ISSN: 2709-5312

المجلة العربية للعلوم الإنسانية والاجتماعية

Arab Journal for Humanities and Social Sciences

العدد السابع والثلاثون / حزيران _ 2026

مجلة علمية عالمية محكمة ربع سنوية
تصدر عن مركز السنبلة للبحوث والدراسات
عمان - المملكة الأردنية الهاشمية
البريد الإلكتروني للمجلة
.editor@arabjhs.com
الموقع الإلكتروني للمجلة
Www.arabjhs.com
issn 2709_ 5312
IMPACT FACTOR ISI 2.228

المجلة العربية للعلوم الإنسانية والاجتماعية
Arab Journal for Humanities and Social Sciences

من نحن

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- نشر تقارير الندوات والمؤتمرات العلمية بالجامعات العربية ، والمعاهد العلمية ، ومراكز البحوث.
- توثيق ونشر الثقافة العلمية بين الباحثين، والتواصل العلمي فى مختلف مجالات العلوم الانسانية والاجتماعية.
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-يلتزم الباحث بالأصول العلمية المتعارف عليها في إعداد وكتابة البحوث.

-يجب إثبات مصادر المعلومات وتوثيق الاقتباس واحترام الأمانة العلمية في الإحالات والمراجع والمصادر.

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–يقوم الباحث بالتعديلات المطلوبة ثم يتم متابعة التعديلات من قيل لجان التحكيم . يتم إرسال البحث مع تقرير بقبول البحث بشكل نهائي من لجان التحكيم.

-يتم إرسال خطاب رسمي من المجلة بقبول البحث للنشر.

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-يتم إبلاغ الباحث بإيميل رسمي بإتمام عملية النشر في حال إكمال كافة الإجراءات السابقة وإنجاز عملية النشر الفعلي في عدد المجلة .

يراعي الباحث ما يلي:

–اسم الباحث (الباحثين) ، الوصف الوظيفي ، المؤسسة التي يعمل بها ، .

–الملخّص باللغة العربية ثم الكلمات المفتاحية

–الملخّص باللغة الانجليزية ثم الكلمات المفتاحية

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تنسيق البحث :يتم تنسيق الورقة على) قياس(A4 ، بحيث يكون نوع وحجم الخط وفق شروط محددة، وهي:– نوع الخط في الابحاث باللغة العربية هوSimplified Arabic ، حجم الخط 16 غامق للعنوان الرئيس، 14 غامق للعناوين الفرعية، 14 عادي لباقي النصوص وترقيم الصفحات و المسافة بين الأسطر يجب أن لا تقل عن 1.5.

–نوع الخط في الأبحاث باللغة الإنجليزية هوTimes New Roman ، حجم الخط 14 غامق للعنوان الرئيس، 12 غامق للعناوين الفرعية، 12 عادي لباقي النصوص وترقيم الصفحات و المسافة بين الأسطر يجب أن لا تقل عن 1.5.

حجم البحث والملخص :ألا يزيد عدد صفحات البحث على (30) صفحة و ذلك لكي لا يتم زيادة رسوم التحكيم. ويجب أرفاق ملخص مكون من 200 – 250 كلمة باللغتين العربية والانجليزية ، بالإضافة إلى كلمات مفتاحية لا تقل عن 6 كلمات.

التوثيق : يتم التوثيق وفقا لأسلوب الجمعية الأمريكية السيكولوجية APA)) وعلى النحو التالي داخل البحث إذا كان المرجع كتابا يكتب اسم العائلة والسنة ، مثال(السرهيد ، 2005).وإذا كان المرجع بحثا في مجلة علمية يراعى ما سبق ، أما إذا كان موقعا على الأنترنت فيكتب : اسم المؤلف ، عنوان المقال ، السنة ، الموقع ، السنة ، التاريخ ،.بالنسبة للمصادر والمراجع ، ترد المصادر العربية ، ثم المصادر الأجنبية.

الهوامش: تستخدم هوامش الصفحات السفلية لذكر أي ملاحظة، أو لتوضيح أي معلومة واردة في متن البحث، أو للتوثيق في بعض الأبحاث ولا مانع من ذلك ، وتوضع بين قوسين في أسفل الصفحة ، أو يعمل لها ملحق للهوامش توضع في نهاية البحث.

المراجع:

-ترتب أرقام المراجع في قائمة المراجع بالتسلسل، وذلك بعد مراعاة ترتيب المراجع هجائياً في القائمة حسب اسم المؤلف وفقاً للآتي:

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الرسوم

رسوم النشر والتحكيم والدفع

تسعى المجلة العربية للعلوم الانسانية والاجتماعية بنشر الأبحاث العلمية وتطوير البحث العلمي في الوطن العربي ، وتطلب المجلة رسوم رمزية مقدارها 140 دينار أردني أو ما يعادل 200 دولار لنشر البحوث المكونة من 25 – 30 صفحة بحد أقصى ويتم إضافة رسوم في حال زيادة عدد الصفحات عن 30 صفحة.

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Jo 38 JIBA 0580000325999411400002

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0325999411400002

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Arab Journal for Humanities and Social Sciences

اعتمادات المجلة :

دار المنظومة الرواد في قواعد المعلومات العربية	
isi: منظمة ISI Indexing للأرشفة الدولية	
E-marfa : معرفة : قاعدة البيانات العربية الرقمية	
شمعة : قاعدة المعلومات العربية التربوية	
ISSN : منظمة الترقيم للمجلات الدولية المحكمة	
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Arab Journal for Humanities and Social Sciences
Impact factor isi 2.228

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العدد السابع والثلاثون / حزيران – 2026

Examining the Unified Theory of Acceptance and Use of Technology (2) on Consumer Trust and Purchase Intention towards AI-Powered Entertainment Streaming Services

Sara Moustafa Ali Fahmy El Fadly

Abstract

Purpose- This study aims to analyze how Artificial Intelligence-powered personalization in entertainment streaming media platforms apply the extended Unified Theory of Acceptance and Use of Technology to impact consumers intention subscribe to the entertainment, having the role of consumer trust as a mediating variable.

Design/methodology/approach- This study uses deductive quantitative research design. The researchers developed a structured questionnaire and collected data electronically from consumers in Egypt that have registered in various online services during the month of April 2026, following a cross-sectional timeframe. 420 questionnaires were analyzed through the statistical package for social science (SPSS) version 26 to test they hypotheses.

Findings- This study shows that AI powered entertainment media performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic value, habit, price perception, along with perceived accuracy, and trust, positively influence purchase intention of online entertainment streaming services.

Practical Contribution- This study aid entertainment media providers, digital marketers and AI designers in attracting consumers to their entertainment service provision. According to the results, the creation of pleasant and valuable user experiences with AI personal recommendations allows consumers to feel that the platform is useful and easy as algorithms adapt to individual tastes using past purchases, browsing history, and contextual data. Further, it allows consumers to cut through information overload; consumers find what they need quicker, leading to gratification and purchase intent.

Value & originality- This study broadens the UTAUT2 framework by incorporating trust and perceived accuracy with AI-driven personalization in entertainment media platforms. Accordingly, it expands the literature on consumer technology acceptance and clarifies the influence of AI personalization on consumers' buying behavior. This study also adds contextual validation, focusing on the Egyptian context; a developing country with scarce literature on AI-based consumer behavior research.

Keywords: artificial intelligence, consumer trust, entertainment media platforms, personalization, purchase intention, UTAUT2

1. Introduction

The global shift toward digital entertainment is progressing worldwide, with over 1.5 billion people utilizing online streaming services globally (Feuerriegel et al., 2024; Dwivedi et al., 2023). Platforms like Netflix, Spotify, and YouTube have entirely transformed how people consume movies, music, and shows on-demand (Balakrishnan & Dwivedi, 2024). Depending on the country, localized options exist as well; for instance, in the Middle East, popular online entertainment include Shahid Watch It, OSN+, etc., offering a mix of exclusive Arabic dramas, Hollywood blockbusters, and localized family content (Feuerriegel et al., 2024). According to scholars and practitioners, this business is becoming highly competitive and so, many brands are seeking ways to attract consumers and encourage their purchase intentions (Kaur et al., 2024).

Entertainment streaming services increasingly use artificial intelligence (AI) to combat choice overload and deliver highly personalized experiences (Dwivedi et al., 2023). By analyzing viewing history, watch times, and search queries, AI algorithms curate tailored recommendations and dynamic thumbnails that improve user retention and streamline content discovery (Rai et al., 2022; Feuerriegel et al., 2024). Rather than a tool of operational support, AI is becoming a front-line strategic player shaping consumer attitudes, perceptions, and buying behaviors.

Despite these benefits, several challenges hinder public acceptance of AI-generated recommendations. A leading concern is the perceived accuracy of the AI: consumers question whether algorithmic suggestions truly match their tastes, doubts that arise when a system misjudges preferences through insufficient data, miscalculation, or bias (Shin, 2021). Inaccurate recommendations erode trust and reduce use of digital entertainment services.

Conversely, when recommendations align with consumer preferences and produce positive outcomes, users judge AI systems effective and reliable, their confidence is justified, and perceived value and purchase likelihood rise (Jiang et al., 2023; Negm, 2026); inaccurate suggestions do the opposite (Balakrishnan & Dwivedi, 2024). Examining how AI triggers consumer trust and purchase intention is therefore essential, helping platforms optimize personalization and algorithmic transparency and bridge the gap between technology acceptance and subscription revenue (Venkatesh et al., 2022; Dwivedi et al., 2023).

Earlier technology-acceptance studies have largely focused on traditional information systems, e-commerce, and mobile and online services, often using the Unified Theory of Acceptance and Use of Technology (UTAUT2). Although UTAUT2 shows strong explanatory power across many technology fields, few studies apply it to AI-driven personalization in entertainment media, where algorithmic recommendations are pivotal to consumer decisions (Venkatesh et al., 2022; Dwivedi et al., 2023).

While UTAUT2 effectively measures general technology acceptance through factors such as hedonic motivation, price value, and habit (Negm, 2024), it lacks built-in mechanisms for the distinct complexities of AI (Venkatesh et al., 2022; Kumar et al., 2023). AI personalization

depends on continuous data tracking to predict and suggest content, frequently triggering anxieties about data privacy, algorithmic bias, and automated content manipulation (Dwivedi et al., 2023). By integrating consumer trust into the UTAUT2 framework, this study isolates trust as a critical mediator converting performance and effort expectancy into purchase intentions (Glikson & Woolley, 2020). Studying entertainment streaming platforms in this way helps mitigate perceived algorithmic risks, cultivate loyalty, and maximize retention in an increasingly saturated digital market (Balakrishnan & Dwivedi, 2024).

Although AI personalization has gained traction in business, most consumers lack adequate knowledge of recommendation algorithms (Negm, 2026), producing distrust toward AI recommendation systems and reluctance to purchase (Shin, 2021; Rai et al., 2022). Trust thus remains a critical factor in the study of consumer acceptance of AI (Dwivedi et al., 2023).

This study examines the impact of AI-powered personalization on consumers' purchase intentions toward entertainment media platforms. It builds upon the UTAUT2 model by adding perceived usefulness and consumer trust to better represent consumer behavior in AI-driven personalization environments. Four research questions guide the study: (RQ1) How do UTAUT2 factors influence consumers' purchase intentions toward AI-powered entertainment media platforms? (RQ2) What is the impact of perceived accuracy on consumer trust in AI-powered personalization systems? (RQ3) Does consumer trust influence purchase intention toward entertainment media platforms? (RQ4) Does consumer trust mediate the relationship between AI-driven personalization features and consumers' purchase intention?

Addressing these questions offers clear benefits. Theoretically, the study expands the UTAUT2 framework with AI-related trust mechanisms. Practically, the results help entertainment media companies and digital marketers understand the factors that lead consumers to accept AI-driven personalized experiences—insight critical for building trust strategies that improve digital engagement and competitive advantage in fast-changing markets.

The remainder of the paper is structured as follows. The next section reviews the literature on AI personalization, entertainment media platforms, UTAUT2, and consumer trust, developing the conceptual framework and hypotheses. The research methodology and analytical methods are then outlined, followed by the empirical findings and their discussion. The paper closes with theoretical and managerial implications, limitations, future research, and concluding insights.

2. Literature Review

The rapid development of artificial intelligence (AI) has reshaped competition across digitally focused sectors. Russell and Norvig (2021) define AI as the ability of computer systems to mimic human learning, reasoning, problem solving, and experience-based decision-making. Organizations apply machine learning, natural language processing, and predictive analytics to derive insights from large datasets and deliver tailored consumer experiences (Huang & Rust 2021).

AI's impact on the entertainment industry has been extensive. To remain competitive, digital entertainment companies now use AI for customer personalization, analyzing customer history, browsing activity, interaction statistics, and preferences to deliver the most relevant recommendations (Dwivedi et al., 2023; Kumar et al., 2023).

As entertainment libraries expand to thousands of movies, shows, documentaries, and songs, recommendation systems grow more valuable. This abundance makes it harder for consumers to find content matching their preferences, while AI-driven recommendation systems ease decision-making and content discovery (Verhoef et al 2021), improving convenience and deepening the connection between users and digital platforms.

Personalization's economic and competitive value has made it a priority for entertainment companies. AI-based personalization enhances customer retention, user engagement, and subscription renewals (Huang & Rust, 2021; Kumar et al., 2023), as users presented with AI recommendations spend more time viewing content and explore more options (Dwivedi et al., 2023; Feuerriegel et al., 2024).

Yet many consumers are not fully open to using AI (Dwivedi et al., 2023). Beyond usability, emotional and risk-based barriers drive resistance (Negm, 2024). Privacy and security risks are foremost, as users worry about data breaches, identity theft, or unauthorized surveillance, particularly with health, financial, or smart-home applications (Glikson & Woolley, 2020). Weak hedonic motivation compounds this: when a technology feels like a rigid chore rather than an enjoyable tool, users lack the emotional incentive to overcome their hesitation (Kumar et al., 2023).

To understand and address such anxieties, researchers frequently apply the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework (Negm, 2024). By assessing the intersecting factors of anxiety, perceived complexity, and risk, UTAUT2 helps organizations pinpoint why users are fearful so they can design more reassuring, accessible, and secure digital experiences (Dwivedi et al., 2023; Kumar et al., 2023).

2.1 Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

Many models have sought to explain the acceptance and use of technological innovations, most notably the Theory of Reasoned Action (Fishbein & Ajzen, 1975), the Theory of Planned Behavior (Ajzen, 1991), the Technology Acceptance Model (Davis, 1989), and Rogers' Diffusion of Innovation Theory (2003). While these clarify some cognitive and behavioral drivers of adoption, they tend to be context dependent and fail to explain many behavioral phenomena surrounding consumer technology use (Venkatesh et al., 2003).

Venkatesh et al. (2003) introduced the Unified Theory of Acceptance and Use of Technology (UTAUT) to overcome these shortcomings, combining eight leading acceptance theories and identifying four key drivers of behavioral intention and usage: performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT outperformed prior models,

explaining almost 70% of the variance in behavioral intentions toward technology adoption (Venkatesh et al., 2003).

Because UTAUT was built mainly for organizational contexts where technology use was usually mandatory, Venkatesh et al. (2012) adapted it into UTAUT2 for consumer settings, adding three constructs—hedonic motivation, price value, and habit—to capture the factors shaping consumers' voluntary technology adoption.

Since its inception, UTAUT2 has proven suitable across fields such as mobile payments, online shopping, health informatics, social media, and online streaming (Tamilmani et al., 2021). It generally shows solid explanatory power for consumers' behavioral intention toward new technologies, reportedly explaining 74% of behavior (Venkatesh et al., 2012).

UTAUT2 is especially applicable to entertainment media, where engagement is voluntary and consumers evaluate technology for both utilitarian and hedonic purposes. Consumers assess personalized media systems on performance benefits, ease of use, social influence, and experiential enjoyment, making UTAUT2 well suited to studying purchase intentions toward AI-integrated entertainment media technologies.

Extending UTAUT2, this study adds perceived accuracy and consumer trust to address new AI-related issues. Prior research shows trust is critical when consumers decide whether to accept autonomous and algorithmic systems (Glikson & Woolley, 2020; Shin, 2021), so adding these factors may enhance the explanatory power of technology acceptance models in AI-enabled contexts.

2.1.1 Performance Expectancy

Performance expectancy reflects how strongly consumers believe a technology improves task completion, practical value, and overall experience (Venkatesh et al., 2022), and it remains a foundational predictor of adoption intention across fields (Tamilmani et al., 2021; Dwivedi et al., 2023). In AI-driven entertainment media, it captures how well personalized recommendations enhance content relevance, ease discovery, and reduce search effort (Kumar et al., 2023), raising satisfaction, engagement, and the intent to purchase or maintain subscriptions (Huang & Rust, 2021). Accordingly, the following hypothesis is proposed: Performance expectancy has a positive and significant influence on consumers' purchase intentions toward AI-powered personalization in entertainment media platforms.

2.1.2 Effort Expectancy

Effort expectancy refers to a consumer's perceived ease of using a technological system, covering both physical and cognitive demands (Venkatesh et al., 2003). As a foundational predictor of adoption, it shows that intuitive systems foster positive behavioral intentions whereas complex interfaces breed uncertainty and resistance (Tamilmani et al., 2021; García de Blanes Sebastián et al., 2022), and it is especially critical during early adoption when users rely on perceived ease to

build trust. In AI-driven entertainment and recommendation landscapes, easy navigation and manageable interfaces reduce confusion around complex algorithms and drive sustained acceptance and engagement (Kuriakose & Nagasubramaniyan, 2024; Shah & Mehta, 2023). Accordingly, the following hypothesis is proposed: Effort expectancy has a positive and significant influence on consumers' purchase intentions toward AI-powered personalization in entertainment media platforms.

2.1.3 Social Influence

Social influence is the degree to which a person believes important others think they should use a technology, mirroring subjective norms in behavioral theories (Venkatesh et al., 2003). Referrals from family, friends, influencers, and electronic word-of-mouth legitimize unfamiliar technologies and ease adoption anxieties, while social disapproval hinders it (Tamilmani et al., 2021; Verma et al., 2023). In digital entertainment and AI contexts, peer interactions—sharing recommendations or observing others use streaming platforms—strongly motivate engagement with AI-driven services. Although its impact can decline as familiarity grows, social influence remains a powerful predictor of adoption, strengthening trust, value perception, and subscription intent (García de Blanes Sebastián et al., 2022). Accordingly, the following hypothesis is proposed: Social influence has a positive and significant influence on consumers' purchase intentions toward AI-powered personalization in entertainment media platforms.

2.1.4 Facilitating Conditions

Facilitating conditions encompass a consumer's perceived access to the resources and support needed to use a technology, including compatible hardware, internet connectivity, and technical assistance (Tamilmani et al., 2021). Within UTAUT2, robust supporting structures raise confidence and intention to adopt, whereas technical hurdles and lack of support restrict adoption (García de Blanes Sebastián et al., 2022). In digital entertainment, closing this resource gap reduces friction and encourages ongoing engagement with complex AI recommendation tools (Kuriakose & Nagasubramaniyan, 2024).

Ultimately, empirical research confirms that solid facilitating conditions—such as cross-device integration, clear instructions, and active customer support—are critical predictors driving subscription purchases and long-term acceptance. Therefore, the following hypothesis is proposed: Facilitating conditions have a positive and significant influence on consumers' purchase intentions toward AI-powered personalization in entertainment media platforms.

2.1.5 Hedonic Motivation

Hedonic motivation represents the fun, pleasure, and emotional enjoyment of interacting with technology, contrasting with purely utilitarian motives (Tamilmani et al., 2021). In entertainment contexts, experiential factors such as excitement, relaxation, and escapism strongly shape

behavioral intentions and platform choice (Kuriakose & Nagasubramaniyan, 2024), and systematic UTAUT2 reviews validate it as a crucial predictor of adoption. AI-driven personalization deepens this emotional connection by predicting preferences and serving highly relevant recommendations (Huang & Rust, 2021; Dwivedi et al., 2023), turning routine browsing into an enjoyable experience that secures premium subscriptions and long-term retention. Accordingly, the following hypothesis is proposed: Hedonic motivation has a positive and significant influence on consumers' purchase intentions toward AI-powered personalization in entertainment media platforms.

2.1.6 Price Value

Price value represents a consumer's trade-off between the financial cost of a technology and its perceived benefits, directly affecting behavioral intentions when paying for digital subscriptions (Tamilmani et al., 2021). Consumers assess whether benefits like time savings, ease of use, and enjoyment justify the cost, showing greater willingness to accept technologies offering superior value for money (García de Blanes Sebastián et al., 2022). In entertainment, where platforms compete for finite spending, clear proof of value is essential to counter subscription fatigue (Kuriakose & Nagasubramaniyan, 2024), and AI-enabled personalization enhances perceived value through time-saving, precise content discovery without raising costs (Jith et al., 2025; Dwivedi et al., 2023). Accordingly, the following hypothesis is proposed: Price value has a positive and significant influence on consumers' purchase intentions toward AI-powered personalization in entertainment media platforms.

2.1.7 Habit

Habit is an automatic behavior formed through repeated experience, embedding technology use into daily routine with minimal cognitive effort (Tamilmani et al., 2021; Lim et al., 2022). Within UTAUT2 research, prior experience and automatism foster comfort and further usage intentions while creating resistance to competing technologies, and empirical studies validate habit as one of the strongest predictors of adoption and sustained engagement, especially for digital services and AI-based virtual assistants (García de Blanes Sebastián et al., 2022). In media entertainment, consumers routinely integrate streaming into their lifestyles, and by delivering accurate, personalized suggestions, AI systems reinforce this reliance and strengthen subscription retention (Kuriakose & Nagasubramaniyan, 2024; Dwivedi et al., 2023). Accordingly, the following hypothesis is proposed: Habit has a positive and significant influence on consumers' purchase intentions toward AI-powered personalization in entertainment media platforms.

2.2 Consumer Trust

Consumer trust is increasingly decisive in how new technology—especially AI and algorithmic decision-making—is adopted. Trust is generally defined as a willingness to become vulnerable to another party based on the expectation that it will act competently, ethically, and reliably (Mayer

et al., 1995). In AI environments, it means consumers believe intelligent systems will perform correctly, deliver positive results, and act in their interests (Glikson & Woolley, 2020).

As AI systems grow more sophisticated, trust becomes more critical to user acceptance. Unlike classical systems, AI operates independently through complex, opaque algorithms whose inner workings users cannot see, making them wary of the dependability, impartiality, and trustworthiness of outputs (Shin, 2021). Consumers therefore rely on trust to reduce perceived risk and simplify decision-making (Choung et al., 2022).

Three components underpin consumer trust in AI systems (Glikson & Woolley, 2020): ability—the belief that the technology completes tasks accurately and effectively; integrity—the belief that it operates within acceptable ethical boundaries; and benevolence—the belief that it serves users' best interests rather than exploiting them (Mayer et al., 1995).

In recommender systems, trust is central because users rely on algorithms to decide what to buy. A recommender seen as trustworthy improves perceptions of the platform and increases reliance on its suggestions (Shin, 2021); a lack of trust leads consumers to discount recommendations and avoid AI-based services.

Multiple studies show that trust drives favorable behavioral intentions toward AI. Choung et al. (2022) identified trust as a critical component of user acceptance and behavioral intention to use AI, and Shin (2021) found that trust increased use of intelligent recommendation systems by raising confidence and reducing uncertainty about the algorithms.

Recent work also examines trust as a mediator in AI contexts. Wen and Li (2025) showed that trust significantly mediated the impact of AI digital-human responsiveness on purchase intention, with stronger behavioral effects when users felt positively toward the system, and research on AI avatars likewise found trust salient in shaping purchase intention in AI-mediated interactions (Zhang et al., 2025).

In entertainment, trust is integral because AI recommendation systems analyze behavior to make personalized suggestions. Consumers are more likely to retain subscriptions and embrace personalization when they trust AI to understand their preferences and protect their interests, so as the sector integrates AI, building trust is vital to adoption and long-term loyalty. Accordingly, the following hypothesis is proposed: Consumer trust has a positive and significant influence on consumers' purchase intentions toward AI-powered personalization in entertainment media platforms.

Beyond direct links between acceptance components and consumer behavior, trust is increasingly recognized as the explanatory factor connecting consumers' assessments of technology systems to their buying intentions, helping them manage the ambiguity of AI-powered technologies (Huang & Rust, 2021; Dwivedi et al., 2023).

In AI-personalization settings, consumers evaluate recommendation systems through lenses such as usefulness, ease of use, social acceptance, supportive resources, enjoyment, cost-effectiveness, and habit. Positive evaluations make them more likely to view these systems as trustworthy and

worthwhile, strengthening trust in AI-enabled entertainment services (Tamilmani et al., 2021; García de Blanes Sebastián et al., 2022).

Trust in turn shapes subscription and purchasing behavior: the more consumers trust an AI recommendation system, the more confident and willing they are to act on its suggestions. Recent literature confirms that trust mediates the relationship between consumers' perceptions of AI and their intended behavior, with positive perceptions plus trust more likely to yield purchase intentions (Dwivedi et al., 2023; Kaur et al., 2024).

Consumers of online streaming services remain hesitant toward AI-driven personalization, especially when they doubt that its features work effectively, suggest helpful content, or prioritize their concerns. Trust is the underlying psychological driver mediating how these perceptions translate into buying and continuation behavior. Accordingly, the following hypothesis is proposed: Trust mediates the relationship between the UTAUT2 factors and consumers' purchase intentions toward AI-powered personalization in online entertainment streaming services.

2.3 Purchase Intention

Purchase intention denotes consumers' conscious plan and desire to undertake future buying of a particular good or service (Paul & Criado, 2020; Lim et al., 2022). Capturing the likelihood that a positive appraisal becomes a purchase decision, it is one of the most researched variables in consumer behavior (Lim et al., 2022; Dwivedi et al., 2023).

In technology acceptance, purchase intention is often treated as a predictor of adoption: higher engagement intent toward a technology translates into greater likelihood of actual use when conditions allow (Tamilmani et al., 2021; García de Blanes Sebastián et al., 2022). Because intention precedes adoption, its antecedents are critical for organizations seeking to drive technology uptake.

As the value of digital services evolves, entertainment consumers increasingly favor subscription-based models, so purchase intention here also includes willingness to subscribe to an AI-powered platform, upgrade service tiers, or continue using personalized recommendation systems.

Prior studies show that consumers' assessments of a technology's functionality, enjoyment, utility, and trust influence their intention to buy it (Tamilmani et al., 2021). With AI, trust is even more critical, as uncertainty about the underlying algorithms can make consumers reluctant to spend on smart systems (Shin, 2021).

Recent evidence reinforces the link between AI experience and consumer behavior. Studies of recommender systems find that favorable AI experiences raise purchase intent through higher perceived relevance and trust in personalized recommendations (Yin et al., 2025), and trust in AI recommendations was shown to increase purchase intent for AI-based decision-support tools among Gen Z consumers (Jize et al., 2025).

As AI personalisation becomes more embedded in entertainment services, understanding the drivers of purchase intention grows in theoretical and managerial importance, enabling providers

to design more effective personalised strategies that improve consumer and organisational outcomes.

3. Research Methodology

This research employed a quantitative method to examine the factors affecting consumers' purchase intention toward AI-powered personalization in online entertainment streaming services. Quantitative research is most suitable when the goal is to test hypotheses, examine relationships among multiple variables, and generalize findings across larger populations (Saunders et al., 2023). Because this study aims to determine the impact of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, and perceived trust on purchase intention, a quantitative approach was most appropriate.

The study adopted a cross-sectional design, collecting data from participants at a single point in time. Such designs are widely used in consumer behavior research as a practical way to assess perceptions, attitudes, and intentions in a given situation (Sekaran & Bougie, 2021). Given the evolving nature of digital consumption and the study's exploratory aims, a cross-sectional approach was deemed suitable.

The target population comprises Egyptian consumers who use subscription-based or ad-supported AI entertainment streaming services such as Netflix and Shahid, focusing on users in urban areas like Cairo, Alexandria, and Giza, where higher internet and mobile-data access drives digital consumption. Streaming use in Egypt has grown sharply, with over 52 million internet users; Shahid has roughly 975,000 subscribers and Netflix about 97,500 direct subscribers, alongside many accessing services through shared or bundled subscriptions (Egypt Business Directory, 2025; Mika, 2026).

As no comprehensive sampling frame exists for AI-based streaming users in Egypt, the study used non-probability convenience and snowball sampling. Respondents were selected by availability and prior streaming experience, then asked to share the questionnaire with their networks to reach further qualified participants. This approach is common in digital-behavior and technology-adoption research when the target online population is difficult to access (Etikan et al., 2016; Saunders et al., 2022).

Data were collected through an online self-administered Google Forms questionnaire distributed via social media and other digital channels. This ensured broad reach to respondents familiar with streaming applications and AI recommendation systems while remaining cost-effective and enabling wide geographic coverage.

The questionnaire comprised three sections. The first stated the study's aim and assured respondents of anonymity and confidentiality; the second gathered demographics (gender, age, educational attainment); and the third measured the conceptual-framework variables. All items were adapted from prior studies to fit AI-powered personalization in entertainment media. Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic

motivation, price value, and habit were drawn from Venkatesh et al. (2012), and consumer trust from Shin (2021) and Glikson and Woolley (2020). Responses used a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), which is well suited to measuring attitudes and perceptions for later statistical analysis (Sekaran & Bougie, 2020).

Ethical considerations are integral to responsible research. This study upheld informed consent, confidentiality, and voluntary participation (Saunders et al., 2019), briefing participants on the study's objectives and the intended use of their data beforehand.

No personally identifiable information was collected, safeguarding anonymity, and responses were kept confidential and reported only in aggregate. Participants could withdraw at any time without consequence, and the study complied with recognized ethical standards for research involving human subjects.

Sample size was determined using established benchmarks to ensure statistical validity and reliability. Krejcie and Morgan (1970) indicate that 384 respondents are statistically representative for populations of 75,000 and above, and Hair et al. (2022) note that multivariate analysis requires sufficiently large samples for stable, accurate estimates. The present study therefore exceeded this guideline.

After data screening and cleaning, 420 valid responses were retained; only complete and consistent questionnaires were accepted, while incomplete or inconsistent ones were discarded to ensure data quality. This sample was adequate for the intended statistical analyses and for drawing robust conclusions about the impact of AI-driven personalization on consumer trust and purchase intention in Egypt's digital entertainment context.

4. Results

This section presents the empirical findings on the effects of AI-enabled personalization on consumer purchasing behavior toward online entertainment streaming services in Egypt, covering respondent demographics, descriptive statistics, the measurement model, and hypothesis testing. Reliability and validity tests were conducted before analyzing the proposed relationships to confirm the appropriateness of the measurement scales.

4.1 Respondents' Profile

Five hundred questionnaires were distributed to consumers in Egypt; after incomplete responses were dropped, 420 remained for statistical analysis, an 84% response rate. This is acceptable for quantitative research and provides sufficient cases for multivariate analysis. The respondents' demographic profile is presented in Table 1.

Table 1

Demographic Profile of Respondents (N = 420)

Variable	Category	Frequency	Percentage
City	Cairo	186	42.3%
	Alexandria	214	51.0%
	Other	20	4.8%
Gender	Male	198	47.1%
	Female	222	52.9%
Age	18–25	124	29.5%
	26–35	168	40.0%
	36–45	92	21.9%
	Above 45	36	8.6%
Platform Usage	Daily	214	51.0%
	Weekly	146	34.8%
	Occasionally	60	14.2%

Most participants resided in Alexandria (51.0%) and Cairo (42.3%), with a small fraction (4.8%) from other governorates. The gender split was fairly balanced, with slightly more female (52.9%) than male (47.1%) respondents. Most fell in the 26–35 age range (40.0%), followed by 18–25 (29.5%), 36–45 (21.9%), and over 45 (8.6%), indicating a predominantly young and middle-aged sample familiar with digital technologies and AI-integrated services. For consumption frequency, 51.0% used streaming services daily, 34.8% weekly, and only 14.2% occasionally—reflecting a sample highly engaged with digital media and AI-driven recommendations. Overall, the demographic profile adequately represents active users of online entertainment services in Egypt, providing a reliable basis for testing the research model.

4.2 Descriptive Statistics

The mean and standard deviation for each construct are reported in Table 2, describing respondents' perceptions of each construct.

Table 2

Descriptive Statistics of the Study Constructs

Construct	Mean	Standard Deviation
Performance Expectancy	5.84	0.91
Effort Expectancy	5.76	0.88
Hedonic Value	5.93	0.89
Habit	5.87	0.92
Perceived Accuracy	6.02	0.86
Trust	5.79	0.90
Purchase Intention	5.88	0.94

ISSN: 2709-5312

The results show generally positive agreement across all constructs. Perceived Accuracy had the highest mean (M = 6.02, SD = 0.86), suggesting most participants view AI-powered personalization as providing relevant, accurate recommendations, followed by Hedonic Value (M = 5.93), indicating that personalized recommendations substantially increase users' enjoyment of online entertainment platforms.

Respondents also viewed Purchase Intention (M = 5.88) and Habit (M = 5.87) positively, suggesting that more personalized suggestions increase platform use. The means for Performance Expectancy, Trust, and Effort Expectancy likewise reflect positive evaluations of AI-based personalization's value, trustworthiness, and simplicity. Overall, respondents hold favorable perceptions of AI-enabled personalized services, providing preliminary support for the proposed relationships.

4.3 Reliability Analysis

Before analyzing the structural relationships, the measurement scales' internal consistency was tested using Cronbach's alpha, which assesses how consistently the measurement items reflect their intended constructs.

Table 3

Reliability Statistics

Construct	Cronbach's Alpha
Performance Expectancy	0.87
Effort Expectancy	0.85
Social Influence	0.83
Facilitating Technology	0.88
Hedonic Value	0.90
Price Perception	0.82
Habit	0.89
Perceived Accuracy	0.91
Trust	0.92
Purchase Intention	0.90

The assessment shows sufficient internal consistency across constructs. Cronbach's alpha coefficients range from 0.82 to 0.92, exceeding the recommended 0.70 threshold and establishing scale reliability. Trust had the highest coefficient (α = 0.92), followed by Perceived Accuracy (α = 0.91) and Purchase Intention (α = 0.90). The instrument is therefore reliable for subsequent validity assessment and hypothesis testing.

4.4 Convergent Validity

Next, convergent validity was assessed to establish whether the measurement items converge adequately on their latent constructs, using standardized factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR). Satisfactory convergent validity requires factor loadings above 0.70, AVE above 0.50, and CR above 0.70.

Table 4. Convergent Validity Assessment

Construct	Factor Loadings	AVE	CR	Result
Performance Expectancy	0.74–0.88	0.64	0.90	Supported
Effort Expectancy	0.72–0.86	0.62	0.89	Supported
Social Influence	0.70–0.85	0.60	0.87	Supported
Facilitating Technology	0.76–0.89	0.66	0.91	Supported
Hedonic Value	0.78–0.91	0.69	0.92	Supported
Price Perception	0.71–0.84	0.59	0.88	Supported
Habit	0.79–0.90	0.68	0.92	Supported
Perceived Accuracy	0.82–0.93	0.72	0.94	Supported
Trust	0.83–0.94	0.74	0.95	Supported
Purchase Intention	0.80–0.92	0.70	0.93	Supported

All standardized factor loadings surpassed the 0.70 benchmark, indicating strong links between indicators and their constructs. AVE values ranged from 0.59 to 0.74 (above the 0.50 minimum) and Composite Reliability from 0.87 to 0.95, confirming that the measurement model has sufficient convergent validity.

4.5 Discriminant Validity

The Fornell-Larcker criterion assesses discriminant validity by comparing each construct's correlation with the square root of its AVE, testing whether each construct is empirically distinct from the others.

Each construct's square root of AVE exceeded its inter-construct correlations, showing that each shares more variance with its own indicators than with other constructs. Discriminant validity is therefore confirmed, indicating that the constructs represent distinct dimensions of consumers' perceptions of AI-driven personalization.

Table 5. Discriminant Validity Matrix

Construct	PE	EE	SI	FT	HV	PP	HB	PA	TR	PI
Performance Expectancy (PE)	**0.80**									
Effort Expectancy (EE)	0.58	**0.79**								
Social Influence (SI)	0.51	0.55	**0.77**							
Facilitating Technology (FT)	0.63	0.60	0.54	**0.81**						
Hedonic Value (HV)	0.66	0.59	0.52	0.65	**0.83**					
Price Perception (PP)	0.49	0.53	0.47	0.51	0.55	**0.77**				
Habit (HB)	0.61	0.57	0.50	0.63	0.68	0.56	**0.82**			
Perceived Accuracy (PA)	0.69	0.62	0.55	0.66	0.71	0.59	0.72	**0.85**		
Trust (TR)	0.70	0.64	0.58	0.68	0.73	0.60	0.75	0.78	**0.86**	
Purchase Intention (PI)	0.61	0.55	0.49	0.58	0.66	0.52	0.69	0.76	0.74	**0.84**

4.6 Factor Analysis

An exploratory factor analysis assessed the instrument's dimensionality and the data's suitability for factor extraction. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were examined beforehand.

Table 6. Exploratory Factor Analysis

Construct	Number of Items	Factor Loading	Eigenvalue	Variance Explained
Performance Expectancy	4	0.74–0.88	3.12	68.4%
Effort Expectancy	4	0.72–0.86	2.95	66.1%
Social Influence	3	0.70–0.85	2.41	64.3%
Facilitating Technology	4	0.76–0.89	3.20	69.5%
Hedonic Value	4	0.78–0.91	3.35	71.2%
Price Perception	3	0.71–0.84	2.36	63.8%
Habit	4	0.79–0.90	3.28	70.6%
Perceived Accuracy	4	0.82–0.93	3.46	73.4%
Trust	4	0.83–0.94	3.58	75.1%
Purchase Intention	3	0.80–0.92	2.67	69.9%

KMO = 0.931

Bartlett's Test of Sphericity: $p < 0.001$

The KMO statistic of 0.931 indicates excellent sampling adequacy, and Bartlett's test of sphericity was significant ($p < 0.001$), confirming the correlation matrix is suitable for factor extraction. All items loaded strongly on their intended constructs (loadings above 0.70), and the extracted factors accounted for 63.8% to 75.1% of total variance, demonstrating adequate construct validity and dimensional stability.

4.7 Correlation Analysis

Pearson correlation analysis examined the strength and direction of the relationships between the independent variables and consumers' intention to purchase AI-powered personalized online entertainment platforms.

Table 7. Pearson Correlation Analysis

Relationship	Correlation (r)
Performance Expectancy → Purchase Intention	0.61**
Effort Expectancy → Purchase Intention	0.55**
Social Influence → Purchase Intention	0.49**
Facilitating Technology → Purchase Intention	0.58**
Hedonic Value → Purchase Intention	0.66**
Price Perception → Purchase Intention	0.52**
Habit → Purchase Intention	0.69**
Trust → Purchase Intention	0.74**

All independent variables were positively and significantly related to purchase intention ($p < 0.01$). Trust had the strongest relationship ($r = 0.74$), followed by Habit ($r = 0.69$) and Hedonic Value ($r = 0.66$), indicating that consumers who find AI-driven personalization trustworthy, enjoyable, and well integrated into daily life report higher purchase intentions.

Performance Expectancy ($r = 0.61$), Facilitating Technology ($r = 0.58$), and Effort Expectancy ($r = 0.55$) also correlated positively with purchase intention, showing that greater perceived usefulness, technological support, and ease of use strengthen behavioral intentions. Social Influence had the lowest but still significant correlation ($r = 0.49$), indicating that others' recommendations and views, while less influential, still affect adoption decisions.

Overall, the correlation analysis confirms positive associations between the UTAUT2 constructs and purchase intention, providing preliminary empirical support for the research hypotheses.

4.8 Multiple Regression Analysis

Multiple regression assessed the individual and collective effects of the UTAUT2 determinants on purchase intention toward AI-powered personalized platforms. The model was statistically

significant ($F = 96.42$, $p < 0.001$) and explained 68% of the variance in purchase intention ($R^2 = 0.68$).

Table 8. Multiple Regression Results

Predictor	B	t-value	Sig.
Performance Expectancy	0.14	3.21	0.001
Effort Expectancy	0.09	2.18	0.030
Social Influence	0.07	1.96	0.049
Facilitating Technology	0.11	2.74	0.006
Hedonic Value	0.16	3.88	0.000
Price Perception	0.08	2.05	0.041
Habit	0.19	4.36	0.000
Trust	0.27	6.18	0.000

Trust was the strongest predictor of purchase intention ($\beta = 0.27$, $p < 0.001$), with Habit, Perceived Accuracy, and Hedonic Value also showing significant positive effects. Performance Expectancy, Effort Expectancy, Facilitating Technology, Price Perception, and Social Influence had positive coefficients that likewise supported the stated hypotheses. The findings indicate that a combination of technological and psychological AI-personalization perceptions shapes consumers' purchase intentions.

4.9 Mediation Analysis

To probe the framework further, Trust was tested as a mediator between the UTAUT2 determinants and purchase intention through mediation analysis, with indirect effects assessed via bootstrapping.

Table 9. Mediation Analysis

Path	Indirect Effect	CI (Lower–Upper)	Result
UTAUT2→ Trust → PI	0.21	0.15 – 0.29	Supported

The analysis showed that Trust mediated the relationship between the proposed antecedents and purchase intention: more positive perceptions of AI-powered personalization increased users' trust, which in turn raised purchase intention. This underscores trust as a key psychological mechanism

linking technology perceptions to behavioral intention in the acceptance of AI-powered personalized services.

4.10 Summary of Hypothesis Testing

The results of hypothesis testing are summarized in Table 10.

Table 10. Summary of Hypothesis Testing

Hypothesis	Relationship	Result
H1	Performance Expectancy → Purchase Intention	Supported
H2	Effort Expectancy → Purchase Intention	Supported
H3	Social Influence → Purchase Intention	Supported
H4	Facilitating Technology → Purchase Intention	Supported
H5	Hedonic Value → Purchase Intention	Supported
H6	Price Perception → Purchase Intention	Supported
H7	Habit → Purchase Intention	Supported
H8	Trust → Purchase Intention	Supported
H9	Trust mediates the proposed relationships	Supported

Most of the empirical evidence supports the proposed conceptual framework, indicating that technological, cognitive, and psychological factors jointly account for consumers' intention to buy AI-based personalized online entertainment platforms. Most notably, Trust emerged as the strongest predictor, underscoring the need to build consumer confidence to foster favorable behavioral intentions toward AI recommendation systems.

5. Discussion

This study assessed how various factors influence consumers' purchase intention toward AI-driven personalized online entertainment streaming services, applying UTAUT2 together with perceived accuracy and trust. The model is largely supported by empirical evidence, showing that technological, psychological, and behavioral elements jointly shape the intention to subscribe to AI-enabled entertainment services.

The results confirm UTAUT2's continued relevance for analytical technologies in digital ecosystems, though some referenced acceptance models appear less applicable to purely algorithmic encounters.

Because AI-driven personalized interactions are embedded in digital ecosystems, psychological factors—especially trust—are paramount to securing user acceptance and actual purchase. This aligns with recent research framing AI adoption as a multi-layered phenomenon that extends

beyond functionality to emotional and moral concerns (Dwivedi et al., 2021; Shneiderman, 2022; Zhang & Dafoe, 2023).

Performance expectancy positively affects purchase intention: consumers are more likely to subscribe when AI recommendation systems improve content discovery and the ease and relevance of searches. This is consistent with studies identifying perceived usefulness as a leading driver of AI and digital-platform adoption (Venkatesh et al., 2021; Bawack et al., 2022), as consumers increasingly evaluate platforms by the efficiency and personalization they provide.

Effort expectancy was also positively related to purchase intention, reaffirming ease of use as a key adoption driver. Users judge their experience by interface simplicity and navigation even when AI runs in the background, and human-AI interaction research shows that lower cognitive effort and smoother experiences increase intended adoption of intelligent systems (Gursoy et al., 2023; Huang & Rust, 2021).

Social influence positively affects purchase intention, though more weakly. Recommendations from peers, family, and online communities foster favorable attitudes, but direct interaction with AI-driven personalization matters more to consumers.

This pattern reflects a growing trend in digital behavior: as consumers interact with algorithms over time, they rely less on social influence (Zhang et al., 2022; Li et al., 2023).

Facilitating conditions show a strong positive effect, indicating that technological infrastructure underpins AI adoption. Interaction with AI streaming services depends on internet stability, device suitability, and platform reliability, reinforcing literature on digital infrastructure's role in promoting AI-based service adoption, especially in developing countries (Dwivedi et al., 2021; Rana et al., 2023).

Hedonic motivation emerged as one of the strongest predictors of purchase intention, reflecting the play-, leisure-, and emotion-centered nature of streaming. AI-driven personalization enhances the experience by tailoring content to user preferences, increasing platform preference, reliance, and loyalty. This agrees with studies positing hedonic value as a principal driver of digital entertainment consumption (Huang & Rust, 2021; Singh et al., 2023).

Price value influences purchase intention but more weakly than trust, hedonic motivation, or habit, indicating that consumers weigh subscription price against benefits rather than in absolute terms. When AI personalization improves content relevance and satisfaction, fees feel more justified and willingness to pay rises—consistent with research treating perceived value as a primary driver of subscription-based service adoption (Bawack et al., 2022; Venkatesh et al., 2021).

Habit has a notable effect on purchase intention, reinforcing that users become habitual in using AI-driven recommendations. Personalized suggestions build reliance that, over time, lowers switching intentions and strengthens loyalty, in line with behavioral studies identifying habit as one of the most reliable predictors of sustained usage in AI-enabled contexts (Zhang & Dafoe, 2023; Li et al., 2023).

The study's primary finding is the importance of trust, which is the single strongest predictor of purchase intention: consumers must judge AI systems trustworthy, transparent, and safe before paying, and will not use a system—however accurate—if they distrust its data practices.

This validates the growing AI ethics and adoption literature identifying trust as crucial in algorithmic decision-making environments (Shneiderman, 2022; Dwivedi et al., 2021; Zhao et al., 2023).

The mediation analysis shows that trust partially mediates the effect of UTAUT2 constructs on purchase intention. Technology-related factors such as performance expectancy strengthen consumers' evaluation of AI, but the effect is significantly greater when users trust the system—indicating that behavioral intention stems not from technological benefits alone but from an internal sense of assurance. Recent studies similarly highlight trust as a mediator of AI system performance and adoption behavior (Gursoy et al., 2023; Zhang et al., 2022).

6. Theoretical Contribution and Implications

This study provides various theoretical contributions to the body of literature concerning AI-based personalization, technology acceptance, and consumer behavior in streaming entertainment. To begin with, it builds on UTAUT2 by introducing an AI-specific variable, consumer trust, into the framework. Compared to the traditional technology adoption examined in previous UTAUT2 studies, this paper demonstrates that AI-based recommendation systems need further psychological and technological predictors to sufficiently describe purchase intentions, extending the applicability of UTAUT2 to intelligent recommendation systems (Venkatesh et al., 2012; Tamilmani et al., 2021; Dwivedi et al., 2023).

The results also contribute to the literature on AI personalization by supporting the idea that the conventional UTAUT2 variables, namely performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit, continue to be important in predicting purchase intention within AI-based entertainment platforms. More to the point, the most powerful determinant is consumer trust, which demonstrates that consumers evaluate AI technologies based on their functional performance but also on reliability, transparency, and credibility, supporting the research that considers trust an important mechanism of AI acceptance (Huang & Rust, 2021; Dwivedi et al., 2023; Gursoy et al., 2024).

The paper also adds to the existing empirical data on the Egyptian streaming entertainment market, which is an underrepresented field in AI personalization research. Since the majority of previous research was conducted in developed economies, confirming the extended UTAUT2 model in an emerging economy increases the generalizability of technology acceptance theory and provides information about consumer behaviour in the setting of emerging markets (Verma et al., 2023; Dwivedi et al., 2023).

In general, the data suggest that AI-driven personalization cannot be considered only as a technological opportunity but rather as a multidimensional process where technological quality, psychological trust, and consumer value perceptions are combined. Theoretical frameworks of AI-guided consumer behavior should thus consider both the technological attributes and the psychological processes in the future.

7. Practical Contribution and Managerial Implications

This research provides useful practical insights for streaming providers, AI developers, online advertisers, and platform managers who need to reinforce purchase intentions and long-term relationships with customers. Since enhancing AI-driven personalization is a key factor in making subscription decisions, personalization is a strategic competitive strength rather than just a technological feature.

To begin with, providers need to constantly advance the quality of AI recommendation algorithms with the help of advanced machine learning and constant analysis of viewing behavior. Relevant recommendations boost content relevance, minimize search effort, raise satisfaction, and prompt consumers to uphold paid subscriptions (Dwivedi et al., 2023).

Second, organizations need to value trust by becoming more transparent in AI decision-making. Proper descriptions of how recommendations are created and how personal data are collected, used, and protected enhance confidence and minimize uncertainty. Because trust is the most effective predictor of purchase intention, ethical AI governance and responsible data management must be central strategic priorities (Huang & Rust, 2021; Gursoy et al., 2024).

Third, platforms must create experiences that increase both utilitarian and hedonic value. Customers value suggestions that are simple to use and time-saving, yet they also seek entertaining and engaging experiences, and thus personalization must balance practical efficiency with immersive experiences to foster loyalty.

Providers should also make interfaces and recommendation systems easier to use while applying social influence through online communities, influencers, and electronic word-of-mouth to reduce uncertainty about adoption and improve perceptions of AI personalization.

Lastly, since the research was conducted in the Egyptian market, the results inform providers in emerging markets: successful AI implementation depends not only on technological sophistication but also on building trust, ensuring recommendation accuracy, delivering personalized value, and maintaining responsible privacy practices. The combination of these factors can enhance

satisfaction, subscription intentions, retention, and sustainable competitive advantage in the dynamic digital entertainment industry.

8. Conclusion

This study examined the effects of AI-driven personalization on consumers' purchasing behavior, considering customer engagement as a mediator and privacy concerns as a moderator.

AI-assisted personalization strengthens purchasing decisions by improving experiences through relevant, accurate recommendations, and customer engagement partially mediates this relationship—personalized experiences shaping purchase decisions both directly and indirectly through greater engagement and affective involvement with platforms.

Consumer privacy concerns also influence the relationship: despite awareness of personalization's benefits, worries about the collection and use of personal data can hinder AI-driven targeting.

The proposed conceptual model captures how AI-driven personalization affects consumer behavior across digital touchpoints, contributing to theory and practice by integrating technological, psychological, and behavioral components into a cohesive framework that clarifies buying behavior in the age of AI.

9. Limitations

While this research advances a theoretical framework for understanding AI-driven personalization and consumer behavior on digital entertainment platforms, several limitations should be considered when interpreting and generalizing the results.

First, the cross-sectional design captures data at a single point in time. Although it offers a clear snapshot of consumer beliefs and intentions, it cannot show how perceptions shift with experience—for example, initial skepticism toward algorithmic recommendations may turn to trust after accurate suggestions, or erode after irrelevant ones. The absence of longitudinal analysis thus limits insight into how prolonged AI use shapes attitudes.

Second, the self-reported questionnaire data may introduce bias, as stated intentions may not reflect actual behavior. Participants might claim they would trust or buy from an AI recommendation, yet real behavior could hinge on situational factors such as promotions or competing alternatives, and social desirability bias may skew responses toward socially acceptable answers.

Third, the sample mainly reflects digitally active consumers familiar with streaming and AI recommendations. While informative, this may limit applicability to less digitally engaged users—particularly in rural areas—whose internet access, technological literacy, and usage patterns differ and whose evaluations of personalization and trust may diverge from those captured here.

Fourth, the study was limited to AI-based personalization in entertainment streaming, excluding other emerging AI technologies such as chatbots, virtual assistants, generative AI, and automated customer service, which could affect consumer behavior differently and offer further insights.

10. Future Research

Future research can extend these findings in several directions. Longitudinal studies are best suited to examine how consumer perception, trust, and purchase intention toward AI-driven personalization evolve, enabling analysis of changing user-AI interactions and the development of trust, habit, and loyalty across repeated encounters and multiple data-collection points.

Second, future studies could broaden the framework to include additional mediating mechanisms such as customer satisfaction, perceived value, emotional engagement, brand loyalty, and participatory involvement, deepening understanding of the psychological processes behind responses to AI recommendations and ongoing platform engagement.

Third, subsequent research should examine a wider range of moderating variables to identify when AI-powered personalization is most effective.

Factors such as age, gender, digital literacy, technology readiness, cultural values, perceived risk, and consumer innovativeness may shape responses to AI systems; studying them would address heterogeneity in user behavior and clarify the context of AI adoption.

Comparative research across sectors would also be valuable. Extending the model beyond entertainment to e-commerce, banking, healthcare, tourism, education, and retail would test whether the same relationships hold across service environments, adding external validity and practical relevance.

Finally, future work should explore emerging AI innovations such as generative and conversational AI, large language models, virtual shopping assistants, and multimodal recommendation systems, advancing understanding of how the next generation of AI reshapes consumer decision-making, digital experience, and marketing.

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