context also proved to be a significant, albeit more modest, driver. The support for H3 confirms that **Social Influence** positively affects adoption intention [49, 54]. The opinions and behaviors of peers, family, and mentors create a normative pressure that encourages individuals to engage with AI, reflecting the deeply social nature of technology adoption.

Finally, our analysis of **Trust** and **Perceived Risk** provides critical insights into the security and reliability aspects of AI acceptance. As hypothesized (H5), perceived risks related to privacy and functionality are powerful destroyers of trust. This trust, in turn, is a significant positive predictor of adoption intention (H7). The confirmation of our mediation hypothesis (H8) is particularly illuminating: Perceived Risk exerts its negative influence not directly on behavior, but indirectly by eroding the user's trust in the system [112]. This finding is critical for developers and policymakers; simply reducing risk is not enough. The key is to build and communicate trustworthiness, as it is the level of trust that ultimately shapes the user's willingness to engage with the technology [96].

4.2 Comparison with Literature

Our findings both reinforce and extend the existing body of literature on technology acceptance. The strong influence of performance expectancy is a direct confirmation of foundational models like TAM and UTAUT, and it aligns with numerous AI-specific studies across sectors like healthcare [17, 40], business [42], and education [39]. Our contribution lies in demonstrating the persistent dominance of this factor even when tested alongside a host of emotional and social variables.

The non-significant finding for effort expectancy contributes to an ongoing debate in the literature. While many studies find it to be a key predictor [77, 81], our result resonates with research by Norzelan et al. [43] and Bisht et al. [41], who also found it to be non-significant in specific professional contexts. This suggests that as users become more technologically savvy and as AI interfaces become more intuitive through advancements in natural language processing [22], the cognitive load associated with learning a new system (effort expectancy) may become a less critical barrier to adoption compared to its perceived benefits and emotional impact.

The significant role of hedonic motivation in our model supports a growing stream of research arguing that user experience is not purely instrumental [58, 62, 64]. Our finding aligns with Gursoy et al. [27], who found that enjoyment strongly influenced performance expectations and acceptance of AI in service delivery. The strength of this predictor in our general model suggests that hedonic value is no longer a niche factor relevant only to gaming or entertainment but is a core component of user acceptance for a wide range of modern AI technologies.

Our results regarding the negative influence of AI anxiety are highly consistent with recent literature highlighting the "dark side" of AI adoption [116]. Studies by Cho & Seo [99], Cengiz & Peker [101], and Wen et al. [102] have all reported a significant negative relationship between AI anxiety and acceptance or behavioral intention. Our study solidifies this finding by demonstrating its significance even when controlling for powerful utilitarian drivers, confirming that emotional barriers can create significant friction in the adoption process [98, 106].

The confirmation of trust as a crucial mediator between perceived risk and behavioral intention is a key contribution. While many studies have looked at trust as a direct antecedent of adoption [40, 113] or have examined the negative impact of risk [88, 92], our model clarifies the causal chain. It supports the theoretical position that users assess risks to form a judgment about the technology's trustworthiness, and it is this judgment of trust that more directly informs their decision to use the technology [96, 112]. This contrasts with the findings of Tran et al. [114], who did not find a significant effect for trust, again highlighting how the relationships between these factors can vary depending on the specific context and model specification. Our integrated approach helps to reconcile some of these differences by showing how trust functions as a critical node connecting cognitive risk assessment with behavioral outcomes.

4.3 Strengths and Limitations

This study has several strengths. First, its primary contribution is the development and testing of a comprehensive, integrated model that simultaneously assesses cognitive, social, and affective determinants of AI acceptance. This holistic approach provides a more ecologically valid representation of the complex decision-making process users undergo when faced with new AI technologies. Second, the use of a large and academically diverse sample of university students, who are at the forefront of AI adoption, enhances the relevance of our findings. Third, the rigorous application of a two-stage SEM analysis, including a full measurement model validation and bootstrapping for mediation, lends statistical robustness to our conclusions.

Despite these strengths, the study is subject to several limitations that must be acknowledged. First, the cross-sectional design captures data at a single point in time, which prevents us from making definitive causal claims or understanding how perceptions and intentions may evolve with increased experience and exposure to AI. Longitudinal studies are needed to track these dynamics over time. Second, our reliance on self-report survey data may be subject to social desirability bias and common method variance, although the use of validated scales and the confirmation of the measurement model's integrity mitigate this concern to some extent. Third, our sample consisted exclusively of university students from a single geographic region. While this group is highly relevant, the findings may not be generalizable to other populations, such as older adults, professionals in specific industries, or individuals in different cultural contexts. Future research should test this model across more diverse demographics and settings. Finally, our study treated "AI devices" as a general category. In reality, the factors influencing the adoption of a functional AI assistant may differ from those influencing the acceptance of a social AI companion [24] or a high-stakes medical diagnostic tool [32]. Future studies should examine whether the proposed model holds for specific types of AI applications.

4.4 Implications

The findings of this research offer several important implications for both theory and practice.

Theoretical Implications: Our study contributes to technology acceptance literature by providing empirical support for an integrated model that extends beyond the traditional utilitarian focus of frameworks like TAM and UTAUT. It demonstrates the necessity of incorporating affective constructs like hedonic motivation and AI anxiety as first-order determinants of behavioral intention. Furthermore, by confirming the mediating role of trust, our model provides a more precise understanding of the causal pathway through which risk perceptions influence user behavior. This encourages a move towards more complex, socio-technical-emotional models of human-AI interaction.

Practical Implications for Developers and Designers: For those creating AI technologies, our findings offer clear guidance.

1. **Prioritize Value and Performance:** The core functionality and ability of the AI to deliver tangible benefits remains paramount. Developers must ensure their products are effective and genuinely enhance user productivity [41].

2. **Design for Enjoyment:** Beyond functionality, the user experience matters. Incorporating elements of enjoyment, engagement, and aesthetic appeal can significantly boost adoption, especially for mainstream audiences [60].

3. **Build Trust by Mitigating Risk:** Developers must proactively address user concerns about privacy, security, and algorithmic bias. This involves not only implementing robust technical safeguards but also communicating these measures transparently to build user trust [111]. Features that enhance user control and explainability (XAI) can be critical in this regard [20].

4. **Actively Reduce Anxiety:** Onboarding processes, intuitive user interfaces, accessible technical support, and clear documentation can help demystify AI and reduce user apprehension [106]. Avoiding overly technical jargon in user-facing communication is essential.

Implications for Educators and Policymakers: As AI becomes more integrated into education and society, educators have a role in fostering AI literacy, which can help mitigate anxiety and promote informed and critical use of these tools [8, 10]. Policymakers should focus on creating regulatory frameworks that address the risks associated with AI, thereby fostering a general climate of trust and ensuring that AI is developed and deployed in an ethical and human-centric manner [34].

4.5 Conclusion and Future Directions

The decision to accept or reject artificial intelligence is not a simple calculation of costs and benefits. It is a deeply human process, shaped by a complex interplay of rational evaluations, emotional responses, social context, and underlying trust. This study demonstrated that while performance expectancy remains a powerful driver of AI adoption, factors such as the enjoyment derived from its use (hedonic motivation) and the fear it may inspire (AI anxiety) are also critical determinants. Trust acts as a crucial gateway, translating perceptions of risk into behavioral consequences.

The future of AI will be defined not only by technological advancement but by our ability to foster a healthy and productive relationship between humans and machines. To that end, future research should continue to explore this dynamic relationship from multiple angles. Longitudinal studies are needed to understand how user perceptions evolve from initial adoption to long-term, routinized use. Qualitative research, such as in-depth interviews and focus groups, could provide richer insights into the specific nature of user anxieties and the experiences that build or erode trust. Cross-cultural research is essential to determine whether the relative importance of these factors—particularly social influence and hedonic motivation—varies across different societies. Finally, future models should explore additional variables, such as personal innovativeness, ethical perceptions, and the role of paradoxical mindsets in navigating the challenges of AI [97].

By continuing to investigate the human element in the machine age, we can guide the development of AI technologies that are not only intelligent in their function but also wise in their integration into the fabric of human society.

References

[1] Goi V, Proskurnina N, Kovalenko M, Mamonov K, Haidenko S. Prospects and Challenges of the Impact of Artificial Intelligence and Machine Learning on Social and Economic Progress. Pak.J.Life.Soc.Sci. 2024;22.

[2] Gurjar K, Jangra A, Baber H, Islam M, Sheikh SA. An Analytical Review on the Impact of Artificial Intelligence on the Business Industry: Applications Trends and Challenges. IEEE Eng Manag Rev. 2024;52:84-102.

[3] Rashid AB, Kausik MA. AI Revolutionizing Industries Worldwide: A Comprehensive Overview of Its Diverse Applications. Hybrid Adv. 2024;7:100277.

[4] Rafee SM, Prasad M, Kumar MS, Easwaran B. 2 AI Technologies Tools and Industrial Use Cases. In: De Gruyter eBooks. 2023:21-52.

[5] Frank DA, Chrysochou P, Mitkidis P, Otterbring T, Ariely D. Navigating Uncertainty: Exploring Consumer Acceptance of Artificial Intelligence Under Self-Threats and High-Stakes Decisions. Technol Soc. Dec. 2024;79:102732.

[6] Tursunbayeva A, Chalutz-Ben Gal HC. Adoption of Artificial Intelligence: A Top Framework-Based Checklist for Digital Leaders. Bus Horiz. 2024;67:357-368.

[7] Prasad Babu PP, Vasumathi A. Contemporary Issues in

Applying AI Applications: Challenges and Opportunities. Multidiscip Rev. 2023;6:e2023010.

[8] Farina A, Stevenson CN. Ethical navigations: Adaptable frameworks for responsible AI use in higher education. InExploring the ethical implications of generative AI.IGI Global. 2024:63-87.

[9] González J. Campos. J.L. – núñez, and C.A. – Pérez. Educación Superior E Inteligencia Artificial: Desafíos Para la Universidad Del Siglo XXI. Aloma: Revista de Psicologia, Ciències de l'Educació i de l'Esport. 2024;42:79–90.

[10] Helmiatin N, Hidayat A, Kahar MR. Investigating the Adoption of AI in Higher Education: A Study of Public Universities in Indonesia. Cogent Educ. 2024;11: 2380175.

[11] Makarenko O, Borysenko O, Horokhivska T, Kozub V, Yaremenko D. Embracing Artificial Intelligence in Education: Shaping the Learning Path for Future Professionals. Multidiscip Sci J. 2024;6:e2024ss0720.

[12] Raja S, Jebadurai DJ, Ivan L, Mykola RV, Ruslan K, et al. Impact of Artificial Intelligence in Students Learning Life. Stud Syst Decis Control. 2024;516:3-17.

[13] Sova R, Tudor C, Tartavulea CV, Dieaconescu RI. Artificial Intelligence Tool Adoption in Higher Education: A Structural Equation Modeling Approach to Understanding Impact Factors Among Economics Students. Electronics. 2024;13:3632.

[14] Tang X, Yuan Z, Qu S. Factors Influencing University Students Behavioural Intention to Use Generative Artificial Intelligence for Educational Purposes Based on a Revised UTAUT2 Model. J Comput Assist Learn. 2025;41:e13105.

[15] Shang Z, Chauhan V, Devi K, Patil S. Artificial Intelligence the Digital Surgeon: Unravelling Its Emerging Footprint in Healthcare—The Narrative Review. J Multidiscip Healthc. Aug. 2024;17:4011-4022.

[16] Chew HS, Achananuparp P. Perceptions and Needs of Artificial Intelligence in Health Care to Increase Adoption: Scoping Review. J Med Internet Res. Jan. 2022;24:e32939.

[17] Cheng M, Li X, Xu J. Promoting Healthcare Workers Adoption Intention of Artificial-Intelligence-Assisted Diagnosis and Treatment: The Chain Mediation of Social Influence and Human–Computer Trust. Int J Environ Res Public Health. 2022;19:13311.

[18] Fousiani K, Michelakis G, Minnigh PA, De Jonge KM. Competitive Organizational Climate and Artificial Intelligence (AI) Acceptance: The Moderating Role of Leaders Power Construal. Front Psychol. 2024;15:1359164.

[19] Nzama ML, Epizitone GA, Moyane SP, Nkomo N, Mthalane PP. The Influence of Artificial Intelligence on the Manufacturing Industry in South Africa. S Afr J Econ Manag Sci. 2024;27.

[20] Hulsen T. Explainable Artificial Intelligence (Xai): Concepts and Challenges in Healthcare. AI. 2023;4:652-666.

[21] Lexcellent C. Artificial Intelligence Versus Human Intelligence. Cham: Springer International Publishing. 2019.

[22] Nalini C, Dharani B, Baskar T, Shanthakumari R Abraham A, et al. Review on Sentiment Analysis Using Supervised Machine Learning Techniques. InInternational Conference on Intelligent Systems Design and Applications. 2022:166-177.

[23] Menaga D, Saravanan S. Application of Artificial Intelligence in the Perspective of Data Mining. In: Elsevier eBooks. Amsterdam: Elsevier. 2021:133-154.

[24] Kim J, Merrill K, Collins C. AI as a Friend or Assistant: The Mediating Role of Perceived Usefulness in Social AI vs. functional AI. Telemat Inform. 2021;64:101694.

[25] van Doorn J, Mende M, Noble SM, Hulland J, Ostrom AL, et al. Domo Arigato Mr. Roboto: Emergence of Automated Social Presence in Organizational Frontlines and Customers Service Experiences. J Serv Res. Nov. 2017;20:43-58.

[26] Singh S, Beniwal H. A Survey on Near-Human Conversational Agents. J King Saud Univ Comput Inf Sci. 2022;34:8852-8866.

[27] Gursoy D, Chi OH, Lu L, Nunkoo R. Consumers Acceptance of Artificially Intelligent (AI) Device Use in Service Delivery. Int J Inf Manag. 2019;49:157-169.

[28] Renz S, Kalimeris J, Hofreiter S, Spörrle M. Me Myself and AI: How Gender Personality and Emotions Determine Willingness to Use Strong AI for Self-Improvement. Technol Forecasting Soc Change. 2024;209:123760.

[29] Wang L, Li W. The Impact of AI Usage on University Students Willingness for Autonomous Learning. Behav Sci (Basel). 2024;14:956.

[30] Schwesig R, Brich I, Buder J, Huff M, Said N. Using Artificial Intelligence (AI)? Risk and Opportunity Perception of AI Predict Peoples Willingness to Use AI. J Risk Res. 2023;26:1053-1084.

[31] Chen S, Granitz N. Adoption Rejection or Convergence: Consumer Attitudes Toward Book Digitization. J Bus Res. Aug. 2012;65:1219-1225.

[32] Park EH, Werder K, Cao L, Ramesh B. Why Do Family Members Reject AI in Health Care? Competing Effects of Emotions. J Manag Inf Syst. Jul. 2022;39:765-792.

[33] Rucker DD, Petty RE. Emotion Specificity and Consumer Behavior: Anger Sadness and Preference for Activity. Motiv Emot. Mar. 2004;28:3-21.

[34] Yu S, Carroll F Montasari R, editor. Applications for Artificial Intelligence and Digital Forensics in National Security. Cham: Springer Nature Switzerland. 2023:15-37/152.

[35] Mithun AM, Abu Bakar Z, Yafooz WM. Revised Theoretical Approach of Activity Theory for Human Computer Interaction Design. Adv Intell Syst Comput. 2019:803-815.

[36] Rao A, Kumar S, Acharyulu GV. Cognitive Behavior: Different HumanComputer Interaction Types. Wiley. 2021:1-22/400.

[37] Borders J, Klein G, Besuijen R. Mental Model Matrix: Implications for System Design and Training. J Cogn Eng Decis Mak. Jan. 2024;18:75-98.

[38] Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, et al. The Prisma 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. Br Med J. 2021;372.

[39] Xu S, Chen P, Zhang G. Exploring Chinese University Educators Acceptance and Intention to Use AI Tools: An Application of the UTAUT2 Model. Sage Open. 2024;14.

[40] Hameed BZ, Naik N, Ibrahim S, Tatkar NS, Shah MJ, et al. Breaking Barriers: Unveiling Factors Influencing the Adoption of Artificial Intelligence by Healthcare Providers. Big Data Cogn Comput. 2023;7:105.

[41] Bisht S, Sengupta S, Bisht MK. Adoption of Artificial Intelligence in Business Operations of Technology Firms. lecture notes in networks and systems. 2024:631-638.

[42] Nawaz N, Arunachalam H, Pathi BK, Gajenderan V. The Adoption of Artificial Intelligence in Human Resources Management Practices. Int J Inf Manag Data Insights. 2024;4:100208.

[43] Norzelan NA, Mohamed IS, Mohamad M. Technology Acceptance of Artificial Intelligence (AI) Among Heads of Finance and Accounting Units in the Shared Service Industry. Technol Forecasting Soc Change. 2024;198:123022.

[44] Affandi S, Ishaq MI, Raza A, Talpur Q, Ahmad R. AI Assistant Is My New Best Friend! Role of Emotional Disclosure Performance Expectations and Intention to Reuse. J Retailing Con Serv. 2025;82:104087.

[45] Sharma S, Islam N, Singh G, Dhir A. Why Do Retail Customers Adopt Artificial Intelligence (AI) Based Autonomous Decision-Making Systems?IEEE Trans Eng Manag. 2022:1-16.

[46] Alzyoud M, Al-Shanableh N, Alomar S, As'adAlnaser AM, Mustafad A, et al. Artificial Intelligence in Jordanian Education: Assessing Acceptance via Perceived Cybersecurity Novelty Value and Perceived Trust. Int J Data Netw Sci. 2024;8:823-834.

[47] Nagy AS, Tumiwa JR, Arie FV, Erdey L. An Exploratory Study of Artificial Intelligence Adoption in Higher Education. Cogent Educ. 2024;11.

[48] Boubker O. From Chatting to Self-Educating: Can AI Tools Boost Student Learning Outcomes? Expert Syst Appl. Mar. 2024;238:121820.

[49] Graf-Vlachy L, Buhtz K, König A. Social Influence in Technology Adoption: Taking Stock and Moving Forward. Manag Rev Q. Jan. 2018;68:37-76.

[50] Jain R, Garg N, Khera SN. Adoption of Ai-Enabled Tools in Social Development Organizations in India: An Extension of UTAUT Model. Front Psychol. 2022;13:893691.

[51] Chen CH, Lee WI. Exploring Nurses Behavioural Intention to Adopt AI Technology: The Perspectives of Social Influence Perceived Job Stress and Human–Machine Trust. J Adv Nurs. 2025;81:3739-3752.