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**Psychological Predictors of the Intention to Use AI: The Role of Attitudes,  
Anxiety, Self-Efficacy, Trust and Personality in a TAM3-Based Study in  
Guatemala**

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## **Abstract**

The adoption of artificial intelligence (AI) technologies has become increasingly relevant in everyday life, yet empirical evidence from non-WEIRD countries remains limited. This thesis examined psychological factors associated with the general intention to use AI in Guatemala using the Technology Acceptance Model 3 (TAM3) as a guiding framework. Data were collected through a cross-sectional survey of 351 participants residing in Guatemala (69.5% women, 30.5% men), including university students and working professionals. The study examined whether core acceptance variables, psychological factors, and prior experience were associated with intention to use AI. Pearson correlations, multiple regression analyses, as well as mediation and moderation analyses were conducted.

Results indicate that intention to use AI was most closely related to perceived usefulness, attitudes, and prior experience. In line with this pattern, psychological factors appeared to shape how AI was evaluated. By contrast, personality traits showed limited and inconsistent associations that did not retain explanatory power once psychological and experiential factors were considered. Overall, the findings are consistent with the continued relevance of established technology acceptance mechanisms for understanding AI adoption in a non-WEIRD context. Experience together with proximal psychological factors emerge as central influences on AI use.

**Keywords:** artificial intelligence adoption; Technology Acceptance Model; TAM3; non-WEIRD context; psychological factors; prior experience; behavioral intention; attitudes toward AI; trust in automation; self-efficacy; technology anxiety; personality traits; perceived usefulness

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## Introduction

Artificial intelligence (AI) is more present in people's everyday lives than they often acknowledge. It can be found across multiple domains and applications, supporting individuals in tasks related to information processing, communication, and decision making (Kaya et al., 2022). Rather than being limited to specialized or technical contexts, AI increasingly forms part of how people study, work, and interact with digital tools (Hong, 2022). For this reason, understanding why individuals choose to adopt or engage with these technologies has become an important focus of recent research.

Within this literature, the Technology Acceptance Model (TAM) and its later refinement, TAM3, emphasize how individuals' evaluations of a technology shape intention to use and subsequent behavior (Venkatesh & Bala, 2008). However, TAM-based approaches offer more limited insight into the psychological factors that influence how these evaluations are formed (Hong, 2022). To address this limitation, prior research has often used TAM as a framework while incorporating additional psychological predictors in order to better account for individual differences in technology adoption.

Much of the existing research on AI adoption has been conducted in WEIRD countries (Western, Educated, Industrialized, Rich, and Democratic) (Cemalcilar et al., 2021). This concentration limits the generalizability of findings and raises questions about whether established technology acceptance models operate similarly across different social and cultural contexts. Prior research suggests that in Latin America, AI adoption is still emerging, shaped by uneven access, limited exposure, and ongoing processes of digital development (Gray et al., 2016; Cremaschi et al., 2025). As a result, psychological responses to AI may differ from those observed in contexts where these technologies are already well established.

The present study addresses these gaps by examining psychological predictors of the intention to use AI in Guatemala. Specifically, it investigates the following research question: To what extent are attitudes, anxiety, self-efficacy, trust, and personality traits related to individuals' intention to use artificial intelligence technologies in Guatemala within a TAM3-based framework?

## **Background**

### **Technology Acceptance Model TAM and TAM3**

The Technology Acceptance Model (TAM) was originally developed to explain how individuals form intentions to use new technologies (Davis, 1989). Within this framework, behavioral intention represents the mechanism through which individuals' evaluations of a system translate into actual use (AlMakinah, 2025). In earlier versions of the model, attitudes were assumed to influence intention. Later revisions removed this component to simplify the model and strengthen its predictive focus (Venkatesh & Bala, 2008). As a result, later formulations of TAM place greater emphasis on users' underlying beliefs about a system. Within this structure, perceived usefulness and perceived ease of use function as the two core beliefs shaping behavioral intention (AlMakinah, 2025). Later versions of the model acknowledged that technology adoption is not shaped exclusively by individual cognitive beliefs. As a result, TAM2 was introduced to address this gap (Venkatesh & Bala, 2008). It added additional cognitive components and social influence factors, which reflect how expectations from colleagues or leaders affect technology adoption (Ibrahim et al., 2025). Building on this extension, TAM3 further expanded the framework by specifying how additional psychological, experiential, and contextual factors shape perceived usefulness and perceived ease of use. Importantly, TAM3 also proposes that experience changes the strength of several core relationships in the model (Venkatesh & Bala, 2008; Kleine et al., 2024).

Experience plays a central role in this process, as individuals tend to adjust their evaluations as they become more familiar with a system (Venkatesh & Bala, 2008). In this sense, TAM3 provides a broader platform for examining psychological factors that may influence AI adoption while retaining a relatively simple structure (Venkatesh & Bala, 2008). This simplicity has also been a source of criticism, as the model relies on a limited set of core predictors that some authors consider insufficient to capture the full complexity of technology adoption (Sadeck, 2022). Nevertheless, extensive empirical evidence shows that TAM performs consistently across a wide range of technological domains and populations, supporting its applicability beyond specific systems or user groups (Kleine et al., 2024). At the same time, findings vary across cultural contexts, leading reviews to recommend that TAM-based models be applied cautiously outside the settings in which they were originally

validated (Marangunić & Granić, 2014). These considerations suggest that, despite its extensions, TAM may still offer an incomplete account of technology acceptance, particularly in less studied contexts (AlMakinah, 2025).

### **Core TAM3 Constructs: Perceived Usefulness, Perceived Ease of Use, and Behavioral Intention**

Perceived usefulness and perceived ease of use function as early evaluations of a system. The former reflects the expectation that using a technology will improve performance, whereas the latter refers to the perception that the technology will require little effort (Davis, 1989). Research on TAM shows that ease-of-use perceptions can shape usefulness evaluations, as technologies that feel easier to use are often viewed as more beneficial (Davis, 1989). However, across multiple studies, usefulness tends to be a stronger predictor of technology use than ease of use, individuals often prioritize whether a system improves their performance over how easy it is to operate (Davis, 1989).

Behavioral intention (BI) indicates the degree to which a person is ready to engage in a given action (Ariff et al., 2012). In AI research, intention is commonly used as the primary outcome because actual technology use is often difficult to assess. This is especially the case in contexts where AI adoption remains at an early stage (Rana et al., 2024). Nevertheless, BI alone does not explain the psychological processes that shape these intentions, a limitation that motivated later extensions of TAM.

### **Psychological Predictors Shaping AI Evaluations**

#### ***Attitudes Toward Artificial Intelligence***

The relationship between users' attitudes and their intention to adopt AI has been widely debated in recent research. While some perspectives describe attitude as a central driver of behavioral intention, empirical findings suggest that its influence is not uniform across studies (Zou & Huang, 2023). For example, some investigations report no significant association between attitude and intention (Sohn & Kwon, 2020). Nevertheless, a substantial body of evidence continues to support the view that attitudes remain an important predictor of the intention to use AI systems (Ibrahim et al., 2025). This ongoing debate helps explain why

many studies continue to rely on earlier versions of technology acceptance models or extend existing frameworks in which attitude remains an explicit component.

To account for these mixed findings, attitude is often conceptualized as a complex structure rather than a single evaluative response. From this perspective, attitudes imply that a user's judgment is formed through the interplay of emotional, cognitive, and behavioral assessments (Breckler, 1984). Together, these components produce an overall positive or negative evaluation of the technology (Eagly & Chaiken, 2007). In the context of AI, these evaluations are shaped by the information individuals have about the technology and the mental representations they form, which are in turn influenced by personal dispositions and prior experiences (Park & Woo, 2022). Rather than operating in isolation, attitudes toward AI function as an integrative layer that reflects how prior evaluations are combined before intentions are formed.

### *AI-Anxiety*

The adoption of AI is not determined solely by technical performance, as emotional factors often play a critical role in the process. While many adoption models emphasize functional utility, research shows that emotional dimensions help explain why even efficient systems are sometimes rejected (Budhathoki et al., 2024). This suggests that AI integration is not always a purely rational decision; instead, subjective feelings and emotional responses substantially shape how technology is perceived (De Freitas et al., 2023).

Within the TAM3 framework, this emotional barrier is conceptualized as computer anxiety, defined as the psychological discomfort experienced when anticipating the use of a system (Venkatesh, 2000). These anxious responses operate as a mental filter that distorts users' evaluations of a system's difficulty. From a cognitive perspective, anxiety competes for limited mental resources, making information processing less efficient during interaction with the technology (Kleine et al., 2024). As a result, higher levels of anxiety can lead users to perceive AI systems as more complex, thereby reducing perceived ease of use (Kleine et al., 2024). Importantly, anxiety does not determine technology use directly. Instead, it shapes how other key evaluations within the model are formed, particularly during early stages of interaction. Given that AI-related anxiety is a relatively recent construct, limited evidence

exists on how it interacts with attitudes and broader personality traits, highlighting an important gap in current research (Kaya et al., 2022).

### ***Self-Efficacy***

While anxiety can act as an emotional barrier that limits technology use, self-efficacy functions as a cognitive resource that facilitates engagement. Self-efficacy does not necessarily refer to actual technical skill, but rather to the extent to which persons believe they can successfully use a technological tool to complete a task (Venkatesh & Bala, 2008). Within the TAM3 framework, this internal sense of confidence is conceptualized as an antecedent of perceived ease of use, suggesting that users' evaluations of a system are partly shaped by their perceived competence (Venkatesh & Bala, 2008). In the context of AI, higher self-efficacy may help users perceive complex technologies as more manageable. When individuals trust their ability to navigate these systems, they are more likely to evaluate AI tools positively and approach them with greater openness to learning (Balakrishnan et al., 2022). Rather than directly determining technology use, self-efficacy appears to influence how users engage with AI-related evaluations, increasing their willingness to invest effort in understanding and adapting to these systems over time (Naiseh et al., 2025).

### ***Trust in AI Systems***

Interacting with autonomous technologies involves an inherent level of risk, as users must rely on systems they do not fully control. In this context, trust allows individuals to accept vulnerability under conditions of uncertainty, making it a key factor in AI adoption (Wu et al., 2011; Rousseau et al., 1998). Trust helps users cope with the unpredictability often associated with how AI systems perform, particularly when outcomes cannot be fully anticipated. The autonomy of AI introduces a distinct trust dynamic that extends beyond basic concerns about system reliability. Because AI systems can simulate elements of human reasoning, users may perceive them as social agents rather than as purely technical tools (Glikson & Woolley, 2020). As a result, trust in AI is not static, but varies depending on contextual factors and the perceived human-like qualities of the system (Lankton et al., 2015). Trusting AI therefore involves evaluative processes that resemble those applied in human interactions, rather than being limited to assessments of technical dependability. Empirical

evidence further suggests that trust is closely linked to users' evaluations of system usability. When AI is perceived as difficult or complex, trust tends to decline, whereas systems that provide a more intuitive and transparent experience are more likely to be viewed as reliable and useful (Choung et al., 2022). Accordingly, trust emerges not only from technical characteristics, but also from users' direct experiences with the technology.

### **Prior Experience as a Dynamic Factor in TAM3**

Prior work suggests that experience can change how people evaluate an information system over time (Bhattacharjee, 2001). In TAM3, this is reflected in evidence showing that the contribution of perceived ease of use to behavioral intention is stronger early on and becomes less influential as users gain experience with the technology (Venkatesh & Bala, 2008). Importantly, it is not sufficient for an individual to begin using a technology; what matters is whether they decide to continue using it over time, and this decision is based on how the technology is evaluated as experience accumulates (Venkatesh & Bala, 2008). As a result, experience helps explain why early impressions do not always translate into sustained engagement with a technology.

### **Personality Traits**

Personality traits have been proposed as a source of individual differences in technology adoption, offering additional insight beyond core acceptance mechanisms (Barnett et al., 2014). However, their role in AI adoption remains relatively limited when compared to more proximal psychological predictors such as attitudes, perceived usefulness, or anxiety.

Previous research suggests that certain personality traits are associated with technology-related perceptions (Ibrahim et al., 2025). For example, agreeableness has been linked to higher perceived usefulness (Ibrahim et al., 2025). Furthermore, openness, conscientiousness, and extraversion have been associated with more favorable evaluations of new technologies (Ding et al., 2025). In contrast, higher levels of neuroticism have been related to greater apprehension toward engaging with unfamiliar technologies (Ding et al., 2025). At the same time, findings across studies are mixed, and the role of personality in technology adoption remains a subject of ongoing debate (Stein et al., 2024)

Although personality is often included in studies of technology use, it is rarely integrated explicitly within acceptance models such as TAM (Ibrahim et al., 2025). This is relevant because personality traits may influence how core acceptance constructs are evaluated, rather than directly determining adoption outcomes (Barnett et al., 2014).

### **AI Adoption in a Non-WEIRD Context: Guatemala**

Discussions of AI systems often assume that opportunities to engage with these technologies are distributed equally. Previous research suggests that access to AI tools depends on individuals' living and working conditions, which affects both who is able to use these technologies and how they are experienced in everyday life (Azevedo et al., 2013). These differences matter because they shape who is most likely to benefit from AI-based tools and constrain the empirical evidence available to researchers. As a result, existing findings often capture only part of the picture and do not fully reflect how AI adoption unfolds in lower-resource contexts (Azevedo et al., 2013). Across Latin America, digital access remains uneven, as local conditions influence how people interact with technology. In Guatemala, limited digital development continues to pose a barrier, and even where AI could offer practical benefits, restricted internet access and shortages in technical skills make widespread adoption difficult (Azevedo et al., 2013; Galvez & Revinova, 2025).

Beyond structural access, prior studies indicate that social and institutional factors also influence how AI is evaluated. When ethical behavior and transparency are perceived as present, individuals may feel more comfortable relying on AI tools (Acosta-Enriquez et al., 2025). At the same time, adoption is shaped by social environments. Research suggests that observing how others engage with AI can contribute to shared expectations about what is considered acceptable or appropriate use (Rana et al., 2024). Over time, AI use may become a normalized group practice rather than a purely individual decision. While this process can facilitate adoption, it may also reduce critical reflection if alignment with group practices takes precedence over individual evaluation.

Much of the existing evidence on AI adoption originates from a relatively small and privileged part of the world, resulting in the underrepresentation of Latin American contexts in global adoption research (Galvez & Revinova, 2025). Previous research indicates that interaction with AI is closely tied to structural advantages such as urban residence, higher

income, and regulated employment (Azevedo et al., 2013). Consequently, available data often reflects the experiences of relatively advantaged groups rather than the general population. This imbalance complicates the direct application of international adoption models to countries such as Guatemala, where AI adoption is still emerging and public attitudes are in the process of formation (Galvez & Revinova, 2025). Overall, existing evidence suggests that AI adoption is not a uniform process but reflects structural conditions in which education and income play a central role (Azevedo et al., 2013; Galvez & Revinova, 2025).

Standard technology adoption models provide a general framework for understanding how individuals evaluate and engage with new technologies, yet the literature indicates that they offer limited insight into why people with similar access and exposure may respond differently to AI. Across studies, psychological factors such as anxiety, self-efficacy, and trust are positioned inconsistently within adoption models, sometimes as antecedents of perceived usefulness and ease of use, and sometimes as direct predictors of intention (Graf-Vlachy et al., 2018; Stein et al., 2024). This lack of consistency reflects a fragmented research landscape in which psychological processes are often examined in isolation, limiting understanding of how individual evaluations develop and change as experience with AI increases (Venkatesh & Bala, 2008). These limitations are particularly relevant in contexts where AI adoption is still emerging and exposure remains uneven, such as Guatemala.

### **The Present Study**

The present study is an exploratory investigation grounded in the TAM3 framework. Although TAM3 includes a broad set of variables, only those relevant to the aims of the study were selected (Venkatesh & Bala, 2008). Rather than testing TAM3 as a complete structural model, the study examines specific relationships between acceptance constructs and selected psychological predictors. The focus is on perceived usefulness, perceived ease of use, and behavioral intention as central acceptance variables (Davis, 1989). In addition, AI self-efficacy and AI-related anxiety are examined as psychological factors shaping AI evaluations.

The primary aim of the study is to examine intention to use AI within a TAM3-based framework by focusing on how psychological factors relate to acceptance variables. Rather than assuming uniform adoption processes, the study examines how attitudes toward AI, trust

in AI, prior experience, and selected individual characteristics are associated with perceived usefulness, perceived ease of use, and intention to use AI.

The study was conducted in Guatemala, a non-WEIRD country that has been underrepresented in prior research on technology adoption (Galvez & Revinova, 2025). As a developing country, Guatemala provides a relevant context for examining AI adoption under constrained structural conditions (Azevedo et al., 2013). The study focuses on university students and working professionals, as these groups are more likely to encounter AI technologies in educational and professional settings, even in contexts where access to advanced digital tools remains uneven. This makes them particularly suitable for examining early-stage AI adoption (Azevedo et al., 2013). AI is examined as a general concept rather than as a specific application, allowing the study to capture broader perceptions and intentions toward AI use in a context where adoption remains at an early stage (Galvez & Revinova, 2025).

In the present study, intention to use AI is the primary outcome. Perceived usefulness and perceived ease of use are examined as acceptance variables. Psychological constructs related to attitudes, anxiety, self-efficacy, trust, personality traits, and prior experience are examined in relation to these acceptance variables. Experience with AI is included both as a factor directly associated with AI-related evaluations and as a variable that may condition the strength of selected relationships examined in the study.

### ***Contributions of the Present Study***

This study contributes to the literature on AI adoption by analyzing how psychological factors such as attitudes, anxiety, trust, and self-efficacy are related to intention to use AI within a TAM3-based framework. By situating these factors alongside acceptance variables, the study provides a more detailed account of how AI is evaluated at the individual level. Conducted in Guatemala, a non-WEIRD context where AI adoption is still emerging, the study extends existing research beyond the contexts in which technology acceptance models are most frequently tested.

## ***Objectives and Hypothesis***

Grounded in the TAM3 framework and prior research on technology adoption, the study includes a set of theory-driven hypotheses alongside exploratory analyses examining extensions of the model.

### ***Theory-driven hypotheses.***

H1: Perceived usefulness of AI will positively predict intention to use AI.

H2: Perceived ease of use of AI will positively predict intention to use AI.

H3: Higher perceived ease of use (PEOU) will be associated with greater perceived usefulness (PU).

H4: Attitudes toward AI will be associated with higher intention to use AI.

H5: AI-related anxiety will be negatively associated with perceived ease of use and attitudes toward AI.

H6: Perceived ease of use and AI self-efficacy will be favorably correlated.

### ***Exploratory analyses.***

The following analyses are exploratory in nature and examine how personality traits, psychological factors, and process-related associations relate to key TAM3 variables:

E1: Openness to experience will be positively associated with perceived usefulness and attitudes toward AI.

E2: Neuroticism will be positively associated with AI-related anxiety.

E3: Conscientiousness will be associated with perceived ease of use.

E4: Agreeableness and extraversion will be positively associated with trust in AI.

E5: Trust in AI will mediate the relationship between attitudes toward AI and intention to use AI.

E6: The association between perceived ease of use and perceived usefulness will be weaker for individuals with greater prior experience using AI.

E7: Prior experience with AI will be positively associated with perceived usefulness, perceived ease of use, and intention to use AI.

## **Methods and Design**

### **Study Design and Ethics**

The study adopted a cross-sectional quantitative design using an online, self-administered survey to examine psychological and technology-related constructs associated with the intention to use AI. Data were collected through SUNet Survey, a secure platform provided by Lund University, over a four-week period from early August to late August 2025. Participants were university students and working professionals in Guatemala, recruited through university channels, as well as social and professional online platforms. Several universities in Guatemala supported the distribution of the survey among their student populations. The questionnaire was disseminated using both a direct link and a QR code and administered in Spanish to ensure accessibility and comprehension. Rather than aiming to represent the national population, the study focused on a subgroup of digitally active individuals to examine early-stage AI adoption patterns in a non-WEIRD context. A non-probability, self-selected sampling strategy was used, which limits the generalizability of the findings beyond similar educational and professional contexts.

Ethical considerations were addressed throughout the study in accordance with the Swedish Act (2003:460) concerning the Ethical Review of Research Involving Humans. Participants took part on a voluntary basis and provided informed consent before completing the questionnaire. They were clearly informed about the aim of the study, the confidential handling of their responses, and their right to withdraw at any point without any negative consequences. No personally identifiable information was collected. All data were stored and processed in compliance with the General Data Protection Regulation, and the study adhered to relevant institutional ethical standards.

### **Participants**

The final sample consisted of 351 participants, all of whom resided in Guatemala. Participants' ages ranged from 18 to 74 years. Regarding gender, 69.5% of participants

identified as women and 30.5% as men. In terms of current activity, the sample included both university students and working adults. Specifically, 19.4% of participants reported being students, 46.2% were employed, and 30.2% reported working independently. A small proportion reported other activities, including unemployment or alternative roles. Regarding educational attainment, the sample was predominantly highly educated. 35.3% of participants reported holding a bachelor's degree, 37.6% a master's degree, and 2.6% a doctoral degree, meaning that 75.5% of the sample had completed university-level or postgraduate education. In addition, 20.2% reported secondary education as their highest level of completed studies, while no participants reported primary education only.

## **Materials**

All variables were assessed using an online self-report questionnaire administered in Spanish. Preference was given to open-access licensed instruments explicitly authorized for non-commercial research use. Within this framework, personality traits were measured using an existing Spanish version of the inventory. In addition, attitudes and trust were measured using scales originally developed for artificial intelligence and were therefore administered without conceptual adaptation.

The remaining variables were assessed using technology-related scales that were translated from English and adapted to explicitly refer to artificial intelligence, with items translated into Spanish to preserve conceptual meaning and clarity. ChatGPT (version 4.0) was used as a supportive tool during the translation of some scale items into Spanish. All translated items were subsequently reviewed and refined by the author to ensure conceptual accuracy and consistency with the original instruments. As no formal back-translation procedure was conducted, this is acknowledged as a methodological limitation. The instruments used to assess each study variable are described in the following sections, with the full set of questionnaire items provided in the Appendix.

## **Assessment of Personality Traits**

Personality traits were assessed using the Big Five Inventory–2 Extra-Short Form (Soto & John, 2017). The instrument comprises of 15 items rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). An example item is “Is original, comes up with new ideas.” Item responses were averaged to compute trait scores after

reverse-coded items were recoded according to the scoring instructions. The scale was used to balance personality assessment with survey length (Gallardo-Pujol et al., 2024). Internal consistency varied from ( $\alpha = .26-.70$ ) across traits.

### **Assessment of Attitudes Toward Artificial Intelligence**

Attitudes toward artificial intelligence were measured using the General Attitudes toward Artificial Intelligence scale (GAIA-15) (Hering et al., 2024). The scale consists of 15 items rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The GAIA-15 was selected as a short and validated measure of general attitudes toward artificial intelligence. The items capture different ways in which individuals evaluate artificial intelligence, including beliefs about AI, emotional reactions, and intentions related to AI use. An example item is “I am impressed by what AI can do.” Scale scores were computed by averaging responses across items, with higher scores indicating more favorable attitudes toward artificial intelligence. The scale showed good internal consistency ( $\alpha = .86$ ).

### **Assessment of Trust in Artificial Intelligence**

Trust in artificial intelligence was assessed using the Short Trust in Automation Scale (McGrath et al., 2025). The instrument includes three items answered on a 7-point Likert scale ranging from 1 (not at all) to 7 (extremely). The scale was chosen because it provides a concise and previously validated assessment of trust in AI systems. A sample item is “I am confident in the AI assistant.” Responses were aggregated by computing the mean score across items, such that higher values reflected higher levels of trust in artificial intelligence. In the present sample, the scale demonstrated very high internal consistency (Cronbach’s  $\alpha = .95$ ).

### **Assessment of TAM3-Based Constructs**

Perceived usefulness, perceived ease of use, and behavioral intention to use AI were measured using items derived from the Technology Acceptance Model 3 (TAM3; Venkatesh & Bala, 2008). In addition, AI-related self-efficacy and anxiety were assessed using TAM3-based indicators. All items were adapted to explicitly reference artificial intelligence and translated into Spanish. Participants responded using a 7-point Likert scale ranging from 1 (totally disagree) to 7 (totally agree). For each construct, composite scores were calculated by

averaging item responses, with higher scores indicating stronger higher levels of the respective construct.

### ***Perceived Usefulness***

Perceived usefulness was measured using four items assessing the extent to which AI was perceived as improving productivity and the quality of work results. An example item is “Using AI systems improves my job performance.” The scale showed excellent internal consistency ( $\alpha = .96$ ).

### ***Perceived Ease of Use***

Perceived ease of use was assessed using four items capturing perceptions of how intuitive, straightforward, and cognitively simple AI systems are to operate. An example item is “I find AI systems easy to use.” The scale showed acceptable internal consistency ( $\alpha = .78$ ).

### ***Behavioral Intention to Use AI***

Behavioral intention was measured using three items assessing participants’ intentions to use AI systems in the future. An example item is “If I had access to AI systems, I believe I would use them.” The scale showed excellent internal consistency ( $\alpha = .90$ ).

### ***Self-Efficacy***

AI self-efficacy was assessed using four items measuring participants’ perceived ability to use artificial intelligence tools. An example item is “I could complete a task using an AI tool if someone showed me how to do it first.” The scale showed excellent internal consistency ( $\alpha = .91$ ).

### ***AI-Related Anxiety***

AI-related anxiety was assessed using four items capturing feelings of discomfort when interacting with artificial intelligence. An example item is “AI makes me feel uncomfortable.” The scale showed low internal consistency ( $\alpha = .37$ ) and was interpreted with caution.

## **Assessment of Prior Experience with Artificial Intelligence**

Prior experience with artificial intelligence was assessed using a self-developed scale measuring the frequency of AI tool use across every day, academic, and professional contexts (see Appendix). Based on TAM3, frequency of use was treated as an indicator of prior user experience (Venkatesh and Bala, 2008). Responses were recorded using fixed-response frequency formats, with higher scores indicating greater prior experience with artificial intelligence. This variable was included as a contextual factor. The AI Use scale showed good internal consistency ( $\alpha = .80$ ).

## **Assessment of Demographic Variables**

Demographic information was collected to describe the sample and contextualize the findings. Participants reported their age, gender, highest completed level of education, main current activity, and country of residence. These variables were not included as primary predictors but were used for descriptive purposes.

## **Analysis**

The data were analyzed using the statistical software Jamovi (version 2.7.5). Prior to the analyses, all negatively worded items were reversed. Composite variables were then created by averaging the items belonging to each scale to facilitate interpretation and ensure consistency across measures. All study variables were standardized prior to the regression, mediation, and moderation analyses, where appropriate.

Descriptive statistics, including means and standard deviations, were calculated to provide an overview of the sample characteristics and the distribution of the study variables. Pearson correlation analyses were subsequently conducted to examine bivariate associations between personality traits, psychological variables, the core TAM3 constructs, and behavioral intention. These analyses also included the examination of the association between perceived ease of use and self-efficacy. The internal consistency of the multi-item scales was assessed using Cronbach's alpha. Based on these preliminary analyses, all study variables were retained for subsequent analyses.

Multiple linear regression analyses were used to examine the core TAM3 relationships, assessing the direct effects of perceived usefulness, perceived ease of use, and attitudes toward AI on behavioral intention. A separate linear regression analysis was conducted to examine the association between perceived ease of use and perceived usefulness. Additional regression analyses were conducted to examine the psychological and personality-related hypotheses, focusing on the associations between anxiety, trust, self-efficacy, personality traits, and the core TAM3 constructs.

The mediating role of trust in AI was examined using a regression-based mediation analysis with 5,000 bootstrap resamples. The moderating effect of prior experience with AI was assessed using a regression-based moderation analysis by estimating an interaction term between perceived ease of use and prior experience in predicting perceived usefulness. Finally, prior AI experience was examined as a direct predictor of perceived usefulness, perceived ease of use, and behavioral intention using separate simple linear regression analyses.

All statistical analyses were conducted using two-tailed significance tests, and effects were considered statistically significant if the 95% confidence intervals did not include zero. In addition, an exploratory multiple linear regression analysis was conducted in which all psychological and TAM-related predictors of behavioral intention were entered simultaneously in a single model. This analysis was exploratory in nature and was conducted to examine the relative contribution of each predictor while controlling for shared variance, rather than to formally test specific hypotheses. All predictors were entered simultaneously, without a predefined order.

## **Results**

This section presents the results of the present study. Descriptive statistics and bivariate correlations are reported first, followed by regression analyses examining the core TAM3 relationships. Subsequently, the effects of psychological antecedents are examined, together with mediation and exploratory analyses.

### **Descriptive Statistics**

Overall, participants reported relatively high levels of behavioral intention to use AI ( $M = 5.49$ ,  $SD = 1.35$ ) and perceived usefulness ( $M = 5.20$ ,  $SD = 1.48$ ). Perceived ease of use was rated at moderate levels ( $M = 4.98$ ,  $SD = 1.17$ ), indicating that AI systems were perceived as relatively easy to use.

Regarding psychological variables, attitudes toward AI were moderate ( $M = 3.11$ ,  $SD = 0.66$ ), as was trust in AI systems ( $M = 4.49$ ,  $SD = 1.30$ ). Self-efficacy showed high levels ( $M = 7.25$ ,  $SD = 2.24$ ), whereas anxiety was moderate ( $M = 3.33$ ,  $SD = 1.00$ ).

Regarding personality traits, mean levels were generally moderate across dimensions. Higher average scores were observed for agreeableness and conscientiousness, whereas neuroticism showed lower mean levels. Table 1 reports descriptive statistics for all study variables.

**Table 1***Descriptive Statistics for Study Variables*

<b>Variable</b>	<b>M</b>	<b>SD</b>	<b>Min</b>	<b>Max</b>
Behavioral Intention	5.49	1.35	1.00	7.00
Perceived Usefulness	5.20	1.48	1.00	7.00
Perceived Ease of Use	4.98	1.17	1.00	7.00
Attitudes	3.11	0.66	1.00	4.73
Trust	4.49	1.30	1.00	7.00
Self-Efficacy	7.25	2.24	1.00	10.00
Anxiety	3.33	1.00	1.00	6.25
Experience	2.81	0.78	1.00	5.00
Openness to Experience	3.77	0.69	2.00	5.00
Conscientiousness	4.07	0.79	1.33	5.00
Extraversion	3.47	0.84	1.33	5.00
Agreeableness	4.29	0.62	1.00	5.00
Neuroticism	2.51	0.90	1.00	5.00

*Note.* Behavioral Intention, Perceived Usefulness, Perceived Ease of Use, Trust, and Anxiety were measured on 7-point Likert scales. Attitudes and personality traits were measured on 5-point Likert scales. Experience was measured on a 5-point frequency scale (1 = Never to 5 = Very frequently). Self-Efficacy was measured on a 10-point Likert scale.

**Bivariate Correlations among TAM3 constructs and Psychological Variables**

Bivariate correlations are reported in Table 2. Behavioral intention was significantly associated with all core TAM3 and psychological variables. The strongest associations were observed with perceived usefulness and attitudes, followed by self-efficacy, perceived ease of use, and trust. Prior experience showed a moderate positive association with behavioral intention, whereas anxiety was negatively associated. These strong associations indicate substantial overlap among evaluative constructs, suggesting that perceived usefulness, attitudes, trust, and perceived ease of use are closely related rather than fully independent.

Pronounced associations were also observed among the core TAM3 constructs. Perceived usefulness was closely related to attitudes and trust, while perceived ease of use was strongly associated with attitudes. Consistent with the theory-driven expectations, perceived ease of use was strongly and positively correlated with self-efficacy. In addition, attitudes also had a substantial association with trust and self-efficacy. Anxiety showed negative correlations with all TAM3 constructs, with effect sizes ranging from small to moderate. Among the personality traits, only neuroticism and extraversion showed consistent significant correlations, which were generally weak (see Table A1, Appendix A). Behavioral intention was weakly associated with extraversion and negatively associated with neuroticism (see Table A1, Appendix A). In addition, neuroticism was negatively related to perceived usefulness and perceived ease of use. Regarding psychological variables, neuroticism showed weak associations with self-efficacy and extraversion, while anxiety exhibited moderate negative associations with trust and neuroticism (see Table A3, Appendix A).

**Table 2**

*Bivariate Correlations Among TAM3 Constructs and Psychological Variables*

Variables	1	2	3	4	5	6	7
1. BI	1						
2. PU	0.72***	1					
3. PEOU	0.51***	0.56***	1				
4. ATT	0.72***	0.75***	0.52***	1			
5. Trust	0.55***	0.64***	0.48***	0.68***	1		
6. SE	0.57***	0.58***	0.57***	0.54***	0.50***	1	
7. ANX	-0.32***	-0.27***	-0.24***	-0.34***	-0.34***	-0.30***	1
8. EXP	0.44***	0.44***	0.33***	0.48***	0.37***	0.33***	0.15**

*Note.* Pearson's correlation coefficients are reported. BI = Behavioral Intention, PU = Perceived Usefulness, PEOU = Perceived Ease of Use, ATT = Attitudes, SE = Self-Efficacy, ANX = Anxiety, EXP = Experience. Significance levels: \*\*\*  $p < .001$ , \*\*  $p < .01$ , \*  $p < .05$ .

## Regression Analyses

The core TAM3 relationships were examined using a series of regression analyses focusing on perceived usefulness, perceived ease of use, attitudes, and behavioral intention to use AI. Results indicated that perceived usefulness was a significant positive predictor of behavioral intention ( $\beta = .38, p < .001$ ), supporting H<sub>1</sub>. Perceived ease of use also showed a positive and statistically significant, though smaller, direct effect on behavioral intention ( $\beta = 0.10, p = 0.015$ ), providing support for H<sub>2</sub>. Attitudes toward AI emerged as a significant positive predictor of behavioral intention ( $\beta = .38, p < .001$ ), supporting H<sub>4</sub> (see Table 5).

**Table 5**

*Multiple Regression Predicting Behavioral Intention from Core TAM3 Constructs*

Predictor	$\beta$	SE	t	p
Perceived Usefulness	0.38	0.05	7.17	<.001
Perceived Ease of Use	0.10	0.04	2.45	0.015
Attitudes toward AI	0.38	0.05	7.29	<.001

*Note.* Standardized regression coefficients ( $\beta$ ) are reported. All predictors were standardized prior to analysis.

Perceived usefulness was then regressed on perceived ease of use to test the hypothesized association between these constructs. As shown in Table 6, perceived ease of use was strongly and positively associated with perceived usefulness ( $\beta = .56, p < .001$ )  $R^2 = .31.$ , supporting H<sub>3</sub>.

**Table 6**

*Regression Predicting Perceived Usefulness from Perceived Ease of Use*

Predictor	$\beta$	SE	t	p
Perceived Ease of Use	0.56	0.04	12.6	<.001

*Note.* Standardized regression coefficients ( $\beta$ ) are reported. All predictors were standardized prior to analysis.

Overall, psychological variables showed stronger associations with TAM3-related variables than personality traits, with anxiety emerging as a relevant predictor, whereas direct effects of personality traits were generally small and non-significant. Regression analyses were conducted to examine psychological and individual difference variables as predictors of TAM3-related outcomes (see Table 7). Results indicated that anxiety was negatively and significantly associated with perceived ease of use ( $\beta = -0.24, p < .001$ ) as well as with attitudes toward AI ( $\beta = -0.34, p < .001$ ), providing support for H<sub>5</sub>.

With respect to personality traits, openness to experience was not significantly associated with perceived usefulness or attitudes toward AI, providing no support for H<sub>7</sub>. Neuroticism showed a positive but non-significant association with anxiety ( $\beta = .10, p = .070$ ). Conscientiousness was not significantly associated with perceived ease of use ( $\beta = -.04, p = .527$ ). Finally, neither agreeableness nor extraversion showed significant associations with trust in AI.

**Table 7**

*Regression Analyses of Psychological and Personality Predictors*

Predictor	Outcome	$\beta$	SE	t	p
ANX	PEOU	-0.24	0.05	-4.68	<.001
ANX	ATT	-0.34	0.05	-6.73	<.001
OPN	PU	0.08	0.05	1.57	0.12
OPN	ATT	0.08	0.08	1.51	0.0836
NEU	ANX	0.10	0.05	1.82	0.070
CON	PEOU	-0.04	0.05	-0.63	0.527
AGR	Trust	0.07	0.06	1.17	0.241
EXT	Trust	0.07	0.06	1.17	0.243

*Note.* ANX = Anxiety; CON = Conscientiousness; OPN = Openness to Experience; NEU = Neuroticism; AGR = Agreeableness; EXT = Extraversion; PEOU = Perceived Ease of Use; PU = Perceived Usefulness; ATT = Attitudes. Standardized regression coefficients ( $\beta$ ) are reported. All predictors were standardized prior to analysis.

## Mediation Analysis

A mediation analysis examined whether trust mediated the relationship between attitudes toward AI and behavioral intention (see Table 8). The total effect of attitudes toward AI on behavioral intention was significant ( $\beta = .72, p < .001$ ). The direct effect of attitudes on behavioral intention was also significant ( $\beta = .64, p < .001$ ). However, the indirect effect via trust was small and did not reach conventional levels of statistical significance ( $\beta = .08, 95\% \text{ CI } [0.00, 0.17], p = .051$ ).

**Table 8**

*Mediation of the Relationship Between Attitudes and Behavioral Intention via Trust*

Effect	$\beta$	SE	95% CI	<i>p</i>
Indirect effect (Attitudes $\rightarrow$ Trust $\rightarrow$ BI)	0.08	0.04	[0.00, 0.17]	0.051
Direct effect (Attitudes $\rightarrow$ BI)	0.64	0.05	[0.53, 0.74]	< .001
Total effect	0.72	0.04	[0.64, 0.80]	< .001

*Note.* BI = Behavioral Intention. Standardized path coefficients ( $\beta$ ) are reported. Confidence intervals are based on 5,000 bootstrap resamples. All predictors were standardized prior to analysis.

## Exploratory Analysis

The following exploratory analyses were conducted to extend the main findings and to examine additional relationships beyond the core analyses.

### *Comparative Contribution of Predictors of Behavioral Intention*

An exploratory multiple regression analysis was conducted to examine the relative contribution of multiple predictors of behavioral intention when considered simultaneously. All predictors were standardized prior to analysis to allow for direct comparison of effects. Results for this analysis are reported in Table 9.

When included simultaneously in the regression model, perceived usefulness ( $\beta = .34, p < .001$ ) and attitudes toward AI ( $\beta = .32, p < .001$ ) showed the strongest unique associations

with behavioral intention. Self-efficacy also retained a significant positive association with behavioral intention, although with a more moderate effect size ( $\beta = .15, p = .001$ ). In contrast, perceived ease of use, trust, prior experience, anxiety, and personality traits did not retain significant direct associations with behavioral intention in this multivariate context.

**Table 9**

*Exploratory Multiple Regression Predicting Behavioral Intention*

<b>Predictor</b>	<b><math>\beta</math></b>	<b>SE</b>	<b>t</b>	<b>p</b>
Perceived Usefulness	0.34	0.06	6.08	<.001
Perceived Ease of Use	0.04	0.04	0.92	0.357
Attitudes	0.32	0.06	5.57	<.001
Self-Efficacy	0.15	0.05	3.25	0.001
Anxiety	-0.06	0.04	-1.59	0.112
Trust	-0.03	0.05	-0.60	0.548
Experience	0.07	0.04	1.71	0.088
Extraversion	0.01	0.04	0.21	0.831
Agreeableness	0.00	0.04	0.12	0.902
Openness	0.02	0.04	0.45	0.651
Conscientiousness	-0.04	0.04	-0.94	0.348
Neuroticism	-0.05	0.04	-1.23	0.220

*Note.* Standardized regression coefficients ( $\beta$ ) are reported. All predictors were entered simultaneously in a multiple linear regression model predicting behavioral intention. All predictors were standardized prior to analysis.

***Moderation by Prior Experience***

As an exploratory extension, a moderation analysis examined whether prior experience moderated the relationship between perceived ease of use and perceived usefulness (see Table 10). Perceived ease of use was positively associated with perceived usefulness ( $\beta = .44, p < .001$ ), as was prior experience ( $\beta = .29, p < .001$ ). Importantly, the interaction between perceived ease of use and prior experience was statistically significant ( $\beta = -.10, 95\% \text{ CI } [-0.16, -0.04], p < .001$ ).

### ***Prior Experience as an Exploratory Extension***

As an exploratory extension, prior experience was examined as a direct predictor of the core TAM3 constructs. Results for these analyses are reported in Table 11. Prior experience was positively and significantly associated with perceived usefulness ( $\beta = .44$ ,  $p < .001$ ), perceived ease of use ( $\beta = .33$ ,  $p < .001$ ), and behavioral intention ( $\beta = .44$ ,  $p < .001$ ).

## **Discussion**

This study examined whether psychological predictors influenced the intention to use new technologies such as AI in a non-WEIRD context. TAM3 was used as the theoretical foundation and was extended by incorporating additional psychological variables. AI was examined as a general technology embedded in everyday contexts rather than as a specific application tied to a single task domain. Perceived usefulness and attitudes emerged as the strongest predictors of intention to use AI. This pattern should be interpreted in light of the conceptual proximity of these constructs to behavioral intention, as well as their overlap with other evaluative variables included in the model. On the other hand, psychological factors such as anxiety and self-efficacy, together with prior experience, played a more central role than personality traits in shaping how AI was evaluated. Importantly, experience emerged as a factor associated with differences in how individuals formed and updated their evaluations of AI.

### **Core TAM3 mechanisms in AI adoption**

One clear pattern in the findings was that perceived usefulness played a more central role than perceived ease of use in shaping intention to use AI. This aligns with the basic idea behind technology adoption, where people tend to adopt technologies they perceive as valuable and worth using (Davis, 1989). In the present study, AI was evaluated as a general technology embedded in everyday contexts rather than as a tool tied to a specific task. In this sense, usefulness appears to reflect whether AI was perceived as offering meaningful value rather than whether it was simply easy to operate. Ease of use may still support adoption, but it did not emerge as the main criterion guiding intention to use AI.

This pattern was reflected in the model, where perceived ease of use showed a statistically significant direct association with intention, but its effect was relatively small. Rather than exerting a strong independent influence, ease of use primarily operates earlier in the adoption process by shaping other evaluations, particularly perceived usefulness. (Venkatesh & Bala, 2008). The strength of perceived usefulness should therefore be interpreted in light of its conceptual proximity to behavioral intention, compared to more indirect psychological predictors such as perceived ease of use.

Attitudes toward AI also emerged as a strong predictor of intention to use AI, with an effect comparable to perceived usefulness. In this study, attitudes were treated as a broader evaluative construct rather than as a simple reaction, which is particularly relevant for AI, given its association with uncertainty and mixed emotional responses (Park et al., 2022). Attitudes therefore appear to capture how cognitive and emotional evaluations are combined when individuals decide whether to engage with AI.

However, it is important to clarify why these two constructs emerged as strong predictors. Rather than reflecting independent processes, perceived usefulness and attitudes capture overlapping evaluations that jointly contribute to intention to use AI. This overlap was reflected in the statistical models, where perceived usefulness and attitudes shared a substantial proportion of variance (Nimon & Oswald, 2013). Although collinearity levels remained acceptable for regression analysis, this shared variance complicates direct comparisons of predictor strength. From this perspective, variables closer to intention tend to show stronger associations and greater shared variance. Differences in predictive strength should therefore be understood in relation to each variable's role in the adoption process rather than as direct indicators of relative importance.

### **Distinct roles of psychological factors in AI adoption**

Beyond the core TAM3 mechanisms, anxiety, self-efficacy, and trust showed distinct patterns in their association with AI adoption. Rather than acting as direct and uniform predictors of intention, these variables appeared to influence different stages of how AI was evaluated. Anxiety was associated with several study variables, indicating that higher anxiety was linked to more negative evaluations of AI (Venkatesh & Bala, 2008). When other variables were controlled for, anxiety showed a clear negative association with perceived ease

of use, suggesting that more anxious individuals tended to perceive AI as more difficult to use. This likely reflects an increased perception of effort rather than purely technical limitations. Anxiety was also strongly associated with attitudes toward AI. Given that attitudes include an emotional component, this pattern supports the idea that anxiety shapes broader evaluations of AI, influencing both how difficult it feels to use and how it is emotionally perceived. Importantly, anxiety did not directly predict intention, but this is difficult to interpret given reliability constraints. Instead, its influence appeared to operate through earlier evaluative stages, particularly perceived ease of use and attitudes.

In contrast, self-efficacy functioned as a cognitive resource that supported more positive evaluations of AI (Venkatesh & Bala, 2008). Higher self-efficacy was associated with higher perceived ease of use, greater perceived usefulness, and more favorable attitudes toward AI. This suggests that individuals who felt more capable of using AI were better able to engage with it, even when it was perceived as complex (Balakrishnan et al., 2022). Unlike anxiety, self-efficacy also retained a direct association with intention to use AI when other predictors were considered. This indicates that confidence in one's ability to use AI may support intention both indirectly, by shaping evaluations, and more directly, by encouraging engagement and persistence.

Trust in AI showed a more nuanced pattern. Trust was strongly associated with attitudes and perceived usefulness, indicating that it was closely tied to how AI was evaluated. However, trust did not mediate the relationship between attitudes and intention, nor did it retain a direct association with intention when other predictors were included. This does not necessarily mean that trust is unimportant in the adoption process. Instead, the overlap between trust and other evaluative constructs may have made it harder to detect a clear indirect effect when these variables were examined simultaneously (Nimon & Oswald, 2013). In this context, trust therefore did not function as a necessary bridge between evaluation and intention. Rather, trust appeared to develop alongside other evaluative processes, particularly those related to perceived ease of use and prior experience. When AI was perceived as complex or difficult to use, trust tended to be lower, whereas more intuitive experiences were associated with higher trust (Choung et al., 2022). Overall, these findings indicate that psychological factors do not operate at the same level within the adoption process. Anxiety, self-efficacy, and trust influenced different stages of evaluation rather than acting as

interchangeable predictors of intention. This differentiation may help explain why previous research has reported mixed findings regarding psychological predictors of technology adoption.

### **Limited role of personality traits in AI adoption**

Although the overall effects of personality traits were weak, some patterns emerged at the bivariate level. Neuroticism and extraversion were the only traits that showed consistent associations with AI-related outcomes, although these associations were small. Behavioral intention was weakly positively associated with extraversion and negatively associated with neuroticism. In addition, neuroticism was negatively related to perceived usefulness and perceived ease of use. This pattern suggests that traits related to emotional regulation and affective reactivity may be more relevant for AI-related evaluations than other personality dimensions. Individuals higher in neuroticism may be more prone to experience anxiety and uncertainty, which can translate into more negative evaluations of AI. However, these associations did not remain strong once more proximal psychological variables, such as anxiety and self-efficacy, were taken into account. This supports the view that broad personality traits play a limited role in explaining AI adoption when more context-specific psychological factors are considered. The characteristics of the study sample may also help explain these weak effects. Participants were primarily students and working professionals with relatively high levels of education, which may have led to more shared ways of evaluating AI. In such contexts, evaluations may be shaped less by stable individual traits and more by common academic and professional norms, thereby reducing the explanatory power of broad personality traits (Cemalcilar et al., 2021).

### **The role of experience as a dynamic factor**

Experience played an important role in how AI was evaluated. Prior experience with AI was positively associated with perceived usefulness, perceived ease of use, and intention to use AI. This indicates that individuals who were more familiar with AI tended to evaluate it more positively and were more willing to use it (Bhattacharjee, 2001).

Experience also shaped how the core TAM3 mechanisms operated. The association between perceived ease of use and perceived usefulness was weaker among more experienced

users, suggesting that ease of use became less central for judging AI as experience increased. For less experienced users, ease of use appeared to play a more important role in early evaluations. These findings suggest that experience reshapes how AI is evaluated. As familiarity increases, users appear less influenced by preliminary assessments, such as whether AI is easy to use, and more focused on its perceived value. In this way, experience did not simply increase intention to use AI, but functioned as a contextual factor that influenced how adoption evaluations were formed.

### **AI adoption beyond WEIRD contexts**

This study provides evidence that core technology adoption models such as TAM3 remain relevant in a non-WEIRD context. The central mechanisms of the model were able to explain intention to use AI in this sample, indicating that these processes are not limited to WEIRD settings. However, the findings also show that the relative importance of the model's components differed. In this context, psychological factors such as experience, anxiety, and self-efficacy played a particularly important role in shaping how AI was evaluated. Rather than invalidating TAM3, the results suggest that the model benefits from contextual interpretation, as adoption mechanisms may operate differently depending on users' familiarity with AI and their psychological resources. Overall, the findings indicate that AI adoption in Guatemala can be understood using established theoretical frameworks, while also highlighting the importance of considering contextual and psychological factors when examining AI adoption in non-WEIRD environments.

### **Limitations and Directions for Future Research**

Although the study was grounded in the Technology Acceptance Model 3 (TAM3), only a subset of its original components was examined. As a result, the model evaluated here does not represent a full test of TAM3 as an integrated theoretical system. In addition, several constructs included in the model, such as attitudes toward AI, trust in AI, and personality traits, are not part of the core TAM3 framework and were incorporated as external extensions. The study therefore examined an adapted version of TAM3 rather than a strict replication of the original model. Future research could compare TAM3-based models with and without these additional psychological constructs to clarify when such extensions provide added explanatory value.

The inclusion of multiple evaluative constructs may have introduced conceptual overlap (Davis, 1989). Strong associations between perceived usefulness, attitudes, and trust suggest that these variables capture related aspects of how AI is evaluated, which makes it difficult to isolate their unique psychological roles. This reflects a broader challenge in technology acceptance research, where psychological factors are often added as extensions rather than integrated into a unified theoretical structure (Kaya et al., 2022). Future studies could address this issue by developing more integrated models or by using latent-variable approaches to better separate cognitive, affective, and evaluative processes.

Several limitations are related to measurement. Most notably, the AI-related anxiety scale showed low internal consistency, which limits construct validity and may have attenuated associations with other variables. Findings related to anxiety should therefore be interpreted with caution. Future research should prioritize the development of more reliable and culturally sensitive measures of AI-related anxiety.

Personality traits were assessed using an ultra-short inventory. While this reduced participant burden, it also limited construct coverage and sensitivity to small effects (Cemalcilar et al., 2021). The weak associations observed for personality traits may therefore reflect measurement constraints rather than the absence of meaningful relationships. Future research could focus on refining brief personality measures by optimizing item selection for AI-related evaluations, rather than increasing scale length.

Experience with AI was measured using a self-developed scale based primarily on frequency of use across different contexts. As this measure has not been formally validated, its construct validity may be limited. In addition, operationalizing experience as frequency does not capture qualitative aspects such as task complexity or depth of interaction. Future studies could validate more comprehensive measures of AI experience or use multidimensional and longitudinal approaches to better capture how experience shapes technology evaluations.

AI was assessed as a general concept rather than as a specific application. Participants may therefore have had different technologies in mind when responding, which could have increased heterogeneity in evaluations. Future research could focus on specific AI applications or compare different usage domains to improve interpretability.

The study used a cross-sectional design, which limits conclusions about directionality and change over time. This limitation is particularly relevant given the central role of

experience in TAM3. Longitudinal designs would allow future research to examine how perceived usefulness, perceived ease of use, and related evaluations evolve as users gain experience with AI.

All variables were measured using self-report questionnaires, which increases the risk of common method variance and may have inflated associations between evaluative constructs. Future studies could incorporate behavioral measures, objective usage indicators, or multi-source data to reduce this risk (Podsakoff et al., 2003).

The analyses relied on multiple regression rather than a full structural equation model (Hong, 2022). While this approach allowed for stable and transparent estimation of specific relationships, it did not allow for explicit modeling of measurement error or simultaneous testing of the full theoretical structure. Future research with more robust measurement instruments and larger samples could employ structural equation modeling to examine more complex relationships. Finally, the sample consisted mainly of highly educated and digitally active individuals, which limits the generalizability of the findings to the Guatemalan population as a whole. The study also did not distinguish between participants from the capital city and those from other regions of the country, which may obscure regional differences in access and exposure to digital technologies (Belanche et al., 2012). Moreover, the study was conducted in a single non-WEIRD context, which limits the ability to assess whether the structure of the model and the relative importance of predictors differ across WEIRD and non-WEIRD populations (Cemalcilar et al., 2021). Future research could address these issues by including more diverse samples, incorporating subnational comparisons, and using cross-cultural comparative designs.

### ***Practical Implications***

The findings of this study have several practical implications for those applying or studying AI adoption in real-world settings. The results indicate that intention to use AI is more strongly related to how individuals evaluate the technology and to their level of prior experience than to stable personality traits. This suggests that adoption processes may be shaped by factors that are open to change rather than by fixed user characteristics. Perceived usefulness and attitudes toward AI were the strongest predictors of intention. This implies that introducing AI as a tool linked to concrete academic or work-related tasks may be more effective than presenting it as a general innovation. In daily basis, users may be more willing

to engage with AI when its practical value is clear and directly connected to their everyday activities.

The role of perceived ease of use appeared to depend on prior experience. For individuals with lower levels of experience, ease of use was more strongly related to how useful AI was perceived to be. For individuals with higher levels of experience, usefulness remained central even when ease of use was less salient. This suggests that practical approaches should account for experience-related differences rather than assuming that all users evaluate AI in the same way. Self-efficacy showed a direct association with intention to use AI. This indicates that feeling capable of using AI may encourage engagement even when the technology is perceived as complex. In applied settings, providing opportunities for guided interaction with AI may help strengthen perceived competence and support adoption.

AI-related anxiety influenced evaluations of AI but did not directly predict intention to use. This suggests that anxiety shapes how AI is initially judged rather than acting as a direct barrier to use. In contexts such as Guatemala, where exposure to advanced technologies can vary widely, addressing uncertainty and discomfort early may help prevent negative evaluations from forming. Personality traits showed limited explanatory power once psychological and experiential factors were considered. This implies that practical efforts may benefit more from focusing on experience, confidence, and evaluation processes than from segmenting users based on broad dispositional traits.

The findings also have implications for the design and application of similar studies. The results suggest that experience should not be treated only as a control variable, as it may condition how key adoption mechanisms operate. In addition, the limited role of personality highlights the value of prioritizing technology-specific psychological variables when studying AI adoption, particularly in applied and non-WEIRD contexts. Finally, the findings highlight the importance of context. Even within a highly educated sample in Guatemala, levels of experience and psychological responses to AI varied substantially. This suggests that adoption models developed in WEIRD contexts may not transfer directly to non-WEIRD settings without considering local conditions and unequal exposure to technology. These implications should be interpreted in light of the study's methodological limitations and are most relevant for applied settings and research designs similar to those examined here.

## **Conclusions**

This study examined psychological factors associated with the general intention to use artificial intelligence in a non-WEIRD context, using a TAM3-based framework. The findings indicate that established technology acceptance mechanisms remain relevant for understanding AI adoption in Guatemala, while also highlighting the importance of experience and proximal psychological factors in shaping how AI is evaluated and adopted.

Rather than being driven by stable dispositional characteristics, intention to use AI appears to be more closely related to how individuals perceive and engage with the technology in everyday life. By focusing on general AI use in an underrepresented context, this study contributes to the growing literature on AI adoption beyond WEIRD settings and underscores the need to consider contextual and experiential factors when applying technology acceptance models to emerging technologies.

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## Appendix

### Appendix A

**Table A1**

*Bivariate Pearson Correlations Between Personality Traits and TAM3 Constructs*

Variable	1	2	3	4	5	6	7
1.BI	1						
2.PU	0.72***	1					
3.PEOU	0.51***	0.56***	1				
4.OPN	0.09	0.08	0.00	1			
5.CON	-0.05	-0.06	-0.03	0.22***	1		
5.EXT	0.12*	0.09	0.08	0.26***	0.36***	1	
7.AGR	0.07	0.06	0.05	0.25***	0.41***	0.30***	1
8.NEU	-0.20***	-0.17**	-0.20***	-0.21***	-0.39***	-0.41***	-0.30***

*Note.* BI = Behavioral Intention, PU = Perceived Usefulness, PEOU = Perceived Ease of Use, OPN = Openness, CON = Conscientiousness, EXT = Extraversion, AGR = Agreeableness, NEU = Neuroticism. Significance levels: \*\*\*  $p < .001$ , \*\*  $p < .01$ , \*  $p < .05$ .

**Table A2**

*Bivariate Pearson Correlations Between Personality Traits and Experience*

Variable	1	2	3	4	5
1.Experience	1				
2.EXT	0.18***	1			
3.AGR	0.07	0.30***	1		
4.CON	-0.01	0.36***	0.41***	1	
5.NEU	-0.09	-0.41***	-0.30***	-0.39***	1
6.OPN	0.10	0.26***	0.25***	0.22***	-0.21***

*Note.* OPN = Openness, CON = Conscientiousness, EXT = Extraversion, AGR = Agreeableness, NEU = Neuroticism. Significance levels: \*\*\*  $p < .001$ , \*\*  $p < .01$ , \*  $p < .05$ .

**Table A3***Bivariate Pearson Correlations Between Personality Traits and Psychological Variables*

<b>Variables</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>
1. ATT	1						
2. Trust	0.68***	1					
3. ANX	-0.34***	-0.34***	1				
4. OPN	0.08	0.08	-0.04	1			
5. CON	-0.02	-0.04	0.03	0.22***	1		
6. EXT	0.13*	0.09	-0.01	0.26***	0.36***	1	
7. AGR	0.07	0.09	-0.02	0.25***	0.41***	0.30***	1
8. NEU	-0.22***	-0.16**	0.10	-0.21***	-0.39***	-0.41***	-0.30***

*Note.* Pearson's correlation coefficients are reported. ATT = Attitudes, ANX = Anxiety, OPN = Openness, CON = Conscientiousness, EXT = Extraversion, AGR = Agreeableness, NEU = Neuroticism. Significance levels: \*\*\*  $p < .001$ , \*\*  $p < .01$ , \*  $p < .05$ .

**Table A4***Moderating Effect of Experience on the Relationship Between PEOU and PU*

<b>Predictor</b>	<b><math>\beta</math></b>	<b>SE</b>	<b>95% CI</b>	<b><math>p</math></b>
Perceived Ease of Use (PEOU)	0.44	0.05	[0.33, 0.54]	< .001
Experience	0.29	0.04	[0.21, 0.37]	< .001
PEOU $\times$ Experience	-0.10	0.03	[-0.16, -0.04]	< .001

*Note.* PU = Perceived Usefulness; PEOU = Perceived Ease of Use. Standardized path coefficients ( $\beta$ ) are reported. Confidence intervals are based on 5,000 bootstrap resamples. All predictors were standardized prior to analysis.

**Table A5***Linear Regression: Prior Experience as a Predictor of Core TAM3 Constructs*

<b>Predictor</b>	<b>Outcome</b>	<b><math>\beta</math></b>	<b>SE</b>	<b>t</b>	<b>p</b>
Experience	BI	0.44	0.05	9.07	< .001
Experience	PU	0.44	0.05	9.18	< .001
Experience	PEOU	0.33	0.05	6.42	< .001

*Note.* PU = Perceived Usefulness; PEOU = Perceived Ease of Use; BI = Behavioral Intention. Standardized path coefficients ( $\beta$ ) are reported. Standardized regression coefficients ( $\beta$ ) are reported. Each row represents a separate simple linear regression model with prior experience as the predictor. All predictors were standardized prior to analysis.

## **Appendix B**

### **Survey Questionnaire and Instructions**

#### **Demographic Information**

Instructions: Please answer the following questions by selecting the option that best describes your current situation.

1. What is your age?
2. What is your gender?
3. What is your highest completed level of education?
4. What is your main current activity?
5. In which country do you currently live?

#### **Experience With Artificial Intelligence**

Instructions: Please indicate how often you use the following artificial intelligence tools or services.

Response scale: 1 (Never) – 2 (Rarely) – 3 (Sometimes) – 4 (Frequently) – 5 (Very frequently)

1. I use AI chatbots (e.g., ChatGPT, Gemini, Perplexity, or bots on WhatsApp).
2. I receive suggestions from AI-based recommendation systems (e.g., Netflix or Spotify).

3. I use machine translation tools (e.g., Google Translate or DeepL).
4. I use intelligent filters for emails or online content (e.g., spam filters).
5. I interact with voice assistants (e.g., Siri, Alexa, or Google Assistant).
6. I receive personalized advertisements generated by AI (e.g., Instagram or Facebook).
7. I use AI features in banking or financial applications.
8. I use health or fitness applications that incorporate AI.

### **Personality Traits (BFI-2-XS)**

Instructions: Below you will find a series of statements that may or may not describe you.

Please indicate the extent to which you agree or disagree with each statement.

Response scale: 1 (Strongly disagree) – 2 (Disagree) – 3 (Neutral / No opinion) – 4 (Agree) – 5 (Strongly agree)

1. Tends to be quiet.
2. Is compassionate, has a soft heart.
3. Tends to be disorganized.
4. Worries a lot.
5. Is fascinated by art, music, or literature.
6. Is dominant, acts as a leader.
7. Is sometimes rude to others.
8. Has difficulty getting started on tasks.
9. Tends to feel depressed, blue.
10. Has little interest in abstract ideas.
11. Is full of energy.
12. Assumes the best about people.
13. Is reliable, can always be counted on.
14. Is emotionally stable, not easily upset.
15. Is original, comes up with new ideas.

### **Attitudes Toward Artificial Intelligence (GAIA-15)**

Instructions: The following statements refer to Artificial Intelligence (AI). AI refers to technologies capable of performing tasks that normally require human intelligence, such as learning, reasoning, and decision making.

Please indicate how much you agree or disagree with each statement.

Response scale: 1 (Strongly disagree) – 2 (Disagree) – 3 (Neutral) – 4 (Agree) – 5 (Strongly agree)

1. I am impressed by what AI can do.
2. I am interested in using AI in my daily life.
3. AI is exciting.
4. I shiver with discomfort when I think about the future uses of AI.
5. When I think about AI, I mostly have positive feelings.
6. I would invest my money in a bank managed solely by AI.
7. I would buy a piece of AI-generated artwork at an auction.
8. To decide how to prioritize aid during humanitarian crises, I would seek advice from AI.
9. I would ride in an autonomously driving car.
10. I would let an AI treat me instead of a human doctor in a general practice.
11. There are many beneficial applications of AI.
12. AI can have a positive impact on people's well-being.
13. I believe AI will improve my life.
14. AI has more disadvantages than advantages.
15. AI will cause many job losses.

### **Trust in Artificial Intelligence (S-TIAS)**

Instructions: Please indicate the extent to which you agree with the following statements about an artificial intelligence assistant.

Response scale: 1 (Not at all) – 2 (Very little) – 3 (Little) – 4 (Neither little nor much) – 5 (Somewhat) – 6 (Much) – 7 (Extremely)

1. I am confident in the AI assistant.
2. The AI assistant is reliable.
3. I can trust the AI assistant.

### **Technology Acceptance Model Constructs (TAM3)**

Instructions: The following statements relate to your use of artificial intelligence systems.

Please indicate how much you agree or disagree with each statement.

Response scale: 1 (Strongly disagree) – 2 (Disagree) – 3 (Slightly disagree) – 4 (Neither agree nor disagree) – 5 (Slightly agree) – 6 (Agree) – 7 (Strongly agree)

### **Perceived Usefulness**

1. Using AI systems improves my job performance.
2. Using AI systems in my work increases my productivity.
3. Using AI systems enhances my effectiveness at work.
4. I find AI systems useful in my job.

### **Perceived Ease of Use**

5. My interaction with AI systems is clear and understandable.
6. Interacting with AI systems does not require a lot of mental effort.
7. I find AI systems easy to use.
8. It is easy for me to get AI systems to do what I want them to do.

### **AI Anxiety**

9. AI does not scare me at all.
10. Working with AI makes me feel nervous.
11. AI makes me feel uncomfortable.
12. AI makes me feel uneasy.

### **Behavioral Intention to Use AI**

13. If I had access to AI systems, I would intend to use them.
14. If I had access to AI systems, I believe I would use them.
15. I plan to use AI systems in the coming months.

## **Self-Efficacy in Using AI**

Instructions: Please indicate how confident you are in your ability to perform the following actions using artificial intelligence tools.

Response scale: 1 (Not confident at all) – 10 (Completely confident)

16. I could complete a task using an AI tool even if no one were around to tell me what to do.
17. I could complete a task using an AI tool if I only had help features or tutorials available.
18. I could complete a task using an AI tool if someone showed me how to do it first.
19. I could complete a task using an AI tool if I had used similar tools before for similar tasks.