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Exploring Consumer Acceptance of Metaverse Marketing for Branding Activities and the Pre-Purchase Stage

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Abstract

Metaverse is reshaping how brands approach marketing, providing alternative and innovative methods for marketers to redefine their brands and reinvent the customer experience. Different sectors are still exploring the possibilities of the metaverse and are now adopting a test-and-learning mindset. This study explores consumer acceptance of metaverse marketing for branding and pre-purchase activities, comparing its effectiveness with social media platforms. Using a survey of 197 participants (45% experiencing a metaverse space on Spatial.io, 55% using Instagram), we investigated factors influencing intention to use and purchase intention through a closed-ended questionnaire. The results show that perceived usefulness is the primary driver of use intention in the metaverse ($\beta = 0.573$, $p < 0.001$), while habit significantly influences platform preference, particularly for social media ($\beta = 0.767$, $p < 0.001$). These findings provide marketers with actionable insights to leverage interactive virtual environments, enhancing branding and pre-purchase experiences by prioritizing usability and familiarity.

Keywords: metaverse; digital marketing; branding; pre-purchase stage; social media

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1. Introduction

In the realm of marketing, branding activities and the pre-purchase stage are essential components that significantly shape consumer perceptions and influence purchasing decisions. Branding creates distinct identities and values that resonate with audiences, fostering recognition and loyalty in competitive markets [1]. Effective branding differentiates products and builds emotional connections, driving long-term customer loyalty. The pre-purchase stage is critical as it involves consumers meticulously evaluating available information and forming expectations that will ultimately affect their satisfaction and loyalty [2]. During this stage, consumers engage in extensive research, often turning to digital platforms and social media to gather insights and recommendations. Current approaches leverage digital platforms, social media, and influencer marketing to build brand awareness and foster engagement [3]. However, these methods encounter several deficiencies, including content oversaturation that results in consumer fatigue [4], diminishing returns on engagement [5], and difficulties in creating emotional connections with consumers [1]. As consumers increasingly seek meaningful interactions with brands, there is an urgent need for innovative strategies that integrate advanced technologies and create memorable pre-purchase experiences. Digitalization has accelerated this need, transforming interactions and introducing the metaverse as a novel marketing platform.

Digitalization has shifted consumer activities online, with young adults aged 18–24 spending approximately eight hours daily on electronic devices [6]. As this trend continues, metaverse comprises a technological megatrend that began in 2021 and attracts the attention of everyone. The term "metaverse" was first used in 1992, defined as a "world where virtual and reality interact and create value through various social activities" [7]. With the enormous rate of technological advancement, the "metaverse" we are discussing now differs from previous forms of the metaverse. The metaverse is no longer limited to "social activities". Instead, the scope and scale of the current one is much greater. The metaverse has an "immersive interface", and it can host all sorts of activities and events, from running political campaigns and conducting economic activities, to having social gatherings [8]. It is basically like the real world we are living in, but in a virtual 3D platform. Therefore, some would describe the metaverse as an extension of life [9].

The metaverse's interactive and immersive experience is attracting growing interest from fields ranging from education to engineering. In particular, research shows that the metaverse could expand the scope of human activities [10], affect the decision-making process [11], provide psychological stability and emotional connection [10], and enrich the spiritual and cultural life of people. Scholars widely agree that this emerging network is transforming the ways in which we live and interact, leading to notable shifts in our behaviors and lifestyles.

The metaverse would greatly affect the business world as well. In an uncertain and dynamic business environment, customer experience is highly prioritized. This is because a meaningful and unique customer experience is key to achieving competitive advantage, and is pivotal to having satisfied customers [12]. As conventional marketing and brand-building methods might not be as prevalent as before, business companies are exploring more non-traditional approaches to attract and retain customers [13]. The metaverse is a multi-space business environment, and it provides new ways for customers to interact. It revolutionizes the marketing industry. It overcomes the time and location limits imposed by brick and mortar and enriches the consumer experience by providing a networked, interactive, and immersive environment to customers [14,15], which could not be attained by current marketing methods. The use of emerging technology such as virtual reality (VR) integrates the real and virtual realms [16]. Such characteristics of the metaverse have created new ways for brands to interact with the public. With the potential to deliver new kinds of business value, companies of all shapes and sizes are entering the metaverse. Global brands have recognized this digital transformation, and are making use of different metaverse gateways to execute marketing strategies in order to grow their brands in the digital world [14,17].

In the meantime, marketing scholars have recently found the need to study this digital transformation. Lee and Oh [18] demonstrated how VR could effectively improve consumers' awareness of products, Rauschnabel and Felix [19] suggested that using augmented reality (AR) apps could increase consumers' positive attitudes towards the brand, and Syed and Gaol [14] reported that VR and AR could lead to a satisfying cognitive state in the consumer. While prior studies compare VR technology acceptance [20,21], consumer behavior and motivations in metaverse marketing remain underexplored. Previously popular marketing methods such as engaging consumers on social networking sites are already not as prevalent as before. The metaverse is believed to be a more sophisticated marketing tool, as it utilizes cutting-edge technologies [22]. It also provides unique and immersive experiences for the customers, which could not be achieved by any other marketing tools. The metaverse will probably play an unprecedentedly important role in the future of marketing, and it has the potential to capitalize on future marketing techniques. Yet, few studies examine the public acceptance of metaverse marketing or factors driving use and purchase intentions in unfamiliar 3D environments. Understanding these factors is crucial for crafting strategies that overcome adoption barriers and boost engagement, especially in the pre-purchase stage [23]. Hence, the objectives are to explore the factors influencing the acceptance of metaverse marketing and purchase intention, and determine how the platform differs from conventional digital marketing methods in the pre-purchase stage. The key questions include the following:

RQ1. What are the factors influencing consumers' adoption of the metaverse for marketing activities (i.e., obtaining product information)?

RQ2. How do the factors influencing use intention differ when comparing metaverse and social media?

RQ3. How do the factors influencing purchase intention differ when comparing the metaverse and social media?

RQ4. Are there any suggestions for future developers and marketers when developing a metaverse space for marketing activities?

2. Literature Review

2.1. Digital Marketing

Since several years ago, marketers have been focusing on shifting marketing strategies from offline to online in order to keep up with the marketing trend. For instance, Instagram has become a popular channel for marketers to communicate with customers due to its visual nature [24]. However, despite the recognition of the need for digital marketing, there are still challenges in delivering seamless customer experience. Khatri [25] and Lee and Oh [18] highlight that online marketing often lacks instant feedback and fails to provide the same level of product actuality as offline marketing. This lack of immediacy and tangibility can hinder customer engagement and connection.

The advent of digital technologies has brought about a revolution in marketing tools. Specifically, it enables the development of electronic space, and has led to the rise of the metaverse. It is foreseen that the metaverse is going to rewrite the rules of marketing, and will gradually replace online retailing and transform the current social media framework to an online 3D social media world [25,26]. The metaverse offers differentiated experiences for users and opens new avenues for companies to achieve their brand-related goals.

2.2. Metaverse Marketing

The metaverse presents a paradigm shift in how marketers connect with customers, revolutionizing traditional marketing and communication methods. The main factor leading to the ample opportunities is related to the "immersive environment" provided by the metaverse. Customers nowadays are looking for innovative experiences, and the metaverse is able to create a more robust, engaging, and unique immersive experience for the customers [25]. This immersive quality generates a "vividness" and "sense of presence" that allows customers to interact in real time, enhancing their satisfaction [25,27].

Unlike virtual game worlds, the metaverse provides a flexible space where avatars can engage in various activities, including economic transactions [13]. This flexibility has motivated business owners to establish online businesses and launch marketing campaigns within the metaverse. Moreover, with a substantial user base, such as Facebook's active users, the metaverse offers marketers an extended market reach and an opportunity to connect with their target customers in a virtual environment [25].

The metaverse is not only another medium for business companies to use to undertake marketing. As the metaverse is interactive in nature, it also activates the consumer–brand interaction [28]. Companies can now draw the attention of users and engage them in real-time immersive environments [25]. To marketers, this means a completely new way to approach customers while pushing the boundaries of brand innovation. Virtual marketing also allows marketers to present all kinds of products in a 3D space, and from there, a competitive advantage could be gained. To capitalize on the metaverse's potential, companies need to adapt their marketing models and embrace the first-mover advantage. By leveraging the metaverse, companies can connect with more customers and build their brands through activities tailored to this virtual realm. The metaverse offers marketers ample opportunities to redefine their marketing strategies and thrive in an ever-evolving digital landscape.

2.3. Theoretical Framework

This study is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT2) developed by Venkatesh and Thong [29]. UTAUT2 is particularly suitable for examining metaverse marketing due to its focus on user acceptance in novel technological contexts. In this study, we extend UTAUT2 by incorporating perceived value and purchase intention to capture the unique dynamics of metaverse marketing, such as the immersive branding experience and pre-purchase decision-making. The metaverse, characterized by its 3D immersive environment, avatar-based interactions, and real-time engagement, introduces distinct dynamics that may alter traditional UTAUT2 relationships. For instance, the immersive nature of the metaverse may amplify the role of effort expectancy, as users must navigate unfamiliar virtual spaces, potentially heightening the importance of ease of use compared to 2D platforms like social media. Similarly, the interactive and social features of the metaverse may enhance hedonic motivation by offering novel experiences, such as virtual product trials, that differ from traditional digital marketing. By examining these constructs in the metaverse context, this study aims to uncover how its unique technological attributes reshape user acceptance and behavior, contributing to the theoretical evolution of UTAUT2 in immersive virtual environments. This theoretical framework underpins our research model, providing a robust basis for understanding adoption behaviors in virtual environments [29].

2.4. Hypothesis Development

Based on the analysis of Venkatesh and Thong [29], 10 hypotheses have been developed to predict user technology adoption and purchase intention in the pre-purchase stage, as shown in Table 1.

H1: *Perceived value positively influences consumers' use intention in relation to the technology.*

Perceived value (PV) includes beneficial components such as special features, quality, physical attributes, service attributes, and technical support, as well as factors like time, energy, and effort expended to obtain the product [30]. Research has consistently shown that PV significantly predicts consumers' intention to use technology, as it is closely tied to satisfaction and intention [31]. Previous studies across various technologies have emphasized the importance of PV as a predictor of use [32]. Huang and Wang [33] also highlight the dependence of technology use on perceived value. Hence, this leads to the first hypothesis.

H2: *Performance expectancy positively influences consumers' perceived value of the technology.*

Performance expectancy (PE), playing a vital role in determining technology adoption, is determined by the belief that using a system enhances job performance. Dhiman and

Arora [34] conducted studies and determined that the intention to use a technology is significantly predicted by the notion of performance expectancy. Similarly, Alalwan and Dwivedi [35] discovered that the likelihood of technology adoption by consumers increases when they perceive it as useful in their everyday lives. Performance expectancy holds the highest predictive power for determining the intention to use, and various studies have confirmed its significant influence [36]. The benefits associated with performance expectancy include time savings and increased productivity.

H3: *Performance expectancy positively influences consumers' purchase intention.*

Consequently, a correlation exists between performance expectancy (PE) and consumers' purchase intention (PIN). Such an idea is agreed upon and confirmed by Lin and Kim [37], Sharifi fard, Tamam [38], Alalwan [39], Shafnaz [40], and Chen and Rashidin [41].

H4: *Effort expectancy positively influences consumers' perceived value of the technology.*

The ease of using a system, known as effort expectancy, plays a crucial role in users' willingness to adopt technology. Research studies have consistently revealed that a system that is simple and user-friendly positively influences acceptance and attitudes towards the technology [42]. In this study, effort refers to the skills and knowledge required when using the metaverse or social media. In the metaverse, the complexity of navigating a 3D virtual space with avatars may make effort expectancy more critical to perceived value, as users may face a steeper learning curve compared to the familiar interfaces of social media platforms. Lower effort expectancy is expected to result in higher perceived value [32]. Empirical studies have revealed a significant impact of effort expectancy on the perceived value of mobile payment, financial technology platforms, and smartphones [32].

H5: *Hedonic motivation positively influences consumers' use intention of the technology.*

Hedonic motivations refer to the fun and pleasure derived from using technology, and they play a significant role in users' acceptance beyond functional motivations [29]. Users have a need for entertainment, emotional involvement, and escapism, which can be fulfilled through technology [43]. Enjoyment, creative features, and interactivity contribute to users' intention to adopt technology [34]. The correlation of hedonic motivation with behavioral intention has been validated across diverse contexts. In this study, HM represents the happiness, enjoyment, and satisfaction derived from using the metaverse space or social media for product information.

H6: *Hedonic motivation positively influences consumers' purchase intention.*

On the other hand, HM is also related to PIN, as when a service provider can create a memorable experience for consumers to fulfil their needs for enjoyment, it could shape their attitudes and purchase intention [44]. Alalwan [39] and Shafnaz [40] have also confirmed there is a positive relationship between the two variables.

H7: *Habit positively influences consumers' use intention in relation to the technology.*

In this study, habit (HT) is conceptualized as prior experience with digital platforms similar to the metaverse, such as social media or virtual reality environments, rather than the habitual use of the metaverse itself. Limayem, Hirt [45] define Habit (HT) as "the extent to which people tend to perform behaviors automatically because of learning", while Isa and Wong [46] associate it with "automaticity", which in this context refers to familiarity with technology from past experiences. This familiarity reduces perceived complexity and enhances comfort with virtual interactions, thereby driving initial intention to use metaverse platforms for marketing activities. Previous studies, such as those by Sharifi fard, Tamam [38], and Megadewandanu [47] confirm that prior digital experience significantly influences use intention, supporting the hypothesis that habit positively affects intention to use in both metaverse and social media contexts.

H8: *Facilitating conditions positively influences consumers' use intention of the technology.*

Adequate resources and assistance are crucial for technology acceptance, as a lack of support can hinder adoption [48]. Favorable circumstances and sufficient infrastructure encourage users to adopt technology [49]. The substantial impact of facilitating conditions on technology acceptance has been confirmed through previous studies in various domains, such as learning management systems, autonomous delivery vehicles, e-books, and online shopping [32].

H9: *Personal innovativeness positively influences consumers' use intention in relation to the technology.*

Personal innovativeness pertains to an individual's inherent inclination towards embracing and adopting new technologies with an innovative mindset, and it fills the gap between technology acceptance and personal factors [50]. Highly innovative individuals, including early adopters, who are comfortable with unfamiliar products and willing to take risks, are more likely to adopt new technologies [51]. Previous studies have consistently found a strong relationship between personal innovativeness and use intention across various domains [51,52], highlighting the significance of individual differences in innovativeness in the adoption process.

H10: *Personal innovativeness positively influences consumers' purchase intention.*

Also, Dewi and Mohaidin [50] suggested that more innovative consumers who are willing to accept the technology are found to have a higher level of purchase intention.

Table 1. Summary of the ten hypotheses proposed in the study.

Hypothesis	Description	Literature Review
H1	Perceived value positively influences consumers' use intention of the technology.	Mooradian, Matzler [53] Ledden, Kalafatis [31] Huang, Wang [33] Sweeney and Soutar [30] Fatima, Kashif [32]
H2	Performance expectancy positively influences consumers' perceived value of the technology.	Venkatesh, Morris [54] Dhiman, Arora [34] Alalwan, Dwivedi [35] Miladinovic and Hong [36]
H3	Performance expectancy positively influences consumers' purchase intention.	Lin and Kim [37] Sharifi fard, Tamam [38] Alalwan [39] Shafnaz [40] Chen, Rashidin [41]

Table 1. *Cont.*

Hypothesis	Description	Literature Review
H4	Effort expectancy positively influences consumers' perceived value of the technology.	Venkatesh, Morris [54] Fatima, Kashif [32] Zhao and Bacao [42]
H5	Hedonic motivation positively influences consumers' use intention of the technology.	Eneizan, Mohammed [43] Dhiman, Arora [34]
H6	Hedonic motivation positively influences consumers' purchase intention.	Mustafi and Hosain [44] Alalwan [39] Shafnaz [40]
H7	Habit positively influences consumers' use intention of the technology.	Limayem, Hirt [45] Isa and Wong [46] Gansser and Reich [51] Tam, Santos [55] Megadewandanu [47]
H8	Facilitating conditions positively influence consumers' use intention of the technology.	Venkatesh, Morris [54] Nanayakkara [48] Alalwan, Dwivedi [49] Fatima, Kashif [32]
H9	Personal innovativeness positively influences consumers' use intention of the technology.	Dewi, Mohaidin [50] Gansser and Reich [51] An, Han [52]
H10	Personal innovativeness positively influences consumers' purchase intention.	Dewi, Mohaidin [50]

3. Methodology

A quantitative research approach was employed to examine the factors influencing users' intention to use the metaverse and social media platforms for engaging in businesses' marketing activities, as well as purchase intention. A new research model was proposed to predict user technology adoption and purchase intention in the pre-purchase stage, as shown in Figure 1. The research model considers the various sub-attributes associated with each construct, which will be elucidated in subsequent sections. By considering these factors, the research model provides a comprehensive understanding of the mechanisms underlying user behavior and their intentions when it comes to adopting new technologies and making purchase decisions in the pre-purchase stage.

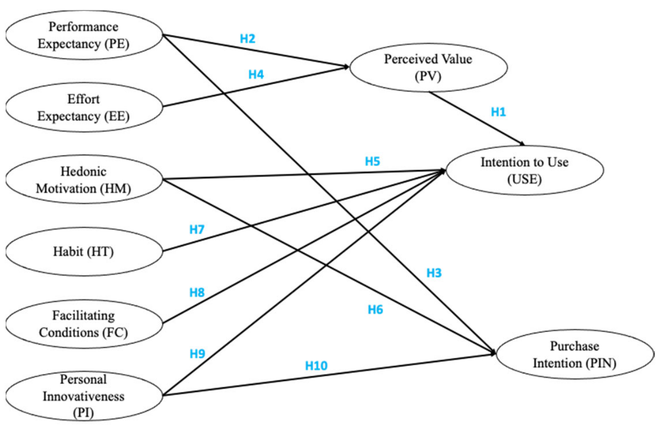


Figure 1. The proposed improved model of UTAUT2.

3.1. The Metaverse Space and Digital Marketing

The study utilized a between-subjects design to compare consumer acceptance of metaverse marketing on Spatial.io with social media marketing on Instagram (IG). For the metaverse group, a virtual space was developed on Spatial.io. It was selected for its accessible, browser-based interface and robust features for creating interactive 3D marketing spaces to simulate branding and pre-purchase activities. The space was designed to replicate a real-world shopping experience, featuring virtual storefronts, interactive 3D product displays, and real-time engagement options such as avatar-based interactions and live chat functionalities. Participants interacted with the platform for approximately 15–20 min to explore branding and pre-purchase content. Table 2 provides a detailed breakdown of the metaverse space design.

Table 2. Design of the metaverse space.

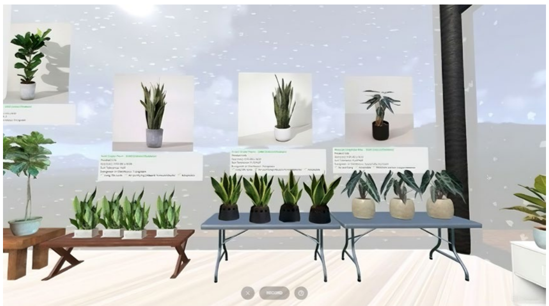
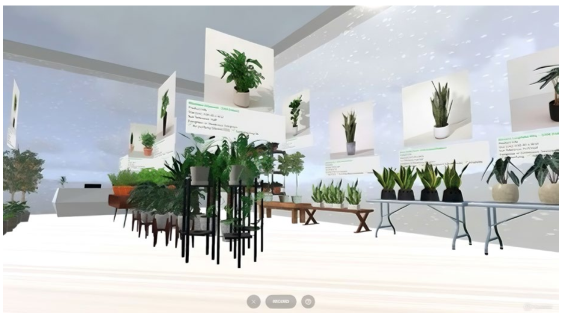
Exterior design		
Entrance		
Products and descriptions		
		

Table 2. *Cont.*

Other facilities	

For the Instagram group, the study utilized the official Instagram profile of the same company in the case study. Instagram posts were curated to mirror the metaverse's product information and branding visuals, ensuring comparable marketing stimuli. Figure 2 illustrates the Instagram setup, which included a profile page with a bio, contact details, and a series of posts showcasing products. Interactive elements such as likes, comments, and direct messaging were available to simulate real-world social media engagement. The Instagram content was designed to mirror the branding and pre-purchase information provided in the Metaverse space, ensuring consistency in marketing stimuli across both platforms.

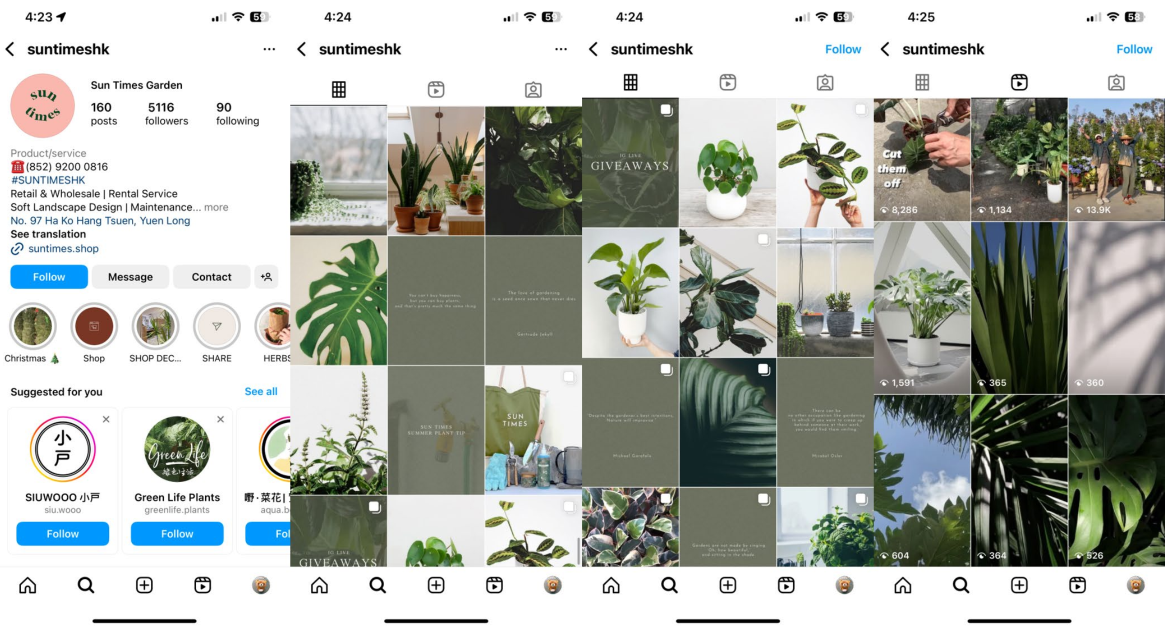


Figure 2. Contents of the shop including profile page and product information.

To validate the research model and achieve the research purpose, primary data were gathered online. The research instrument selected for this study was a questionnaire due to its easy access for most of the people, ensuring the responses are completely answered and thus helping to yield a 100% of completion rate of the survey [49].

The online questionnaire was designed to collect data on people's attitudes towards metaverse marketing and social media platform marketing. The study recruited 197 participants from Hong Kong using snowball sampling, initiated through university networks and expanded via referrals. Snowball sampling was chosen to efficiently reach a tech-savvy population familiar with digital platforms, which is ideal for exploring emerging metaverse adoption. Of these, 89 participants (45%) experienced the metaverse space on Spatial.io, engaging in branding and pre-purchase activities, while 108 participants (55%) interacted with similar content on Instagram, serving as a social media control group. This comparative design allows for a robust analysis of differences in consumer acceptance between immersive virtual platforms and traditional social media. The participants' demographics (53.8% aged 18–24, 60% female, reflect a tech-savvy population, typical of early adopters of digital platforms, making them suitable for studying metaverse marketing adoption. Participation was voluntary, with informed consent obtained, ensuring ethical compliance.

3.2. Questionnaire Design and Measurements

Section 1 of the questionnaire concerns the demographics of the participants, i.e., age and gender. Section 2 consists of 33 items regarding the opinions of participants regarding the metaverse or social media platform. The relationships between various constructs were evaluated to investigate the level of acceptance of the metaverse and social media. The questionnaire, which was developed in English, consisted of 33 items, and encompassed 9 constructs. A 5-point Likert scale was used, and the participants' backgrounds were collected by the demographic questions. The measurement items were formulated based on previous empirical studies that demonstrated validity and reliability. Table 3 illustrates the constructs and references used.

Table 3. The constructs and references used in the questionnaire.

Construct	References
Performance Expectancy (PE)	Venkatesh, Thong [29] Tam, Santos [55] Shin and Lee [56]
Effort Expectancy (EE)	Venkatesh, Thong [29] Yu, Chao [57] Nguyen, Nguyen [58] Rudhumbu [59]
Hedonic Motivation (HM)	Venkatesh, Thong [29] Tak and Panwar [60] Gharaibeh, Gharaibeh [61] Alalwan [39]
Habit (HT)	Venkatesh, Thong [29] Tak and Panwar [60] Singh and Matsui [62]
Facilitating Conditions (FC)	Venkatesh, Thong [29] Paulo, Rita [63] Park and Kim [64]
Personal Innovativeness (PI)	Gansser and Reich [51] Kourouthanassis, Boletsis [65]
Perceived Value (PV)	Liu, Zhao [66] Shaw and Sergueeva [67]

Table 3. *Cont.*

Construct	References
Intention to Use (USE)	Sitar-Taut and Mican [68] Shaw and Sergueeva [67]
Purchase Intention (PIN)	Alalwan [39] Duffett [69]

3.3. Data Analysis

The data were analyzed using IBM SPSS Statistics (Version 29), Amos (Version 26), and SmartPLS 4. First, descriptive statistics were computed to summarize the sample characteristics and construct scores. Second, the measurement model was evaluated to ensure reliability and validity, involving normality tests (Mardia's test), exploratory factor analysis (EFA), and assessments of internal consistency (Cronbach's Alpha), convergent validity (Composite Reliability and AVE), and discriminant validity (Fornell-Larcker criterion). Third, the structural model was tested using structural equation modeling (SEM) with SmartPLS 4 to examine the hypothesized relationships, with path coefficients, *t*-values, and *p*-values calculated to assess hypothesis support. Finally, independent samples *t*-tests were conducted to explore demographic differences (e.g., gender) in construct scores between the metaverse and Instagram groups.

4. Results

The research model was tested using the software packages IBM SPSS Statistics (Version 29), SmartPLS 4, and Amos (Version 26). In the first part, a descriptive analysis was conducted to provide a quantitative description of the sample. In the second part, the measurement model was evaluated to ensure the quality of criteria before examining the structural model. In the last part, the hypotheses of the structural model were tested.

4.1. Descriptive Statistics

The sample was composed of 197 people; 45% of the participants were invited to experience the metaverse and the remaining 55% were invited to browse through the social media platform. Among the 197 answers, 77 (39.09%) of them were given by males and the remaining 120 (60.91%) by females. Participants were divided into several age groups, dominated by the group of 18–24 years old (Table 4).

Table 4. Demographic characteristics of participants across metaverse and social media groups.

Variable	Overall (n)	Metaverse Group (n)	Social Media Group (n)
Age			
18–24 years	106 (53.8%)	40 (44.9%)	66 (61.1%)
25–34 years	29 (14.72%)	17 (19.1%)	12 (11.1%)
35–44 years	17 (8.63%)	13 (14.6%)	4 (3.7%)
45–54 years	28 (14.21%)	8 (9%)	20 (18.5%)
55–64 years	17 (8.63%)	11 (12.4%)	6 (5.56%)
Total	197 (100%)	89 (100%)	108 (100%)
Gender			
Male	77 (39.09%)	45 (50.6%)	32 (29.6%)
Female	120 (60.91%)	44 (49.4%)	76 (70.4%)
Total	197 (100%)	89 (100%)	108 (100%)

4.2. Measurement Model

4.2.1. Normality Test

Multivariate normality was assessed using Mardia's test to ensure the data's suitability for structural equation modeling (SEM), as shown in Table 5. For the metaverse group (n = 89), skewness ranged from −0.968 to 0.227, and kurtosis ranged from −1.351 to 0.397. For the social media group (n = 108), skewness ranged from −1.262 to 0.495, and kurtosis ranged from −1.036 to 1.995. These values fall within the recommended thresholds of ±2 for skewness and ±7 for kurtosis, indicating that the data approximate a normal distribution with neither platykurtic nor leptokurtic tendencies. Thus, the data are suitable for SEM analysis [70].

Table 5. Descriptive analysis.

	Mean	SD	VIF	Skewness		Kurtosis	
				Statistic	Std. Error	Statistic	Std. Error
PE	3.393 (3.618)	0.785 (0.795)	1.535 (1.560)	0.020 (−0.841)	0.255 (0.233)	−0.824 (1.368)	0.506 (0.461)
EE	3.715 (4.269)	0.799 (0.638)	1.535 (1.560)	−0.1 (−1.087)	0.255 (0.233)	−0.82 (1.854)	0.506 (0.461)
HM	3.757 (4.025)	0.866 (0.874)	1.781 (1.569)	−0.212 (−0.78)	0.255 (0.233)	−0.589 (−0.134)	0.506 (0.461)
HT	2.596 (2.833)	1.137 (1.093)	1.360 (1.987)	0230 (0.189)	0.255 (0.233)	−0.0968 (−0.89)	0.506 (0.461)
FC	3.467 (4.065)	0.825 (0.66)	1.975 (1.915)	−0.146 (−0.998)	0.255 (0.233)	−0.947 (1.758)	0.506 (0.461)
PI	3.626 (3.577)	0.712 (0.83)	1.889 (1.518)	−0.529 (−0.431)	0.255 (0.233)	−0.013 (−0.016)	0.506 (0.461)
PV	3.64 (3.875)	0.897 (0.691)	1.562 (3.226)	−0.63 (−0.621)	0.255 (0.233)	−0.111 (1.303)	0.506 (0.461)
USE	3.191 (3.296)	1.102 (1.006)	1.975 (3.226)	−0.204 (−0.033)	0.255 (0.233)	−0.757 (−0.799)	0.506 (0.461)
PIN	3.188 (3.051)	0.914 (0.986)	1.548 (1.457)	−0.507 (0.362)	0.255 (0.233)	−0.051 (−0.589)	0.506 (0.461)

[Note] Results related to the metaverse group are presented outside the brackets and the social media group ones are presented in brackets.

Common method bias (CMB) is a potential concern in survey studies, as it may inflate or deflate correlations among variables [51]. To mitigate this, data were collected anonymously, and participants were informed about the use of their responses. We initially conducted a Harman's single-factor test, which showed that the single factor accounted for 43.44% of the variance in the metaverse group and 44.251% in the social media group, both below the recommended threshold of 50%, suggesting minimal CMB [71]. Recognizing the critiques of Harman's test [72], we further applied the Kock and Lynn [73] full collinearity method, calculating VIF values for all constructs in both groups. VIF ranged from 1.360 to 3.226 across all constructs in both groups, which values are well below the threshold of 3.3 [74], confirming the absence of significant CMB.

4.2.2. Exploratory Factor Analysis

Although the questionnaire items were adapted from validated scales, exploratory factor analysis (EFA) was conducted to confirm the factor structure in the specific context of the metaverse and social media marketing. This step ensures that constructs such as perceived usefulness and hedonic motivation are appropriately measured for our Hong Kong-based sample, accounting for potential cultural or platform-specific variations that might affect item applicability. Confirming the factor structure in this novel context strengthens the reliability and validity of the measurement model for subsequent SEM analysis.

The Kaiser–Meyer–Olkin (KMO) index is "an indicator of predictive relevance" [75] used to assess factor analysis suitability. Kaiser [76], Pett, and Lackey [77] consider a KMO index of greater than 0.6 as acceptable and reasonable. The KMO results are shown in Table 6, which show that the KMO index was 0.758 and 0.849, respectively, which values are greater than the cut off for adequacy. The Bartlett's Test of Sphericity was also employed to measure the strength of correlation between variables [78]. Having a p-value of lower than 0.05 is considered suitable [79]. Good sphericity was obtained from both groups, as they had a significance (or p-value) of 0, which is acceptable for further analysis. Additionally, the results of EFA show that the data collected displayed total variance values of 81.9525% and 77.177% for seven factors and six factors, respectively. In the Metaverse group, PE3, PE4 and EE4 were deleted, and in the social media group, EE1-4, FC3, PV2, and PV3 were deleted, as the indicators had a significance of loading below 0.4.

Table 6. Findings from Kaiser-Meyer-Olkin and Bartlett's Test.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.758 (0.849)
Bartlett's Test of Sphericity	Approx. Chi-Square	3826.112 (3639.87)
	df	528 (528)
	Sig.	0 (0)

4.2.3. Reliability and Validity

A reliability test was conducted to measure the internal consistency of the items and the instrument [80]. Cronbach's alpha (α) values indicate the reliability of the measurement scale and the constructs [81]. Taber [82] suggests that having an alpha (α) coefficient >0.7 is deemed to be reliable. The overall results for the metaverse and social media group were 0.952 and 0.951, respectively, which are above the threshold of 0.7, and this indicates that overall, the constructs in both groups were highly reliable. The reliability of each individual factor was assessed, showing α values larger than 0.7, suggesting all are reliable (Table 7).

In order to meet the convergent validity requirement, the composite reliability (CR) and the average variance extracted (AVE) should be >0.7 and >0.5, respectively [70]. For the metaverse group, after conducting the confirmatory factor analysis, it was found that the CR ranged 0.774–0.961, which values are above the threshold level. However, the AVE of FC was considered unacceptable, with a value of 0.489, which is below 0.5. Therefore, FC4 was removed and the validity test was rerun. The final result of the test is shown in Figure 3, wherein we can see that the CR value and AVE value range from 0.805 to 0.961 and from 0.598 to 0.861, which are above the acceptable level, suggesting adequate convergent validity.

Table 7. Reliability and validity statistics of the metaverse and social media groups.

	Reliability and Validity Statistics		
	Cronbach's Alpha	**CR**	**AVE**
Overall	**0.952 (0.951)**		
PE	0.832 (0.889)	0.841 (0.894)	0.727 (0.679)
EE	0.848 (-)	0.873 (-)	0.696 (-)
HM	0.910 (0.921)	0.923 (0.924)	0.8 (0.802)
HT	0.959 (0.923)	0.961 (0.927)	0.861 (0.761)
FC	0.787 (0.714)	0.805 (0.798)	0.598 (0.59)
PI	0.828 (0.872)	0.832 (0.874)	0.626 (0.7)
PV	0.943 (0.71)	0.947 (0.739)	0.817 (0.592)
USE	0.921 (0.927)	0.924 (0.929)	0.801 (0.813)
PIN	0.951 (0.927)	0.952 (0.927)	0.834 (0.761)

Note Values outside brackets represent the metaverse group; values inside brackets represent the social media group. – indicates no result due to the removal of the factor.

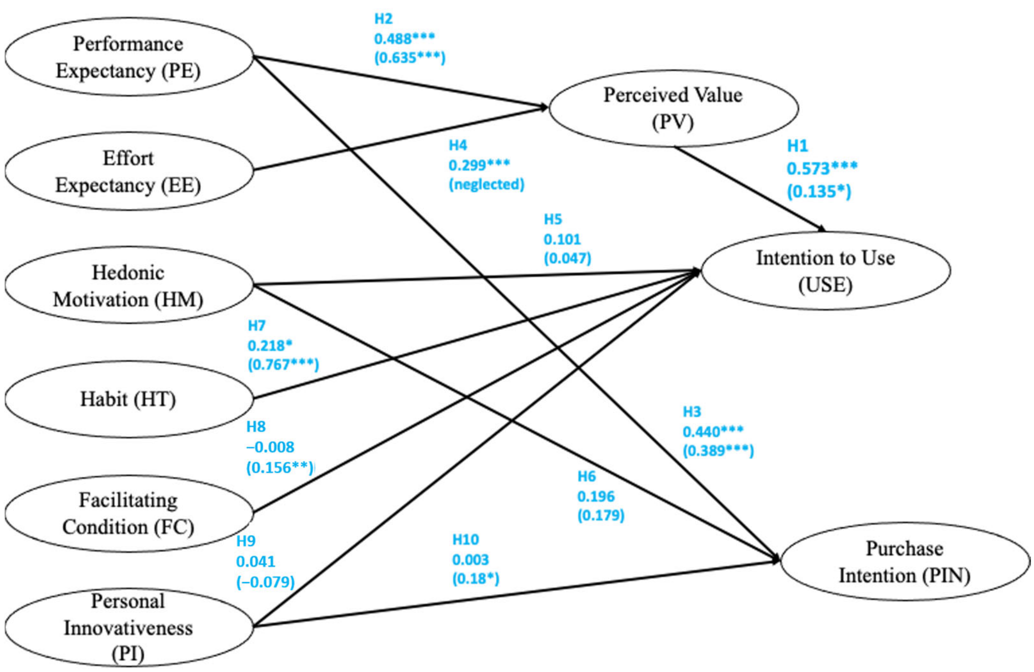


Figure 3. Structural model results. Note Path coefficients (β) and significance levels (* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$) are labeled on paths in blue color. Solid lines indicate significant paths. Values outside brackets represent the metaverse group; values inside brackets represent the social media group.

As for the social media group, all constructs displayed sufficient convergent validity. The CR valued from 0.739 to 0.929, which values are above the threshold of 0.7. Regarding the AVE values, they ranged from 0.59 to 0.813, which values also exceed the acceptable level of 0.5. Therefore, the social media group exhibited a satisfactory level of validity.

The Fornell–Larcker criterion was applied to assess the discriminant validity of the measurement model for both the metaverse and social media groups. As shown in Table 8, the square roots of the average variance extracted (AVE) for each construct—0.851 for EE, 0.777 for FC, 0.927 for HM, 0.945 for HT, 0.441 for PE, 0.859 for PI, 0.934 for PIN, 0.754 for PV, and 0.931 for USE (diagonal values for the metaverse group)—are all greater than the corresponding inter-construct correlations (off-diagonal values), confirming satisfactory discriminant validity [83,84]. Similarly, for the social media group, the square roots of the AVE—0.871 for EE, 0.800 for FC, 0.930 for HM, 0.902 for HT, 0.481 for PE, 0.893 for PI, 0.906 for PIN, 0.861 for PV, and 0.935 for USE (diagonal values in brackets)—are also greater than the corresponding inter-construct correlations, further supporting discriminant validity across both groups. This suggests that each construct shares more variance with its own indicators than with other constructs in both the metaverse and social media contexts.

Table 8. Discriminant validity of the metaverse and social media groups.

	EE	FC	HM	HT	PE	PI	PIN	PV	USE
EE	0.851 (0.871)								
FC	0.569 (0.613)	0.777 (0.800)							
HM	0.623 (0.576)	0.481 (0.300)	0.927 (0.930)						
HT	0.297 (0.271)	0.401 (0.183)	0.425 (0.424)	0.945 (0.902)					
PE	0.590 (0.552)	0.508 (0.377)	0.441 (0.481)	0.303 (0.523)	0.809 (0.868)				
PI	0.536 (0.474)	0.611 (0.501)	0.543 (0.321)	0.213 (0.399)	0.401 (0.288)	0.859 (0.893)			
PIN	0.381 (0.351)	0.507 (0.424)	0.386 (0.431)	0.330 (0.788)	0.642 (0.542)	0.317 (0.355)	0.934 (0.906)		
PV	0.527 (0.606)	0.516 (0.574)	0.498 (0.576)	0.367 (0.639)	0.698 (0.652)	0.423 (0.475)	0.754 (0.657)	0.928 (0.861)	
USE	0.462 (0.389)	0.455 (0.328)	0.494 (0.455)	0.486 (0.867)	0.704 (0.636)	0.394 (0.381)	0.791 (0.803)	0.715 (0.717)	0.931 (0.935)

Note Values outside brackets represent the metaverse group; values inside brackets represent the social media group.

4.2.4. Model Fit Assessment

Table 9 indicates an acceptable fit across the IG and metaverse models. For the IG measurement model, χ^2/df = 1.38, CFI = 0.89, TLI = 0.88, and RMSEA = 0.045. The IG structural model showed similar results, with χ^2/df = 1.37, CFI = 0.87, TLI = 0.86, and RMSEA = 0.047, all meeting the thresholds. For the metaverse measurement model, χ^2/df = 1.24, CFI = 0.89, TLI = 0.88, and RMSEA = 0.051, while the metaverse structural model had χ^2/df = 1.20, CFI = 0.88, TLI = 0.87, and RMSEA = 0.052, also aligning with the thresholds.

Table 9. Model fit indices for measurement and structural models across metaverse and IG groups.

Model Type	χ^2/df	CFI	TLI	RMSEA
Measurement Model	1.24 (1.38)	0.89 (0.89)	0.88 (0.88)	0.051 (0.045)
Structural Model	1.20 (1.37)	0.88 (0.87)	0.87 (0.86)	0.052 (0.047)
Threshold	<3 [85]	≥0.85 [86]	≥0.85 [86]	≤0.06 [87]

Note Results related to the metaverse group are presented outside the brackets and the social media group ones are presented in brackets.

4.3. Structural Model

The results of this study are presented in Table 10. To test the hypotheses, two main measurements—path coefficient (β) and *p*-value—are calculated. The beta coefficient ranges from −1 to +1 [88], wherein a beta coefficient approaching +1 means a strong positive relationship and −1 indicates the opposite. In this study, the acceptable level of significance is below 0.05 for a 95% confidence interval. Therefore, when the *p*-value is below 0.05, a statistically significant test result could be obtained, and the hypothesis could be accepted and documented.

Table 10. Results of hypothesis testing.

Hypothesis	Regression Path	Path Coefficient (β)	Std Errors	Effect Size	CI 95%	*t*-Value	*p*-Value
H1	PV → USE	0.573 (0.135)	0.085 (0.08)	0.489 0.489	[0.397, 0.733] [0.053, 0.370]	6.602 (1.993)	<0.001 (0.049)
H2	PE → PV	0.488 (0.635)	0.073 (0.08)	0.167 0.167	[0.457, 0.744] [0.303, 0.629]	5.626 (8.468)	<0.001 (<0.001)
H3	PE → PIN	0.440 (0.389)	0.095 (0.071)	0.457 0.457	[0.380, 0.749] [0.237, 0.527]	4.368 (4.255)	<0.001 (<0.001)
H4	EE → PV	0.299 (-)	0.100 (0.09)	0.041 0.041	[−0.031, 0.361] [0.187, 0.525]	3.443 (-)	<0.001 (-)
H5	HM →USE	0.101 (0.047)	0.078 (0.053)	0.029 0.029	[−0.075, 0.232] [−0.089, 0.116]	1.066 (0.880)	0.290 (0.381)
H6	HM → PIN	0.196 (0.179)	0.107 (0.081)	0.041 0.016	[−0.087, 0.324] [−0.001. 0.332]	1.746 (1.940)	0.084 (0.055)
H7	HT → USE	0.218 (0.767)	0.090 (0.053)	0.098 0.098	[0.058, 0.414] [0.612, 0.841]	2.593 (12.657)	0.011 (<0.001)
H8	FC → USE	−0.008 (0.156)	0.112 (0.072)	0.000 0.000	[−0.236, 0.209] [−0.018, 0.247]	−0.074 (2.733)	0.941 (0.007)
H9	PI → USE	0.041 (−0.079)	0.089 (0.06)	0.009 0.000	[−0.087, 0.261] [−0.19, 0.042]	0.385 (−1.395)	0.701 (0.166)
H10	PI→ PIN	0.003 (0.18)	0.091 (0.076)	0.000	[−0.087, 0.261] [0.03. 0.335]	0.026 (2.124)	0.980 (0.036)

Note Results related to the metaverse group are presented outside the brackets and the social media group ones are presented in brackets. – indicates no result due to the removal of the factor.

In this model, 10 hypothesis relationships were tested. The structural model results (Table 10, Figure 3) show that for the metaverse group, perceived value (PV) had the strongest positive effect on intention to use (USE) (β = 0.573, $p < 0.001$), supporting H1. Performance expectancy (PE) significantly influenced PV (β = 0.432, $p < 0.01$) and purchase intention (PIN) (β = 0.389, $p < 0.01$), supporting H2 and H3. Effort expectancy (EE) positively affected PV (β = 0.498, $p < 0.001$), supporting H4. Habit (HT) significantly predicted USE (β = 0.573, $p < 0.001$), supporting H7. However, hedonic motivation (HM) had no significant effect on USE or PIN, thus rejecting H5 and H6. Facilitating conditions (FC) and personal innovativeness (PI) also had no significant impact on USE, rejecting H8 and H9, and PI did not affect PIN, rejecting H10.

For the social media group, PV positively influenced USE (β = 0.135, $p < 0.05$), supporting H1. PE significantly affected PV (β = 0.445, $p < 0.01$) and PIN (β = 0.402, $p < 0.01$), supporting H2 and H3. EE was not significant (items dropped during EFA), so H4 was not tested. HM had no effect on USE or PIN, rejecting H5 and H6. HT significantly predicted USE (β = 0.767, $p < 0.001$), supporting H7. FC positively influenced USE (β = 0.412,

$p < 0.01$), supporting H8. PI did not affect USE, rejecting H9, but significantly influenced PIN ($\beta = 0.388$, $p < 0.05$), supporting H10.

Lastly, to explore demographic influences on metaverse and social media acceptance, Table 11 presents the results of independent samples *t*-tests comparing the mean scores of key constructs between male and female participants. The results are illustrated in Table 10. For the metaverse group, the Levene's Test for Equality of Variances, PE, EE, PI, PV, and PIN results were not significantly different. For the sig (p) value, PI had a value of 0.018, which means there is a significant difference between males and females. For the social media group, males and females showed approximately equal variance in HT, PI, PV, and PIN. None of the variables showed significant differences for males and females in the social media group.

Table 11. Results of independent samples test.

		Levene's Test		***t*-Test**		
		F	**Sig.**	**t**	**df**	**Significance Two-Sided *p***
PE	Equal variances assumed	0.075 (16.059)	0.784 (0)	0.456 (2.305)	87 (106)	0.649 (0.023)
	Equal variances not assumed			0.456 (1.85)	86.987 (39.397)	0.649 (0.072)
EE	Equal variances assumed	0.007 (-)	0.933 (-)	0.491 (-)	87 (-)	0.625 (-)
	Equal variances not assumed			0.491 (-)	87 (-)	0.625 (-)
HM	Equal variances assumed	4.724 (5.174)	0.032 (0.025)	0.58 (0.03)	87 (106)	0.563 (0.976)
	Equal variances not assumed			0.579 (0.028)	84.278 (50.07)	0.564 (0.978)
HT	Equal variances assumed	12.216 (1.932)	0.001 (0.167)	−1.111 (1.487)	87 (106)	0.27 (0.14)
	Equal variances not assumed			−1.116 (1.375)	78.592 (49.67)	0.268 (0.175)
FC	Equal variances assumed	3.962 (5.1)	0.05 (0.026)	−1.963 (−2.834)	87 (106)	0.053 (0.006)
	Equal variances not assumed			−1.969 (−2.489)	82.326 (45.234)	0.052 (0.017)
PI	Equal variances assumed	0.471 (1.212)	0.494 (0.273)	−2.401 (−0.556)	87 (106)	0.018 (0.579)
	Equal variances not assumed			−2.407 (−0.521)	83.557 (50.888)	0.018 (0.605)
PV	Equal variances assumed	0.637 (3.876)	0.427 (0.052)	0.134 (−0.152)	87 (106)	0.894 (0.88)
	Equal variances not assumed			0.134 (−0.136)	85.096 (46.675)	0.894 (0.893)

Table 11. *Cont.*

		Levene's Test		*t*-Test		
		F	**Sig.**	**t**	**df**	**Significance Two-Sided *p***
USE	Equal variances assumed	7.982 (6.959)	0.006 (0.01)	1.143 (2.162)	87 (106)	0.256 (0.033)
	Equal variances not assumed			1.147 (1.872)	79.477 (44.171)	0.255 (0.068)
PIN	Equal variances assumed	2.559 (3.181)	0.113 (0.077)	1.273 (−0.238)	87 (106)	0.206 (0.812)
	Equal variances not assumed			1.277 (−0.217)	82.659 (48.413)	0.205 (0.829)

Note Results related to the metaverse group are presented outside the brackets and the social media group ones are presented in brackets. – indicates no result due to the removal of the factor.

5. Discussion

The findings of this study establish the significant effects of performance expectancy (PE) on users' perceived value (PV) in both groups. Additionally, effort expectancy (EE) was found to have a significant positive impact on PV, specifically within the metaverse group. Furthermore, it was observed that perceived value (PV) and habit (HT) directly influenced the actual use in both groups. Meanwhile, performance expectancy (PE) also had a direct impact on purchase intention in both groups. Specifically, for the social media group, the relationships between facilitating conditions (FC) and intention to use, as well as between personal innovativeness (PI) and purchase intention (PIN), were significant. The findings related to the interpretation of the results are discussed below.

According to the regression paths, perceived value was affected by performance expectancy and effort expectancy, and it had a noteworthy progressive effect (β = 0.573) on the intention to use the metaverse for obtaining product information. The social media group also showed PV's significant impact on USE, but the effect was not as great as that of the metaverse (β = 0.135). This strong positive effect aligns with the findings of Mooradian, Matzler [53] and Ledden et al. [31], who argued that consumers are more likely to adopt a technology when they perceive it as offering substantial benefits relative to costs. In the metaverse context, the immersive and interactive environment likely enhances perceived value by providing a novel pre-purchase experience, as evidenced by the higher beta coefficient. For social media, the weaker effect may reflect users' familiarity with the platform, where value is more incremental than transformative. This suggests that marketers should emphasize the unique value propositions of metaverse environments, such as 3D product visualization, to drive adoption.

Performance expectancy had a positive impact on both perceived value and purchase intention in both the metaverse and social media groups. This finding is consistent with those of previous studies [37,89], which have highlighted the role of performance expectations in shaping user perceptions and intentions. The slightly higher impact in the social media group may indicate that users already associate established platforms with efficiency, whereas metaverse users may require more evidence of utility due to its novelty. Users who believe that the metaverse or social media platforms would deliver valuable and effective marketing information were more likely to perceive value and express a willingness to make a purchase.

Similarly, effort expectancy was shown to impact perceived value significantly in the metaverse group, and this finding was also supported by Fatima and Kashif [32]. Effort expectancy is related to the extent of ease to use. It implies that if the use of the system is effortless, users will perceive its value as higher. The lack of significance in the social media group, where EE items were dropped during EFA, may reflect users' established proficiency with the platform, reducing the relevance of effort as a factor. For metaverse developers, simplifying navigation and interaction (e.g., intuitive avatar controls) could enhance perceived value and encourage adoption.

Contrary to prior research [90], hedonic motivation did not significantly influence the intention to use either the metaverse or social media for obtaining marketing information. This finding challenges the notion that the enjoyment and gratification derived from using these platforms play a significant role in driving usage intentions. The lack of effect may be attributed to the design of the metaverse space in this study, which prioritized functional elements like product displays over highly dynamic or gamified interactions that could trigger enjoyment-related responses. This suggests that while immersive features are appealing, they may not yet be the primary motivator for metaverse marketing adoption in task-oriented contexts, and future studies should explore metaverse designs with richer entertainment elements to test HM's role more comprehensively.

Habit emerged as a positive predictor of the intention to use both the metaverse and social media. The relationship was further confirmed by Tam, Santos [55] and Megadewandanu [47]. This indicates that familiarity and habitual usage patterns contribute to customers' intentions to engage with these platforms to derive marketing information. Herein lies the risk that the process of adopting the metaverse would stagnate if individuals get used to utilizing social media platforms or online websites for obtaining product information. To mitigate this risk, the metaverse space should be designed to be attractive and interactive in a way that could make users emotionally connected to the environment and system. Digital marketers could also provide additional services to make users access the system more frequently, such as offering 24/7 technical support, communicating with potential customers in real-time through avatars, and providing after-sales service.

For the metaverse group, the results reveal that facilitating conditions had no direct effect on the intention to use the metaverse. This is inconsistent with previous studies that suggest FC is a significant predictor of USE [32,91], while the result in this study has been confirmed by Megadewandanu [47]. The limited support available and the unfamiliarity of new users with the Metaverse in Hong Kong may explain this result. Therefore, enhancing technical support and accessibility for the metaverse could bridge this gap. On the contrary, for the social media group, it was found that the influence of facilitating conditions on intention to use was significant. This result was derived in the studies by Raza and Shah [92] and Fatima and Kashif [32]. One possible reason leading to the difference between the two systems is that most of the people in Hong Kong already have the essential infrastructure or technology required for using social media. They also have sufficient knowledge of how to operate social media. Thus, they would be more inclined to use the system.

For the metaverse group, personal innovativeness was observed to have no significant impact on the intention to use the metaverse for obtaining marketing information and the purchase intention in relation to the products displayed in the space. This contradicts previous research by Gansser and Reich [51], and suggests that users in the metaverse are driven more by utilitarian purposes than their inherent innovative personality. The lack of effect in the metaverse group may indicate that the participants, despite being tech-savvy, prioritized practical utility over novelty-seeking behavior in this pre-purchase context. The metaverse's complexity and unfamiliarity might have overshadowed the influence of innovativeness, as users may have been more focused on functional aspects like ease of use and value. In contrast, the social media finding suggests that innovative users are more inclined to purchase based on platform familiarity, in which context the technology is less novel and more integrated into daily routines. Further, it is also worth investigating whether other personal attributes, such as openness, conscientiousness, or extraversion, will become a determinant of USE in the adoption process. Interestingly, for the social media group, a significant relationship between personal innovativeness and purchase intention is shown. A further exploration of this relationship is required to investigate whether users will be less inclined to use social media for marketing activities if they are less innovative.

Furthermore, the *t*-test results in Table 11 indicate gender differences in metaverse and Instagram acceptance. In the metaverse group, a significant difference in personal innovativeness (PI) suggests males may be more innovative, aligning with findings by Korn and Zallio [93], who identified gender-related differences in perceptions of virtual worlds, with males showing greater engagement due to a higher tolerance for technology-driven interactions. In the Instagram group, no significant gender differences emerged, consistent with the findings of Ma and Wang [94], who noted that mature social media platforms like Instagram show uniform adoption across genders due to widespread accessibility and cultural normalization. This suggests that gender influences metaverse adoption more, likely due to innovativeness, while Instagram's maturity reduces such effects. These findings imply that metaverse developers should tailor marketing strategies to highlight innovative features for males while creating more inclusive onboarding experiences to attract females, and Instagram developers can continue focusing on universal features that appeal across genders.

6. Conclusions

The prime objectives of this study were to investigate factors that influence the use of the metaverse and social media platforms for obtaining product information. Factors that impact the purchase intention were also studied. We proposed a new research model by adding additional constructs, i.e., perceived value, personal innovativeness, and purchase intention, for investigation. The statistical results confirm the acceptance of 5 out of 10 hypotheses for the metaverse group and 6 out of 10 for the social media group. Contrary to expectations, hedonic motivation did not drive use intention or purchase intention, indicating that functional benefits like usefulness and ease of use are more critical for metaverse adoption in task-oriented contexts.

The findings have several practical implications for marketers and developers. First, given the strong influence of perceived value on intention to use in the metaverse group, marketers should focus on highlighting the unique benefits of metaverse environments, such as 3D product visualization, to enhance adoption. Second, the significant role of effort expectancy in the metaverse group suggests that developers should prioritize user-friendly interfaces, such as intuitive avatar controls, to reduce perceived complexity and boost perceived value. Third, the strong effect of habit in the social media group indicates that marketers can leverage users' existing social media routines by designing metaverse spaces with familiar interaction patterns to facilitate adoption. Finally, the significant influence of performance expectancy on purchase intention in both groups underscores the need to emphasize practical benefits, such as efficient information access, to drive purchasing decisions on both platforms.

Although this research paper represents an explicit attempt to explain consumers' acceptance of metaverse marketing and social media platform marketing, it is restricted by a number of limitations. The use of snowball sampling and a young, Hong Kong-based sample (mostly aged 18–24) may have amplified the role of habits due to familiarity with digital platforms, limiting the generalizability of the findings to older or culturally diverse populations. Cross-cultural evaluations and broader demographics could yield different results. Future research should validate these findings in a broader, more diverse population to enhance generalizability and explore whether demographic and cultural differences influence metaverse adoption. Future studies could also consider extending the research model, and examining the effects of risk and trust factor, when planning their marketing activities in the metaverse and on digital marketing platforms.

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