

CHAPTER I INTRODUCTION

1.1 Research Background

The rapid adoption of Artificial Intelligence (AI) has become mainstream across the globe, broadly designed to assist humans with their tasks and improve quality of life (Briskman, 2025; Russell & Norvig, 2021). One significant type of AI at the moment is Generative Artificial Intelligence (GenAI), which refers to an artificial intelligence system that produces content in texts, images, audios and more (Kshetri, 2025) Artificial Intelligence had long existed as a specialized technology, the launch of OpenAI's ChatGPT in 2022 marked a major milestone in the development of Generative AI adoption. Since then, AI has become increasingly integrated across industries, reshaping how individuals, organizations and societies work.

By early 2025, accumulated estimation from multiple Generative AI, the Global Active User for Generative AI lies between 115 million and 180 million individuals (Guadamuz, 2025). Singla et al. (2024) through Mckinsey.com survey shows that AI adoption in businesses increased from 55% in 2023 to 72% in 2024, while the adoption of Generative AI nearly doubled to 65% in the same period.

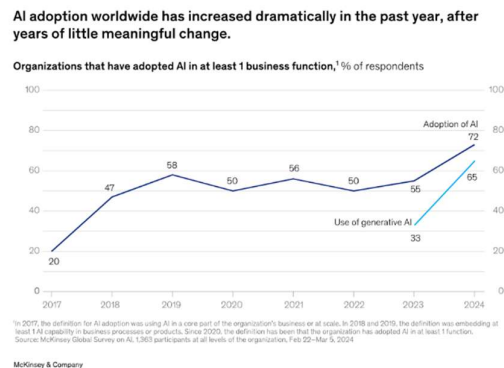


Figure 1. 1 Organizations that have adopted AI in at least 1 business function

Source: <https://www.mckinsey.com/>

The usage of AI is not limited towards only one type of organization or industry. Data from Sensortower.com (2025), on ChatGPT's US usage patterns (Q2

2024-Q2 2025) show sustained categories such as Work and Education, indicating that these remain core drivers of AI tool utilization.

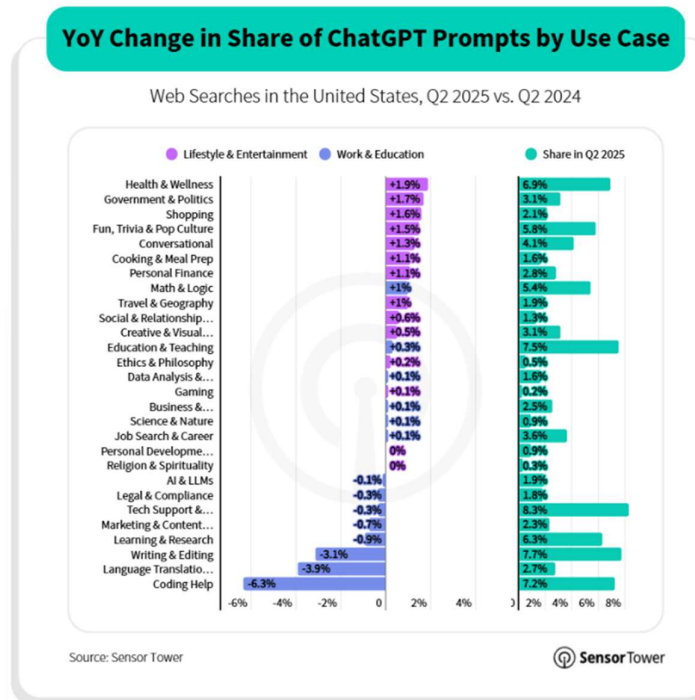


Figure 1. 2 Prompts data of ChatGPT in the US, Q2 2025 vs Q2 2024
 Source: <https://sensortower.com/blog/state-of-ai-apps-report-2025>

Within the education sector, the Global Student Survey 2025 by Chegg Inc. (2025) found that 80% of student respondents had used Generative AI to support their universities tasks. Remarkably, Indonesia ranked among the top five countries in terms of AI adoption rates, moreover, showing that students use Generative AI as academic tasks support. Students increasingly use Generative AI to complete tasks across subjects and other materials, making this technology as a tool integrated into the student’s academic routines.

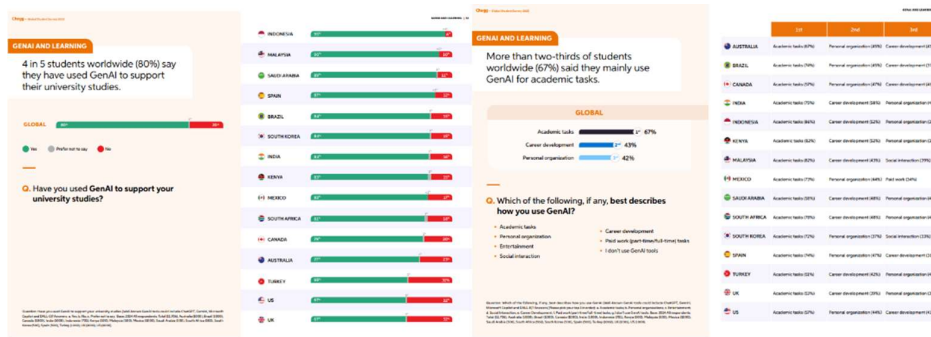


Figure 1.3 GenAI and Learning usage Global Student Survey Chegg 2025
Source: <https://www.chegg.org/global-student-survey-2025>

The scale of this is not random. Generative AI is estimated to generate \$2.6 trillion to \$4.4 trillion in value across industries, which increases businesses economic benefits (Chui et al., 2023). This potential leads to competitions among major tech companies such as Microsoft, Google, Amazon, and others within the technology industry. Beyond technological development and company investments (Michaels, 2024; Ponciano, 2025; Carugati, 2023), competition increasingly involves brand positioning and user trust, implying the importance of marketing in the AI industry (Nellis, 2025). As platforms continue to introduce new features and extensively expand their reach toward student markets, understanding what drives consumers, specifically students' intention to adopt and actual usage of particular platforms is essential.

In this competitive landscape, marketing plays a critical role in driving visibility and customer acquisition or adoption and retention (Whitaker, 2023). AI companies employ both organic content on their private platforms such as Instagram, X and Youtube as well as social media ads on Youtube, Facebook and Instagram. These ads often emphasize productivity efficiency, upgraded features, safety and reliability. According to Briskman (2025) from Sensortower.com, Generative AI brands had digital advertising expenditure growth in Q2 2025 compared to Q2 in 2024. It was observed that the increase was found in developing markets such as India and Brazil, indicating that AI companies are expanding globally. Further support, evidence from Meta Ads Library shows that several AI

brands, including OpenAI, Google Gemini, and Perplexity, have deployed more than 20 active paid ads, most of which focus primarily on promoting their features and usability.

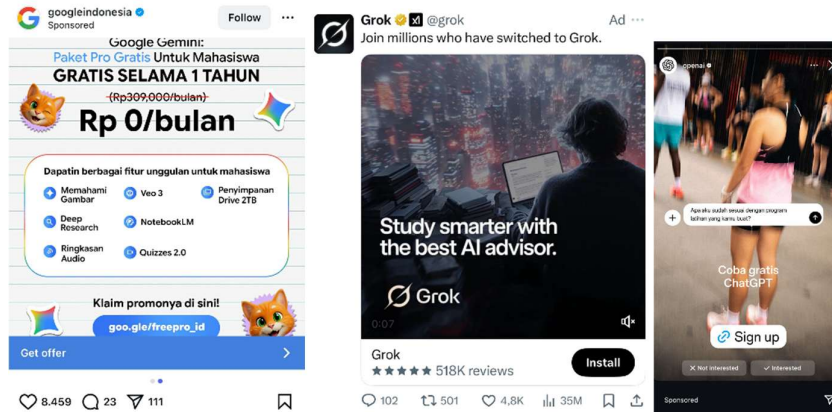


Figure 1. 4 AI brands’ social media advertisement (Google Gemini, Grok, & ChatGPT)
Source: Instagram & X

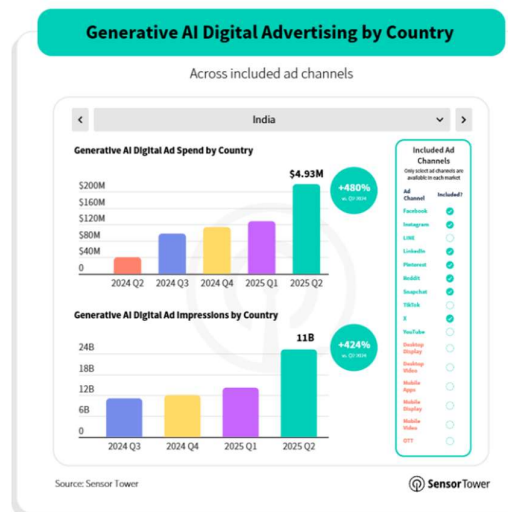


Figure 1. 5 Generative AI Digital Advertising by Country
Source: Sensortower.com

Despite differences in advertising strategies across companies, advertising remains a key tool in attracting emotional and social responsibility, shaping purchase intention through brand impressions such as brand credibility and trust (Pan, 2024). This aligns with research showing that social media ads influenced consumer purchase decisions through the enhancement of brand awareness as a critical determinant of purchasing behavior, reputation and positive product reviews (Rajalakshmi & Thabassum, 2024).

In addition to paid advertising, organic digital content such as product reviews in the form of Electronic Word-of-Mouth (EWOM) positively influences consumers' purchase intention and information usefulness (Ayuni, 2020; Sardar et al., 2021). E-WOM is defined as the digital evolution of traditional word-of-mouth (WOM), which enables marketing information to spread in online environments (Hennig-Thurau et al., 2010; Jan & Ahmad Bhat, 2021). In the context of technology adoption, research on cryptocurrency adoption, quality, consistency, and volume of eWOM significantly shapes consumer expectation and adoption behavior, suggesting that eWOM contributes in technology-related decision making (Mladenović et al., 2024).



Figure 1. 6 E-WOM regarding AI usage recommendation in X

Source: X

This shows that social media advertising and EWOM represent external channels through which students perceive generative AI platforms. According to

the Technology Acceptance Model, external variables operate through users' internal perceptual evaluations (Davis, 1989). These perceptions therefore, ultimately build whether the perception of them being exposed to AI platforms marketing translates into actual usage.

In explaining the perception, TAM framework identifies two primary perceptual determinants, perceived usefulness (PU), a degree of when a person considers a technology enhancing or increasing the efficiency of their job performance, and perceived ease of use, the degree which they expect to use with minimal effort (Davis, 1989; Mugo et al., 2017). In the context of generative AI, students often perceive platforms such as ChatGPT as useful due to their ability to efficiently help academic tasks and improve productivity. Prior research confirms that Perceived Usefulness positively influences consumers' decision, including purchase intention (O. R. C. Wijaya & Susilo, 2021), shapes attitude towards brand loyalty (Sari, 2022), and positive attitude towards continued usage (Rahmayanti et al., 2021).



Figure 1. 7 TedTalks regarding AI
Source: Youtube & X

Despite its benefits, perceived risk remains a significant concern in AI adoption. As generative AI use has expanded, documented concern over its

limitations has occurred through media and public discourse as well as literature. Concerns related to environments, copyrighted model issues (Shrivastava, 2025), leading to accusations of illegal data scraping from the internet and potential vulnerabilities in cybersecurity or data privacy. Perceived risk, in this context, refers to the user's subjective assessment of potential negative consequences of using platforms. In Indonesia, issues such as theft of personal data, financial and accessibility barriers, bias and ethical risks are all compounded by the crucial academic environment (Batubara et al., 2024; Zaki, 2025). Within the academic settings, where reliability and integrity hold an essential place, risks such as academic integrity, authenticity and misinformation ("AI hallucination") arise (Mukherjee, 2025; Raharjo & Rohmadi, 2025; Yingzhe LI, 2025). However, students tend to prefer the tools' comprehensiveness and responsive structure, overlooking inaccuracies or misinformation within the AI generated content (Kabir et al., 2024). Moreover, the increasing use of AI generated content in a portion of student submissions raises concerns about originality and ethical usage (Turnitin, 2024). Previous studies shows that risks and concerns negatively affect consumers' intentions and behaviors to purchase and recommend the platform, while also reducing trust and weakening continuance of usage (Ma et al., 2025; Helmiatin et al. 2024). The interplay between the perceptions of its usefulness, ease of use, and risk shape users' behavioral intention, which define as the degree to which a person has conscious plans to use or not use a platform, which in turn drives actual use behavior (Davis, 1989; Venkatesh & Bala, 2008)

Yet despite the widely used of generative AI by students, it remains unclear how students' perceptions of social media advertising and eWOM shape their evaluations of generative AI platforms, encompassing its perceived usefulness, perceived ease of use, and perceived risk, and how these technology evaluations eventually drive intention further to use behavior.

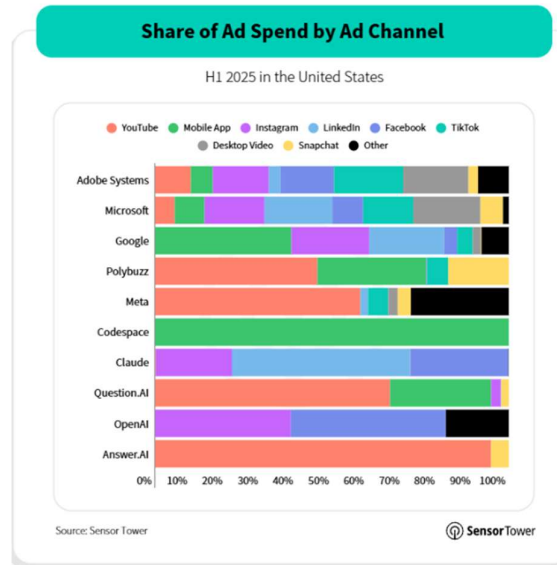


Figure 1. 8 Share of Ad Spend by Ad Channel (US)
Source: (Sensor Tower, 2025)

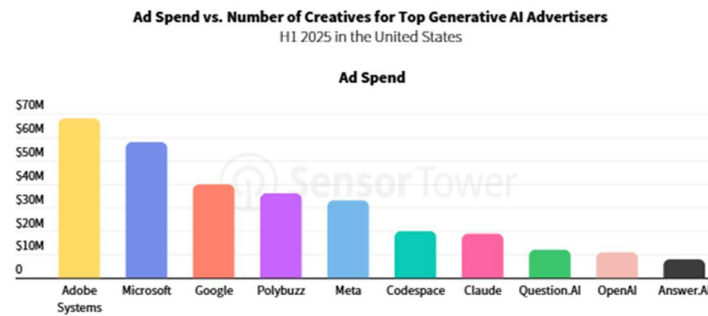


Figure 1. 9 Ad Spend for Top Generative AI Advertisers (US)
Source: (Sensor Tower, 2025)

This issue can be observed in platforms such as Google Gemini. Within the competitive AI industry, Gemini has plenty of marketing visibility through extensive digital advertising across multiple mobile applications and social media platforms (Briskman, 2025). Despite the significant investment and targeted campaigns, Gemini does not consistently achieve the highest user preference, as reflected in platform rankings and web traffic data in Indonesia (Semrush, 2026).

Most Visited AI Websites in Indonesia, Updated March 2026






Position	Website	Change	Visits	Pages / Visit	Bounce rate
1	 chatgpt.com	–	125,813,635	3.44	37.65%
2	 gemini.google.com	–	37,945,165	4.16	15.22%
3	 character.ai	–	13,006,444	4.77	50.8%
4	 claude.ai	↑ 4	9,351,933	4.18	31.91%
5	 openai.com	↓ 1	8,366,916	2.07	70.65%

Figure 1. 10 Generative AI Most Visited in Indonesia

Source: (Semrush, 2026)

Therefore, this study investigates how social media advertising perception and electronic-word-of-mouth (eWOM) perception, mediated by students' perceived usefulness, perceived ease of use, and perceived risk, and behavioral intention influence the use behavior of Indonesian university students toward Generative AI platform, in this context, Google Gemini.

1.2 Research Problem

The rapid growth of generative AI in the educational sector showed how it is integrated into students' learning activities. With the increasingly growing market, AI companies invest heavily in promotion, including marketing efforts such as social media advertising and eWOM. These efforts are supposed to increase awareness and encourage adoption by shaping positive perceptions of these platforms.

However, strong marketing efforts do not always translate into sustained usage. While platforms such as Google Gemini are widely promoted, they do not consistently achieve the highest use behavior among Indonesian students. This indicates that marketing exposure and actual use behavior may have a more complex relationship. As a result, it is necessary to examine how students interpret and evaluate marketing information, through perceptions of usefulness, ease of use,

and risk, and how these perceptions influence their intention to use, ultimately actually using the platform. Thus, the problems are constructed as below:

1. How do perceptions of social media advertising and eWOM influence perceived usefulness, perceived ease of use, and perceived risk?
2. How do perceived usefulness, perceived ease of use, and perceived risk influence behavioral intention?
3. How are perceived usefulness, ease of use, and risk related?
4. How does behavioral intention mediate user perceptions towards use behavior?

1.3 Research Objectives

This study's general objective is to analyze how marketing exposure and perceptions influence students' use behavior of Generative AI, in this case, Google Gemini, which constructed as below:

1. To examine the effect of social media advertising perception and eWOM perception on perceived usefulness, perceived ease of use, and perceived risk.
2. To analyze the influence of perceived usefulness, perceived ease of use, and perceived risk on behavioral intention.
3. To analyze the relation of perceived usefulness, ease of use and risk.
4. To identify the influence of behavioral intention towards use behavior.

1.4 Research Significance

a. Theoretical Significance:

This study uses Technology Acceptance Model (TAM) as a framework within the context of AI use behavior. It provides empirical evidence on how perceived usefulness, perceived ease of use and perceived risk as mediating factors function in the relationship between the perception of digital marketing exposure (social media advertising and eWOM) and actual usage behavior, thus enhancing

the theoretical understanding of technology adoption and digital consumer behavior.

b. Practical Significance:

This research offers insights, particularly for Generative AI companies in developing strategies to strengthen use behavior among student users. The findings proposed to guide marketers in designing more effective social media campaigns that not only highlight the utility of AI tools but also address users' concerns and risks, ultimately fostering trust and sustained engagement.

c. Academic Significance:

This study helps academic better understand how perceptions of usefulness, ease of use, and risk are formed, and how these perceptions influence their use of Generative AI in academic activities.

1.5 Theoretical Framework

In the current evolving academic landscape regarding Generative AI (Gen AI), literature primarily utilized the Technology Acceptance Model (TAM) as a framework to investigate the intent to adopt AI tools. This model provides a foundational understanding of how perceived usefulness and perceived ease of use shape acceptance behavior. Recent studies have extended TAM by integrating social and other contextual factors relevant to technology and AI.

Sari (2022) extended the TAM framework by incorporating perception of enjoyment, social influence perception, towards the intention of being loyal in the context of gamification e-commerce. The study quantitatively tested whether perceived enjoyment, perceived social influence, and perceived usefulness affected consumers' brand attitudes and loyalty. Findings revealed that users' sense of usefulness, enjoyment, and social influence positively and significantly influenced how users viewed the brand. In contrast, perceived ease of use did not contribute much impact on the brand attitude. Moreover, brand attitude was found to have a

significant effect on loyalty intention. These results suggest that emotional and social motivations play a role in consumers' decision-making process.

In the field of AI adoption, (Helmiatin et al., 2024) investigate Indonesia's higher education of public university AI adoption. Similar to TAM, this study uses Unified theory of Technology Acceptance and Use (UTAUT) to explain the adoption of technology with variables such as performance expectation (PE) as an extent individual believes that using a system will enhance their job performance, Effort Expectation (EE) refers to convenience, social influence (SI) as influential individuals, and facilitation conditions (FC) refers to availability of infrastructure and support. This study aimed to explore how educators and policymakers might adapt AI into learning environment. The result of this study is that users tend to develop positive attitudes toward AI when they believe that it has both the ability to improve their work performance and easy to operate, while concerned risks reduce their willingness to adopt. The study underscores that educators' perceptions of AI's usefulness and ease of use are crucial to its acceptance, though perceived risk remains a barrier.

Another study determining adoption intention in higher education by (Balaskas et al., 2025) expanded TAM to include trust and perception of risk as mediating determinants in analyzing how students decide to adopt ChatGPT in university context. The study revealed that perceived ease of use (PEOU) and perceived intelligence (PI) contribute significantly to students' willingness to use the tool, while perceived usefulness (PU) contributes to a limited extent. Furthermore, perceived risk (PR) served as a strong mediator, affecting the perceived usefulness on adoption and partially mediates PI and PEOU to adoption. Conversely, perceived trust (PT) fully mediates PU to adoption and partially mediates PEOU to adoption, and does not mediate the PI to adoption. These findings showed that ease of use and intelligence drive adoption, but perceived trust

and perceived risk strongly influence whether those factors actually lead to adoption of ChatGPT.

With the same TAM model, (Alshammari & Babu, 2025) investigate the mediating role of satisfaction in the relationship between perceived usefulness, perceived ease of use, and behavioral intention to use ChatGPT. The research found that perceived usefulness and perceived ease of use significantly influence satisfaction. In direct influence, only perceived usefulness and satisfaction directly influence behavioral intention. Perceived ease of use was found to need satisfaction as a mediator to influence behavioral intention. These findings suggest that usefulness contributes more in terms of the intention of using ChatGPT.

Expanding beyond initial adoption, Kang et al. (2024) focused on the continuance intention of GenAI service users, researching motivational factors with trust and acceptance attitude as mediators. The study aimed to find the relationship between motivational factors categorized as; individual, social, technical, of GenAI users and their intention to continue in using the service. The study found that all motivational factors positively influenced trust and acceptance attitude on the attitude toward accepting GenAI services with social factors as the strongest influence. Individual factors such as self-efficacy, innovation and playful desire affect acceptance attitude, moreover, social reputation or awareness directly affects the trust in usability. This suggests that users' willingness to continuously use GenAI services, which refers to loyalty, depends not only on functional efficiency but also social attitude of the technology.

Collectively, these studies contribute to understand literature on technology acceptance and continuance behavior in both educational and digital consumer contexts. Consistently, relevant variables such as perceived risk, social influence, trust, increasingly define users' interactions with generative AI and other technologies.

1.6 Hypothesis

a. Social Media Advertising Perception on Perception Mediators

Along the line of the literature review, prior research had identified variables similar to this study. Social media advertising, as a marketing strategy to engage with the target audience, has been shown to enhance user engagement and strengthen brand reputation (Rajalakshmi & Thabassum, 2024) Apart from that, social media marketing such as ads with description of the brand's utility and benefits express tendency to purchase intention (Hendra et al., 2025). Similarly, Salhab et al., 2023) found that social media marketing can positively influence brand image and brand trust which contribute to purchase intention. An experimental study by (Dwesar et al., 2025) examined psychological mechanisms in the case of online reviews and advertisement. The result has shown that combining online reviews and ads reduced skepticism and led to stronger brand attitude subsequently purchase intention. Nevertheless, (Aurush et al., 2024) observed that informativeness has a significant influence on consumer emotion, however less on consumer purchase intention. This suggests that social media ads may shape consumer perceptions and attitudes, though their influence on actual purchase behavior is often indirect or mediated by other psychological factors (Tariq et al., 2023; Pan, 2024)

Based on these foundational arguments, the following hypotheses are proposed regarding social media ad exposure:

H1a: Social Media Ad Perception (X1) has an effect on Perceived Ease of Use (M3)

H1b: Social Media Ad Perception (X1) has an effect on Perceived Usefulness (M1)

H1c: Social Media Ad Perception (X1) has an effect on Perceived Risk (M2)

b. Electronic Word-of-Mouth Perceptions on Perception Mediators

In prior research, several studies have shown eWOM can influence related variables. Wahyudi & Sudarmiatin (2024) found that eWOM positively and significantly influences not only purchase intention but also trust and brand image, indicating positive reviews and recommendations persuasiveness help strengthen

brand-related perceptions. In mobile banking adoption context, K. A. W. Wijaya and Gayatri (2025) found that eWOM enhanced perceived ease of use, perceived usefulness, and trust while reducing perceived risk, which increases users' intention to adopt consequently. The findings resonate with this research framework. Thus, the following hypotheses are proposed regarding eWOM to adoption intention:

H2a: eWOM Perception (X2) has an effect on Perceived Ease of Use (M3)

H2b: eWOM Perception (X2) has an effect on Perceived Usefulness (M1)

H2c: eWOM Perception (X2) has an effect on Perceived Risk (M2)

c. Perceived Usefulness, Ease of Use, and Risk

In classical TAM, Davis (1989) showed that perceived ease of use tends to be precedent to usefulness, indicating when users believe a system is easy to use, they may be more likely to perceive it as useful. Consequent studies support this premise, where perceived ease of use significantly impacts perceived usefulness in the usage of smart phones in Arab (Abbas, 2016). Moreover, perceived risk has a significant effect on perceived usefulness, meaning that the lower the risk, the higher the perceived usefulness (Kumara & Laksmidewi, 2024). This indicates that risk controls whether or not usefulness is effective.

H3: PEOU has an effect on PU

H4: PR has an effect on PU

d. Perception Mediators on Behavioral Intention to Adoption

Several studies support the assumption that perceived usefulness, perceived ease of use, and perceived risk influence behavioral intention to adopt AI or related technology. A study that applied TAM in brand attitude and intention, resulted in perceived usefulness positively influencing brand attitude then subsequently driving loyalty intention (Sari, 2022). Moreover, in terms of ChatGPT adoption of students', it was revealed that perceived usefulness significantly influenced behavioral intentions to use GPT (Alshammari & Babu, 2025). Balaskas et al. (2025) found that perceived ease of use influences adoption intention. Furthermore, Helmiatin et al. (2024) showed that perceived risk has a negative effect on adoption.

Hence, based on the studies, the following hypotheses regarding behavioral intention of adoption are proposed:

H5: PU has an effect on Behavioral Intention of Adoption

H6: PEOU has an effect on Behavioral Intention of Adoption

H7: Perceived Risk has an effect on Behavioral Intention of Adoption

e. Brand Intention on Use Behavior

Prior research demonstrates that behavioral intention plays a role in predicting use behavior in the context of digital and technology adoption. Studies show that users with stronger intention to adopt or use are more likely to be positively significant to actual usage (Ballesteros et al., 2025; Biswas et al., 2025). This relationship highlights the role of behavioral intention as an antecedent of use behavior. Therefore, consistent with these findings, the hypotheses proposed regarding brand intention to brand loyalty as followed:

H8: Behavioral Intention has an effect on Use Behavior

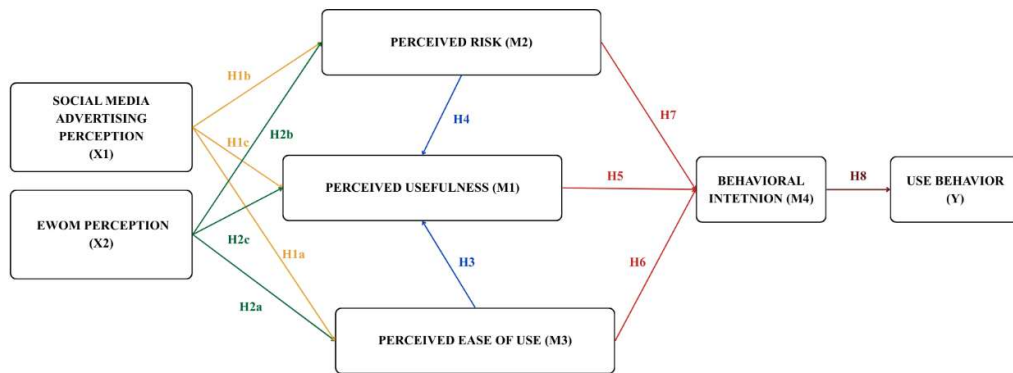


Figure 1. 11 Proposed Hypothesis Framework

1.7 Conceptual Definition

1.7.1 Technology Acceptance Model (TAM theory)

The Technology Acceptance Model was originally proposed by Fred Davis in 1985, refined incorporating variables and relationships in accordance to Fishbein and Ajzen Theory of Reasoned Action (TRA) in 1975 (Mugo et al., 2017). TAM was developed to explain and predict users’ acceptance of technology with two

primary determinants: Perceived usefulness, perceived ease of use. These constructs influence attitude towards usage as determinants to behavioral intention subsequent usage (Davis, 1989; Mugo et al., 2017; Venkatesh & Davis, 2000a).

The model evolved through several extensions: TAM1, TAM2, and TAM3, incorporating additional contextual factors. As proposed by Venkatesh & Bala (2008), TAM3 integrated experience, self-efficacy and anxiety, and external control as antecedents of perceived ease of use, while including social influence and practical reasoning as determinants of perceived usefulness. In this implementation, experience as a mediator between perceived ease of use and perceived usefulness, which subsequently affects behavioral intention. This provides a more comprehensive understanding of technology adoption. Thus, TAM3 offers as a theoretical foundation for analyzing users' acceptance of technologies, in this study, Generative AI, by linking perceptions of usefulness and ease with behavioral intention shaped by external factors and perceptions.

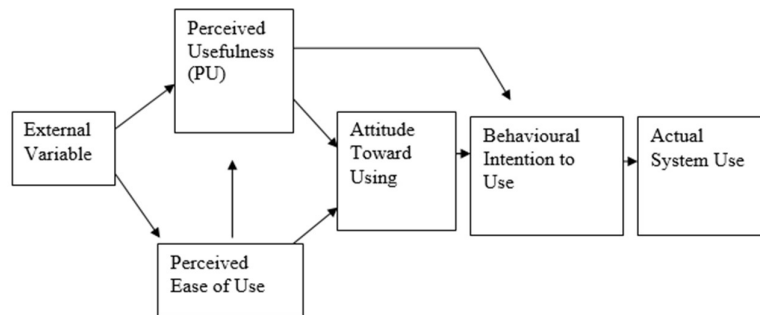


Figure 1. 12 TAM 1 framework (Davis, 1989)

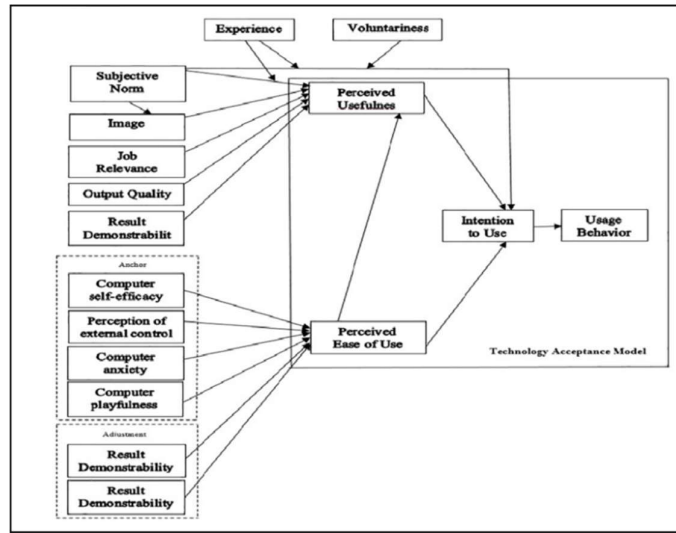


Figure 1. 13 TAM 3 framework (Venkatesh & Bala, 2008)

1.7.2 Social Media Advertising Perception

Social media advertising is defined as an assistant for brands to boost awareness and expand its base throughout the social network platforms, including Facebook, Twitter, Tiktok, Snapchat, Whatsapp, Linkedin, Youtube, Pinterest, Instagram, and others (Vitalis et al., 2024). Unlike traditional media, social media advertising is integrated with algorithmic targeting allowing brands to target their target audience specifically, prioritizing relevance and personalization which impacts consumers' attention to the ad and influence consumer attitudes subsequently consumer behavior (Apriansyah et al., 2025; Chen et al., 2023; Kuncoro Broto, 2023).

Social media advertising is conceptualized as users' interactions with advertising messages, which collectively contributes to awareness, engagement, or conversion, depending on the platform's characteristics, advertising goals and message type (Voorveld et al., 2018). Research on online advertising suggests that consumers evaluate advertising content based on specific characteristics that shape their overall perception of the advertisement. Lütjens et al. (2022) build up the development of advertising value model introduced by Ducoffe (1996), emphasizing features such as informativeness, entertainment, and negative emotions influence how users evaluate and respond to advertising content

(Hanaysha & Alhyasat, 2025; Moiescu et al., 2026; Voorveld et al., 2018). By controlling format, content and behavior, instagram advertising influences consumer behavior, shaping consumer purchase intention and trust (Azizah et al., 2024).

Consequently, users' perceptions of advertising messages are conceptualized as an external variable that may contribute to student's cognitive processing of the Generative AI brand in this study, including their perception of usefulness, ease of use, and risk.

1.7.3 Electronic Word-of-Mouth (eWOM) Perception

Electronic Word-of-Mouth (eWOM) is defined as either positive or negative consumer-generated communication experiences about a brand, disseminate through different digital channels, providing consumers with opportunities to read others' consumption experiences and opinions and share their own (Hennig-Thurau et al., 2004; Jan & Ahmad Bhat, 2021). This form of communication is generated primarily by peer consumers without direct commercial intent which is assumed to be more trustworthy as a source of information compared to advertiser generated impact, contributing to consumer attitudes and beliefs (Brown et al., 2007).

There are several factors for consumers to accept eWOM. Argument quality, consistency, volume, source credibility, authenticity, experience, and source homophily how users evaluate reliability and relevance of the eWOM content (Ghosh et al., 2026; Le-Hoang, 2020; Rusdiana et al., 2019).

Functionally, eWOM contributes as a crucial component of consumer information seeking behavior, which aims to resolve the need of consumers to satisfy some goal, in this case choice uncertainty which increase search (Wilson, 2000 cited by Al Suqri and Al Aofi, 2015; Urbany et al., 1989) This mechanism has been empirically shown that eWOM reduces perceived risk in terms of level of uncertainty by providing insights, subsequently intention to purchase (Anastasiei & Dospinescu, 2025). Therefore, eWOM serves as source of information in the model

which increases trust and affecting entire consumer experience from awareness to post purchase loyalty(Bharej & Singh, 2025)

1.7.4 Perceived Usefulness of AI

Fundamentally, Davis (1989) refer perceived usefulness as the extent to which an individual expects or believe that using a particular system or technology will improve their job or task performance. Within the Technology Acceptance Model (TAM), perceived usefulness and perceived ease of use are thoroughly scrutinised as determinants of technology adoption and user acceptance. It was found that perceived usefulness has strong correlation to user acceptance (Davis, 1989). It is represented as an extrinsic motivation, where individuals perceive technology as a tool to achieve valued outcomes such as improved job performance, productivity-wise or academic performance (Davis et al., 1992). Studies consistently showed that perceived usefulness exerts a stronger influence on behavioral intention and technology usage (Davis et al., 1992; Teo et al., 1999).

In the context of higher education, perceived usefulness captures how students or users to evaluate the brand's capability to deliver effective and efficient academic results. Mugo et al. (2017) found that both internal variables (users' attitude, beliefs, competence) and external variables (organizational, technological, and social support) were tested to influence perceived usefulness and perceived ease of use. External variables include barriers to adopt technology in the framework. Both variables work together to strengthen perceived usefulness and perceived ease of use, which in turn contribute to attitude, intention and usage.

In present studies, perceived usefulness remained a central determinant along with other variables in the adoption intention of AI tools (Alshammari & Babu, 2025; Balaskas et al., 2025; Sari, 2022). Thus, perceived usefulness is a pivotal construct of technology acceptance.

1.7.5 Perceived Ease of Use of AI

Perceived ease of use, as introduced by Davis (1989) refers how strongly an individual feels that using with a specific system will be effortless. As a

fundamental construct of the Technology Acceptance Model (TAM), perceived ease of use contributes as an important determinant towards attitude (Rahmayanti et al., 2021). This perception was closely similar to Bandura's (1982) concept of self-efficacy, referring to judgments of how well one can execute certain actions in certain conditions, said to be similar to perceived ease of use (Davis, 1989; Gu et al., 2009). Both constructs emphasize competence in technology use, explaining whether users find a system easy or difficult. Furthermore, users' experience, computer self-efficacy, and performance expectancy have been found to be precedent to perceived ease of use, suggesting that perception of ease occur from intrinsic motivation, including confidence and familiarity with the technology (Venkatesh & Bala, 2008b)

Venkatesh and Davis (2000) suggests that perceived ease of use was a key driver to acceptance and usage. In recent studies, perceived ease of use serves as one of the important drivers to adoption in terms of technologies such as AI and digital learning tools (Alshammari & Babu, 2025; Balaskas et al., 2025). Therefore, perceived ease of use represents the users' belief that a system can be operated with minimal effort, serving as an important determinant of technology adoption.

1.7.6 Perceived Risk of AI

Bauer (1960) defined perceived risk as consumers' perception of uncertainty and consequences of engaging in purchase activity (Pathak & Pathak, 2017; Rodgers III, 1966). Fundamentally, as cited by (Mitchell, 1992), Cunningham (1967) and Peter and Ryan (1976) suggests that risk has two core components; uncertainty (the likelihood that a negative outcome will occur) and consequences (severity of loss if it happens). The notion believes that both combined may help understand consumer risk. As a crucial determinant in decision-making process, perceived risk is found to negatively affect consumers' intentions, reducing trust levels, subsequently, behavioral intentions (Ma et al., 2025).

Furthermore, perceived risk is measured across several sub-dimension in service consumer buying behavior, which includes social, financial (monetary loss),

physical, performance (satisfaction), time, and psychological (self-perception). In academic context, students reduce their intention to adopt Generative AI in their academic studies when there are academic risks involving, academic misconduct, misinformation, confidentiality and data privacy issues (Carcary & Buckland, 2025). Thus, perceived risk acts as a filter that has a powerful influence on consumers' decision-making process.

1.7.7 Behavioral Intention

Behavioral Intention defined as an individual's planned decision or intention whether they will commit in doing or not doing a behavior in the future (Warshaw and Davis, 1984). Implemented in both the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA) and Unified Theory of Acceptance and Use of Technology (UTAUT), behavioral intention serves as an important direct determinant of actual behavior (Lu et al., 2013; Montano and Kasprzyk, 2002; Venkatesh and Bala, 2008). It represents users' attitude and perceptions, including usefulness, trust and ease of use which contribute to their likelihood to adopt a technology (Helmiatin et al., 2024; Rahmayanti et al., 2021).

Previous research had found that increased behavioral intention affected technology adoption in terms of retail technology and education (Andika et al., 2025). In educational and AI contexts, a users' motivation to adopt technology is tied to how much they perceive as useful, effortless, and how strongly the environment supports the adoption (Abdi et al., 2025). Moreover, Helmiatin et al. (2024) identified behavioral intention as a mediator that connects users' perceptions to eventually reach adoption. Therefore, behavioral intention represents a bridge to adopt technology.

1.7.8 Use Behavior

In the initial Technology Acceptance Model (TAM), Davis (1989) refers Use Behavior as the actual system use. This construct is also embedded in other adoption theories such as Unified Theory of Acceptance and Use of Technology (UTAUT) as well as Theory of Reasoned Action (TRA) and Theory of Planned

Behavior (TPB), where behavioral intention is considered a key antecedent of actual usage.

Generally, Use Behavior refers to the extent to which individuals engage with a technology in their daily activities, which can be reflected through frequency, duration and intensity of usage (Davis, 1989; Qiu et al., 2024; Schorr, 2023a). Therefore, use behavior represents how often and how extensively users utilize a technology practically.

1.8 Operational Definition

In accordance with the conceptual definition, the operational definition outlines how each variable is measured and observed. Each variable is represented through measurable indicators from prior studies.

1.8.1 Social Media Advertising Perception

Social media advertising perception refers to how students evaluate advertising content. Based on Ducoffe (1996), there are three key factors which include informativeness, entertainment and irritation.

a. Informativeness

This dimension refers to the ability of advertising to inform consumers regarding the product, encompassing the questions of whether the platform's advertisement provide the information needed by the consumers and the extent they clearly explain the features of the platform (Moisescu et al., 2026)

b. Entertainment

This dimension specified the pleasant or likeable emotional release. This is measured by seeing the degree of entertaining and pleased feelings occurred when consumers encountered the content (Voorveld et al., 2018).

c. Irritation

The nature of this dimension serves as the opposing feeling of entertainment, whereas consumers would feel annoyed by the content. This is measured by looking at how often they feel disturbed and disappointed after seeing the content (Voorveld et al., 2018).

1.8.2 EWOM Perception

Electronic word-of-mouth (eWOM) perception is defined as students' evaluation of generated content about generative AI platforms across digital channels. This is measured through the quality of the arguments, the consistency of information across different digital platforms, and the total volume of available user reviews evaluated by the students exposed by it (Ghosh et al., 2026).

1.8.3 Perceived Usefulness

Perceived usefulness is operationally defined as the degree to which students believe that using a platform improves their productivity. This will be measured through student's evaluation of the system's effectiveness and efficiency to their academic tasks (Davis, 1989; Madi et al., 2024)

1.8.4 Perceived Ease of Use

Perceived ease of use is defined as the degree to which students find a platform is effortless to use. This is measured through students' evaluation of how little effort is required to interact with and navigate the platform (Davis, 1989; Madi et al., 2024).

1.8.5 Perceived Risk

Based on Carcary & Buckland (2025) Perceived risk is defined as the degree of students' concerns regarding academic performance, social or psychological risks, and privacy risks.

a. Academic performance risk

This concern was considered as it is about whether the platform's output is reliable enough to support academic tasks. This is rooted in AI hallucination, whereas the content given by the AI might be incorrect and eventually risk affecting the academic performance.

b. Social or psychological risk

This concerns the social and ethical consequences of using generative AI in the academic layout. This is measured by whether students are concerned in accusations of misconduct or plagiarism.

c. Privacy risk

This concerns what happens to data the students had given to the platform. This measures whether risks of personal data misuse by the platform might be considered.

1.8.6 Behavioral Intention

Behavioral intention is defined as the degree to which students' intend, predict, and likelihood to use the generative AI platforms in their academic activities. This is measured through indicators reflecting students' conscious plans and willingness to continue using the platform (Davis, 1989).

1.8.7 Use Behavior

Use behavior refers as the actual extent to which students utilize an AI platform in their daily activities. This is measured through the frequency and intensity of platform usage over time (Qiu et al., 2024).

The following table incorporated every aspect of the statement describing the variable.

Table 1. 1 Operational Definition Table Variables

Variable	Operational Definition	Indicator	Scale	Source
Social Media Ad Perception	Students' evaluation of informativeness, enjoyment, and irritation from exposed advertising content	Informativeness	Scale 1-5 Likert: 1 = Strongly Disagree 5 = Strongly Agree	Moisescu et al., (2026); Voorveld et al., (2018)
		Entertainment		
		Negative Experience		
Electronic Word-of-Mouth (E-WOM) Perception	The quality, consistency, and volume of reviews across digital platforms encountered by students	Argument Quality	Scale 1-5 Likert: 1 = Strongly Disagree 5 = Strongly Agree	Ghosh et al (2026)
		Consistency		
		Volume		
Perceived Usefulness	Students; evaluation of the system's effectiveness and efficiency	Effectiveness	Scale 1-5 Likert: 1 = Strongly Disagree	Madi et al. (2024)

Variable	Operational Definition	Indicator	Scale	Source
		Efficiency	5 = Strongly Agree	
Perceived Ease of Use	The extent to which students perceive the AI platform as effortless to use	Easy to learn	Scale 1-5 Likert: 1 = Strongly Disagree 5 = Strongly Agree	Madi et al. (2024)
		Easy to operate		
Perceived Risk	The level of students' concerns regarding academic performance, social or psychological, and privacy risks when using the AI brand	Inaccurate information	Scale 1-5 Likert: 1 = Strongly Disagree 5 = Strongly Agree	Carcary & Buckland, (2025)
		Academic Misconduct Concern		
		Privacy Concern		
Behavioral Intention	The students' intention to use the AI brand in their academic activities	Intention to Use	Scale 1-5 Likert: 1 = Strongly Disagree 5 = Strongly Agree	Rojas-Osorio & Alvarez-Risco, (2019)
		Willingness to Continue		
		Likelihood of Future Usage		
Use Behavior	The actual usage of Generative AI tools by students in their daily routines	Frequency	Scale 1-5 Likert: 1 = Strongly Disagree 5 = Strongly Agree	Qiu et al., (2024)
		Intensity		

1.9 Research Methodology

1.9.1 Research Type

This study employs quantitative explanatory research design to examine the relationships among the variables and test influence of social media advertisements exposure, electronic Word-of-Mouth (eWOM), perceived usefulness, and perceived risk on generative AI brand loyalty.

1.9.2 Population and Sampling

1.9.2.1 Population

The population for this study is defined as all active university students in Indonesia who currently use Generative AI brands including ChatGPT, Gemini, and others, for their academic purposes. The population is considered unknown due to an exhaustive list of all individuals who meet the criteria.

1.9.2.2 Sampling

The sample size was calculated using G Power application. For a large or unknown population, the minimum sample size is calculated with a 95% Confidence Level ($z=1.96$) and a 5% margin of error ($e=0.05$), resulting in approximately 138 respondents. Therefore, this study aims for 150 respondents.

1.9.3 Sample Collection Techniques

This study applies a non-probability sampling method. Due to the accessibility of respondents' availability and relevance to the research criteria which are the university students who use Generative AI in Indonesia, the convenience sampling technique is selected.

1.9.4 Data Types and Sources

The data used in this study is quantitative data. This study utilizes both primary and secondary data sources. Primary data are collected directly from respondents through structured questionnaires distributed online to university students, while secondary data are collected from scholarly sources including prior studies, journal articles and books relevant to social media advertising, eWOM, TAM theory, and brand loyalty. Both data complement the fundamentals in understanding the overall objective of this study.

1.9.5 Research Instrument and Data Collection Techniques

The primary research instrument is a structured questionnaire developed based on indicators from prior studies. Each construct is measured using a 5-Point Likert scale (1 = “strongly disagree” to 5 = “strongly agree”).

The data will be collected using self-administered online surveys or questionnaires distributed by various platforms and digital communication channels while still maintaining the component. Initial respondents will be asked to share the survey link with other students who meet the research criteria.

1.9.6 Data Processing Technique

a. Editing

Raw data will be collected from the questionnaire. This process will include the checking of completeness, clarity and consistency preventing bias.

b. Coding

This process includes converting the responses from the questionnaire to numerical values for analysis (Sarwono, 2018), ensuring the measurement scale is ready for input in the statistical software.

c. Tabulation

After arranging the edited and coded data, tabulation compiled the data into a structured matrix, representing one unique respondent and single indicator item.

1.9.7 Data Analysis Technique

This study uses Structural Equation Modeling–Partial Least Squares (SEM-PLS) to analyze the quantified data. The method is selected in order to explore more complex relationships among multiple dependent and independent variables providing a causal-predictive result (Sarstedt et al., 2017).

1.9.7.1 Measurement Model Evaluation (Outer Model)

The measurement model evaluation (outer model) is assessed to evaluate the measurement construct before doing an analysis on the structural model (Hair et al., 2021). In this study, all constructs are reflective, meaning that the indicators represent or reflect latent variables (Hair et al., 2021). To assess the quality of the reflective measurement model, variables are measured by four criteria, including reflective indicator loadings, internal consistency reliability, convergent validity, and discriminant validity.

a. Indicator Reliability

Indicator reliability evaluates how effectively each indicator explain its construct. This is measured by the outer loadings. A loading value of 0.708 or higher is considered acceptable because it indicates that the construct explains at least 50% of the indicator's variance. Indicators with loadings between 0.40 and 0.708 can still be considered, but should only be removed if doing so improves the overall reliability or validity of the construct. Meanwhile, indicators with loadings below 0.40 should be removed (Hair et al., 2021).

b. Internal Consistency Reliability

This criterion evaluates how consistently the indicators measure a construct (Hair et al., 2021). It is assessed using Composite Reliability (ρ_C), Cronbach's Alpha, and ρ_A . Values between 0.70 and 0.90 are generally considered as good, while values ranging 0.60 and 0.70 may still be acceptable in exploratory research. However, values above 0.90 (especially above 0.95) is considered as problematic as it indicates similarity, which can reduce the quality of the construct. Among these measures, ρ_A is often seen as a more accurate estimate, as it falls between Cronbach's Alpha and Composite Reliability.

c. Convergent Validity

Convergent validity refers to how efficient a construct explains the variance of its indicators (Hair et al., 2021). This is measured using the average variance

extracted (AVE). A value of 0.50 or higher indicates that the construct explains at least half (50%) of the variance of its indicators, which is considered acceptable.

d. Discriminant Validity

Discriminant validity measures the extent to which a construct is empirically distinct from each other in the model (Hair et al., 2021). This is done to ensure the variables do not overlap conceptually. This can be assessed using the Heteroite-monotrait ratio correlations (HTMT). In general, HTMT values should be below 0.90 for conceptually similar constructs, or more strictly distinct below 0.85 as a way to assess discriminant validity. The higher it is (> 0.90) HTMT will be a problem.

1.9.7.2 Structural Model Evaluation (Inner Model)

This criterion examines the relationship between the constructs, showing how each construct influences each other (Hair et al., 2021). In this study, three mediating variables are included meaning that the effect of exogenous latent variable (independent variable or cause) on endogenous latent variable (dependent variable or effect) is mediated.

a. Collinearity (VIF)

Collinearity measures the predictor constructs' redundancy, whether the variables are too similar to each other. This is assessed by the Variance inflation factor (VIF) values. A VIF value below 3 indicates no collinearity issues, values between 3 and 5 suggest potential concerns, and values above 5 indicate serious collinearity problems. If collinearity occurs, higher-order constructs may be considered to be used (Hair et al., 2021).

b. Significance and Relevance of the Path Coefficient

Path coefficients show the strength and direction of the relationship between variables (Hair et al., 2021) Their significance is tested using bootstrapping, based on t-statistics and p-values. A relationship is considered significant if the t-statistic

is greater than 1.96 and the p-value is less than 0.05. This measurement helps determine whether the hypotheses are supported.

c. R-square

R^2 shows the extent to which the independent variable can explain the variation in the dependent variable variables (Hair et al., 2021). Higher values mean better explanatory power. Generally, values of 0.75 are considered strong, 0.50 moderate, and 0.25 weak, although this depends on the research context.

d. F-square

The F^2 measures how much each independent variable contributes to the R^2 of the dependent variable, showing how important each predictor is in the model. The effect size is categorized as small (> 0.02), medium (> 0.15), and large (> 0.35) (Hair et al., 2021).