Beyond the prompt:

understanding ChatGPT outcomes through the lens of IT identity

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Abstract

Purpose: As the use of ChatGPT continues to expand, understanding its impact on users remains an emerging area of study. This research investigates how individuals form a sense of identity around ChatGPT, applying the Information Technology (IT) identity framework, with an added outcomes component, to assess the psychological relationship users develop with the tool.

Design/methodology/approach: A survey of 312 active ChatGPT users was conducted to evaluate the framework's applicability in this context and to explore the resulting behavioral and experiential outcomes. The model was tested using partial least squares structural equation modeling (PLS-SEM).

Findings: The results provide partial support for the IT identity framework in the ChatGPT context. The analysis indicates that regular interaction with ChatGPT is associated with the development of a distinct IT identity. Moreover, the presence of sufficient resources and organizational or contextual support significantly moderates this relationship, shaping user behaviors in meaningful ways. These behaviors, in turn, were linked to improvements in both individual performance and perceived social well-being. The findings also suggest that some relationships established in traditional IT contexts may operate differently in generative AI environments.

Originality/value: By extending the IT identity framework to include specific outcome measures, this study offers a nuanced understanding of how AI-based tools like ChatGPT influence user identity and behavior based on the IT identity framework. The findings further contribute to understanding how AI-related identities form and highlight opportunities for refining IT identity theory in the context of generative AI assistants.

Keywords: IT identity; ChatGPT; AI Assistants; Outcomes (instrumental and humanistic).

Beyond the Prompt: Understanding ChatGPT Outcomes Through the Lens of IT Identity

1. Introduction

ChatGPT and its content-generation capabilities significantly reshaped the global landscape (Schlagwein & Willcocks, 2023), reaching 200 million weekly active users worldwide (Singh, 2024). This impact can be mostly attributed to its self-generative capabilities (Susarla et al., 2023), highlighting ChatGPT's potential as a conversational agent and as a robust analytical tool (Alzeiby et al., 2025; Kshetri et al., 2024). As individuals become immersed in the use of these technologies, they may begin forming what is known as an information technology (IT) identity, a phenomenon that occurs when an individual views IT as a channel for self-expression and an indispensable tool to their sense of integrity (Carter & Grover, 2015). Experimental evidence has demonstrated an increase in productivity in professional writing tasks that use ChatGPT (Noy & Zhang, 2023) and better overall performance (Kumar et al., 2023). Consequently, as organizations begin to leverage generative AI tools (Ye et al., 2024), the work sphere can evolve into a technology-dependent environment. Employees can now explore and adapt to their new resources, and identify the positive aspects in their implementation and the consequent productivity gains (Abubakre et al., 2017). After getting used to a specific IT and developing an identity around it, users may increase their engagement, leading to compulsive use (Gong et al., 2021; Stein et al., 2013), which may be heightened depending on the strength of the IT identity (Alarabiat et al., 2021; Chiu & Huang, 2015).

This study seeks to differentiate from existing literature by responding to Carter and Grover's call for papers in the 2015 MIS Quarterly publication, titled "*Me, my self, and I(T): Conceptualizing information technology identity and its implications*", to further explore the intertwinement of IT and identity, relating to how it can be a mechanism towards not only maintaining the self but also expanding it. Hence, this study adapts Carter and Grover's (2015) framework, adding a component of outcomes to further deepen the understanding of the impact of technology-based identity. The IT characteristics section was the only component excluded from the original framework, as the aim of this study is to validate the psychological aspects of IT, rather than to examine specific system characteristics. ChatGPT was chosen as the base technology for this study due to its significant rise in popularity. While prior studies have explored individual components of the IT identity framework in AI contexts, none have empirically validated the framework as a holistic psychological process. Consequently, the full pathway linking experiences, IT identity, behaviors, and outcomes remains limited. To address these gaps, this study pursues the following research objectives: (1) empirically test and validate the psychological aspects of the IT identity framework in the context of ChatGPT; (2) understand if behaviors stemming from IT identity can impact outcomes of individual performance and social well-being.

While our approach preserves the original structure of the framework, this validation is not merely confirmatory. **First**, it addresses a critical gap in the literature: comprehensive validation in AI-assisted environments. In doing so, we demonstrate the framework's robustness and applicability to contemporary IT contexts. **Second**, by incorporating an outcomes layer, we extend the framework in a way that yields empirically grounded and insightful findings. **Thirdly**, the findings provide actionable insights for AI assistant developers, regulators, and organizations, particularly in guiding the design, governance, and integration of AI tools. **Finally**, by examining the outcomes of ChatGPT-related identity and behavior, this study opens new paths for research across broader human and organizational dimensions. It invites future work to further explore the societal, psychological, and humanistic implications of AI use.

2. Theoretical background

2.1. Artificial intelligence and ChatGPT

The core of ChatGPT can be described as a multifaceted domain with systems that algorithmically perform certain tasks that closely replicate those originating from human intelligence (Wolf & Maier, 2024). Smith (2020) argues that AI systems lack the capacity to assess the plausibility of their findings autonomously. In contrast, other academics suggest that AI can exhibit intelligence through its ability to learn from data and adapt to new perspectives (Nishant et al., 2024). Contemporary AI can learn from large training datasets rather than relying on human-defined rules (Fügener et al., 2022). Whether ChatGPT possesses true intelligence remains a subject of debate. However, prior research has supported that these systems have significant potential to assist users with decision-making and data analysis (Kumar et al., 2023; Ma et al., 2021).

2.2. IT identity

Identity is a complex concept that explains the development of the self. We systematically search for ways to affirm our identities and present ourselves to the world through our appearance, behaviors, personality, and group memberships (Kim et al., 2012). Previous literature posits that self-identity influences intentions and behaviors (Arbore et al., 2014; Kessler & Milkman, 2018). Humans inherently seek a sense of belonging and relatedness. As a result, the role of technology in shaping self-identity can be amplified through platforms like social media, where people can create and manage their identities in the digital landscape (Gonibeed & Saqib, 2022; Yau et al., 2019). In 2015, the concept of IT identity emerged as a crucial element in understanding how individuals perceive themselves in relation to technology (Carter & Grover, 2015). IT identity can also be found within organizational contexts, where the existing literature highlights that an organization's technology choice is intrinsically related to its perceived identity (Tyworth, 2014). The complexity of IT identity lies not only in distinguishing its presence within the self and within organizations, but also in identifying its multiplicity inside each individual (McCall & Simmons, 1978). Ultimately, research supports IT identity to be mainly a personal construction despite its organizational impact, evaluating dimensions of dependence, emotional energy, and relatedness, since there is a fundamental need inside people to expand the self and use ITs as resources to facilitate achievements of personal goals (Aron & Aron, 1997; Carter & Grover, 2015).

2.3. Individual and social outcomes of technology and AI

Increasing technology use has introduced new dynamics to users' social well-being (Wang et al., 2021), which has been found to improve overall well-being (Schifano et al., 2021). However, the increasing shift in remote work and constant interaction with technology has also led to feelings of disconnection (Yin et al., 2022). Emerging research has found that individuals may adapt their behavioral responses and experiences in response to AI-generated outputs (Jussupow et al., 2021; Tarafdar et al., 2023). AI systems may also introduce new forms of control leading to disengagement and impacting well-being outcomes (Berente et al., 2021; Cram et al., 2022). By engaging with AI assistants users may be able to satisfy their emotional support and conversation needs, potentially alleviating feelings of alienation among peers, but the possibility of the adverse effects of emotional overreliance should not be overlooked (Duong et al., 2024).

2.4. Prior research on AI and IT identity

Few studies have emerged to understand and test the concept of IT identity in relation to AI – AI identity, based on the proposed framework by Carter & Grover (2015). This concept has been linked to traditional frameworks such as the unified theory of acceptance and use of technology (UTAUT) and the technology acceptance model (TAM) (Esmaeilzadeh et al., 2025). UTAUT has significantly contributed to explain technology acceptance through factors such as performance expectancy, effort expectancy, social influence and facilitating conditions, while TAM posits that an individual's perceived usefulness and perceived ease of use significantly influence their intention to use technology (King & He, 2006; Venkatesh et al., 2016; Venkatesh & Davis, 2000), despite criticisms on its lack of actionable guidance in scientific research (Lee et al., 2003). Although both frameworks have proven effective in explaining technology acceptance, IT identity extends beyond adoption intentions by focusing on the extent to which technology becomes integrated into an individual's self-concept (Carter & Grover, 2015). To overcome potential limitations, TAM has previously been integrated with UTAUT to provide a more comprehensive framework for understanding technology acceptance (Althuizen, 2017). A study conducted in 2025 applied this theoretical background combined with IT identity, including continued use of AI chatbots, which falls in line with the predictions made by the IT identity framework (Carter & Grover, 2015; Esmaeilzadeh et al., 2025).

At the organizational level, several studies have adopted different approaches: (1) focusing on technological features (Althuizen, 2017; Esmaeilzadeh et al., 2025; King & He, 2006; Venkatesh & Davis, 2000); and (2) focusing on ethical aspects, governance, and the dark side of technology use (Liu & Du, 2025; Mirbabaie et al., 2022; Shonhe & Min, 2025). Research on AI identity has also explored the concept in the context of role identity theory (Alahmad & Robert, 2020; Cao et al., 2023; Marikyan et al., 2024). These findings exacerbate the need to provide stability when implementing new technologies with adequate support and opportunities to employees in order to reduce feelings of distress and threat to individuals' identities, correlating to Carter & Grover's (2015) line of thinking in the IT identity framework.

Table 1 presents a summary of the prior research on AI and IT identity.

Table 1. Research overview

Source	Theory	Description	Main findings
Esmaeilzadeh et al. (2025)	UTAUT + TAM + IT identity	Offers insights into the motivations and behaviors behind technology use, relating to IT identity	Experiences like satisfaction shape IT identity, which in turn positively influences behavioral intentions.
Alahmad & Robert (2020) and Cao et al. (2023)	Role identity theory + IT identity	Investigates whether IT identity can shape self-views and other outcomes in individuals performing specific roles	Role identity and organizational identity are key drivers of IT identity development. These identities can shape outcomes like job performance.
Qin et al. (2024)	Motivation theory + IT identity	Concludes which incentives and stimuli motivate individuals towards specific behaviors based on their IT identity	IT identity can affect proactive behaviors in its users, with effective incentives and stimuli reinforcing positive behaviors.
Mirbabaie et al. (2022) and Shonhe & Min (2025)	Professional identity threat theory (PIT) + IT identity	Theorizes that the introduction of new technologies challenges existing notions of identity, which may be linked to feelings of distress	IT identity can reduce PIT and enhance technology adoption. Adequate support is necessary to provide stability and reduce feelings of anxiety toward professional identity.
Liu & Du (2025)	User ethical perception framework + IT identity	Provides a basis to observe how people with different levels of IT identity may react to ethical challenges in different contexts	Ethical aspects of technology were found to positively shape users' IT identity, which in turn affects their intention to continue using the technology.
Alawi (2021) and Alawi et al. (2023)	Similarity attraction theory + Social impact theory + IT identity	Posits that technology similarities and capabilities can influence IT identity development	IT identity is positively impacted by the perceived similarities between technologies and their users. This affects their intention to continue using and their perceived competence with said technology.

2.5. Summary of current gaps and contributions

In summary, this study addresses prominent gaps in the current literature. First, existing research in the IT identity literature has not tested the framework as an integrated model, particularly in AI contexts. Prior work mostly delved into IT identity constructs selectively and combined the framework with models such as UTAUT, TAM, role identity, and others (Alahmad & Robert, 2020; Cao et al., 2023; Esmaeilzadeh et al., 2025; Mirbabaie et al., 2022; Ogbanufe & Gerhart, 2020). While these models are well-grounded, they are limited in capturing the deeper psychological integration of technology into the self.

In contrast, IT identity enables the examination of a full psychological pathway from experiences to identity, behavior, and outcomes. Second, current literature frequently emphasizes behavioral and intention constructs, potentially overlooking significant outcomes. This aspect is especially prominent in AI identity studies, where the humanistic impact on users is currently overlooked (Carter & Grover, 2015; Yau et al., 2019). This study addresses this gap by incorporating social well-being into the proposed conceptual model. Finally, existing research has investigated IT identity constructs without acknowledging contextual factors and situational influences (Alawi, 2021; Esmaeilzadeh et al., 2025; Ogbanufe & Gerhart, 2020).

The gaps presented position the current study primarily as a tentative empirical validation and extension of the IT identity framework rather than the development of a new theoretical model. The study's novelty lies in testing the full IT identity pathway by linking experiences, IT identity, behaviors, and outcomes, in the context of ChatGPT. By applying the framework to this generative AI tool and including instrumental and humanistic outcomes, this research evaluates the extent to which established IT identity relationships transfer to AI environments.

3. Conceptual model

Based on the IT identity framework proposed by Carter and Grover (2015), this study's model aims to understand how individuals develop an IT identity when using ChatGPT. To enhance conceptual clarity, the model is organized around a core explanatory pathway that links user experiences → IT identity → behaviors → outcomes, capturing the study's central theoretical logic. More specifically, identity formation refers to the psychological relationship users develop with generative AI, including the extent to which ChatGPT becomes integrated into their self-concept or professional identity. Technology use behavior refers to how users interact with ChatGPT in practice, including the frequency, intensity, and depth of use. Finally, user outcomes refer to the consequences of these interactions, such as social well-being and performance. This distinction helps clarify the causal ordering proposed in the model, whereby user experiences and situational factors shape IT identity, IT identity influences subsequent technology use behaviors, and these behaviors ultimately affect user outcomes. The resulting conceptual model is illustrated in Figure 1.

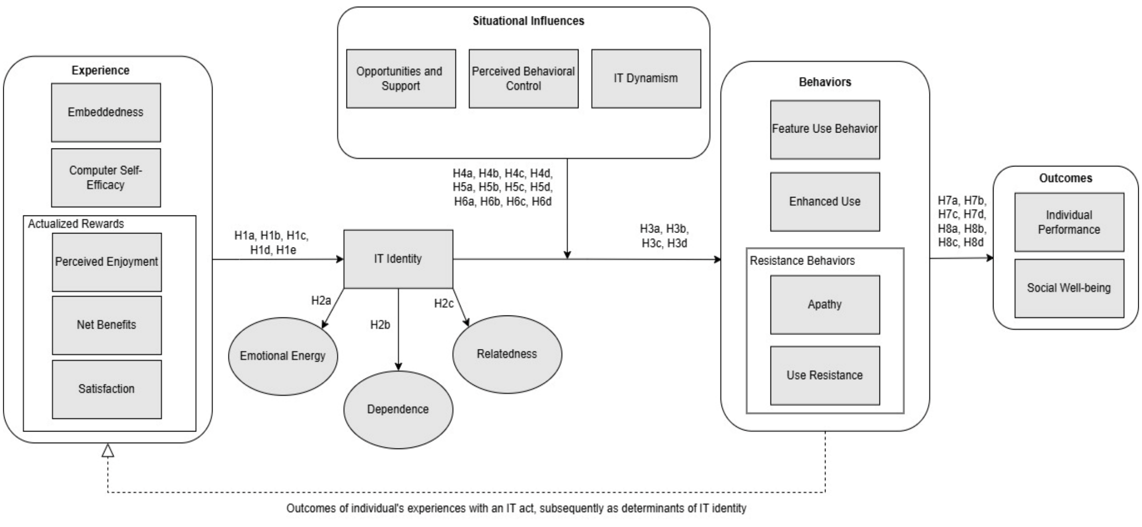


Figure 1. *Conceptual model*

A user's experience with technology has been theorized to precede IT identity creation and directly influence its strength (Carter & Grover, 2015). Carter and Grover (2015) divided experiences into five constructs: embeddedness, computer self-efficacy, perceived enjoyment, net benefits, and satisfaction, with the last three being grouped as actualized rewards. Embeddedness in technology has been compared to the extent to which an individual has invested in an identity, which was previously found to be a significant determinant of identity creation (Carter & Grover, 2015; McCall & Simmons, 1978). Additionally, emotional energy, relatedness, and dependence have been theorized to result from embeddedness within IT (Mcmillan & Morrison, 2006; Vincent, 2006) as well as from computer self-efficacy (Aggarwal et al., 2015; Venkatesh & Windeler, 2012). Finally, regarding experiences, actualized rewards and gratifications have been found to be correlated to higher technology dependence and commitment (Carter & Grover, 2015; Rai et al., 2002; Venkatesh & Bala, 2008). The multitude of emotions and satisfaction a user can feel toward an AI assistant like ChatGPT has been shown to encourage continued use of these technologies (Gkinko & Elbanna, 2022), possibly enhancing future IT identity. Hence, we hypothesize that:

H1a. Embeddedness is positively associated with IT identity.
H1b. Computer self-efficacy is positively associated with IT identity.
H1c. Perceived enjoyment is positively associated with IT identity.
H1d. Net benefits are positively associated with IT identity.
H1e. Satisfaction is positively associated with IT identity.

IT identity was proposed as a second-order construct in the original study, with three related dimensions: emotional energy, dependence, and relatedness. Emotional energy refers to an individual's emotional attachment in relation to an IT (Carter & Grover, 2015), which can be a strong determinant of technology acceptance and adoption. Dependence encapsulates the reliance on technology we may develop when we use it frequently, which seems to be increasing every day and is becoming an important factor in maintaining our social relationships (Carter & Grover, 2015; Mcmillan & Morrison, 2006). Lastly, relatedness refers to the degree to which we see ourselves in a specific IT, and the original study proposes that a strong connection to a certain IT can be a main driver of IT identity formation around it (Carter & Grover, 2015). Hence, we hypothesize that:

H2a. IT identity will be reflected in individuals' emotional energy in relation to ChatGPT.
H2b. IT identity will be reflected in individuals' feelings of dependence in relation to ChatGPT.
H2c. IT identity will be reflected in individuals' feelings of relatedness in relation to ChatGPT.

Previous studies have drawn connections between behaviors and identity, presenting findings that show that the norms associated with one's sense of identity are primary influences in their daily behaviors (Kessler & Milkman, 2018). Carter and Grover (2015) propose that a strong IT identity can be responsible for an individual's willingness to explore IT features, defined as feature use behavior, which encompasses the dimensions of extended use, extent of use, and breadth of use (Carter & Grover, 2015). Additionally, a consequent increase in technology use may arise from strong identities, as users become more familiar with the technology they relate to (Carter & Grover, 2015). The perceived social engagement of chatting with AI, such as ChatGPT, can also be a determinant of enhanced use, since social engagement with technology may foster a sense of community and contribute to this phenomenon (Ghazali et al., 2018; Guo et al., 2022). Hence, we hypothesize that:

H3a. IT identity in relation to ChatGPT is positively associated with feature use behavior.
H3b. IT identity in relation to ChatGPT is positively associated with enhanced use.

In the original IT identity framework, it was theorized that strong IT identities would increase apathy and resistance to use (Valtonen & Holopainen, 2025). However, despite this being a valuable lens for study, we opted to explore how strong IT identities could negatively influence these behaviors in relation to the technology people are connected to. This shift in focus was driven by the growing number of studies in apathy toward AI technologies and the growing ambition in studying the psychological aspects of these technologies. Previous research supports this line of thought, as it has been found that once inertia has set in, known as status quo, technology users are more prone to resist engagement with new technologies (Polites & Karahanna, 2012), possibly developing an even stronger identity with the technologies they already know (Struijk et al., 2023). Despite the extensive use of AI assistants, a certain apathy, skepticism, and resistance are present towards the outputs these technologies provide (Jin & Zhang, 2023). This distrust has been found to stem from a user's perceived competence with the AI platform (Jin & Zhang, 2023). Therefore, individuals who develop a stronger IT identity around ChatGPT may be less likely to exhibit apathetic attitudes toward the tool, as stronger identification is generally associated with greater engagement and involvement. Hence, we hypothesize that:

H3c. IT identity in relation to ChatGPT is negatively associated with apathy.
H3d. IT identity in relation to ChatGPT is negatively associated with use resistance.

According to the IT identity framework, it was hypothesized that situational influences could moderate the relationship between IT identity and consequent behaviors (Carter & Grover, 2015). It was proposed that the main influences stem from perceived behavioral control, IT dynamism, and opportunities and support. An individual's perceived control of their technology use can be a strong moderator of identity and behaviors, as it has been found that even in situations where bring-your-own-device (BYOD) practices are discouraged, individuals seek to indulge in the IT they are familiar with (French et al., 2014), thereby enacting behavior according to their IT identity. Previous research on attitudes and behaviors also finds that attitudes translate into behavior when situational conditions allow enactment; therefore, a higher perceived control over use behavior toward IT may strengthen the relationship between IT identity and behavior (Ajzen & Fishbein, 1977). Current research reveals a gap in understanding the role of perceived behavioral control in shaping users' behavior, particularly with technologies like ChatGPT. Given the unpredictability of AI tools, perceived control over AI-generated outputs may be particularly relevant in shaping users' willingness to engage with and depend on generative AI systems. Hence, we hypothesize that:

H4a. Perceived behavioral control positively moderates the relationship between IT identity and feature use behavior.
H4b. Perceived behavioral control positively moderates the relationship between IT identity and enhanced use.
H4c. Perceived behavioral control positively moderates the relationship between IT identity and apathy.
H4d. Perceived behavioral control positively moderates the relationship between IT identity and use resistance.

Carter and Grover (2015) hypothesized that IT dynamism can be a strong influence in behavior, as people tend to seek dynamic technologies as a channel for self-expansion and enhanced use. Since the original authors predicted a relationship between IT identity and feature use behavior, we can theorize that the more dynamic an IT feature set is, the greater the opportunity to enact IT identity-driven behavior. This phenomenon may be relevant in generative AI contexts, where frequent model updates, new features, and evolving capabilities may continuously impact user experience. IT dynamism has yet to be studied as a moderator of technology behavior regarding AI assistants like ChatGPT, as it remains unclear whether users perceive these technologies as dynamic. Hence, we hypothesize that:

H5a. IT dynamism positively moderates the relationship between IT identity and feature use behavior.
H5b. IT dynamism positively moderates the relationship between IT identity and enhanced use.
H5c. IT dynamism positively moderates the relationship between IT identity and apathy.
H5d. IT dynamism positively moderates the relationship between IT identity and use resistance.

Previous literature validates that users who do not receive adequate opportunities and support from their organizations tend to exhibit behaviors of inadequacy and technology rejection (Alavi et al., 2024; Tan & Teo, 2000). Carter & Grover (2015) incorporated this moderator in the original framework as they explained that previous literature found that opportunity structures created by individuals allowed them to feel that their needs were supported. This aspect would have a positive effect on IT identity and behaviors, as opportunities and support increase the likelihood of enacting behaviors consistent with IT identity levels (Carter & Grover, 2015). In generative AI contexts, opportunities and support may be particularly relevant given the technology's novelty. Because AI system users engage in prompting, output evaluation, and iterative refinement practices, access to adequate support and learning opportunities may positively influence their engagement with these tools. Hence, we hypothesize that:

H6a. Opportunities and support positively moderate the relationship between IT identity and feature use behavior.
H6b. Opportunities and support positively moderate the relationship between IT identity and enhanced use.
H6c. Opportunities and support positively moderate the relationship between IT identity and apathy.
H6d. Opportunities and support positively moderate the relationship between IT identity and use resistance.

Lastly, as an additional component of the original framework, we opted to include two outcomes stemming from users' behavior: individual performance and social well-being. Individual performance and productivity have been attributed to the use of AI assistants (Chang et al., 2022; Liao et al., 2024; Lichtenthaler, 2020). With this construct, we aim to determine whether IT identity-related behaviors can also affect individual performance, whether positively or negatively. This facet could help determine whether behaviors arising from identities created around ChatGPT have a strong impact on individual performance and align with previous findings in the AI literature. Hence, we hypothesize that:

H7a. Feature use behavior in relation to ChatGPT is positively associated with individual performance.
H7b. Enhanced use in relation to ChatGPT is positively associated with individual performance.
H7c. Apathy in relation to ChatGPT is positively associated with individual performance.
H7d. Use resistance in relation to ChatGPT is positively associated with individual performance.

The impact on social well-being has been debated (Wang et al., 2021). Despite extensive research on performance, social well-being remains, to our knowledge, a very understudied field. Social well-being refers to the extent to which individuals perceive themselves as functioning positively within their social and work environments, including their sense of contribution, connectedness, and perceived quality of life within their community. In organizational contexts, whether academic or enterprise, AI tools can play an important role in fostering a better work environment among peers, i.e., within the work community. Prior research has shown that these tools have increasingly supported communication, problem-solving, and everyday cognitive tasks (Kumar et al., 2023; Ma et al., 2021), which, in turn, could indirectly influence individuals' perceptions of connectedness and peer support, especially in digitally mediated environments. These capabilities may reduce cognitive burden, improve collaborative efficiency, and strengthen individuals' perceptions of support and effectiveness within their work communities. Because IT identity shapes how individuals psychologically relate to technology, it may also influence whether AI is perceived as a resource that enhances social and work functioning. Users who develop stronger identity alignment with ChatGPT may be more likely to integrate the tool into collaborative and professional practices, potentially increasing their perceived social well-being. However, research on these dynamics remains underdeveloped; therefore, we believe this outcome may provide valuable insights and a broader perspective on the humanistic impact on identity creation, particularly in relation to ChatGPT use. Hence, we hypothesize that:

H8a. Feature use behavior in relation to ChatGPT is positively associated with social well-being.
H8b. Enhanced use in relation to ChatGPT is positively associated with social well-being.
H8c. Apathy in relation to ChatGPT is positively associated with social well-being.
H8d. Use resistance in relation to ChatGPT is positively associated with social well-being.

4. Methods

4.1. Measurement

An online survey was conducted to evaluate the proposed research model. All constructs in the questionnaire (see Appendix A) were adapted from existing literature and measured using a seven-point scale. The survey was conducted in English, was anonymous, and included an attention-check question added halfway.

4.2. Data collection

A pilot survey was conducted with 39 responses. After estimating the model, no modifications to the survey instrument were necessary. Therefore, the pilot responses were included in the final dataset for analysis, as a sensitivity analysis using an independent-samples t-test indicated no statistically significant differences between the pilot and post-pilot data ($p > 0.10$).

The survey was shared online, on social media platforms and forums from January 2025 to February 2025 and was open to all respondents aged 18 or older who had previously interacted with ChatGPT. A briefing section was included at the beginning of the survey. A total of 329 responses were collected; 312 (95%) were considered valid and complete. According to the 10-times rule, 312 is considered a sufficient sample size, since multiplying the largest number of structural paths directed at any single construct yields a minimum sample size of 70 (Hair et al., 2011). A statistical power analysis conducted indicated that a minimum sample of approximately 80 observations was required, based on seven predictors, an expected R^2 of 0.23, a significance level of 0.05, and a statistical power of 0.80.

To assess common method bias, three complementary procedures were applied: Harman's one-factor test, variance inflation factor (VIF) analysis, and the use of a theoretically unrelated marker variable. The results showed that no single factor explained more than 50% of the variance (the largest factor accounted for only 30%) (Podsakoff et al., 2003), all VIF values were below the recommended threshold of 3.3 (Lindell & Whitney 2001), and the maximum shared variance with the marker variable was only 3.6% (Johnson et al., 2011). Together, these findings indicate that common method bias was not a significant concern in this study. Table 2 presents the demographic data for the survey respondents.

Table 2. *Sample Characteristics*

Descriptive Statistics		n=312	% of total
Gender	Feminine	199	64%
	Masculine	107	34%
	Other	6	2%
Age (average)		26	
Education Level	High School	67	21%
	Bachelors Degree	151	48%
	Master's Degree	84	27%
	Doctoral Degree	10	3%
Employment Status	Unemployed	13	4%
	Student	139	45%
	Working Student	10	3%
	Employed – Part-Time	79	25%
	Employed – Full-Time	2	1%
	Prefer not to respond	69	22%
Duration of ChatGPT usage	Less than 6 months	37	12%
	Close to 1 year	134	43%
	1-2 years	81	26%
	2-3 years	60	19%
Frequency of ChatGPT usage (last 2 weeks)	Rarely	63	20%
	A few times	85	27%
	A lot of times	88	28%
	Every day	76	25%

The survey did not collect information regarding respondents' industry sector, specific task contexts, or whether their ChatGPT use occurred within organizational or academic settings. Consequently, findings are interpreted broadly, and implications are drawn through an exploratory lens.

5. Data analysis and results

Partial least squares (PLS) using SmartPLS 4.0 was selected as the analytical tool since (1) it allows for an exploratory type of research with large complexity, which is the case of our model; (2) it does not have any restrictive assumptions on data distributions; and (3) it is known for its robust predictive capabilities (Chin et al., 2008; Hair et al., 2011; Ringle et al., 2012).

5.1. Measurement model

In order to assess the measurement model, as presented in Table 3, convergent validity was validated with an AVE above 0.5; the scales were deemed reliable as composite reliability values fell above 0.7 for every construct on the table, and Cronbach's alpha showed values above 0.8 for every construct on the table, reinforcing internal consistency reliability (Bagozzi & Yi, 1988; Fornell & Larcker, 1981; Hair et al., 2011).

Table 3. *Mean, SD, CR, Cronbach's alpha (Cα) and Fornell-Larcker table*

	Mean	SD	CR	Cα	EMB	CSE	PE	NB	S	D	EE	R	OS	PBC	DYN	FUB	EU	APT	UR	IP	SW
EMB	4.95	1.63	0.96	0.94	**0.92**																
CSE	4.54	1.42	0.85	0.83	0.36	**0.72**															
PE	4.96	1.45	0.95	0.92	0.67	0.33	**0.93**														
NB	5.18	1.55	0.96	0.93	0.64	0.39	0.63	**0.94**													
S	5.09	1.40	0.95	0.94	0.63	0.31	0.78	0.69	**0.92**												
D	3.72	1.70	0.95	0.93	0.56	0.28	0.49	0.52	0.45	**0.93**											
EE	3.65	1.69	0.97	0.96	0.48	0.23	0.54	0.54	0.49	0.66	**0.96**										
R	3.52	1.65	0.95	0.93	0.49	0.22	0.50	0.48	0.45	0.70	0.81	**0.94**									
OS	3.81	1.34	0.90	0.86	0.27	0.16	0.30	0.35	0.32	0.45	0.49	0.46	**0.80**								
PBC	5.56	1.30	0.93	0.89	0.54	0.36	0.50	0.58	0.53	0.31	0.26	0.27	0.19	**0.91**							
DYN	5.27	1.23	0.90	0.83	0.39	0.25	0.43	0.35	0.42	0.21	0.25	0.21	0.30	0.41	**0.87**						
FUB	4.47	1.50	0.94	0.91	0.67	0.31	0.55	0.64	0.57	0.62	0.59	0.59	0.42	0.48	0.41	**0.89**					
EU	4.42	1.55	0.93	0.88	0.63	0.30	0.56	0.66	0.58	0.65	0.65	0.64	0.44	0.43	0.38	0.75	**0.90**				
APT	2.48	1.39	0.90	0.83	-0.41	-0.12	-0.43	-0.39	-0.44	-0.11	-0.13	-0.10	0.05	-0.44	-0.25	-0.26	-0.29	**0.86**			
UR	3.04	1.48	0.90	0.86	-0.48	-0.12	-0.39	-0.46	-0.42	-0.20	-0.21	-0.20	0.04	-0.37	-0.18	-0.35	-0.34	0.72	**0.84**		
IP	5.24	1.38	0.95	0.93	0.65	0.37	0.59	0.80	0.64	0.54	0.55	0.50	0.37	0.66	0.41	0.68	0.69	-0.46	-0.52	**0.88**	
SW	3.73	1.50	0.91	0.86	0.52	0.28	0.50	0.55	0.47	0.71	0.63	0.67	0.48	0.33	0.25	0.61	0.63	-0.11	-0.22	0.58	**0.84**

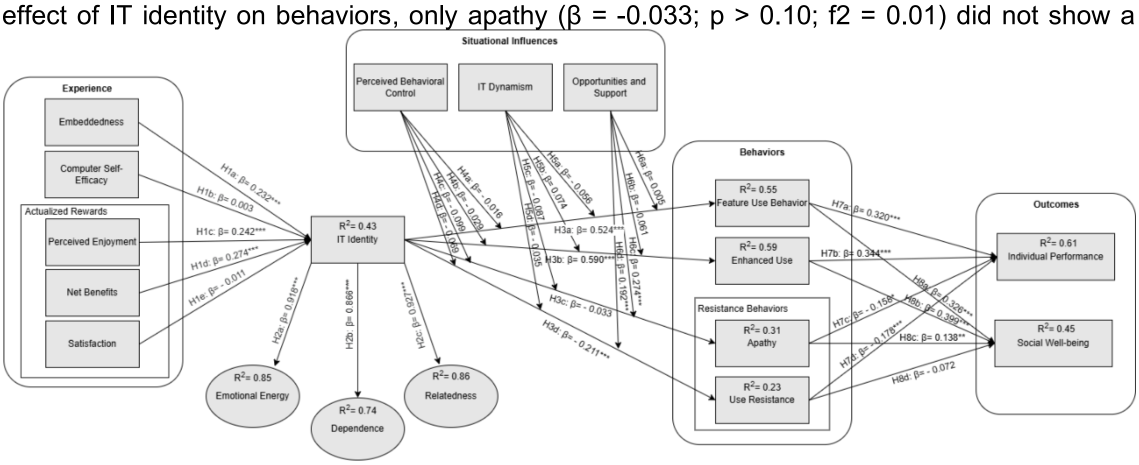
Notes: EMB - Embeddedness; CSE – Computer Self-Efficacy; PE – Perceived Enjoyment; NB – Net Benefits; S – Satisfaction; D – Dependence; EE – Emotional Energy; R – Relatedness; OS – Opportunities and Support; PBC – Perceived Behavioral Control; DYN – IT Dynamism; FUB – Feature Use Behavior; EU – Enhanced Use; APT – Apathy; UR – Use Resistance; IP – Individual Performance; SW – Social Well-Being.

To assess discriminant validity, three criteria were employed: the Fornell-Larcker criterion, cross-loadings, and the Heterotrait-Monotrait Ratio (HTMT). Regarding the first, results show that the square root of the AVE, shown diagonally in bold, is higher than the correlations between the constructs, satisfying the Fornell-Larcker criterion (Fornell & Larcker, 1981). The cross-loadings criterion was also met (see Table B1 in Appendix B) (Chin, 1998). Finally, the assessment of the HTMT criterion was also successful, as values were lower than 0.9 (see Table B2 in Appendix B). It is worth noting that IT identity was modeled as a reflective-reflective second-order construct using the repeated indicators approach in PLS-SEM.

5.2. Structural model

Path coefficient significance was determined using bootstrapping with 10,000 resampling iterations (Hair et al., 2011). Figure 2 presents the model.

Regarding the experience component, only computer self-efficacy (β= 0.003; $p > 0.10$; f^2=0.04) and satisfaction (β= -0.011; $p > 0.10$; f^2=0.00) proved not to be statistically significant. As for the effect of IT identity on behaviors, only apathy (β = -0.033; $p > 0.10$; f2 = 0.01) did not show a



statistically significant correlation with feature use behaviors. Moderating effects were assessed using interaction terms constructed from mean-centered standardized latent variable scores. Opportunities and support, despite not moderating feature use behavior ($\beta= 0.005$; $p > 0.10$; $f^2=0.05$), seemed to be statistically significant as a moderator of enhanced use ($\beta= -0.061$; $p < 0.10$; $f^2=0.004$), apathy ($\beta= 0.274$; $p < 0.10$; $f^2=0.037$) and use resistance ($\beta= 0.192$; $p < 0.10$; $f^2=0.047$), despite not supporting the moderation effect expected on enhanced use. The effect of behavior on the outcomes was statistically significant for all path coefficients except in the path between use resistance and social well-being, which presented a p value above 0.10 ($\beta= -0.072$; $p > 0.10$; $f^2=0.004$). Apathy ($\beta = 0.138$; $p < 0.10$; $f2 = 0.016$) in relation to social well-being was found to have a significant impact, yet the proposed hypothesis was not supported, as we theorized that apathy would have a negative effect on social well-being, yet the opposite was found.

Figure 2. Structural model results

6. Discussion

This study aimed to implement the IT identity framework in the context of ChatGPT use and consequent outcomes. A summary of the presented hypotheses and results is shown in Table 4. Although the IT identity framework provided useful explanatory power in the present study, several relationships established in traditional IT contexts were not supported in the ChatGPT setting, given the distinct interaction paradigms and user expectations associated with AI systems. The relationships examined in this study should be interpreted within specific contextual boundary conditions that may influence how IT identity forms and translates into behavior in generative AI environments. As these factors were not directly examined in the present study, future research should investigate their role more explicitly. Nevertheless, a multigroup analysis was conducted to compare infrequent and frequent users, thereby allowing identification of potential differences in usage patterns. The results are reported in Appendix C.

Table 4. *Summary of Hypothesis*

Hypothesis	Path coefficients	p-value	f^2	Results
H1a. Embeddedness will positively influence IT identity	0.232	<0.01	0.04	Supported
H1b. Computer self-efficacy will positively influence IT identity	0.003	0.942	0.00	Not supported
H1c. Perceived enjoyment will positively influence IT identity	0.242	<0.01	0.04	Supported
H1d. Net benefits will positively influence IT identity	0.274	<0.01	0.056	Supported
H1e. Satisfaction will positively influence IT identity	-0.011	0.898	0.000	Not supported
H2a. IT identity will be reflected in individuals' emotional energy in relation to ChatGPT	0.918	<0.01	5.371	Supported
H2b. IT identity will be reflected in individuals' feelings of dependence in relation to ChatGPT	0.866	<0.01	2.992	Supported
H2c. IT identity will be reflected in individuals' feelings of relatedness in relation to ChatGPT	0.927	<0.01	6.127	Supported
H3a. A strong IT identity in relation to ChatGPT will positively influence feature use behavior	0.524	<0.01	0.403	Supported
H3b. A strong IT identity in relation to ChatGPT will positively influence enhanced use	0.590	<0.01	0.551	Supported
H3c. A strong IT identity in relation to ChatGPT will negatively influence apathy	-0.033	0.637	0.001	Not supported
H3d. A strong IT identity in relation to ChatGPT will negatively influence use resistance	-0.211	<0.01	0.038	Supported
H4a. Perceived behavioral control will positively moderate the relationship between IT identity and feature use behavior	-0.016	0.711	0.066	Not supported
H4b. Perceived behavioral control will positively moderate the relationship between IT identity and enhanced use	-0.029	0.503	0.028	Not supported
H4c. Perceived behavioral control will positively moderate the relationship between IT identity and apathy	-0.099	0.123	0.151	Not supported
H4d. Perceived behavioral control will positively moderate the relationship between IT identity and use resistance	-0.069	0.285	0.082	Not supported
H5a. IT dynamism will positively moderate the relationship between IT identity and feature use behavior	-0.056	0.244	0.035	Not supported
H5b. IT dynamism will positively moderate the relationship between IT identity and enhanced use	0.074	0.143	0.047	Not supported
H5c. IT dynamism will positively moderate the relationship between IT identity and apathy	-0.087	0.142	0.019	Not supported
H5d. IT dynamism will positively moderate the relationship between IT identity and use resistance	-0.035	0.610	0.003	Not supported
H6a. Opportunities and support will positively moderate the relationship between IT identity and feature use behavior	0.005	0.886	0.005	Not supported
H6b. Opportunities and support will positively moderate the relationship between IT identity and enhanced use	-0.061	0.073	0.004	Not supported
H6c. Opportunities and support will positively moderate the relationship between IT identity and apathy	0.274	<0.01	0.037	Supported
H6d. Opportunities and support will positively moderate the relationship between IT identity and use resistance	0.192	<0.01	0.047	Supported
H7a. Feature use behavior in relation to ChatGPT will positively influence individual performance	0.320	<0.01	0.114	Supported
H7b. Enhanced use in relation to ChatGPT will positively influence individual performance	0.344	<0.01	0.133	Supported
H7c. Apathy in relation to ChatGPT will negatively influence individual performance	-0.158	<0.01	0.031	Supported
H7d. Use resistance in relation to ChatGPT will negatively influence individual performance	-0.171	<0.01	0.034	Supported
H8a. Feature use behavior in relation to ChatGPT will positively influence social well-being	0.326	<0.01	0.083	Supported
H8b. Enhanced use in relation to ChatGPT will positively influence social well-being	0.399	<0.01	0.126	Supported
H8c. Apathy in relation to ChatGPT will negatively influence social well-being	0.138	0.036	0.016	Not supported
H8d. Use resistance in relation to ChatGPT will negatively influence social well-being	-0.072	0.303	0.004	Not supported

In line with the original study and previous research (Carter & Grover, 2015; Rai et al., 2002; Venkatesh & Bala, 2008), experiences of embeddedness, perceived enjoyment, and net benefits were shown to be positively associated with IT identity creation. However, computer self-efficacy and satisfaction did not show significant associations regarding this phenomenon. One possible explanation lies in the distinctive characteristics of generative AI tools when compared to traditional IT. AI assistants, through intuitive conversational interfaces and natural language inputs, may substantially reduce the technical barriers typically associated with traditional systems use. As a result, users can effectively interact with AI assistants regardless of their computer self-efficacy, aligning with the known widespread use of ChatGPT for routine and everyday tasks (Kumar et al., 2023), where advanced technical skills may be less relevant. Similarly, satisfaction may also be impacted by the distinctive characteristics of generative AI tools. Unlike traditional IT, AI systems are commonly characterized by variability, experimentation, and iterative interactions, therefore users may continue engaging with and developing an identity around ChatGPT despite occasional dissatisfaction with specific outputs, as the perceived value of the technology extends beyond the quality of individual interactions. These findings suggest that some antecedents of IT identity established in traditional IT settings may function differently in AI contexts, highlighting opportunities for future refinement of the framework. Importantly, while the supported relationships are statistically significant, their effect sizes ($f^2 \approx 0.04$-0.056) are small, suggesting that these variables contribute incrementally to IT identity formation rather than acting as dominant drivers. This factor indicates that IT identity in AI contexts is likely shaped by a broader combination of factors beyond those captured in this model.

IT identity proved to be a significant construct. It was positively associated with feature use behavior and enhanced ChatGPT use, which may be due to users learning to engage more efficiently with the AI as they feel more connected to it. Those relationships exhibit moderate effect sizes (f^2 = 0.403 and 0.551), suggesting that IT identity is a meaningful predictor of active and enriched system use. This finding reinforces the central role of IT identity as a key mechanism through which users engage more deeply with AI tools. Since the sample used for this study reflected different use frequencies, we theorized that negative effects on apathy and use-resistance behaviors were likely to be observed, as frequent ChatGPT use and identity creation do not necessarily indicate that end users ultimately wish to keep relying on the tool or even fully comprehend it. Following this line of thought, IT identity was found to be negatively associated with use resistance, as use resistance reflects intentional opposition or avoidance and poses a threat to identity verification. Individuals with a strong IT identity are less likely to resist the technology, resulting in a negative relationship between IT identity and use resistance, as predicted. However, the effect size for use resistance ($f^2 = 0.038$) is small, indicating that while the relationship exists, its practical impact may be limited. Additionally, IT identity was not negatively associated with apathy, suggesting that even though individuals might rely on ChatGPT and form an identity around it, they do not necessarily lower their skepticism toward its competence (Jin & Zhang, 2023).

Regarding moderation effects, perceived behavioral control and IT dynamism did not significantly influence any of the proposed relationships between IT identity and behaviors. It is possible that, whether users have control over their ChatGPT usage or not, their behavior is not altered in relation to their identities, possibly infringing rules that restrict their AI use. Since ChatGPT seems to have a more static set of features, the weight of IT dynamism may not be relevant to moderate user behaviors, since they do not perceive feature changes as drastic. However, the largely non-significant moderation effects should be interpreted with caution. Given the relatively small effect sizes and the model's complexity, it is possible that smaller moderation effects were not detected.

Regarding opportunities and support, the results show that although feature use behaviors and enhanced use are not moderated, a weak but statistically significant moderation effect exists for apathy (see Figure 3a) and use resistance (see Figure 3b). However, these effects are associated with small effect sizes ($f^2 \approx 0.037$–0.047), indicating limited practical impact. Therefore, the following interpretations should be considered exploratory and interpreted with caution. Figures 3a and 3b were developed using mean-centered latent-variable scores and depict simple slopes at high and low levels of the moderator.

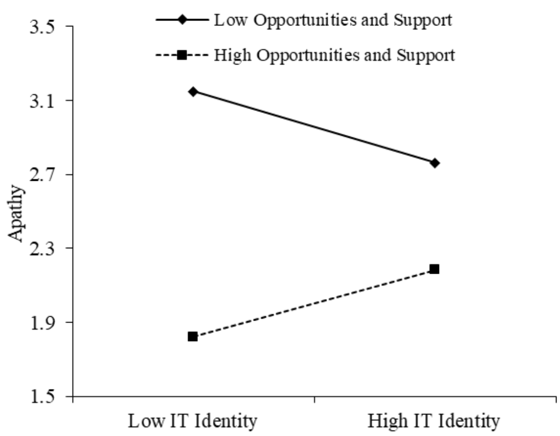


Figure 3a. *Moderating effect of opportunities and support between IT identity and apathy*

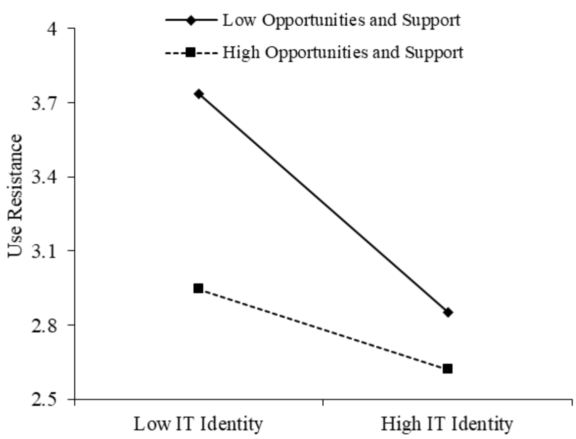


Figure 3b. *Moderating effect of opportunities and support between IT identity and use resistance*

The interaction effects depicted in Figures 3a and 3b indicate that opportunities and support moderate the relationship between IT identity and negative behavioral outcomes. A stronger IT identity was generally associated with lower apathy and use resistance when opportunities and support were limited. However, when opportunities and support were readily available, IT identity appeared less relevant in explaining these behaviors. These findings may provide preliminary evidence that supportive and opportunity-prevalent environments may reduce negative AI-related behaviors independently of users' IT identity levels. However, given the small effect sizes, these results should be interpreted cautiously and viewed as exploratory until replicated in future studies with different populations and greater statistical power.

As for outcomes, individual performance was positively associated with both feature use behavior and enhanced use and negatively associated with apathy and use resistance, as expected (Abubakre et al., 2017) and resistance behaviors may hinder performance. Social well-being has been shown to be associated only with feature use behaviors, enhanced use behaviors, and apathy, with use resistance showing no significant association. The impact of behaviors in well-being falls in line with previous research, as human-AI interaction and collaboration have been found to shape experiences and behaviors in users (Berente et al., 2021; Jussupow et al., 2021; Tarafdar et al., 2023), which in turn can impact user well-being as new forms of AI control and coordination are introduced (Cram et al., 2022). Apathy is found to be positively associated with social well-being, contrary to previous theory. The original hypothesis was grounded in prior IT literature, which generally associates apathy with disengagement from technology and less favorable outcomes. Under this assumption, apathetic users would be expected to experience lower levels of social well-being. However, the positive relationship observed in this study suggests that generative AI assistants may not be interpreted in the same way as traditional IT.

Given the unexpected nature of this finding, the following interpretations should be considered exploratory and intended to provide possible explanations rather than definitive causal mechanisms. This finding, therefore, suggests that assumptions about apathetic technology use may need reconsideration when applied to generative AI environments. We propose autonomy-preserving disengagement as the most plausible explanatory mechanism. Drawing on self-determination theory, autonomy represents a fundamental psychological need and a well-established predictor of well-being. In the context of generative AI, apathetic users may maintain greater psychological distance from ChatGPT, engaging with it instrumentally rather than emotionally. Importantly, such apathy may not indicate complete rejection of the technology, but instead a controlled and selective usage pattern in which users rely on ChatGPT only when it provides clear practical value. This detached mode of interaction may enable users to benefit from efficiency gains, reduced cognitive load, and rapid informational support while avoiding dependency, identity threat, or pressure to engage continuously. As a result, users may preserve a stronger sense of control over their work processes, which can positively influence social well-being. This interpretation is particularly relevant given that the social well-being construct used in this study primarily captures functional contributions to work and community quality of life rather than emotional attachment to AI. Therefore, emotional disengagement from ChatGPT may coexist with positive evaluations of its practical utility. Alternative explanations, such as a stronger preference for human-centered interactions among apathetic users, remain possible but appear secondary to the autonomy-based explanation.

Overall, our findings challenge traditional technology adoption models that focus solely on technical factors and neglect the psychological integration of technology into users' sense of self. Thus, the results suggest that individuals who associate with AI tools may increasingly rely on them, not only in a technical sense, but as a cognitive partner, highlighting identity-based mechanisms as crucial in understanding human-AI interactions. While the findings support several proposed relationships, they should be interpreted in light of the study's cross-sectional design, which allows only inferences about association rather than causation.

6.1. Theoretical implications

This study empirically tests and validates the psychological aspects of the IT identity framework, with an added component on outcomes (Carter & Grover, 2015), providing significant support for its applicability in the context of ChatGPT identity in individuals and advancing the literature on the bridge between identity and technology. While the core IT identity construct and its dimensions were strongly supported, several antecedent, moderating, and behavioral relationships established in traditional IT settings were not replicated. These results suggest that the framework remains useful for understanding identity formation around generative AI technologies but may require refinement to account for the distinctive characteristics of AI assistants and human-AI interaction. While previous research focused on IT identity in general technology contexts, this study confirms not only that AI assistants may also be integral to users' own identities but also that experiences, situational influences, behaviors, and outcomes are key dimensions. Regarding the model, an incorporated layer of outcomes provides deeper insight into the ChatGPT user experience. These outcomes expand our understanding of how IT identity may relate to both instrumental and humanistic dimensions of technology use.

Second, this study demonstrates that IT identity remains a strong driver of active and enhanced use, but does not necessarily reduce negative behaviors such as apathy. This factor indicates that identity formation in AI contexts may coexist with skepticism and critical distance, contrasting with prior assumptions. Regarding outcomes, the surprising effect of apathy on social well-being presents an interesting avenue for future research. Since the nature of the discussion on this topic was mainly exploratory, this could offer an interesting theoretical lens for future qualitative studies.

Moreover, this study identifies opportunities and support as a relevant boundary condition, showing that the influence of IT identity on behavior is stronger in low-support environments and attenuated when external support is available. This aspect highlights that identity-driven engagement becomes more critical when institutional or contextual support is limited. By highlighting opportunities and support as strong moderators in IT identity's effects on behavior, we find that external conditions may be associated with differences in user engagement, acceptance, and outcomes. This factor provides an open door for future scholars to explore which opportunities and support could strongly impact behaviors derived from IT identity.

Furthermore, by identifying which constructs are significant from the original framework in explaining IT identity regarding ChatGPT, we highlight that perhaps this framework does not entirely fit every type of technology, needing future alterations in order to conclude more accurate results.

6.2. Practical implications

Regarding practical implications, first, embeddedness, perceived enjoyment, and net benefits were shown to significantly strengthen IT identity, albeit with small effect sizes; therefore, developers should prioritize features that integrate AI assistants into daily workflows to enhance user support. Features such as seamless integration across workspaces, session continuity, and intelligent task automation could help users progressively build meaningful, enhanced interactions with technologies like ChatGPT. Second, given the strong connection between IT identity and feature use behavior, developers should encourage feature discovery through adaptive prompt suggestions and recommend advanced features to users who demonstrate confident, repeated use of the tool. Finally, as reductions in apathy and use resistance are not as significant as expected, we underscore that identity alone does not eliminate skepticism and resistance towards AI use and outputs. Developers should provide AI users with transparency-oriented features (e.g., explanations of outputs and uncertainty cues) and education on AI capabilities and limitations.

The development of a strong ChatGPT identity also raises potential risks, as over-reliance on AI outputs may contribute to the erosion of critical thinking, unhealthy dependence, shortsightedness, and a lack of accountability regarding AI output quality. Managers and/or leadership roles should aim to foster a beneficial IT identity toward ChatGPT without promoting excessive dependence. Although the present study does not directly examine organizational contexts, a tentative implication is that environments where critical thinking is most leveraged – such as enterprises and educational institutions – may benefit from positioning ChatGPT as a complementary tool that supports, rather than replaces, human expertise. This objective can be achieved by implementing practices that promote reflective AI engagement, such as requiring verification of AI-generated outputs, encouraging employees to evaluate responses critically, and maintaining human oversight in decision-making. Additionally, managers should preserve opportunities for peer interaction, collaborative problem solving, and knowledge sharing, ensuring that AI complements rather than replaces human social dynamics in the workplace. Nevertheless, future research involving professional populations could examine whether a stronger AI identity is associated with these potential risks and assess how organizations can balance AI-assisted productivity with critical evaluation practices. The results indicate that opportunities and support moderate some ChatGPT-related behaviors. This element could be relevant for entities that can regulate AI use and provide clear-cut strategies, opportunities, governance, and infrastructure, as well as discussions on ChatGPT and its benefits and risks. However, our sample does not allow for direct conclusions, and further research is necessary for conclusive suggestions. A tentative implication is that adequate environments, training programs, AI onboarding, workshops, and policies could evoke stronger AI engagement and encourage responsible use practices, which could be implemented in learning or working environments in order to reduce resistance behaviors and enhance use. In particular, these interventions may be especially important in low-support environments, where users rely more heavily on IT identity to sustain engagement.

Finally, to further enhance the practical contributions and improve clarity for practitioners, it is important to distinguish the implications of this study across three key stakeholder groups: AI developers, organizations (including managers and educators), and policymakers. For AI developers, the findings primarily highlight the importance of designing systems that support meaningful integration into users' workflows while maintaining transparency, usability, and guided feature exploration. For organizations, the results suggest the need to foster a balanced IT identity that encourages productive and autonomous use of ChatGPT while avoiding overdependence through practices such as critical evaluation, verification of AI outputs, and preservation of human collaboration. Finally, for policymakers, the study underscores the importance of AI literacy initiatives, governance frameworks, and regulatory measures that ensure responsible use, data protection, and user awareness of AI limitations. Together, these three levels of implication highlight that the value of ChatGPT depends not only on technological design but also on organizational practices and broader institutional support structures that shape how IT identity translates into real-world outcomes.

6.3. Limitations and further research

This study has several methodological limitations that suggest directions for future research. Because data were collected over a one-month period using a cross-sectional survey design, the findings cannot establish causality or capture how ChatGPT identity evolves over time. Future longitudinal studies could provide deeper insights into the development of IT identity and its effects on user experiences. Additionally, the reliance on self-reported data from social media, AI forums, and survey platforms may introduce response inaccuracies and self-selection bias, particularly since participants were already active ChatGPT users. The predominantly young, highly educated, and AI-experienced sample also limits conclusions about cultural, gender, and age-related differences. Furthermore, while the quantitative approach supports generalizability, qualitative methods such as interviews and focus groups could help explain nuanced or unexpected findings, including the positive relationship observed between apathy and social well-being.

From a scope perspective, the study tested the IT identity framework but excluded the IT characteristics component and focused only on individual performance and social well-being as outcomes. Future research should examine how specific AI characteristics influence identity formation and explore additional outcomes such as job performance, emotional well-being, dependence, cognitive load, and technostress. Several hypotheses were unsupported, and some expected predictors, such as satisfaction and self-efficacy, were not significant, suggesting that the traditional IT identity framework may require adaptation for AI contexts. Moreover, the model's complexity and generally small effect sizes may have limited the detection of subtle relationships. Since the study examined ChatGPT use broadly without considering specific tasks or contexts, future studies should investigate different AI assistants, technologies, and environments, such as educational and enterprise settings, to determine whether the findings generalize across contexts.

7. Conclusion

This study provides insights into ChatGPT identity creation among users, using the IT identity framework and outcomes as the empirical model. A quantitative study was conducted via an online survey of ChatGPT users. The findings suggest that ChatGPT users do form identities around this AI assistant, and that opportunities and support can influence certain behaviors, highlighting the need to educate individuals about ChatGPT use and to provide resources to leverage this technology correctly, validating the first proposed objective of this study. The second objective was also confirmed, as individual performance and social well-being were found to be positively associated with ChatGPT identity and user behaviors, opening the door to explore other outcomes in future research and providing an added lens on IT identity. The proposed model seeks to encourage future scholars to implement the IT identity framework, contribute to discussions on responsible AI adoption, and provide a basis for future research on ChatGPT, AI assistants, and their impact on user identity.

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Appendix A

***Table A1**. Survey items*

Construct		Item	Item Description
Embeddedness (Fang et al., 2023)		EMB1	I have interacted with ChatGPT across a broad daily affairs
		EMB2	I have used ChatGPT across a variety of situations to deal with daily affairs
		EMB3	In my past interactions with ChatGPT, I have used a wide range of its features across a variety of situations
		EMB4	Overall, I have used ChatGPT's applications across a broad range of situations to support my daily life
Computer self-efficacy (Compeau et al., 1999)		CSE1	I could complete my tasks using ChatGPT if there was no one around to tell me what to do as I go
		CSE2	I could complete my tasks using ChatGPT if I had seen someone else using it before trying it myself
		CSE3	I could complete my tasks using ChatGPT if I could call someone for help if I got stuck
		CSE4	I could complete my tasks using ChatGPT if someone else had helped me get started
		CSE5	I could complete my tasks using ChatGPT if someone showed me how to do it first
Perceived Enjoyment (Venkatesh & Bala, 2008)		PE1	I find using ChatGPT to be enjoyable
		PE2	The actual process of using ChatGPT is pleasant
		PE3	I have fun using ChatGPT
Net Benefits (Laumer et al., 2017)		NB1	Using ChatGPT improves my content-related work
		NB2	Overall, using ChatGPT enhances my content-related work
		NB3	ChatGPT helps me improve my work efficiency
Satisfaction (Bhattacherjee & Premkumar, 2004)		S1	I am pleased with my use of ChatGPT
		S2	I am contended with my use of ChatGPT
		S3	I am delighted with my use of ChatGPT
		S4	I am satisfied with my use of ChatGPT
IT Identity (Fang et al., 2023)	Dependence	D1	Thinking about myself with ChatGPT, I am reliant on ChatGPT
		D2	Thinking about myself with ChatGPT, I am dependent on ChatGPT
		D3	Thinking about myself with ChatGPT, I am counting on ChatGPT
	Emotional Energy	EE1	Thinking about myself with ChatGPT, I feel energized
		EE2	Thinking about myself with ChatGPT, I feel pumped up
		EE3	Thinking about myself with ChatGPT, I feel enthusiastic
	Relatedness	R1	Thinking about myself with ChatGPT, I am in coordination with ChatGPT
		R2	Thinking about myself with ChatGPT, I am linked with ChatGPT
		R3	Thinking about myself with ChatGPT, I am connected with ChatGPT
Opportunities and Support (Carter & Grover, 2015)		OS1	Having access to adequate training is _ for my usage of ChatGPT
		OS2	Having adequate policies is _ for my usage of ChatGPT
		OS3	Having access to adequate infrastructure is _ for my usage of ChatGPT
		OS4	The number and strength of my interpersonal ties are _ for my usage of ChatGPT
		OS5	The number and strength of my technological ties are _ for my usage of ChatGPT
Perceived Behavioral Control (George, 2004)		PBC1	I am capable of using ChatGPT to complete my tasks
		PBC2	Using ChatGPT to complete my tasks is entirely within my control
		PBC3	I have the resources *and* the knowledge *and* the ability to use ChatGPT to complete my tasks
IT Dynamism (Newkirk et al., 2008)		DYN1	ChatGPT is rapidly changing its features
		DYN2	ChatGPT's features today differ from its features three years ago
		DYN3	ChatGPT's features three years from now will differ from its features today
Feature Use Behavior (Esmaeilzadeh, 2020)		FUB1	I will use most of ChatGPT's features to complete my tasks
		FUB2	I will frequently use different ChatGPT features
		FUB3	I will use ChatGPT's features in different situations to complete my tasks
		FUB4	I would think to use ChatGPT's features to manage tasks rather than alternative means
Enhanced Use (Esmaeilzadeh, 2020)		EU1	I will use ChatGPT for additional tasks
		EU2	I will use the feature extensions (upgraded plan) of ChatGPT for completing my tasks
		EU3	Overall, I will enhance my usage of ChatGPT
Apathy (Taneja et al., 2015)		APT1	I do not get along with ChatGPT
		APT2	I am not interested in ChatGPT
		APT3	I have trouble understanding ChatGPT
Use Resistance (Hajiheydari et al., 2021)		UR1	I'm likely to be opposed to the use of ChatGPT
		UR2	It's unlikely I use ChatGPT in my job
		UR3	In the near future, using ChatGPT would be connected with too many uncertainties
		UR4	I would be making a mistake by using ChatGPT
Individual Performance (Urbach et al., 2010)		IP1	ChatGPT enables me to accomplish tasks more quickly
		IP2	ChatGPT improves my job performance
		IP3	ChatGPT increases my productivity
		IP4	ChatGPT makes it easier to accomplish tasks
		IP5	ChatGPT is useful for my job
Social Well-being (El Hedhli et al., 2013)		SW1	ChatGPT satisfies my overall work needs
		SW2	ChatGPT plays a role in my social well-being
		SW3	ChatGPT plays a very important role in my work well-being
		SW4	ChatGPT plays an important role in enhancing the quality of life in my community

Appendix B

***Table B1**. Loadings and cross-loadings*

	EMB	CSE	PE	NB	S	D	EE	R	OS	PBC	DYN	FUB	EU	APT	UR	IP	SW
EMB1	**0.91**	0.33	0.63	0.58	0.58	0.49	0.36	0.38	0.19	0.53	0.36	0.58	0.54	-0.44	-0.46	0.60	0.44
EMB2	**0.93**	0.32	0.63	0.59	0.59	0.51	0.43	0.44	0.27	0.51	0.38	0.59	0.56	-0.39	-0.46	0.61	0.46
EMB3	**0.90**	0.33	0.59	0.59	0.55	0.54	0.49	0.51	0.27	0.50	0.33	0.66	0.61	-0.32	-0.39	0.58	0.52
EMB4	**0.95**	0.35	0.62	0.59	0.60	0.53	0.46	0.47	0.26	0.48	0.38	0.65	0.60	-0.39	-0.45	0.59	0.50
CSE1	0.47	**0.82**	0.39	0.42	0.38	0.32	0.31	0.25	0.09	0.43	0.27	0.38	0.34	-0.29	-0.27	0.42	0.29
CSE2	0.18	**0.79**	0.21	0.28	0.18	0.19	0.12	0.11	0.14	0.26	0.16	0.21	0.20	-0.03	-0.04	0.26	0.24
CSE3	0.15	**0.69**	0.15	0.18	0.13	0.12	0.04	0.09	0.18	0.10	0.12	0.12	0.14	0.05	0.03	0.13	0.15
CSE4	0.07	**0.65**	0.11	0.15	0.05	0.09	0.03	0.11	0.15	0.13	0.11	0.06	0.09	0.13	0.14	0.12	0.11
CSE5	0.02	**0.64**	0.08	0.13	0.07	0.10	0.04	0.11	0.14	0.07	0.10	0.06	0.09	0.14	0.13	0.11	0.09
PE1	0.68	0.33	**0.94**	0.63	0.76	0.49	0.51	0.48	0.28	0.50	0.40	0.53	0.55	-0.42	-0.40	0.60	0.49
PE2	0.60	0.30	**0.92**	0.57	0.69	0.41	0.47	0.41	0.28	0.45	0.40	0.48	0.47	-0.43	-0.38	0.52	0.40
PE3	0.59	0.29	**0.93**	0.57	0.72	0.47	0.51	0.49	0.29	0.45	0.40	0.52	0.54	-0.34	-0.31	0.53	0.49
NB1	0.59	0.33	0.57	**0.93**	0.62	0.47	0.47	0.42	0.29	0.50	0.30	0.56	0.60	-0.35	-0.40	0.72	0.48
NB2	0.61	0.40	0.60	**0.96**	0.66	0.50	0.54	0.50	0.37	0.56	0.36	0.63	0.65	-0.38	-0.44	0.76	0.54
NB3	0.59	0.38	0.61	**0.94**	0.66	0.49	0.51	0.45	0.32	0.56	0.33	0.61	0.61	-0.38	-0.46	0.79	0.54
S1	0.56	0.26	0.73	0.62	**0.93**	0.40	0.43	0.39	0.28	0.52	0.42	0.51	0.51	-0.40	-0.37	0.59	0.41
S2	0.55	0.26	0.67	0.60	**0.90**	0.38	0.43	0.38	0.29	0.49	0.37	0.52	0.51	-0.37	-0.35	0.57	0.36
S3	0.61	0.30	0.74	0.65	**0.93**	0.50	0.51	0.51	0.33	0.46	0.35	0.55	0.58	-0.41	-0.39	0.59	0.51
S4	0.58	0.31	0.71	0.66	**0.91**	0.35	0.39	0.33	0.25	0.50	0.42	0.49	0.50	-0.45	-0.43	0.59	0.40
D1	0.56	0.28	0.48	0.53	0.46	**0.94**	0.63	0.65	0.45	0.31	0.25	0.61	0.65	-0.13	-0.19	0.53	0.66
D2	0.48	0.22	0.42	0.43	0.39	**0.94**	0.60	0.68	0.41	0.25	0.16	0.54	0.57	-0.05	-0.14	0.46	0.70
D3	0.54	0.29	0.47	0.49	0.42	**0.93**	0.63	0.63	0.40	0.33	0.19	0.57	0.59	-0.12	-0.23	0.53	0.63
EE1	0.48	0.22	0.52	0.53	0.47	0.67	**0.96**	0.77	0.46	0.24	0.23	0.58	0.63	-0.14	-0.22	0.53	0.63
EE2	0.46	0.20	0.48	0.50	0.43	0.65	**0.97**	0.81	0.49	0.23	0.21	0.56	0.62	-0.09	-0.19	0.52	0.63
EE3	0.44	0.24	0.55	0.53	0.50	0.59	**0.95**	0.77	0.47	0.28	0.28	0.56	0.62	-0.14	-0.20	0.53	0.57
R1	0.50	0.26	0.51	0.53	0.47	0.65	0.78	**0.91**	0.41	0.35	0.24	0.55	0.62	-0.17	-0.26	0.55	0.64
R2	0.44	0.18	0.44	0.43	0.38	0.68	0.76	**0.95**	0.45	0.21	0.15	0.56	0.58	-0.03	-0.14	0.43	0.62
R3	0.44	0.18	0.44	0.40	0.40	0.64	0.74	**0.95**	0.42	0.21	0.19	0.55	0.59	-0.07	-0.15	0.42	0.63
OS1	0.14	0.13	0.22	0.26	0.22	0.32	0.34	0.35	**0.81**	0.07	0.25	0.30	0.30	0.12	0.09	0.26	0.35
OS2	0.10	0.09	0.16	0.16	0.20	0.19	0.21	0.16	**0.71**	0.16	0.22	0.17	0.14	0.08	0.10	0.19	0.19
OS3	0.30	0.18	0.28	0.33	0.33	0.39	0.37	0.36	**0.79**	0.25	0.28	0.35	0.37	-0.03	-0.07	0.39	0.39
OS4	0.24	0.09	0.27	0.29	0.28	0.43	0.50	0.47	**0.84**	0.13	0.21	0.42	0.43	0.05	0.05	0.28	0.47
OS5	0.23	0.14	0.24	0.29	0.23	0.38	0.43	0.38	**0.82**	0.14	0.25	0.36	0.39	0.00	0.02	0.30	0.38
PBC1	0.52	0.36	0.47	0.55	0.50	0.34	0.29	0.30	0.21	**0.91**	0.41	0.48	0.45	-0.39	-0.35	0.64	0.32
PBC2	0.41	0.24	0.40	0.45	0.44	0.20	0.16	0.18	0.13	**0.88**	0.31	0.35	0.31	-0.37	-0.27	0.54	0.23
PBC3	0.54	0.37	0.49	0.55	0.51	0.30	0.24	0.26	0.15	**0.93**	0.38	0.46	0.40	-0.43	-0.37	0.62	0.32
DYN1	0.40	0.21	0.41	0.33	0.37	0.26	0.32	0.26	0.36	0.32	**0.82**	0.41	0.37	-0.10	-0.05	0.36	0.33
DYN2	0.31	0.23	0.33	0.26	0.34	0.19	0.18	0.16	0.25	0.35	**0.89**	0.35	0.31	-0.22	-0.19	0.35	0.17
DYN3	0.32	0.20	0.38	0.32	0.39	0.12	0.15	0.12	0.17	0.39	**0.89**	0.29	0.30	-0.32	-0.22	0.36	0.15
FUB1	0.63	0.32	0.52	0.63	0.54	0.63	0.56	0.57	0.46	0.44	0.40	**0.90**	0.68	-0.22	-0.31	0.64	0.61
FUB2	0.60	0.24	0.46	0.54	0.49	0.54	0.52	0.55	0.35	0.39	0.35	**0.91**	0.67	-0.21	-0.30	0.57	0.56
FUB3	0.63	0.30	0.52	0.57	0.50	0.50	0.49	0.48	0.33	0.46	0.38	**0.90**	0.62	-0.26	-0.33	0.60	0.49
FUB4	0.53	0.25	0.44	0.53	0.48	0.51	0.51	0.50	0.35	0.42	0.30	**0.85**	0.68	-0.24	-0.33	0.60	0.53
EU1	0.64	0.30	0.57	0.65	0.58	0.59	0.57	0.53	0.37	0.48	0.43	0.73	**0.89**	-0.34	-0.36	0.70	0.56
EU2	0.45	0.21	0.41	0.48	0.41	0.53	0.56	0.58	0.39	0.27	0.26	0.56	**0.85**	-0.14	-0.21	0.49	0.54
EU3	0.59	0.28	0.51	0.62	0.55	0.62	0.61	0.61	0.43	0.39	0.32	0.70	**0.95**	-0.27	-0.33	0.64	0.59
APT1	-0.31	-0.08	-0.34	-0.33	-0.39	-0.08	-0.12	-0.12	0.00	-0.34	-0.14	-0.22	-0.25	**0.87**	0.63	-0.38	-0.11
APT2	-0.47	-0.13	-0.47	-0.43	-0.44	-0.20	-0.22	-0.17	-0.02	-0.43	-0.28	-0.35	-0.37	**0.92**	0.69	-0.49	-0.19
APT3	-0.26	-0.10	-0.26	-0.24	-0.30	0.04	0.04	0.07	0.16	-0.36	-0.22	-0.08	-0.10	**0.80**	0.55	-0.32	0.03
UR1	-0.41	-0.09	-0.35	-0.49	-0.39	-0.20	-0.18	-0.17	0.02	-0.30	-0.16	-0.30	-0.32	0.70	**0.89**	-0.43	-0.18
UR2	-0.49	-0.18	-0.35	-0.49	-0.36	-0.25	-0.22	-0.21	-0.06	-0.36	-0.24	-0.37	-0.35	0.63	**0.86**	-0.54	-0.27
UR3	-0.30	-0.05	-0.25	-0.28	-0.26	-0.11	-0.19	-0.14	0.08	-0.25	0.01	-0.24	-0.22	0.49	**0.77**	-0.32	-0.14
UR4	-0.37	-0.07	-0.33	-0.34	-0.39	-0.06	-0.10	-0.13	0.12	-0.31	-0.15	-0.26	-0.23	0.58	**0.83**	-0.39	-0.13
IP1	0.52	0.28	0.51	0.63	0.53	0.39	0.37	0.32	0.24	0.65	0.37	0.51	0.53	-0.44	-0.40	**0.84**	0.39
IP2	0.58	0.35	0.53	0.75	0.58	0.56	0.55	0.50	0.40	0.54	0.35	0.63	0.64	-0.40	-0.48	**0.91**	0.60
IP3	0.56	0.32	0.51	0.75	0.58	0.46	0.53	0.49	0.31	0.56	0.34	0.62	0.64	-0.43	-0.48	**0.89**	0.53
IP4	0.60	0.35	0.56	0.70	0.57	0.45	0.43	0.40	0.29	0.66	0.41	0.62	0.59	-0.42	-0.42	**0.90**	0.48
IP5	0.60	0.35	0.50	0.72	0.56	0.51	0.52	0.48	0.37	0.54	0.34	0.60	0.62	-0.37	-0.49	**0.88**	0.56
SW1	0.57	0.33	0.55	0.66	0.53	0.56	0.51	0.52	0.35	0.48	0.32	0.59	0.56	-0.31	-0.36	0.69	**0.77**
SW2	0.38	0.15	0.34	0.33	0.27	0.58	0.52	0.59	0.41	0.14	0.13	0.48	0.47	0.04	-0.06	0.33	**0.85**
SW3	0.45	0.28	0.39	0.49	0.39	0.67	0.58	0.59	0.40	0.28	0.22	0.51	0.54	-0.13	-0.23	0.53	**0.89**
SW4	0.34	0.18	0.38	0.36	0.35	0.58	0.52	0.56	0.43	0.16	0.16	0.46	0.51	0.04	-0.07	0.37	**0.85**

Notes: EMB - Embeddedness; CSE – Computer Self-Efficacy; PE – Perceived Enjoyment; NB – Net Benefits; S – Satisfaction; D – Dependence; EE – Emotional Energy; R – Relatedness; OS – Opportunities and Support; PBC – Perceived Behavioral Control; DYN – IT Dynamism; FUB – Feature Use Behavior; EU – Enhanced Use; APT – Apathy; UR – Use Resistance; IP – Individual Performance; SW – Social Well-Being

Table B2. *Heterotrait-Monotrait ratio (HTMT)*

	EMB	CSE	PE	NB	S	D	EE	R	OS	PBC	DYN	FUB	EU	APT	UR	IP	SW
EMB																	
CSE	0.26																
PE	0.72	0.28															
NB	0.68	0.34	0.68														
S	0.67	0.24	0.84	0.74													
D	0.60	0.24	0.53	0.55	0.48												
EE	0.50	0.16	0.57	0.57	0.51	0.70											
R	0.52	0.20	0.54	0.52	0.47	0.76	0.86										
OS	0.28	0.21	0.33	0.37	0.35	0.48	0.51	0.48									
PBC	0.59	0.29	0.55	0.62	0.58	0.34	0.28	0.30	0.21								
DYN	0.45	0.24	0.49	0.40	0.48	0.25	0.28	0.24	0.35	0.47							
FUB	0.72	0.25	0.59	0.69	0.61	0.67	0.63	0.64	0.44	0.52	0.46						
EU	0.68	0.26	0.62	0.72	0.63	0.71	0.71	0.71	0.47	0.47	0.44	0.83					
APT	0.46	0.20	0.48	0.44	0.50	0.14	0.16	0.16	0.12	0.50	0.30	0.28	0.31				
UR	0.52	0.19	0.43	0.50	0.47	0.21	0.23	0.22	0.12	0.41	0.21	0.39	0.38	0.84			
IP	0.69	0.31	0.64	0.86	0.68	0.58	0.58	0.53	0.39	0.73	0.47	0.73	0.75	0.52	0.56		
SW	0.57	0.26	0.55	0.61	0.50	0.80	0.70	0.75	0.52	0.36	0.29	0.68	0.72	0.21	0.24	0.64	

Notes: EMB - Embeddedness; CSE – Computer Self-Efficacy; PE – Perceived Enjoyment; NB – Net Benefits; S – Satisfaction; D – Dependence; EE – Emotional Energy; R – Relatedness; OS – Opportunities and Support; PBC – Perceived Behavioral Control; DYN – IT Dynamism; FUB – Feature Use Behavior; EU – Enhanced Use; APT – Apathy; UR – Use Resistance; IP – Individual Performance; SW – Social Well-Being

Appendix C. Multigroup analysis

A multigroup analysis was performed between frequent (164 respondents reporting use a lot of times or every day) and infrequent users (148 respondents reporting use never, rarely, or a few times per day). The analysis reveals meaningful differences. First, IT identity has a significantly stronger effect on feature use behavior and enhanced use among low-frequency users, suggesting that identity plays a more critical role in driving engagement in earlier stages of adoption. Second, the antecedents of IT identity differ across groups: net benefits are a stronger driver for low-frequency users, whereas perceived enjoyment becomes more relevant for high-frequency users, indicating a shift from utility-driven to experience-driven identity formation. Third, opportunities and support are more influential in promoting enhanced use among high-frequency users, suggesting that external resources become more relevant as users gain experience.

In contrast, IT identity significantly reduces use resistance only among low-frequency users, indicating that identity is more important in overcoming initial barriers to adoption. Finally, the impact of negative behaviors on performance varies across groups: apathy affects performance among low-frequency users, while use resistance is more relevant for high-frequency users. Despite these differences, the core dimensions of IT identity remain stable across groups, supporting the robustness of the construct while highlighting that its behavioral implications are context-dependent. Table C1 presents the detailed results of the multigroup analysis.

	Path Coefficient (low use group)	P-value (low use group)	Path Coefficient (high use group)	P-value (high use group)	Difference (low use group - high use group)	P-value (low use group - high use group)
EMB -> IT ID	**0.214**	**0.024**	0.139	0.085	0.075	0.550
CSE -> IT ID	-0.011	0.882	0.073	0.392	-0.084	0.423
PE -> IT ID	0.098	0.542	**0.389**	**0.000**	-0.291	0.126
NB -> IT ID	**0.375**	**0.000**	0.045	0.586	**0.330**	**0.011**
S -> IT ID	-0.047	0.722	0.086	0.463	-0.133	0.454
IT ID -> FUB	**0.588**	**0.000**	**0.364**	**0.000**	**0.224**	**0.029**
PBC -> FUB	**0.220**	**0.000**	**0.236**	**0.001**	-0.017	0.858
DYN -> FUB	0.131	0.063	0.152	0.084	-0.021	0.856
OS -> FUB	-0.020	0.795	0.145	0.058	-0.165	0.125
PBC x IT ID -> FUB	-0.097	0.086	0.037	0.677	-0.133	0.207
DYN x IT ID -> FUB	-0.003	0.966	-0.147	0.129	0.144	0.214
OS x IT ID -> FUB	0.033	0.589	-0.036	0.588	0.069	0.447
IT ID -> EU	**0.720**	**0.000**	**0.384**	**0.000**	**0.337**	**0.000**
PBC -> EU	0.107	0.118	**0.150**	**0.047**	-0.043	0.669
DYN -> EU	**0.167**	**0.036**	**0.219**	**0.016**	-0.052	0.672
OS -> EU	-0.087	0.268	**0.189**	**0.013**	**-0.276**	**0.011**
PBC x IT ID -> EU	-0.058	0.341	-0.019	0.817	-0.039	0.688
DYN x IT ID -> EU	0.037	0.548	0.145	0.146	-0.108	0.354
OS x IT ID -> EU	-0.054	0.386	**-0.154**	**0.016**	0.100	0.261
IT ID -> APT	-0.090	0.476	0.108	0.140	-0.199	0.174
PBC -> APT	**-0.374**	**0.000**	**-0.419**	**0.000**	0.046	0.740
DYN -> APT	-0.103	0.392	-0.140	0.066	0.037	0.815
OS -> APT	**0.245**	**0.013**	**0.142**	**0.038**	0.103	0.384
PBC x IT ID -> APT	-0.025	0.793	**-0.198**	**0.018**	0.173	0.179
DYN x IT ID -> APT	-0.104	0.311	-0.074	0.250	-0.029	0.789
OS x IT ID -> APT	**0.313**	**0.001**	**0.296**	**0.000**	0.017	0.861
IT ID -> UR	**-0.274**	**0.008**	0.010	0.911	**-0.284**	**0.041**
PBC -> UR	**-0.241**	**0.011**	**-0.352**	**0.000**	0.110	0.397
DYN -> UR	0.040	0.764	-0.115	0.171	0.154	0.327
OS -> UR	**0.315**	**0.001**	**0.161**	**0.034**	0.154	0.203
PBC x IT ID -> UR	-0.022	0.825	-0.078	0.411	0.056	0.671
DYN x IT ID -> UR	0.002	0.982	-0.037	0.637	0.039	0.770
OS x IT ID -> UR	**0.242**	**0.007**	**0.205**	**0.019**	0.036	0.763
FUB -> IP	**0.379**	**0.000**	**0.257**	**0.000**	0.122	0.228
EU -> IP	**0.330**	**0.000**	**0.287**	**0.000**	0.043	0.689
APT -> IP	**-0.206**	**0.012**	-0.124	0.221	-0.082	0.529
UR -> IP	-0.083	0.332	**-0.283**	**0.006**	0.200	0.127
FUB -> SW	**0.262**	**0.032**	**0.321**	**0.002**	-0.059	0.704
EU -> SW	**0.423**	**0.000**	**0.321**	**0.000**	0.101	0.495
APT -> SW	0.173	0.124	0.111	0.275	0.061	0.690
UR -> SW	-0.108	0.344	-0.001	0.992	-0.107	0.494

***Table C1**. Multigroup analysis results*

Notes: EMB - Embeddedness; CSE – Computer Self-Efficacy; PE – Perceived Enjoyment; NB – Net Benefits; S – Satisfaction; IT ID – IT Identity; OS – Opportunities and Support; PBC – Perceived Behavioral Control; DYN – IT Dynamism; FUB – Feature Use Behavior; EU – Enhanced Use; APT – Apathy; UR – Use Resistance; IP – Individual Performance; SW – Social Well-Being.

Group differences were assessed in two ways. First, we examined whether individual path coefficients were statistically significant within one subgroup but not the other. Second, and more importantly, we evaluated whether the differences between path coefficients across groups were themselves statistically significant.