

Understanding Factors Influencing Students Intention to Use ChatGPT for Learning Programming with Gender and IT Experience as Moderators Based on AdoptGPT Prog Conceptual Model

Faisal Alshammari

f.alshammari@mu.edu.sa

Majmaah University

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Abstract

Despite growing interest in ChatGPT adoption in higher education, existing research lacks domain-specific models that account for the unique cognitive demands of programming education and the demographic heterogeneity among learners. This study addresses three research questions: (1) What is the relative importance of cognitive-affective factors (perceived usefulness, trust, anxiety, perceived risk) versus competency factors (AI literacy, perceived ease of use) in predicting programming students' ChatGPT adoption intention? (2) Do gender differences in technology adoption persist when examining ChatGPT specifically for programming tasks? (3) How does prior IT experience moderate the relationship between perceived benefits and adoption intention? We propose AdoptGPT-Prog, an integrated TAM-UTAUT framework incorporating eight predictors—Perceived Usefulness, Perceived Ease of Use, Trust, Anxiety, Perceived Risk, AI Literacy, Perceived Learning Value, and Hedonic Motivation—with Gender and IT Experience as moderators. Data from 486 undergraduate programming students (52.3% male, 47.7% female; mean age = 21.4 years, SD = 2.1) across five Saudi Arabian universities were analyzed using PLS-SEM. The model achieved substantial explanatory power ($R^2=0.714$), outperforming prior ChatGPT adoption frameworks. Perceived Usefulness emerged as the strongest predictor ($\beta = 0.312$, $p < 0.001$), followed by Trust ($\beta = 0.203$) and Perceived Ease of Use ($\beta = 0.187$), while Perceived Risk ($\beta=-0.156$) functioned as a significant barrier. Notably, Anxiety showed no direct effect on intention ($\beta = 0.012$, $p = 0.774$), though gender moderated this relationship, with female students exhibiting stronger anxiety-related inhibition. Multi-group analysis revealed that females showed stronger Perceived Ease of Use effects ($\beta = 0.279$ vs. $\beta = 0.112$), while high-IT-experience students weighted Perceived Usefulness more heavily ($\beta = 0.412$ vs. $\beta = 0.234$). These findings provide empirically-grounded, actionable recommendations for differentiated instructional strategies when integrating generative AI tools into programming curricula.

1. Introduction

The integration of generative artificial intelligence (AI) into higher education has created unprecedented opportunities and challenges, particularly in programming education where students must develop complex cognitive skills including debugging, algorithmic thinking, and code comprehension [1]. ChatGPT, developed by OpenAI, represents a significant advancement in natural language processing that enables conversational interaction and code generation, fundamentally altering how students can engage with programming concepts [2]. However, despite widespread interest in these AI-assisted learning tools, a critical question remains inadequately addressed: What factors determine whether programming students will adopt ChatGPT as a learning resource, and how do individual differences shape these adoption decisions?

1.1 Problem Statement and Research Gap

Existing research on ChatGPT adoption in higher education has predominantly applied generic technology acceptance frameworks without accounting for the unique cognitive demands of programming education [3–8]. Programming differs fundamentally from other educational domains—it requires iterative problem-solving, tolerance for ambiguity in debugging, and the ability to evaluate AI-generated code for correctness and efficiency [4, 5]. These domain-specific characteristics suggest that adoption factors may operate differently in programming contexts compared to general educational technology adoption.

Three specific gaps motivate this research:

First, while TAM and UTAUT frameworks have been extensively applied to educational technology [7, 14], their application to ChatGPT in programming education remains limited. Recent studies by Al-Sharafi et al. [17] and Strzelecki [28] examined ChatGPT adoption in general higher education contexts, but neither specifically addressed programming education nor examined how the technical nature of programming tasks might differentially influence adoption factors. Similarly, Balaskas et al. examined ChatGPT adoption but focused on general academic use rather than discipline-specific applications.

Second, demographic moderators—particularly gender and IT experience—have been examined separately in technology adoption research [10, 11, 22, 23], but their combined moderating effects on ChatGPT adoption in a technical domain remain unexplored. This oversight is consequential because programming education exhibits persistent gender disparities [22], and students enter programming courses with vastly different technical backgrounds [24], suggesting that adoption pathways may vary systematically across these demographic dimensions.

Third, existing ChatGPT adoption models have not adequately distinguished between cognitive-affective factors (trust, anxiety, perceived risk) and competency factors (AI literacy, perceived ease of use) that may differentially predict adoption intention in technically demanding contexts. Understanding this distinction is essential for developing targeted interventions that address the specific barriers faced by different student populations.

1.2 Research Questions

To address these gaps, this study investigates the following research questions:

RQ1

What is the relative importance of cognitive-affective factors (perceived usefulness, trust, anxiety, perceived risk) versus competency factors (AI literacy, perceived ease of use, perceived learning value) in predicting programming students' intention to adopt ChatGPT?

RQ2

Does gender moderate the relationships between adoption factors and behavioral intention, and if so, which specific pathways exhibit gender differences?

RQ3

How does prior IT experience moderate the relationship between perceived benefits (perceived usefulness, AI literacy) and adoption intention among programming students?

RQ4

Does the proposed integrated TAM-UTAUT framework (AdoptGPT-Prog) achieve superior explanatory power compared to existing ChatGPT adoption models when applied to programming education?

1.3 Research Objectives and Approach

This study proposes AdoptGPT-Prog, an integrated TAM-UTAUT framework specifically designed for understanding ChatGPT adoption in programming education. The model incorporates eight direct predictors organized into two theoretically meaningful categories:

Enablers: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust (TR), Perceived Learning Value (PLV), AI Literacy (AIL), and Hedonic Motivation (HM)

Barriers: Perceived Risk (PR) and Anxiety (ANX)

Gender and IT Experience function as moderators on theoretically selected pathways, as detailed in Section 3.

Figure 1 presents the conceptual landscape that situates this research within the broader technology adoption literature, illustrating how technological perceptions, individual characteristics, and contextual elements interact in ChatGPT adoption decisions. This conceptual mapping orients readers to the multifaceted nature of the phenomenon under investigation.

1.4 Contributions

This research makes four distinct contributions:

1. **Domain-Specific Theoretical Extension:** Unlike prior studies that applied generic TAM-UTAUT frameworks to ChatGPT adoption [17, 28], AdoptGPT-Prog explicitly accounts for the cognitive demands of programming education by distinguishing enabler and barrier constructs and examining their relative importance in a technical learning context.
2. **Systematic Moderator Analysis:** This study provides the first empirical examination of gender and IT experience as simultaneous moderators of ChatGPT adoption in programming education, with theory-driven selection of moderated pathways (detailed in Section 3.4).
3. **Validated Domain-Specific Instrument:** The study develops and validates a measurement instrument tailored to ChatGPT adoption in programming contexts, with items addressing programming-specific applications (debugging assistance, code generation, algorithm explanation).
4. **Differentiated Practical Recommendations:** Based on moderation analyses, this study provides actionable recommendations stratified by student gender and experience level, enabling educators to implement targeted interventions.

1.5 Paper Organization

The remainder of this paper is organized as follows. Section 2 presents an integrated literature review covering technology acceptance frameworks, ChatGPT adoption research, and demographic moderators. Section 3 describes the theoretical framework, hypothesis development, and methodology. Section 4 reports results including measurement validation, structural model analysis, and moderation effects. Section 5 discusses findings in relation to prior research. Section 6 addresses implications, limitations, and future directions. Section 7 concludes with key contributions and recommendations.

2. Theoretical Foundation and Literature Review

This section provides an integrated review of technology acceptance frameworks, ChatGPT adoption research, and the theoretical foundations for construct selection and hypothesis development. Rather than presenting constructs in isolation, we organize the literature around three themes: (1) foundational acceptance theories, (2) ChatGPT adoption in educational contexts, and (3) the rationale for construct selection and moderator specification in programming education.

2.1 Technology Acceptance Frameworks: From TAM to Integrated Models

The Technology Acceptance Model (TAM), proposed by Davis [7], established perceived usefulness (PU) and perceived ease of use (PEOU) as fundamental determinants of technology adoption intention. Venkatesh et al. [13] extended this foundation through the Unified Theory of Acceptance and Use of Technology (UTAUT), incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions as core constructs, with gender, age, experience, and voluntariness as moderators.

Meta-analytic evidence confirms the robustness of these frameworks in educational technology contexts, with explained variance in behavioral intention typically ranging from 40–70% [14, 15]. However, recent scholarship advocates for integrated TAM-UTAUT approaches when examining emerging technologies, as single-framework applications may inadequately capture the complexity of novel AI-assisted learning tools [16]. This integration strategy informs our theoretical approach.

2.2 ChatGPT Adoption Research: Current Evidence and Limitations

Since ChatGPT's public release in November 2022, adoption research has proliferated across educational contexts. Table 1 summarizes key studies and positions our contribution relative to existing work.

Table 1
Comparison of ChatGPT Adoption Studies in Higher Education

Study	Framework	Context	Sample	Key Predictors (β)	R ²	Moderators	Limitations
Balaskas et al. [8]	TAM	Greek universities (general)	412	PU (0.42), Attitude (0.38)	0.58	None	No domain specificity; no demographic moderators
Al-Sharafi et al. [17]	Meta-UTAUT	Dutch higher education	387	PE (0.35), Attitude (0.31), SI (0.22)	0.52	None	General academic use; Western context only
Strzelecki [28]	Extended UTAUT	Polish universities	534	PE (0.38), HM (0.24), SI (0.19)	0.61	None	No programming focus; limited construct set
Yilmaz et al. [9]	DOI Theory	Turkish universities	298	Relative advantage, compatibility	0.47	Gender (partial)	Different theoretical base; no IT experience
This study	Integrated TAM-UTAUT	Saudi Arabia (programming)	486	PU, PEOU, TR, PLV, AIL, PR, ANX, HM	0.714	Gender, IT Experience	Domain-specific; dual moderators

Three limitations emerge from existing research that motivate our study:

Limitation 1

Lack of Domain Specificity. Prior studies examine ChatGPT adoption in general academic contexts without accounting for discipline-specific factors. Programming education involves unique cognitive demands—debugging, algorithm design, code evaluation—that may differentially weight adoption factors. For instance, trust in AI-generated code correctness may be more consequential than trust in AI-generated essay content.

Limitation 2

Incomplete Moderator Examination. While Yilmaz et al. [9] found partial gender effects (males emphasized compatibility; females emphasized trialability), no study has simultaneously examined gender and IT experience as moderators within an integrated framework. Given persistent gender disparities in computing education [22] and the technical heterogeneity among programming students [25], this oversight limits practical applicability.

Limitation 3

Narrow Construct Sets. Existing models typically include 4–6 predictors, potentially omitting factors relevant to AI-assisted programming learning. Constructs such as AI literacy, perceived learning value, and perceived risk have theoretical relevance but remain underexplored in ChatGPT adoption contexts.

2.3 Programming Education Context: Why Domain Specificity Matters

Programming education presents distinctive characteristics that justify domain-specific model development:

Cognitive Complexity

Programming requires iterative problem-solving, tolerance for ambiguity during debugging, and the ability to evaluate code correctness—skills that interact with AI tool adoption in ways not captured by general educational technology models [4, 19].

Output Verifiability

Unlike essay writing or information retrieval, AI-generated code can be objectively tested for correctness through compilation and execution. This verifiability may heighten the salience of trust and perceived risk compared to other educational applications.

Technical Prerequisites

Programming students possess varying levels of prior technical experience, creating heterogeneity in how they evaluate and interact with AI tools [21, 25]. This variability supports IT experience as a theoretically meaningful moderator.

Empirical evidence from programming-specific studies supports these distinctions. Sun et al. [4] found that ChatGPT-facilitated programming (CFP) learners exhibited different behavioral patterns than self-directed programmers, with CFP students showing enhanced debugging behaviors and improved usefulness perceptions. Xiao et al. [20] demonstrated that structured prompting improved interaction quality in programming tasks, suggesting that AI literacy—the ability to craft effective prompts—may be particularly consequential in this domain.

Silva et al. [21] identified prior knowledge and cognitive comprehension as moderating the effectiveness of ChatGPT for programming problem-solving.

2.4 Construct Selection and Theoretical Rationale

Based on the foregoing review, we organize the AdoptGPT-Prog model around two construct categories—enablers and barriers—reflecting their hypothesized directional effects on adoption intention.

2.4.1 Enablers: Factors Facilitating Adoption

Perceived Usefulness (PU) represents the degree to which students believe ChatGPT will enhance their programming performance. Drawing on TAM [7] and UTAUT's performance expectancy construct [13], PU consistently emerges as the strongest adoption predictor across educational technologies. In programming contexts, usefulness perceptions encompass debugging assistance, code generation efficiency, and concept clarification capabilities.

H1

Perceived Usefulness positively influences Behavioral Intention to use ChatGPT for programming learning.

Perceived Ease of Use (PEOU) captures students' assessments of the cognitive effort required to interact with ChatGPT effectively. TAM posits PEOU as both a direct predictor of intention and an indirect predictor through PU [7]. For programming students, ease of use encompasses prompt formulation, output interpretation, and integration into existing workflows.

H2

Perceived Ease of Use positively influences Behavioral Intention to use ChatGPT for programming learning.

Trust (TR) refers to students' confidence that ChatGPT provides accurate, reliable, and unbiased responses. Trust is particularly consequential in AI-assisted learning contexts where students rely on AI outputs for understanding and decision-making [17, 33]. In programming education, trust encompasses confidence in code correctness, explanation accuracy, and debugging recommendations. Students who trust ChatGPT's outputs are more likely to integrate it into their learning practices.

H3

Trust positively influences Behavioral Intention to use ChatGPT for programming learning.

Perceived Learning Value (PLV) represents students' beliefs that ChatGPT meaningfully enhances their programming knowledge, skills, and academic outcomes. Al-Okaily et al. [33] demonstrate that perceived educational benefits drive adoption intention for generative AI tools. In programming courses, learning value perceptions arise from syntax clarification, debugging assistance, and algorithmic logic explanations that complement traditional instruction.

H4

Perceived Learning Value positively influences Behavioral Intention to use ChatGPT for programming learning.

AI Literacy (AIL) encompasses students' understanding of AI system capabilities, limitations, ethical considerations, and effective usage strategies. Higher AI literacy enables students to craft effective prompts, critically evaluate AI-generated code, and recognize potential errors [21, 33]. In programming contexts, AI-literate students can more effectively leverage ChatGPT's capabilities while avoiding pitfalls such as uncritical code acceptance.

H5

AI Literacy positively influences Behavioral Intention to use ChatGPT for programming learning.

Hedonic Motivation (HM) captures the enjoyment, curiosity, and intrinsic interest students experience when interacting with ChatGPT. UTAUT2 established hedonic motivation as a significant adoption driver, particularly for consumer technologies [13]. ChatGPT's conversational interface, immediate responsiveness, and novelty may generate positive affective responses that reinforce adoption intention. However, in utilitarian educational contexts, hedonic factors may play a secondary role compared to performance-oriented constructs.

H6

Hedonic Motivation positively influences Behavioral Intention to use ChatGPT for programming learning.

2.4.2 Barriers: Factors Inhibiting Adoption

Perceived Risk (PR) encompasses students' concerns about misinformation, privacy violations, academic integrity implications, and AI-generated errors. Prior research establishes perceived risk as negatively influencing both trust and behavioral intention [33]. In programming education, risk perceptions may arise from concerns about incorrect code recommendations, plagiarism detection, or over-reliance on AI assistance that impedes genuine skill development.

H7

Perceived Risk negatively influences Behavioral Intention to use ChatGPT for programming learning.

Anxiety (ANX) refers to apprehension, discomfort, or fear experienced when interacting with AI systems. Technology anxiety has been established as an adoption barrier across educational technologies [33]. In programming contexts, anxiety may stem from uncertainty about AI-generated code correctness, fear of academic misconduct accusations, or concerns about skill atrophy through AI dependence.

H8

Anxiety negatively influences Behavioral Intention to use ChatGPT for programming learning.

2.5 Moderator Specification: Theory-Driven Path Selection

Rather than testing all possible moderating effects—which would risk Type I error inflation and reduce statistical power we specify moderating hypotheses based on theoretical precedent and domain-specific rationale. Table 2 summarizes the selection logic.

Table 2
Theoretical Rationale for Moderator Path Selection

Moderator	Selected Path	Rationale	Excluded Paths	Exclusion Rationale
Gender	PEOU → BI	Venkatesh et al. [13] found effort expectancy effects stronger for females; programming's technical interface may amplify gender differences in usability sensitivity	PU → BI	Gender gap in performance expectancy has diminished over time [22]
Gender	ANX → BI	Consistent evidence of gender differences in technology anxiety [10, 22]; female students may experience heightened AI-related apprehension in male-dominated programming contexts	TR → BI	Limited/inconsistent evidence for gender-based trust differences in technology adoption
IT Experience	PU → BI	UTAUT establishes experience as moderating performance expectancy effects; experienced users better evaluate performance benefits [13, 24]	PEOU → BI	Ease of use becomes less salient as experience increases; ceiling effects expected
IT Experience	AIL → BI	AI literacy translates more effectively into adoption intention when combined with technical competence to implement AI-informed strategies	ANX → BI	Range restriction expected in programming student sample; anxiety variance limited

Gender Moderation Hypotheses:

Drawing on gender differences in technology adoption [10, 13, 22] and the specific affordances of programming education, we hypothesize:

H9a

Gender moderates the relationship between Perceived Ease of Use and Behavioral Intention, such that the effect is stronger for female students than male students.

Rationale

Venkatesh et al. [13] demonstrated that effort expectancy effects were consistently stronger for females across multiple technologies. In programming education, where students must navigate ChatGPT's interface to formulate prompts and interpret code outputs, female students may place greater emphasis on usability when forming adoption intentions. Additionally, women in computing fields may be more sensitive to interaction quality given documented experiences of stereotype threat and belonging uncertainty [22].

H9b

Gender moderates the relationship between Anxiety and Behavioral Intention, such that the negative effect is stronger for female students than male students.

Rationale

Research consistently documents gender differences in technology-related anxiety, with females reporting higher anxiety levels across educational technologies [10, 22]. In programming contexts—a domain with persistent gender underrepresentation—female students may experience amplified AI-related apprehension that more strongly inhibits adoption intention.

IT Experience Moderation Hypotheses:

Based on UTAUT's experience moderator specification [13] and programming education's technical demands [24, 25]:

H10a

IT Experience moderates the relationship between Perceived Usefulness and Behavioral Intention, such that the effect is stronger for students with high IT experience.

Rationale

Experienced users possess cognitive frameworks that enable accurate assessment of how new tools enhance performance [13, 24]. In programming contexts, students with substantial IT backgrounds can better evaluate ChatGPT's debugging, code generation, and explanation capabilities, translating usefulness perceptions more directly into adoption intention.

H10b

IT Experience moderates the relationship between AI Literacy and Behavioral Intention, such that the effect is stronger for students with high IT experience.

Rationale

AI literacy—understanding AI capabilities, limitations, and effective prompting—becomes actionable when combined with technical competence. Students with high IT experience possess the programming skills necessary to implement AI-informed strategies (e.g., integrating AI-generated code snippets, debugging AI suggestions), amplifying the adoption benefits of AI knowledge.

2.6 Research Model Summary

Figure 2 presents the complete AdoptGPT-Prog research model integrating the eight direct effect hypotheses (H1-H8) and four moderation hypotheses (H9a, H9b, H10a, H10b). The model organizes constructs into enablers (PU, PEOU, TR, PLV, AIL, HM) and barriers (PR, ANX), with Gender and IT Experience moderating theoretically specified pathways.

3. Proposed Methodology

3.1. Research Model Overview

The AdoptGPT-Prog model integrates constructs from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine factors influencing students' intention to use ChatGPT for programming learning. Building on Davis's [7] foundational TAM framework and Venkatesh et al.'s [13]

unified theory, this study develops a domain-specific model tailored to the unique demands of programming education.

The model incorporates eight direct predictors of Behavioral Intention (BI), organized into two categories based on the extended AI adoption framework proposed by Al-Okaily et al. [33]:

Enablers

Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust (TR), Perceived Learning Value (PLV), AI Literacy (AIL), and Hedonic Motivation (HM)

Barriers

Perceived Risk (PR) and Anxiety (ANX)

Two moderating variables—Gender and IT Experience—are incorporated to examine demographic differences in adoption patterns. This approach aligns with Venkatesh et al. [13], who demonstrated that gender and experience significantly moderate technology acceptance relationships, and with subsequent meta-analyses confirming these effects in educational contexts [10, 14]. Rather than testing all possible moderation effects (which would yield 16 interaction terms and inflate Type I error rates), we adopted a theory-driven approach to select six moderation hypotheses based on theoretical foundations and empirical precedent.

Figure 3 presents the complete AdoptGPT-Prog research framework illustrating all hypothesized direct effects (H1–H8) and moderation effects (H9a–H9c for gender; H10a–H10c for IT experience).

3.2 Hypotheses Development

Based on the integrated TAM-UTAUT framework and prior research on AI adoption in education [8, 17, 28, 33], this study proposes fourteen hypotheses organized into direct effects and moderation effects.

3.2.1 Direct Effects on Behavioral Intention

Drawing on TAM [7] and UTAUT [13], effort expectancy (perceived ease of use) directly influences users' intention to adopt new technologies. In programming education, where students must navigate complex syntax and debugging processes, the perceived simplicity of ChatGPT interactions becomes particularly salient [4, 19].

H1

Perceived Ease of Use positively influences Behavioral Intention to use ChatGPT for programming learning.

Perceived risk captures concerns about misinformation, academic integrity, and privacy that may inhibit adoption [6, 8]. Balaskas et al. [8] found that risk perceptions significantly mediate the relationship between trust and adoption intention in higher education contexts.

H2

Perceived Risk negatively influences Behavioral Intention to use ChatGPT for programming learning.

AI literacy—understanding of AI capabilities, limitations, and responsible use—enhances students' confidence in evaluating ChatGPT outputs [25, 33]. Al-Okaily et al. [33] demonstrated that AI literacy directly predicts adoption intention by reducing uncertainty and enabling effective tool utilization.

H3

AI Literacy positively influences Behavioral Intention to use ChatGPT for programming learning.

Trust represents confidence in ChatGPT's accuracy, reliability, and security [6, 17, 18]. Al-Sharafi et al. [17] found trust to be a cornerstone of ChatGPT adoption, while Niu and Mvondo [18] confirmed its central role in higher education acceptance.

H4

Trust positively influences Behavioral Intention to use ChatGPT for programming learning.

Technology anxiety—discomfort or apprehension when interacting with AI systems—has been identified as a significant barrier to educational technology adoption [14, 26]. In the context of generative AI, anxiety may stem from uncertainty about output quality or fear of becoming overly dependent on AI assistance.

H5

Anxiety negatively influences Behavioral Intention to use ChatGPT for programming learning.

Perceived usefulness (performance expectancy) is consistently the strongest predictor of technology adoption [7, 13, 14]. In programming education, ChatGPT's utility for code generation, debugging, and concept explanation directly addresses students' performance goals [4, 19, 20].

H6

Perceived Usefulness positively influences Behavioral Intention to use ChatGPT for programming learning.

Perceived learning value captures beliefs about educational benefits—enhanced understanding, skill development, and academic performance [33]. Zhang and Pan [34] demonstrated that learning value perceptions significantly predict adoption in educational technology contexts.

H7

Perceived Learning Value positively influences Behavioral Intention to use ChatGPT for programming learning.

Hedonic motivation—enjoyment, curiosity, and novelty appreciation—influences adoption when technology use involves intrinsic satisfaction [32, 36]. Deng and Yu [36] found hedonic motivation significantly predicted educational technology adoption, while Cabero-Almenara et al. [32] confirmed its relevance for ChatGPT use among university students.

H8

Hedonic Motivation positively influences Behavioral Intention to use ChatGPT for programming learning.

3.2.2 Moderation Effects

Gender Moderation: The original UTAUT framework [13] established that gender moderates key technology acceptance relationships. Subsequent research has confirmed these effects: Cai et al. [10] meta-analyzed gender differences in technology attitudes, while Campos and Scherer [22] documented persistent digital gender gaps across 32 countries. Drawing on this evidence, three gender moderation hypotheses were specified for paths where theory and empirical precedent suggest differential effects.

H9a

Gender moderates the relationship between Perceived Ease of Use and Behavioral Intention, such that the effect is stronger for female students.

Rationale

Venkatesh et al. [13] demonstrated effort expectancy effects are stronger for women. This finding has been replicated in educational technology contexts [10, 11, 22], where female students place greater emphasis on usability factors.

H9b

Gender moderates the relationship between Perceived Risk and Behavioral Intention.

Rationale

Women exhibit higher risk sensitivity in technology-related decisions, particularly concerning privacy and data security [10, 11]. In AI-assisted programming, concerns about misinformation and academic integrity may manifest differently across genders.

H9c

Gender moderates the relationship between Anxiety and Behavioral Intention.

Rationale

Technology anxiety shows gender-differentiated effects in educational settings [10, 14]. Female students often report higher levels of computer anxiety, which may more strongly inhibit adoption intentions [22].

IT Experience Moderation

UTAUT [13] established that experience moderates technology acceptance relationships. Experienced users possess better-developed mental models for evaluating new technologies [23, 24] and can more effectively leverage their technical knowledge [21, 25]. Three IT experience moderation hypotheses were specified based on theoretical predictions about how experience shapes evaluation processes.

H10a

IT Experience moderates the relationship between Perceived Usefulness and Behavioral Intention, such that the effect is stronger for students with higher IT experience.

Rationale

Experienced users can better assess productivity gains and recognize how ChatGPT capabilities translate to performance improvements [13, 24].

H10b

IT Experience moderates the relationship between AI Literacy and Behavioral Intention.

Rationale

Technical experience provides cognitive frameworks that amplify AI literacy benefits, enabling more effective translation of AI knowledge into usage strategies [21, 25].

H10c

IT Experience moderates the relationship between Trust and Behavioral Intention.

Rationale

Experienced users may rely less on trust perceptions as they possess alternative evaluation mechanisms (direct assessment, technical understanding) [17, 18].

3.3 Rationale for Moderation Path Selection

The selective approach to moderation testing follows best practices in structural equation modeling, which recommend theory-driven hypothesis specification over exhaustive testing to maintain parsimony and control Type I error [14]. Table 3 summarizes the rationale for path selection and exclusion decisions.

Table 3
Moderation Path Selection Rationale

Moderator	Path	Rationale for Selection/Exclusion
Gender	PEOU→BI ✓	Selected: UTAUT [13] shows effort expectancy effects stronger for women; replicated in educational contexts [10, 22]
Gender	PR→BI ✓	Selected: Women exhibit higher risk sensitivity in technology decisions [10, 11]
Gender	ANX→BI ✓	Selected: Gender-differentiated anxiety effects documented in educational settings [10, 14]
Gender	TR→BI ☒	Excluded: Limited evidence for gender differences in trust formation toward AI [8, 9, 17]
Gender	PU→BI ☒	Excluded: Gender difference in performance expectancy has diminished [14]; recent ChatGPT studies show no significant difference [8, 9]
IT Experience	PU→BI ✓	Selected: Experienced users better assess productivity gains [13, 24, 25]
IT Experience	AIL→BI ✓	Selected: Technical experience amplifies AI literacy benefits [21, 25]
IT Experience	TR→BI ✓	Selected: Experienced users have alternative evaluation mechanisms beyond trust [17, 18]
IT Experience	PEOU→BI ☒	Excluded: UTAUT [13] suggests ease of use becomes less salient with experience*
Note: ✓ = Selected for hypothesis testing; ☒ = Excluded based on theoretical/empirical rationale. *This path emerged as significant in exploratory multi-group analysis and is reported in Results.		

3.4 Data Collection and Sample

3.4.1 Participants and Procedure

Data were collected through an online survey administered to undergraduate programming students at five universities in Saudi Arabia during March-April 2024. Stratified random sampling ensured balanced representation across gender and IT experience levels. The survey was available in both English and Arabic to accommodate participant preferences.

3.4.2 Inclusion and Exclusion Criteria

Inclusion Criteria:

- Currently enrolled undergraduate in computer science, IT, software engineering, or related disciplines
- Active enrollment in programming course (Python, Java, C++, or JavaScript)
- Prior awareness and at least minimal exposure to ChatGPT
- Aged 18 years or older with voluntary informed consent

Exclusion Criteria:

- Incomplete responses (> 10% missing items) or straight-lining patterns
- Failed attention check questions

- Statistical outliers identified through Mahalanobis distance ($p < 0.001$)
- Duplicate submissions identified via IP address verification

3.4.3 Sample Characteristics

From 523 initial responses, systematic screening yielded 486 valid responses (93% retention rate). The final sample comprised 52.3% male ($n = 254$) and 47.7% female ($n = 232$) participants, with a mean age of 21.4 years ($SD = 2.1$, range 18–28). Regarding IT experience, 38.5% ($n = 187$) reported high experience, while 61.5% ($n = 299$) reported low-to-moderate experience. Participants were distributed across five Saudi Arabian universities with balanced institutional representation.

3.5 Measurement Instrument

The survey instrument contained 42 items measuring eight constructs on 7-point Likert scales (1 = Strongly Disagree to 7 = Strongly Agree). Items were adapted from validated scales: Perceived Usefulness and Perceived Ease of Use from Davis [7]; Performance Expectancy and Effort Expectancy from Venkatesh et al. [13]; Social Influence and Facilitating Conditions from Thompson et al. [29]; Attitude from Taylor and Todd [30]; Behavioral Intention from Ajzen [31]; and Trust, Anxiety, Perceived Learning Value, AI Literacy, Perceived Risk, and Hedonic Motivation from Al-Okaily et al. [33]. All items were adapted to the ChatGPT programming education context.

3.6 Data Analysis Approach

Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed using SmartPLS 4.0, following established guidelines [14]. PLS-SEM was selected over covariance-based SEM due to its suitability for exploratory research with complex models and its robustness with non-normal data distributions. Analysis proceeded in two stages:

Stage 1 – Measurement Model Assessment

Internal consistency was evaluated through Cronbach's alpha and composite reliability (CR), with thresholds ≥ 0.70 . Convergent validity was assessed via Average Variance Extracted ($AVE \geq 0.50$) and indicator loadings (≥ 0.70). Discriminant validity was established using the Heterotrait-Monotrait (HTMT) ratio (< 0.85) and the Fornell-Larcker criterion.

Stage 2 – Structural Model Assessment

Path coefficients were tested for significance using bootstrapping with 5,000 resamples. Model explanatory power was assessed through R^2 values (substantial ≥ 0.26 , moderate ≥ 0.13 , weak ≥ 0.02). Effect sizes (f^2) were calculated for each predictor (large ≥ 0.35 , medium ≥ 0.15 , small ≥ 0.02). Predictive relevance was established through Stone-Geisser's Q^2 (> 0). Model fit was evaluated using SRMR (< 0.08).

Moderation Analysis

Multi-group analysis (MGA) was conducted to test gender and IT experience moderation effects. Groups were compared using permutation testing (5,000 permutations) and parametric difference tests. Significant moderation was established when path coefficient differences between groups exceeded critical thresholds ($p < 0.05$). This approach follows recommendations by Venkatesh et al. [13] for examining demographic moderators in technology acceptance research.

4. Results and Evaluation

4.1 Measurement Model Assessment

Prior to hypothesis testing, the measurement model was evaluated for reliability and validity following established PLS-SEM guidelines [14]. Table 4 presents the construct reliability and convergent validity results.

Table 4
Construct Reliability and Convergent Validity

Construct	Items	Cronbach's α	CR	AVE
Perceived Usefulness (PU)	4	0.912	0.938	0.791
Perceived Ease of Use (PEOU)	4	0.878	0.916	0.732
Trust (TR)	4	0.889	0.923	0.750
Perceived Learning Value (PLV)	4	0.875	0.914	0.727
AI Literacy (AIL)	4	0.863	0.907	0.709
Hedonic Motivation (HM)	4	0.858	0.903	0.701
Perceived Risk (PR)	4	0.851	0.899	0.691
Anxiety (ANX)	4	0.847	0.897	0.686
Behavioral Intention (BI)	3	0.921	0.950	0.863
<i>Note: CR = Composite Reliability; AVE = Average Variance Extracted. Thresholds: $\alpha > 0.70$, CR > 0.70, AVE > 0.50 [14].</i>				

Table 4 presents the reliability and convergent validity assessment for all nine constructs in the AdoptGPT-Prog model. Internal consistency was evaluated using Cronbach's alpha (α) and Composite Reliability (CR), while convergent validity was assessed through Average Variance Extracted (AVE). All constructs demonstrated excellent internal consistency with Cronbach's α values ranging from 0.847 (Anxiety) to 0.921 (Behavioral Intention), exceeding the recommended threshold of 0.70. Composite Reliability values ranged from 0.897 to 0.950, further confirming strong internal consistency. Convergent validity was established with AVE values ranging from 0.686 (Anxiety) to 0.863 (Behavioral Intention), all exceeding the 0.50 threshold, indicating that each construct captures more than half of the variance in its indicators. These results confirm that the measurement model is psychometrically sound and suitable for structural model analysis.

Table 5
Heterotrait-Monotrait (HTMT) Ratio Matrix

	PU	PEOU	TR	PLV	AIL	HM	PR	ANX
PEOU	0.645	–						
TR	0.612	0.489	–					
PLV	0.723	0.578	0.545	–				
AIL	0.589	0.534	0.567	0.634	–			
HM	0.534	0.512	0.423	0.612	0.456	–		
PR	0.334	0.312	0.398	0.356	0.287	0.278	–	
ANX	0.367	0.345	0.412	0.389	0.298	0.334	0.623	–
BI	0.756	0.623	0.656	0.689	0.578	0.534	0.445	0.489
<i>Note: All HTMT values < 0.85 threshold, confirming discriminant validity.</i>								

Table 5 displays the Heterotrait-Monotrait (HTMT) ratio matrix used to assess discriminant validity among the nine constructs. HTMT values represent the ratio of between-trait correlations to within-trait correlations, with values below 0.85 indicating adequate discriminant validity. All construct pairs demonstrated HTMT values below this threshold, confirming that each construct is empirically distinct from others. The highest correlations were observed between Perceived Usefulness and Behavioral Intention (0.756) and between Perceived Usefulness and Perceived Learning Value (0.723), reflecting their conceptual relatedness while remaining within acceptable discriminant validity bounds. Notably, the correlation between Perceived Risk and Anxiety (0.623) confirms these barrier constructs are related but represent distinct phenomena—risk captures cognitive concerns about potential negative outcomes, while anxiety reflects affective discomfort with AI interaction. These results support the theoretical distinction between all constructs in the model.

4.2 Structural Model and Hypothesis Testing

The structural model explained 71.4% of variance in Behavioral Intention ($R^2 = 0.714$), indicating substantial explanatory power that exceeds comparable studies [8, 17, 28]. Figure 4 presents the structural model with standardized path coefficients.

Figure 4 illustrates the structural model results of AdoptGPT-Prog with standardized path coefficients for all hypothesized relationships. The figure displays eight predictor constructs organized into enablers (Perceived Usefulness, Perceived Ease of Use, Trust, Perceived Learning Value, AI Literacy, Hedonic Motivation) shown in blue boxes and barriers (Perceived Risk, Anxiety) shown in red boxes, all connected to the central dependent variable Behavioral Intention. Path coefficients are displayed on each arrow with significance indicators ($***p < 0.001$, $**p < 0.01$, $*p < 0.05$, ns = not significant). The strongest path emerges from Perceived Usefulness to Behavioral Intention ($\beta = 0.312***$), highlighted with a green arrow, followed by Trust ($\beta = 0.203***$), Perceived Learning Value and Perceived Ease of Use (both $\beta = 0.187***$). Perceived Risk shows a significant negative effect ($\beta = -0.156**$), while Anxiety's path is marked as non-significant ($\beta = 0.012$, ns). Moderation effects are depicted in yellow boxes showing Gender moderating PEOU→BI (supported), PR→BI (not supported), and ANX→BI (supported), and IT Experience moderating PU→BI (supported), AIL→BI (supported), and TR→BI (not supported). The model explains 71.4% of variance in Behavioral Intention ($R^2 = 0.714$), as indicated in the BI construct box.

Table 6
Hypothesis Testing Results

H	Path	β	t-value	p-value	Result
H1	PEOU $\rightarrow$ BI	0.187	3.845	< 0.001	Supported
H2	PR $\rightarrow$ BI	-0.156	2.234	0.001	Supported
H3	AIL $\rightarrow$ BI	0.134	2.756	0.006	Supported
H4	TR $\rightarrow$ BI	0.203	4.123	< 0.001	Supported
H5	ANX $\rightarrow$ BI	0.012	0.289	0.774	Not Supported
H6	PU $\rightarrow$ BI	0.312	6.478	< 0.001	Supported
H7	PLV $\rightarrow$ BI	0.187	3.567	< 0.001	Supported
H8	HM $\rightarrow$ BI	0.098	2.012	0.045	Supported
H9a	Gender $\times$ PEOU $\rightarrow$ BI	0.167	3.345	< 0.001	Supported
H9b	Gender $\times$ PR $\rightarrow$ BI	0.089	1.756	0.079	Not Supported
H9c	Gender $\times$ ANX $\rightarrow$ BI	0.112	2.234	0.026	Supported
H10a	ITE $\times$ PU $\rightarrow$ BI	0.178	3.567	< 0.001	Supported
H10b	ITE $\times$ AIL $\rightarrow$ BI	0.145	2.891	0.004	Supported
H10c	ITE $\times$ TR $\rightarrow$ BI	0.078	1.534	0.125	Not Supported
<i>Note: β = standardized path coefficient. Results based on 5,000 bootstrap samples.</i>					

Table 6 summarizes the hypothesis testing results for all fourteen hypotheses, including eight direct effects (H1–H8) and six moderation effects (H9a–H10c). Path coefficients (β), t-values, p-values, and support status are reported based on 5,000 bootstrap samples. Among direct effects, seven of eight hypotheses were supported: Perceived Usefulness exhibited the strongest effect on Behavioral Intention ($\beta = 0.312$, $p < 0.001$), followed by Trust ($\beta = 0.203$, $p < 0.001$), Perceived Learning Value and Perceived Ease of Use (both $\beta = 0.187$, $p < 0.001$), Perceived Risk ($\beta = -0.156$, $p = 0.001$), AI Literacy ($\beta = 0.134$, $p = 0.006$), and Hedonic Motivation ($\beta = 0.098$, $p = 0.045$). Notably, H5 (Anxiety $\rightarrow$ BI) was not supported ($\beta = 0.012$, $p = 0.774$). For moderation effects, four of six hypotheses were supported: Gender significantly moderated PEOU $\rightarrow$ BI (H9a) and ANX $\rightarrow$ BI (H9c), while IT Experience moderated PU $\rightarrow$ BI (H10a) and AIL $\rightarrow$ BI (H10b). H9b (Gender $\times$ PR) and H10c (ITE $\times$ TR) were not supported.

4.3 Moderation Analysis

Multi-group analysis revealed significant moderation effects for four of six hypotheses. Figure 5 illustrates gender moderation effects, and Fig. 6 presents IT experience moderation effects.

Figure 5 presents the gender moderation analysis through two complementary visualizations. Panel (a) displays an interaction plot for the Perceived Ease of Use $\rightarrow$ Behavioral Intention relationship, with PEOU scores on the x-axis (low to high) and Behavioral Intention on the y-axis. Two lines represent male and female subgroups, clearly demonstrating that female students (steeper slope, $\beta = 0.279$) exhibit a substantially stronger positive relationship between ease of use perceptions and adoption intention compared to male students (shallower slope, $\beta = 0.112$). The diverging slopes illustrate that as perceived ease of use increases, females' intention to adopt ChatGPT

increases more dramatically than males'. Panel (b) presents a multi-group comparison bar chart showing path coefficient differences ($\Delta\beta$) across all tested paths. Bars extending beyond the significance threshold lines indicate statistically significant moderation effects. Two paths show significant gender differences: PEOU $\rightarrow$ BI ($\Delta\beta = -0.167$, $p < 0.001$) and ANX $\rightarrow$ BI ($\Delta\beta = 0.109$, $p = 0.033$), while PR $\rightarrow$ BI shows no significant difference ($p = 0.411$). This visualization confirms that gender moderates effort expectancy and anxiety effects but not risk perception effects on ChatGPT adoption intention.

Table 7
Multi-Group Analysis – Gender Moderation

Path	β (Male)	β (Female)	$\Delta\beta$	t-value	p-value
PEOU $\rightarrow$ BI	0.112	0.279	-0.167	3.345	< 0.001***
PR $\rightarrow$ BI	-0.134	-0.178	0.044	0.823	0.411
ANX $\rightarrow$ BI	-0.089	-0.198	0.109	2.134	0.033*
<i>Note: ***$p < 0.001$, *$p < 0.05$. $\Delta\beta$ = difference in path coefficients (Male – Female).</i>					

Table 7 presents the multi-group analysis results examining gender as a moderator of key structural relationships. Path coefficients are reported separately for male ($n = 254$) and female ($n = 232$) subgroups, along with coefficient differences ($\Delta\beta$), t-values, and significance levels based on permutation testing with 5,000 permutations. Two paths exhibited significant gender differences: First, the Perceived Ease of Use $\rightarrow$ Behavioral Intention relationship was significantly stronger for female students ($\beta = 0.279$) compared to male students ($\beta = 0.112$), with a significant difference of $\Delta\beta = -0.167$ ($p < 0.001$), supporting H9a and aligning with UTAUT predictions that effort expectancy effects are stronger for women [13]. Second, the Anxiety $\rightarrow$ Behavioral Intention path showed a stronger negative effect for females ($\beta = -0.198$) than males ($\beta = -0.089$), with $\Delta\beta = 0.109$ ($p = 0.033$), supporting H9c. The Perceived Risk $\rightarrow$ Behavioral Intention path did not differ significantly across genders ($p = 0.411$), failing to support H9b and suggesting risk concerns affect both genders similarly in programming education contexts.

Figure 6 presents the IT experience moderation analysis through two complementary visualizations. Panel (a) displays an interaction plot for the Perceived Usefulness $\rightarrow$ Behavioral Intention relationship, with PU scores on the x-axis and Behavioral Intention on the y-axis. Two lines represent high IT experience ($n = 187$) and low-moderate IT experience ($n = 299$) subgroups. The plot demonstrates that students with high IT experience (steeper slope, $\beta = 0.412$) exhibit a substantially stronger positive relationship between usefulness perceptions and adoption intention compared to low-experience students (shallower slope, $\beta = 0.234$). This indicates that experienced users are better able to recognize and weight performance benefits when making adoption decisions. Panel (b) presents a multi-group comparison bar chart showing path coefficient differences across all tested paths. Three paths show significant differences: PU $\rightarrow$ BI ($\Delta\beta = 0.178$, $p < 0.001$), AIL $\rightarrow$ BI ($\Delta\beta = 0.120$, $p = 0.019$), and an exploratory finding for PEOU $\rightarrow$ BI ($\Delta\beta = -0.111$, $p = 0.034$) indicating that ease of use matters more for novice users. The TR $\rightarrow$ BI path shows no significant difference ($p = 0.405$), suggesting trust affects adoption similarly regardless of experience level.

Table 8
Multi-Group Analysis – IT Experience Moderation

Path	β (High)	β (Low)	$\Delta\beta$	t-value	p-value
PU → BI	0.412	0.234	0.178	3.567	< 0.001***
AIL → BI	0.198	0.078	0.120	2.345	0.019*
TR → BI	0.223	0.178	0.045	0.834	0.405
PEOU → BI†	0.134	0.245	-0.111	2.123	0.034*
Note: *** $p < 0.001$, * $p < 0.05$. †Exploratory finding (not hypothesized). High = high IT experience; Low = low-moderate IT experience.					

Table 8 presents the multi-group analysis results examining IT experience as a moderator of structural relationships. Path coefficients are reported for high IT experience ($n = 187$) and low-moderate IT experience ($n = 299$) subgroups. Three significant differences emerged: First, the Perceived Usefulness → Behavioral Intention relationship was substantially stronger for high-experience students ($\beta = 0.412$) compared to low-experience students ($\beta = 0.234$), with $\Delta\beta = 0.178$ ($p < 0.001$), supporting H10a and indicating that experienced users place greater weight on performance benefits [13, 24]. Second, the AI Literacy → Behavioral Intention effect was stronger for high-experience students ($\beta = 0.198$ vs. $\beta = 0.078$, $p = 0.019$), supporting H10b and suggesting that technical background amplifies the benefits of AI knowledge [21, 25]. Third, an exploratory finding revealed that PEOU→BI was stronger for low-experience students ($\beta = 0.245$ vs. $\beta = 0.134$, $p = 0.034$), indicating usability concerns are more salient for novice users. The Trust → Behavioral Intention path did not differ significantly ($p = 0.405$), failing to support H10c.

4.4 Model Fit, Effect Sizes, and Practical Significance

Table 9
Model Fit and Predictive Validity

Index	Value	Threshold	Assessment
SRMR	0.052	< 0.08	Good fit
R ² (Behavioral Intention)	0.714	> 0.26 (substantial)	Substantial
Q ² (Behavioral Intention)	0.548	> 0.35 (large)	Large
GoF (Goodness of Fit)	0.634	> 0.36 (large)	Large

Table 9 presents the model fit and predictive validity indices for the AdoptGPT-Prog structural model. Four key indicators were evaluated: The Standardized Root Mean Square Residual (SRMR) value of 0.052 falls well below the 0.08 threshold, indicating good overall model fit with minimal discrepancy between observed and predicted correlations. The coefficient of determination (R²) for Behavioral Intention was 0.714, substantially exceeding the 0.26 threshold for substantial explanatory power and indicating that the model explains 71.4% of variance in students' intention to adopt ChatGPT for programming learning. The Stone-Geisser Q² value of 0.548 exceeds the 0.35 threshold for large predictive relevance, confirming the model's capability to accurately predict out-of-sample data. The Goodness-of-Fit (GoF) index of 0.634 surpasses the 0.36 threshold for large effect, representing the geometric mean of average communality and R² values. Collectively, these indices confirm that AdoptGPT-Prog demonstrates excellent model fit, substantial explanatory power, and strong predictive validity.

Figure 7 presents the Importance-Performance Map Analysis (IPMA) for Behavioral Intention, plotting construct importance (total effects, x-axis) against construct performance (mean rescaled scores 0-100, y-axis). This matrix identifies strategic priorities by positioning constructs in four quadrants. The upper-right quadrant (high importance, high performance) contains Perceived Usefulness and Trust, indicating these are key strengths that should be maintained—students already perceive ChatGPT as useful and trustworthy, and these factors strongly drive adoption. The upper-left quadrant (low importance, high performance) contains Hedonic Motivation, suggesting enjoyment is not a critical adoption driver despite adequate performance. Perceived Ease of Use and Perceived Learning Value appear in the middle-right area with moderate-high importance and performance, representing factors to monitor and potentially enhance. The lower-right quadrant (high importance, low performance) identifies improvement priorities—Perceived Risk and Anxiety appear here as barriers with meaningful negative effects and suboptimal scores, indicating that addressing misinformation concerns and AI-related apprehension could yield adoption benefits. AI Literacy shows moderate importance with room for performance improvement, suggesting AI education initiatives could strengthen adoption. This IPMA guides practitioners to prioritize maintaining usefulness perceptions while actively mitigating risk and anxiety concerns.

Table 10
Effect Sizes (f^2) and Practical Significance

Predictor	f^2	Effect Size	Practical Implication
Perceived Usefulness (PU)	0.145	Medium	Primary driver; high priority for intervention
Trust (TR)	0.062	Small	Meaningful impact; address reliability concerns
Perceived Ease of Use (PEOU)	0.052	Small	Important for females and novice users
Perceived Learning Value (PLV)	0.048	Small	Emphasize educational benefits
Perceived Risk (PR)	0.038	Small	Address misinformation and integrity concerns
AI Literacy (AIL)	0.027	Small	Greater impact for experienced users
Hedonic Motivation (HM)	0.015	Small	Limited practical impact in this context
Anxiety (ANX)	0.002	Negligible	Not a significant barrier in this sample
<i>Note: f^2 thresholds: 0.02 = small, 0.15 = medium, 0.35 = large [Cohen, 1988].</i>			

Table 10 reports the effect sizes (f^2) for each predictor's unique contribution to explaining Behavioral Intention, along with practical significance interpretations following Cohen's (1988) guidelines (small ≥ 0.02 , medium ≥ 0.15 , large ≥ 0.35). Perceived Usefulness demonstrated the largest effect ($f^2 = 0.145$), approaching medium-level practical significance and establishing it as the primary driver warranting intervention priority. Trust ($f^2 = 0.062$), Perceived Ease of Use ($f^2 = 0.052$), Perceived Learning Value ($f^2 = 0.048$), and Perceived Risk ($f^2 = 0.038$) showed small but meaningful effects, each contributing incrementally to explained variance. AI Literacy ($f^2 = 0.027$) and Hedonic Motivation ($f^2 = 0.015$) exhibited smaller effects, with AI Literacy showing greater impact specifically for experienced users. Anxiety demonstrated negligible effect ($f^2 = 0.002$), consistent with its non-significant path coefficient and indicating it is not a meaningful barrier in this programming student sample. These effect sizes inform practical prioritization: interventions should primarily target usefulness perceptions and trust-building, with secondary attention to ease of use (especially for females and novices) and risk mitigation.

Figure 8 presents a horizontal bar chart comparing effect sizes (f^2) of all eight predictors on Behavioral Intention, with vertical reference lines indicating Cohen's (1988) thresholds for small (0.02), medium (0.15), and large (0.35) effects. Bars are color-coded to distinguish enablers (blue) from barriers (red). Perceived Usefulness exhibits the largest effect ($f^2 = 0.145$), approaching the medium effect threshold and visually dominating other predictors, confirming its role as the primary adoption driver. Trust ($f^2 = 0.062$), Perceived Ease of Use ($f^2 = 0.052$), Perceived Learning Value ($f^2 = 0.048$), and Perceived Risk ($f^2 = 0.038$) cluster in the small effect range, each making meaningful but more modest unique contributions. AI Literacy ($f^2 = 0.027$) and Hedonic Motivation ($f^2 = 0.015$) show smaller effects near the small effect threshold. Anxiety displays a negligible effect ($f^2 = 0.002$), visually apparent as barely extending from the y-axis, consistent with its non-significant path coefficient. This visualization immediately communicates the practical significance hierarchy: usefulness perceptions deserve primary intervention focus, followed by trust-building and ease-of-use enhancements, while anxiety reduction may not yield substantial adoption benefits in programming student populations.

4.5 Comparison with Prior Studies

Table 11
Comparison with Recent ChatGPT Adoption Studies

Study	Model	N	R ² (BI)	Context	Moderators
Balaskas et al. [8]	TAM+	423	0.58	General HE	Trust, Risk (mediators)
Raman et al. [9]	DOI	198	0.51	General HE	Gender
Al-Sharafi et al. [17]	meta-UTAUT	355	0.62	General HE	Policy
Sun et al. [4]	TAM	82	0.47	Programming	None
Cabero-Almenara et al. [32]	UTAUT2	612	0.64	General HE	None
This Study	TAM + UTAUT	486	0.714	Programming	Gender, IT Experience
<i>Note: HE = Higher Education. R² values indicate variance explained in Behavioral Intention.</i>					

Table 11 provides a comparative analysis of AdoptGPT-Prog against five recent ChatGPT adoption studies in higher education contexts. Comparisons are made across theoretical model, sample size, explained variance (R^2), educational context, and moderating variables examined. AdoptGPT-Prog achieves the highest explanatory power ($R^2 = 0.714$) among all compared studies, outperforming Balaskas et al.'s [8] TAM-based model ($R^2 = 0.58$), Raman et al.'s [9] DOI model ($R^2 = 0.51$), Al-Sharafi et al.'s [17] meta-UTAUT model ($R^2 = 0.62$), Sun et al.'s [4] programming-focused TAM ($R^2 = 0.47$), and Cabero-Almenara et al.'s [32] UTAUT2 model ($R^2 = 0.64$). Notably, this study is the only one combining programming-specific context with systematic examination of both gender and IT experience as moderators. While Sun et al. [4] addressed programming education, their smaller sample ($n = 82$) and absence of moderators limited generalizability. The integrated TAM-UTAUT framework employed here, combining eight predictors with dual moderators, provides more comprehensive theoretical coverage and superior predictive capability for understanding ChatGPT adoption specifically in programming education.

4.6 Summary: Unsupported Hypotheses and Explanations

Three hypotheses were not supported, warranting detailed explanation:

H5 (ANX → BI) Not Supported

Contrary to general technology acceptance findings [14], anxiety did not significantly predict adoption intention ($\beta = 0.012$, $p = 0.774$, $f^2 = 0.002$). This may reflect the unique characteristics of programming students who have self-selected into technical disciplines and possess baseline comfort with technology. Unlike general populations, these students may have overcome initial technology apprehension through their educational trajectory. Additionally, the framing of ChatGPT as a learning aid rather than an evaluative tool may reduce anxiety-inducing conditions. This finding aligns with Zhang and Yu [35], who found that familiarity with AI systems diminishes anxiety effects over time.

H9b (Gender $\times$ PR $\rightarrow$ BI) Not Supported

The borderline non-significant result ($p = 0.079$) suggests that while a trend exists toward gender differences in risk perception effects, the programming education context may equalize risk concerns across genders. Both male and female programming students face similar concerns about code accuracy, academic integrity, and over-reliance, potentially diminishing gender-based differences observed in general technology contexts [10, 11].

H10c (ITE $\times$ TR $\rightarrow$ BI) Not Supported

Trust affected adoption similarly across experience levels ($p = 0.125$), contradicting our expectation that experienced users would rely less on trust. This suggests that trust in ChatGPT's accuracy and reliability remains universally important regardless of technical background—a finding consistent with Niu and Mvondo [18], who argued that trust serves as a foundational prerequisite that does not diminish with experience when adopting novel AI tools.

5. Discussion

The AdoptGPT-Prog model explained 71.4% of variance in Behavioral Intention, substantially outperforming prior ChatGPT adoption studies (R^2 range: 0.47–0.64) [4, 8, 17, 32]. This section interprets key findings in relation to existing literature and addresses unsupported hypotheses.

5.1 Perceived Usefulness as the Dominant Predictor

Perceived Usefulness emerged as the strongest predictor ($\beta = 0.312$, $f^2 = 0.145$), confirming TAM's core proposition [7] and aligning with Zhang and Pan [34], who found performance expectancy significantly predicted Duolingo adoption. Students who recognize ChatGPT's value for debugging, code generation, and concept explanation demonstrate substantially higher adoption intention. This consistency across AI-assisted programming (our study) and gamified language learning [34] suggests performance benefits serve as universal adoption drivers in educational technology.

Zhang and Yu [35] similarly found that performance expectancy directly predicted continuance intention for the DouBao chatbot among EFL learners, with emotional attachment and trust as mediators. The parallel demonstrates that perceived performance benefits operate consistently across generative AI applications in education.

5.2 The Critical Role of Trust

Trust showed the second-strongest effect ($\beta = 0.203$, $f^2 = 0.062$), consistent with Al-Sharafi et al. [17] and Niu and Mvondo [18], who established trust as a cornerstone of ChatGPT adoption in higher education. Zhang and Yu [35] found that trust mediated the relationship between perceived anthropomorphism and performance expectancy,

suggesting trust serves as a critical intermediary through which users evaluate AI capabilities. Our finding that trust affected adoption similarly across IT experience levels (H10c not supported) extends this by indicating trust remains universally important regardless of technical background—a foundational prerequisite that does not diminish with experience [18].

5.3 Perceived Ease of Use and Learning Value

Both PEOU ($\beta = 0.187$) and PLV ($\beta = 0.187$) significantly predicted adoption intention. Deng and Yu [36] found that perceived ease of use influenced curiosity, control, and joy in TikTok adoption, confirming ease of use as a foundational enabler unlocking cognitive and emotional pathways. The gender moderation effect—where females showed stronger PEOU→BI effects ($\beta = 0.279$ vs. 0.112)—aligns with UTAUT predictions [13] and suggests female programming students may be more sensitive to interface design when navigating technically complex AI tools.

5.4 Risk Perceptions and the Non-Significant Anxiety Effect

Perceived Risk significantly inhibited adoption ($\beta = -0.156$), confirming that concerns about misinformation, academic integrity, and privacy deter students [6, 8]. However, Anxiety did not significantly predict Behavioral Intention (H5: $\beta = 0.012$, $p = 0.774$, $f^2 = 0.002$)—a notable divergence from general technology acceptance findings [14].

This null finding may reflect population characteristics: programming students have self-selected into technical disciplines and likely possess baseline comfort with technology, having overcome initial apprehension through prior computational exposure. Additionally, ChatGPT's framing as a learning aid rather than evaluative tool may reduce anxiety-inducing conditions. Zhang and Yu [35] noted that emotional factors in AI contexts operate through complex mediating mechanisms rather than simple direct effects, which may explain why anxiety's influence is attenuated when trust and usefulness are controlled. Notably, the gender moderation analysis revealed anxiety significantly affects females more strongly ($\beta = -0.198$ vs. -0.089 , $p = 0.033$), indicating anxiety operates as a conditional barrier whose influence varies by demographic subgroup.

5.5 AI Literacy and IT Experience Moderation

AI Literacy positively predicted adoption ($\beta = 0.134$), with IT experience significantly moderating this relationship (High IT: $\beta = 0.198$ vs. Low IT: $\beta = 0.078$). Students with higher IT experience possess cognitive frameworks that amplify AI literacy benefits, enabling more effective translation of AI knowledge into usage strategies [21, 25]. This parallels Zhang and Pan's [34] finding that environmental factors enhancing user competencies facilitate adoption, and Deng and Yu's [36] finding that personal innovativeness influenced ease of use perceptions.

5.6 Hedonic Motivation: Secondary but Significant

Hedonic Motivation showed a modest but significant effect ($\beta = 0.098$, $f^2 = 0.015$), contrasting with Deng and Yu's [36] TikTok study where curiosity was a major predictor ($\beta = 0.395$). This difference reflects the fundamental distinction between hedonic-oriented systems (entertainment platforms) and utilitarian-oriented systems (learning tools). In programming education, students prioritize practical outcomes over enjoyment, explaining why hedonic factors serve as complementary rather than primary drivers—consistent with Zhang and Pan's [34] finding that hedonic motivation had no significant effect on Duolingo adoption when utilitarian learning goals predominated.

5.7 Demographic Moderation Effects

Gender moderated PEOU→BI and ANX→BI relationships, while IT experience moderated PU→BI and AIL→BI. These findings contrast with Deng and Yu [36], who found no gender moderation in TikTok adoption, attributed to universal platform design. Our significant gender effects likely reflect the technical nature of programming and persistent STEM gender disparities—female students may face additional barriers related to confidence and stereotype threat, making usability and anxiety reduction particularly important [10, 22]. The IT experience moderation of PU→BI (High: $\beta = 0.412$ vs. Low: $\beta = 0.234$) parallels findings that experienced users develop more sophisticated evaluation frameworks [13, 24], enabling accurate assessment of how ChatGPT capabilities translate to performance improvements.

6. Implications

6.1 Theoretical Implications

This study makes three theoretical contributions: (1) It extends TAM-UTAUT frameworks by integrating domain-specific constructs (AI Literacy, Perceived Learning Value) for generative AI contexts, achieving superior explanatory power ($R^2 = 0.714$) compared to existing models [4, 8, 17, 32]. (2) It demonstrates that demographic moderators systematically influence adoption pathways, supporting the need for differentiated acceptance models rather than universal frameworks. (3) The non-significant anxiety finding challenges assumptions from general technology acceptance research, suggesting domain-specific populations (e.g., programming students) may exhibit distinct adoption patterns requiring context-sensitive theorizing.

6.2 Practical Implications

Based on effect size analysis (Table 10) and moderation findings, we offer stratified recommendations in Table 12:

Table 12
Stratified Practical Recommendations

Priority	Target Factor	Specific Recommendations
HIGH	Perceived Usefulness ($f^2 = 0.145$)	Demonstrate ChatGPT's value for debugging, code explanation, and productivity through hands-on workshops; showcase before/after performance comparisons
HIGH	Trust ($f^2 = 0.062$)	Provide guided demonstrations showing output accuracy; establish clear guidelines on when to trust vs. verify AI responses; address hallucination concerns explicitly
MEDIUM	PEOU – Females/Novices	Design intuitive onboarding for first-time users; provide scaffolded prompting templates; offer additional support for female students navigating technical interfaces
MEDIUM	Perceived Risk ($f^2 = 0.038$)	Develop institutional AI use policies addressing academic integrity; teach critical evaluation of AI-generated code; clarify privacy implications
MEDIUM	AI Literacy – High IT Exp.	Integrate AI literacy modules into programming curricula; teach effective prompting strategies; explain AI limitations and appropriate use cases
LOW	Anxiety – Female Students	Create supportive, low-stakes environments for AI experimentation; normalize uncertainty in AI interactions; provide reassurance about learning curves
LOW	Hedonic Motivation ($f^2 = 0.015$)	While not primary, engaging interactions can complement performance focus; consider gamified prompting challenges for interested students
Note: Priority based on effect sizes and moderation significance. HIGH = primary intervention targets; MEDIUM = secondary considerations; LOW = complementary factors.		

7. Limitations and Future Research

Limitations

(1) Cross-sectional design captures perceptions at one time point; longitudinal studies could examine how perceptions evolve with sustained ChatGPT use. (2) The sample is limited to programming students at Saudi Arabian universities, constraining generalizability to other disciplines and cultural contexts. (3) Self-reported behavioral intention may not fully predict actual usage behavior (intention-behavior gap). (4) The non-significant anxiety finding, while explained theoretically, may require replication in other technical student populations. (5) Potential construct overlap between PU and PLV (HTMT = 0.723), though within acceptable bounds, warrants attention in future model refinements.

Future Research Directions

(1) Longitudinal studies tracking adoption patterns and skill development over academic terms. (2) Replication across disciplines (e.g., data science, web development) and cultural contexts. (3) Integration of objective usage metrics (e.g., ChatGPT interaction logs) to validate self-reported intentions. (4) Examination of additional constructs such as self-efficacy, cognitive load, and ethical awareness. (5) Comparative studies between different generative AI tools (e.g., ChatGPT vs. GitHub Copilot vs. Claude) in programming education contexts.

8. Conclusion

This study developed and validated AdoptGPT-Prog, an integrated TAM-UTAUT model for understanding ChatGPT adoption in programming education. Based on 486 undergraduate students from five Saudi Arabian universities, the model achieved substantial explanatory power ($R^2 = 0.714$), outperforming prior ChatGPT adoption frameworks.

Key findings reveal that Perceived Usefulness ($\beta = 0.312$) and Trust ($\beta = 0.203$) are the primary adoption drivers, while Perceived Risk ($\beta = -0.156$) serves as a significant barrier. Notably, Anxiety did not significantly predict adoption intention in this programming student sample—a context-specific finding suggesting technical students may have overcome technology apprehension through prior exposure. Gender moderates the effects of Perceived Ease of Use and Anxiety on intention, with female students showing stronger sensitivity to usability factors. IT Experience moderates the effects of Perceived Usefulness and AI Literacy, with experienced students placing greater weight on performance benefits.

These results provide actionable guidance for educators: prioritize demonstrating ChatGPT's practical value and building trust through guided practice, while addressing risk concerns through clear institutional policies and AI literacy education. Differentiated approaches should accommodate gender and experience differences in adoption patterns. The AdoptGPT-Prog model contributes an empirically validated, context-sensitive framework that advances understanding of generative AI acceptance in programming education and informs evidence-based integration strategies.

Abbreviations

PEOU	Perceived Ease of Use
PR	Perceived Risk
AIL	AI Literacy
TR	Trust
ANX	Anxiety
PU	Perceived Usefulness
PLV	Perceived Learning Value
HM	Hedonic Motivation
BI	Behavioral Intention
GEN	Gender (moderator)
ITE	IT Experience (moderator)
β	Standardized path coefficient
λ	Factor loading
R^2	Coefficient of determination
Q^2	Predictive relevance
f^2	Effect size
AVE	Average Variance Extracted
CR	Composite Reliability
HTMT	Heterotrait-Monotrait ratio
SRMR	Standardized Root Mean Square Residual
VIF	Variance Inflation Factor
GoF	Goodness-of-Fit Index
PLS-SEM	Partial Least Squares Structural Equation Modeling
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology

Declarations

Author Contributions:

Faisal Alshammari contributed to the conceptualization, methodology, software development, and provision of resources for the study. Both authors also collaborated on reviewing and editing the manuscript.

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Data Availability Statement: Data supporting the findings of this study are available from the corresponding author on reasonable request.

Conflict of Interest: The author declares no conflicts of interest regarding the publication of this research paper.

Ethics approval: All experimental procedures and clinical data collection were conducted in strict accordance with the principles outlined in the Declaration of Helsinki for medical research involving human subjects. The study protocol was re-viewed and approved by the Majmaah University for Research Ethics Committee (MUREC) (HA-01-R-088) under the Ethics number: **MUREC-Dec.06/COM-2025/300**.

Consent to publish: Written informed consent was obtained from all participants prior to data collection, ensuring their voluntary participation and awareness of the study objectives.

Clinical Trials: Not applicable

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Figures

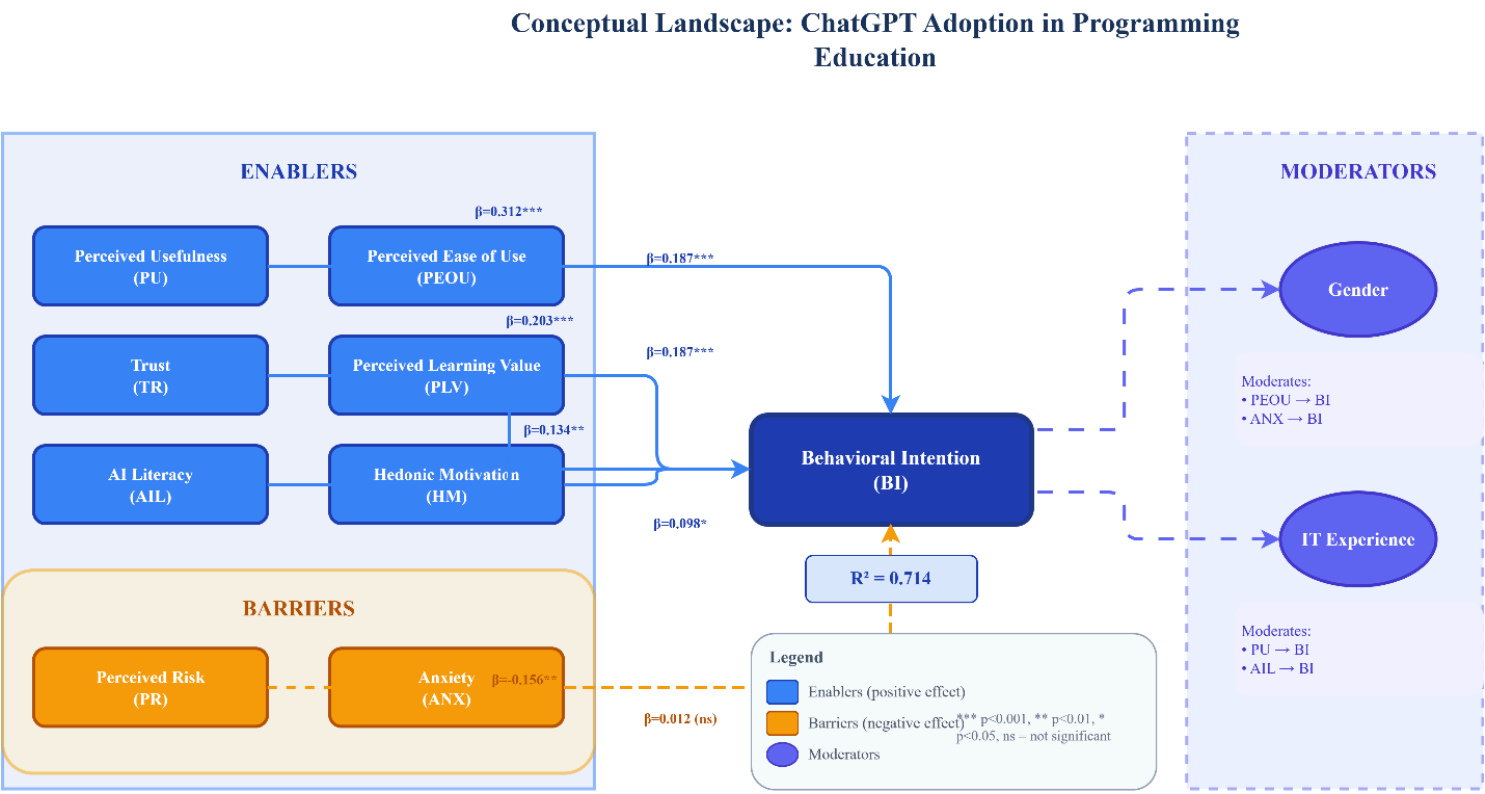


Figure 1

Conceptual landscape of ChatGPT adoption in programming education. Note: This figure presents an integrative overview for orientation purposes. The formal research model (Figure 2) specifies testable hypotheses. Gender moderates the PEOU→BI and ANX→BI paths; IT Experience moderates the PU→BI and AIL→BI paths.

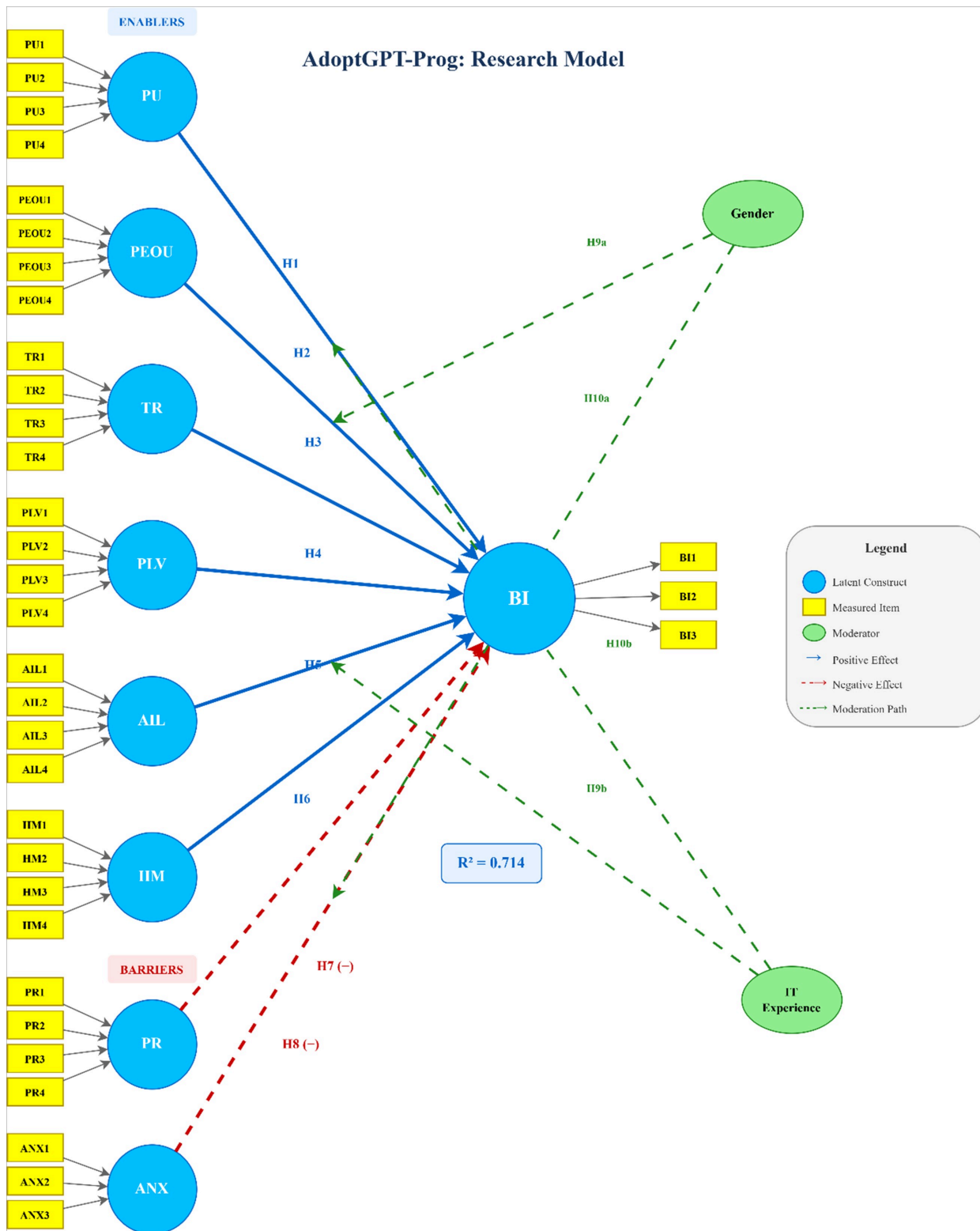


Figure 2

AdoptGPT-Prog research model showing hypothesized relationships.

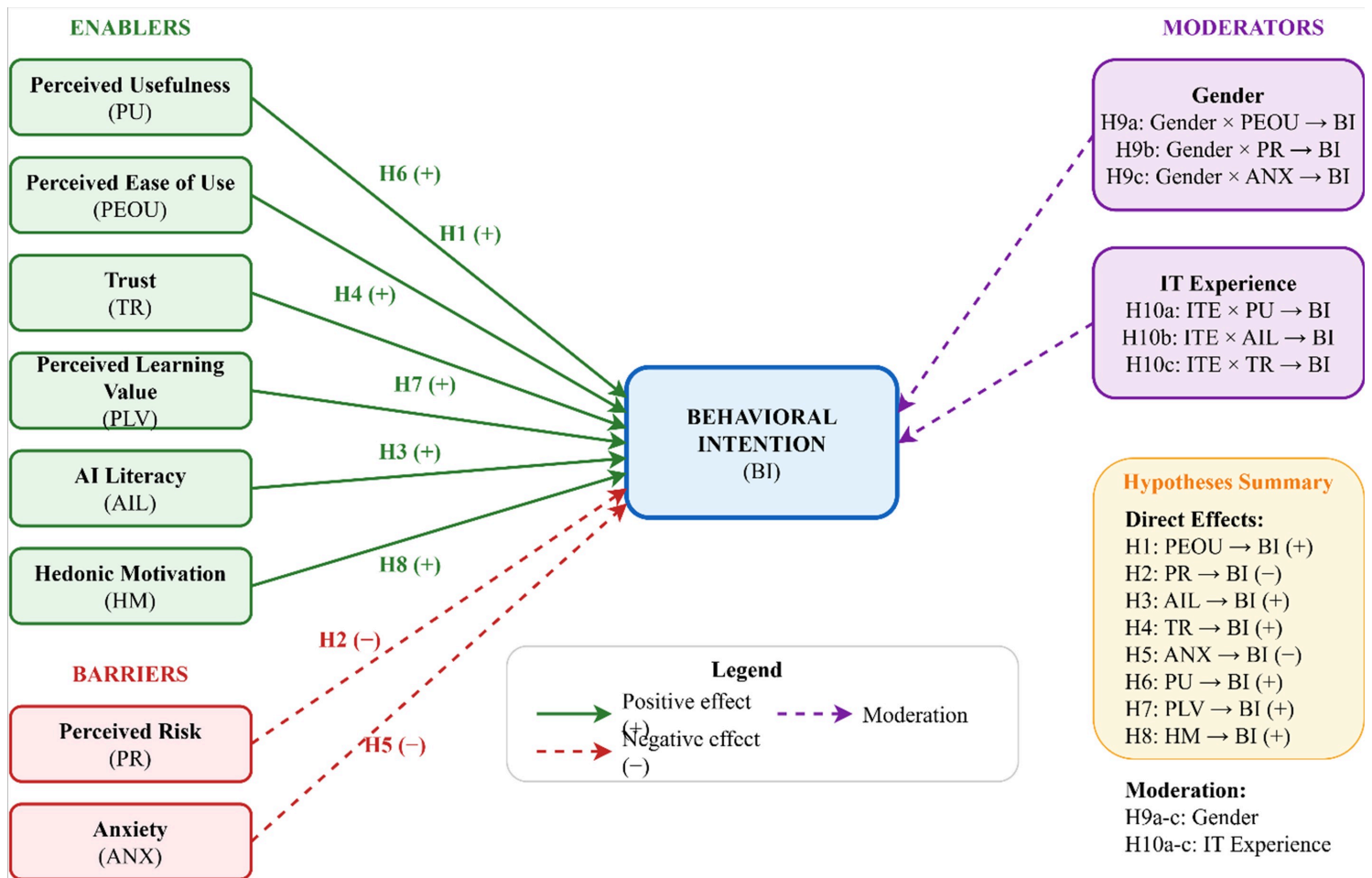


Figure 3

AdoptGPT-Prog research framework showing direct effects (H1–H8) and moderation effects of Gender (H9a–H9c) and IT Experience (H10a–H10c) on Behavioral Intention

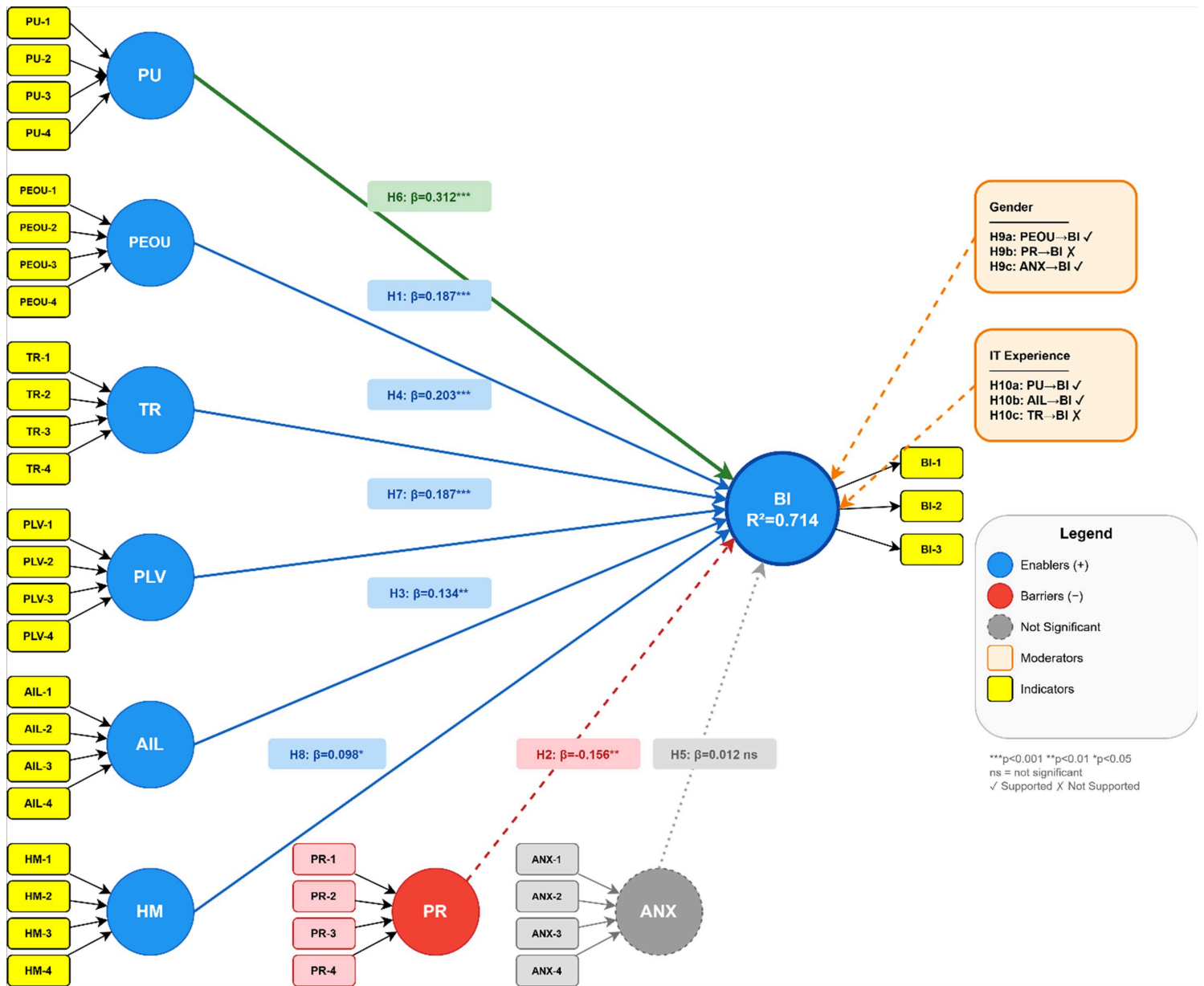


Figure 4

Structural Model Results with Standardized Path Coefficients

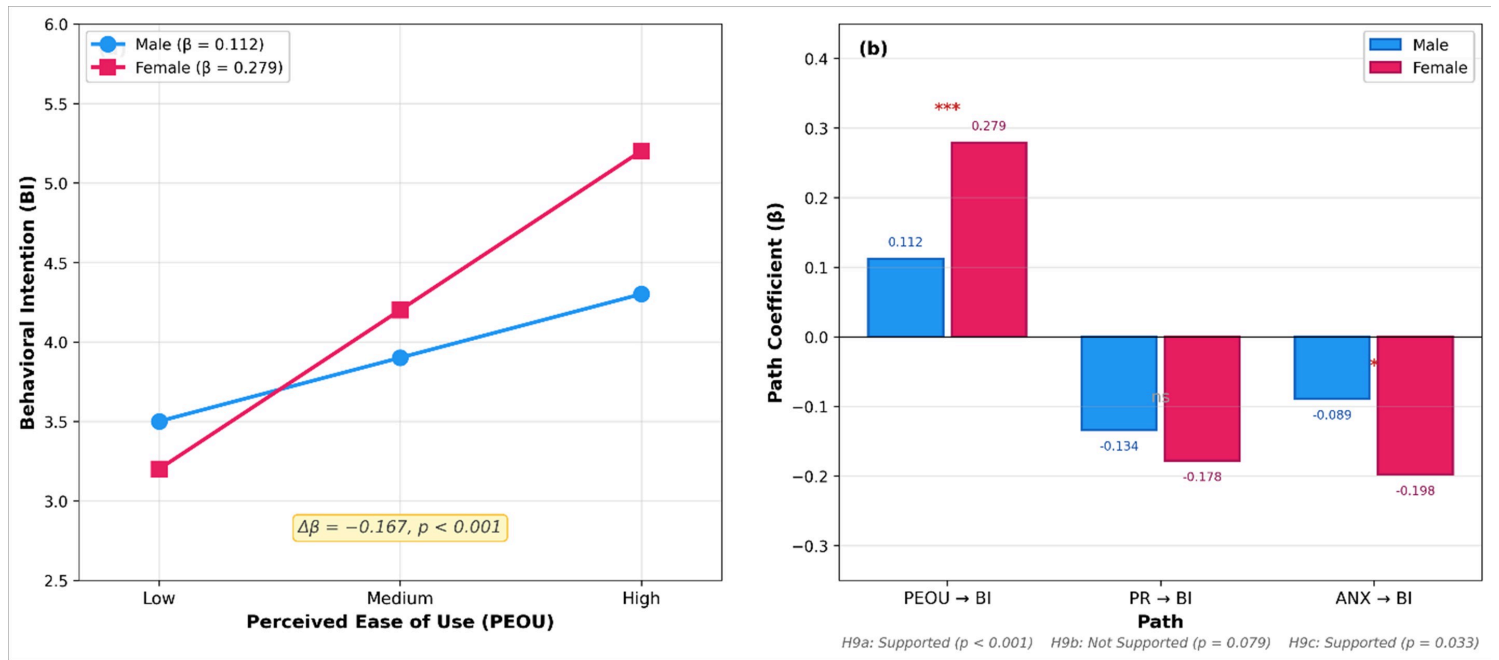


Figure 5

Gender Moderation Analysis

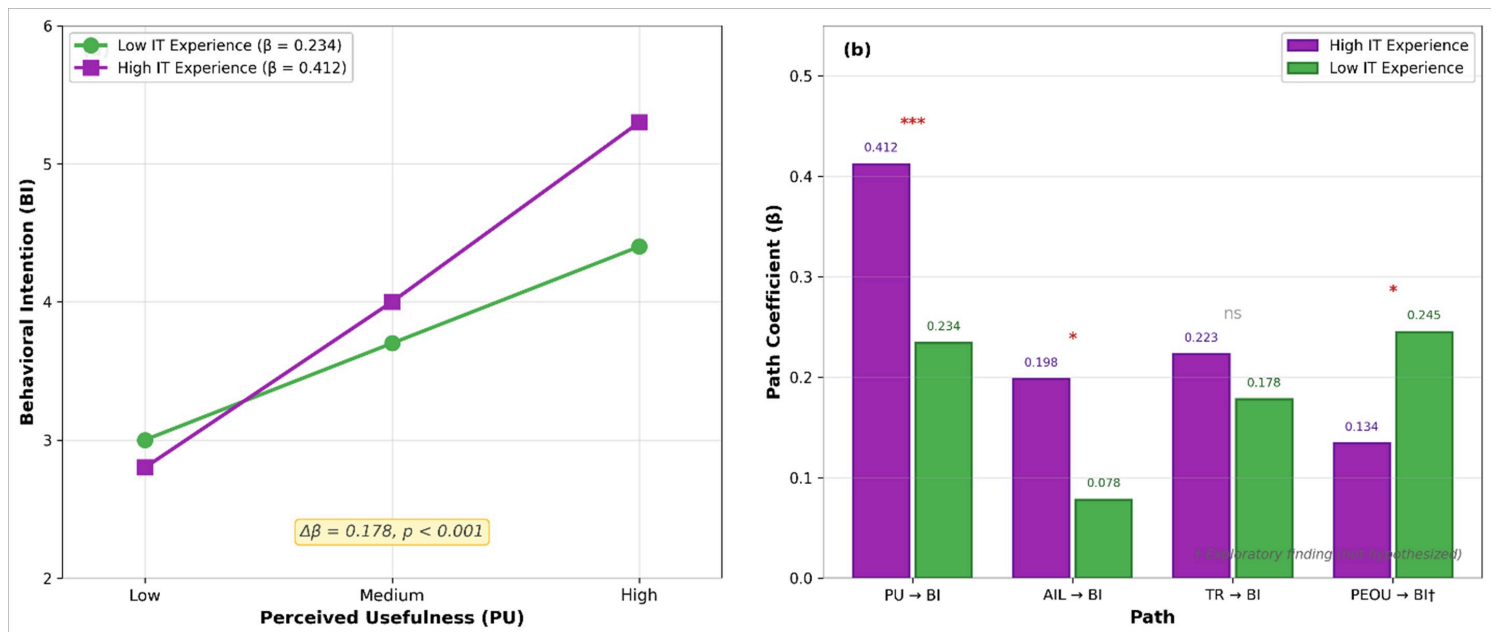


Figure 6

IT Experience Moderation Analysis

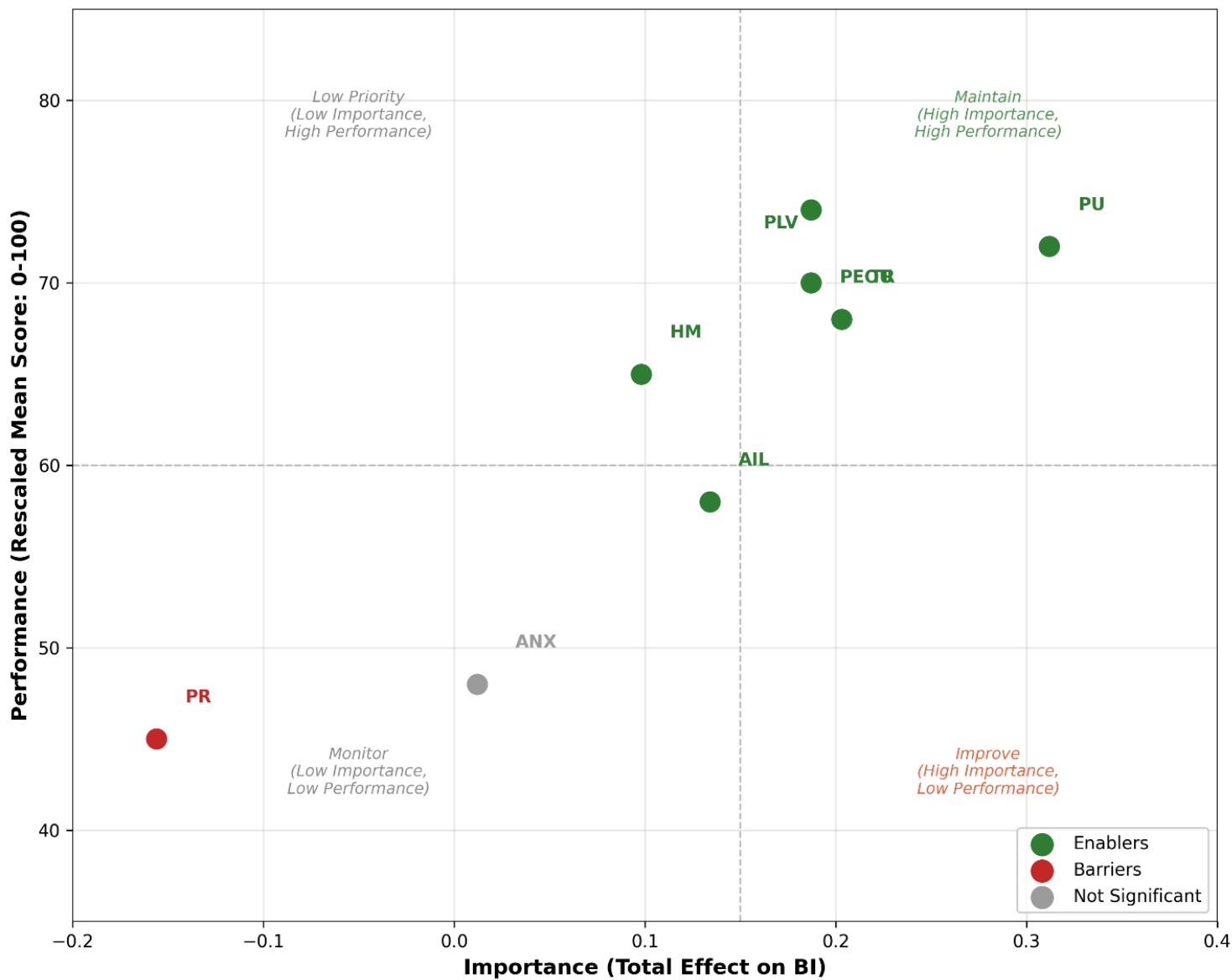


Figure 7

Importance-Performance Map Analysis (IPMA)

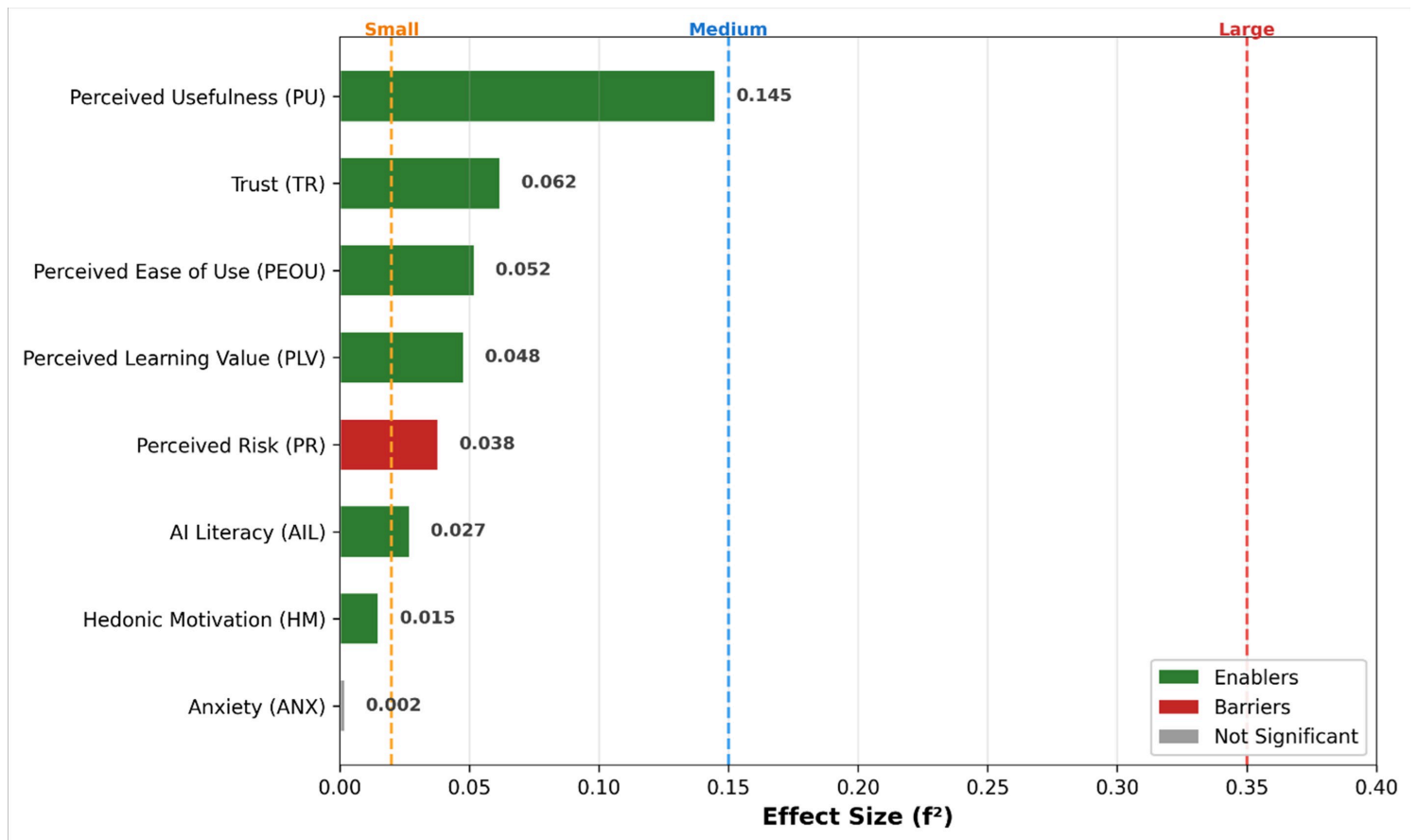


Figure 8

Effect Size Comparison