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Exploring virtual goods purchase intentions: an integrated SEM-NCA approach in online gaming

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Abstract

Purpose – Virtual goods consumption has risen dramatically in recent years. Recognizing the benefits of virtual goods in generating revenue for online game companies, marketers strive to understand the motives behind virtual goods purchases. We investigated the direct and indirect effects of functional, emotional, and social values through player satisfaction on purchase intention toward virtual goods among online players.

Design/methodology/approach – In total, we surveyed 332 online game players utilizing a structured questionnaire. We employed a multi-analytic approach combining partial least squares structural equation modeling (PLS-SEM) and necessary condition analysis (NCA) to examine the proposed relationships.

Findings – The findings show that all dimensions of value and player satisfaction significantly affect the intention to acquire virtual goods. However, social value does not exert a significant effect on player satisfaction. Moreover, we confirmed that player satisfaction mediates the relationships between functional value, emotional value, and purchase intention. Furthermore, NCA results indicated that all predictors in the model are necessary conditions of purchase intention for virtual goods.

Originality/value – These findings contribute to an enhanced understanding of purchase intentions among online game players from a symmetric (PLS-SEM) and asymmetric (NCA) perspective by proposing a multi-analytic approach.

Keywords Virtual goods, PLS-SEM, Necessary condition analysis, Purchase intention

Paper type Research paper

Introduction

Technological advancements have transformed video games into a daily pastime enjoyed worldwide, leading to a significant rise in the number of players across various demographics (Ramírez-Correa, Rondán-Cataluña, Arenas-Gaitán, & Martín-Velicia, 2019). Moreover, the growing reliance on the internet in daily life (Wang, Zhang, Khalid, Iida, & Li, 2021) has contributed to the popularity of online games. Recent estimates indicate a global gamer population ranging from 2.2 to 2.6 billion, with the video game industry surpassing $103.5

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billion in global revenue in 2022 (Ramírez-Correa *et al.*, 2019). The global revenue for the video game industry also exceeded $103.5 billion in 2022 (Newzoo, 2022). This trend is expected to continue with significant growth projected in emerging markets such as Latin America, Asia-Pacific, the Middle East, and Africa (Newzoo, 2022), presenting lucrative opportunities for online game providers to sell virtual goods.

Recently, the sale of virtual goods has become a standard business model for online game providers (Mkedder & Zeynep, 2023). They offer games for free (free-to-play) and generate income by selling virtual items (Ko & Park, 2020). Although the free-to-play strategy is popular, it does not guarantee success. Typically only a small percentage of players, often less than 5%, make in-game purchases (Jang, Lee & Yoo, 2021). Consequently, game developers strive to understand why this small group of players buys virtual goods, aiming to leverage this insight to retain loyal players and encourage others to make purchases, thereby enhancing their overall engagement.

Previous studies (Kim, Gupta, & Koh, 2011; Mäntymäki & Salo, 2015; Hsiao, Lytras, & Chen, 2020) have investigated why players buy virtual goods in online games using the consumption value theory. For instance, Kim *et al.* (2011) assessed factors like price utility, functional quality, aesthetics, playfulness, social self-presentation, and social relationship support influencing users' virtual goods purchases in social networks. Mäntymäki and Salo (2015) explored the impact of fun, status, decoration, and user experience on virtual goods purchase intention among teenagers in virtual worlds. Hsiao *et al.* (2020) investigated several aspects affecting Pokémon Go players' purchasing intentions.

The above-mentioned studies reveal how different values influence player behavior. However, the complex relationships governing players' virtual goods purchases in online games remain largely unexplored. However, we need further research to understand how functional, emotional, and social values affect the players' purchase behavior in online games. In recent years, advancements in technology, such as artificial intelligence, and the internet of things (Chatterjee, Chaudhuri, Thrassou, & Vrontis, 2022) have enhanced the gaming experience and the value of virtual goods (Mkedder & Zeynep, 2023). In this rapidly evolving sector, player behaviors continually change (Bosman, 2020). Factors like new technologies, shifting player demographics, and evolving virtual goods have led to changes in player awareness and knowledge. Players now exhibit novel behaviors to meet their changing needs. To adapt to these transformations in online gaming, player preferences, and virtual goods, we apply Sheth, Newman, and Gross (1991) consumption value theory (CVT) to explore players' intention to purchase virtual goods. We propose that functional, emotional, and social values play key roles in shaping this intent. Moreover, we suggest that player satisfaction acts as a mediator, influencing the relationship between these value dimensions and the intention to purchase virtual goods.

Previous studies on virtual goods purchase intention (Hamari, Alha, *et al.*, 2017; Syahrivar, Chairy, Juwono, & Gyulavári, 2021) often relied on structural equation modeling (SEM), which assumes symmetrical relationships (e.g. X increases Y) between variables (Ramírez-Correa *et al.*, 2019). However, this approach overlooks the asymmetrical causal relationships common in the real world (Olya, 2020). Symmetry emphasizes "sufficiency" but fails to comment on "necessity" aspects. To address this, we examined the influences of functional value, emotional value, social value, and player satisfaction on virtual goods purchase intention from both an asymmetrical perspective using necessary condition analysis (NCA) and a symmetrical perspective using partial least squares structural equation modeling (PLS-SEM). Necessary condition analysis identifies the necessary conditions for a desired outcome (Sharma, Dwivedi, Mariani, & Islam, 2022). Research suggests that considering both sufficiency and necessity logic yields more robust results than solely relying on "sufficiency" (Richter, Schubring, Hauff, Ringle, & Sarstedt, 2020). We expected the combined use of PLS-SEM and NCA to provide deeper insights into the role of functional, emotional, and social values, along with player satisfaction, in influencing virtual goods purchase intention.

This study contributes to the body of literature in several ways. First, it explores how functional, emotional, and social values influence purchase intention for virtual goods. Second, this is the first empirical study to combine sufficiency and necessity assumptions using multi-analytic PLS-SEM and NCA analysis to uncover key factors affecting players' intention to buy virtual goods. This research is valuable for online game providers looking to shape their marketing strategies based on these insights.

The subsequent sections will be as follows. The next two sections will provide the theoretical background and then develop research hypotheses. The fourth section will outline aspects related to research methodology. The fifth section will present the findings of the multi-analytical approach. Finally, the sixth section will include the discussion, theoretical and managerial implications, and conclude the study with suggestions for future research.

Theoretical background

Virtual goods consumption

The purchase and use of virtual goods by online gamers significantly contribute to the annual income of game providers (Mkedder & Zeynep, 2023). Virtual goods such as stickers, tokens, currencies, and skins are regarded as virtual goods that are primarily used, sold, and purchased only in the virtual environment (Lehdonvirta, 2009). Players acquire these items to meet specific needs, such as social interactions, communication, and self-presentation (Kim *et al.*, 2011). As per Lehdonvirta (2009), we may categorize virtual goods into two types based on their functionality: functional goods, which enhance gameplay, and cosmetic goods, which serve aesthetic purposes and foster social connections (Lehdonvirta, 2009). Recently, scholars and game providers have expanded the definition of virtual goods to include functional, decorative, and probability-based goods (Lee, Suh, Park, & Lee, 2018; Cai, Cebollada, & Cortiñas, 2022). Functional goods encompass power-ups, expansion packs, and time-savers, which respectively enhance gameplay, introduce new game elements, and provide shortcuts (Cai *et al.*, 2022). Ornamental items, such as cosmetics and skins, only change how in-game items look. Probability-based goods, like loot boxes, are random draws where players cannot see or control what is inside until they are opened (Lee *et al.*, 2018; Cai *et al.*, 2022). We defined virtual goods as items primarily used, sold, and bought within the context of video games, encompassing all the mentioned virtual goods categories.

As noted by Kim *et al.* (2011), in-game purchases are driven by both intrinsic and extrinsic factors. Scholars in the field of online gaming have extensively explored the factors influencing players' purchasing behavior for virtual goods. These factors have been examined from a variety of perspectives, including consumption value (Bae, Kim, Kim, & Koo, 2019; Hsiao *et al.*, 2020), psychosocial aspects (Hamari & Keronen, 2017), and the quality of the gaming experience (Hamari, Hanner, & Koivisto, 2017). Regarding the value perspective, Park and Lee (2011) observed that the intention to purchase virtual goods is influenced by integrated values, such as character competency, enjoyment, visual authority, and monetary value. Later, Hsiao *et al.* (2020) found that purchasing virtual goods is driven by perceived value, satisfaction, flow, design aesthetics, social self-expression, and good price. From a psychological standpoint, Hamari and Keronen (2017) conducted a meta-analysis of 20 studies, identifying ten psychological factors motivating in-game purchases, namely service use enjoyment, subjective norm, flow, attitude toward purchase, service use intention, perceived ease of use, perceived network size, perceived value, self-presentation, and social presence.

Consumption value theory (CVT)

Consumption value measures how well a product meets a consumer's needs, assessed through an overall evaluation of the customer's satisfaction with the product, accounting for

any gains from giving (Bae *et al.*, 2019). Sheth *et al.* (1991) developed CVT to help understand different aspects affecting consumer choice. Moreover, CVT consists of five distinct consumption values: functional, emotional, social, epistemic, and conditional values Sheth *et al.* (1991). Functional value reflects a product's utility in terms of performance, utility, or physical aspects. Emotional value pertains to a product's ability to evoke feelings or affective states (Witek-Hajduk & Grudecka, 2023). Social value refers to a product's association with specific social groups. Epistemic value is tied to a product's ability to stimulate curiosity, offer novelty, or satisfy a knowledge-seeking desire. Finally, conditional value is "the perceived utility acquired by an alternative as the result of the specific situation or set of circumstances facing the choice maker" Sheth *et al.* (1991).

Numerous studies highlight CVT as an influential theory in explaining consumer purchase behavior (Kim *et al.*, 2011; Mäntymäki & Salo, 2015; Hsiao *et al.*, 2020). Previous research has shown that epistemic and conditional values do not impact online game contexts (Kim *et al.*, 2011; Mkedder & Zeynep, 2023; Hsiao *et al.*, 2020). Building on the CVT Sheth *et al.* (1991), we argue that, among the five consumption values, functional, emotional, and social values play significant roles in influencing players' intention to purchase virtual goods, both directly and indirectly through player satisfaction.

Player satisfaction

Satisfaction represents a consumer's post-purchase assessment and emotional reaction to their overall product or service experience. It is rooted in an individual's feelings of pleasure or disappointment occurring from evaluating the performance of the goods against their expectations (Molinillo, Aguilar-Illescas, Anaya-Sánchez, & Carvajal-Trujillo, 2022). Dissatisfaction is likely to arise when consumers perceive that a product falls short of their expectations, potentially diminishing their willingness to make future purchases (Kim, 2021). Prior research has consistently recognized satisfaction as a pivotal driver of loyalty, consumer purchase intention, and repurchase intention (Hsiao *et al.*, 2020; Molinillo *et al.*, 2022).

In the context of online gaming, players experience a sense of satisfaction by evaluating the free virtual goods that they may obtain from the game as a sales promotion strategy, through their participation and performance, or as gifts from other players (Jang *et al.*, 2021). Moreover, game providers reward players for their engagement and performance. They offer prizes such as in-game coins that can be converted and enable players to exchange virtual goods as gifts. This environment allows players to form their own judgments about virtual goods' performance and whether they meet their expectations.

Hypotheses development

Functional value

Functional value refers to players' perceived utility of virtual goods based on their usability, utility, and performance (Kim *et al.*, 2011). The product's functional value may be determined by its features or characteristics, such as dependability, durability, quality, and cost (Sheth *et al.*, 1991; Mäntymäki & Salo, 2015). Previous studies considered functional value a crucial driver of consumer satisfaction and product choices (Mäntymäki & Salo, 2015; Hsiao *et al.*, 2020). In online games, players find satisfaction and often buy virtual goods based on their instinct to derive utility. This can be due to the appeal of the functionality and performance of virtual goods (Cui, Li, & Zhang, 2022). Therefore, we hypothesized:

H1a. Functional value significantly influences player satisfaction.

H1b. Functional value significantly influences purchase intention for virtual goods.

Emotional value

Emotional value, or hedonic value, is how players see the worth of virtual goods because of their ability to evoke emotions and feelings (Kim *et al.*, 2011). It relates to users' natural motivations, enhancing intrinsic feelings and adding to the enjoyable aspects of these goods (Kim, 2021). Several studies have highlighted the crucial role of emotional value in driving player satisfaction and purchase intention toward virtual goods (Kim *et al.*, 2011; Mäntymäki & Salo, 2015; Hsiao *et al.*, 2020). In this study, we define emotional value as players' enjoyment, fun, fulfillment, and pleasant sensations that they experience through the use and purchase of virtual goods. We hypothesized:

H2a. Emotional value significantly influences player satisfaction.

H2b. Emotional value significantly influences purchase intention for virtual goods.

Social value

Social value in virtual goods refers to the player's perceived utility of virtual goods based on how well virtual goods may make them feel and behave (Kim *et al.*, 2011). When people consume virtual goods, they engage in social behavior that involves forming connections, expressing their identity, adhering to social norms, and conveying symbols (Hamari & Keronen, 2017; Mkedder & Zeynep, 2023). Prior studies have shown that social value exerts a significant influence on player satisfaction and purchase intention for virtual goods (Ashraf, Hou, & Ahmad, 2019; Mäntymäki & Salo, 2015). In the context of online games, social value is how players see the usefulness of virtual goods in improving their image in a virtual setting and boosting their connections and communication skills with others. Accordingly, we hypothesized:

H3a. Social value significantly influences player satisfaction.

H3b. Social value significantly influences purchase intention for virtual goods.

Player satisfaction

Satisfaction refers to individuals' feelings of pleasure or disappointment occurring from evaluating the performance of the goods toward their expectations (Molinillo *et al.*, 2022). In the realm of online games, players often experience satisfaction when they receive free virtual goods as part of sales, promotions, or gifts from other players (Jang *et al.*, 2021). Prior studies considered satisfaction to be a significant predictor of customers' purchase intention (Shi, Zhang, Xie, & Zhou, 2016; Hsiao *et al.*, 2020; Molinillo, Japutra, & Liébana-Cabanillas, 2020; Kim, 2021). Thus:

H4. Player satisfaction significantly influences purchase intention for virtual goods.

Mediation effect of player satisfaction

The existing literature confirms that customer satisfaction plays a mediating role between consumer value perception and behavioral intentions. Maduku and Thusi (2023) suggest that consumer value influences behavioral intentions through satisfaction. According to the fairness theory, customers believe they receive fair treatment in a transaction when their needs are met (Cui *et al.*, 2022). Hence, players do not regret investing in virtual goods when their experience is satisfactory. Regarding online games, previous research shows that player value perception significantly impacts consumer satisfaction, and both factors positively affect purchase intention (Hsiao *et al.*, 2020). Players are driven to fulfill their functional, emotional, and social needs through virtual goods (Mäntymäki & Islam, 2015; Hsiao *et al.*, 2020). However, if players fail to achieve the expected utility, pleasure, and social connections

through these goods, they will not be satisfied and will not make further purchases. In contrast, a high level of satisfaction can enhance a player's value perception of virtual goods and increase their behavioral intentions, thus:

H5(a–c). Player satisfaction significantly mediates the relationships between (a) functional value, (b) emotional value, and (c) social value and purchase intention of virtual goods.

Figure 1 demonstrates the proposed research model.

Research methodology

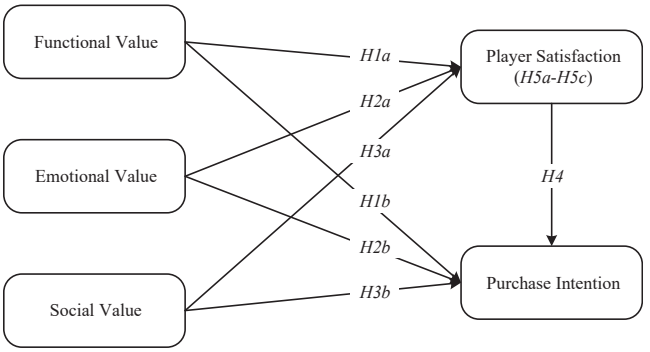
Sample and data collection

We collected data from Algerian online game players using purposive sampling (Sarstedt & Mooi, 2019). We considered the criteria for playing online games and purchasing virtual goods in the game in the respondent's selection. First, we informed respondents about the research objectives and then surveyed them using an online self-administered questionnaire. By employing screening questions, we disqualified from further examination those respondents who have no prior experience with virtual goods and online games.

Before the main study, we conducted a pre-test of the questionnaire with 16 postgraduate students who had experience with online games. Their feedback helped refine the wording of the survey items, ensuring clarity and understanding. Subsequently, we collected data for the main study in June 2022 through a structured web-based survey. We obtained 332 useable responses with no missing data and discarded 22 cases. Following Hair *et al.* (2021), we employed statistical power analysis via G*Power, which revealed that our sample of 332 responses exceeded the minimum requirement of 85 cases with 80% statistical power, a 5% significance level, and a medium effect size of 0.15. Appendix A1 (see: https://osf.io/upked) provides the demographic characteristics of the respondents. They align with the general player population (Hamari, Hanner, & Koivisto, 2017; ESA, 2021; Mrkonjić, 2022; Statista, 2022). Thus, our sample effectively represents the characteristics of the broader population.

Research instrument

We measured the constructs using previously validated multi-item measures. We customized the questionnaire for virtual goods, and translated it into French and Arabic, after which three language specialists reviewed it. Respondents rated each item on a seven-point scale



Source(s): Own elaboration

Figure 1.
Research model

from "strongly disagree" (1) to "strongly agree" (7). The functional value consists of a four-item scale adapted from Xiao *et al.* (2019), emotional and social values with a four-item scale from Rezaei and Godse (2014), and player satisfaction with a four-item scale from Cheung, Shen, Lee, and Chan (2015). Finally, we adopted the purchase intention from Guo and Barnes (2012). Appendix A2 (see: https://osf.io/upked) lists detailed measurement items.

Common method bias

We used a single data source at a specific point of time, thus, we had to address the issue of common method bias (CMB). To this aim, we ensured respondents' confidentiality, and conducted pre-testing to refine item wording and reduce item ambiguity.

Regarding statistical solutions, we employed multiple approaches, including the full collinearity test (FCT; Kock & Lynn, 2012) and the unmeasured latent method construct test (ULMC) (Liang, Saraf, Hu, & Xue, 2007), as displayed in Appendix A3 (see: https://osf.io/upked). As per FCT, CMB is likely not an issue, as the resulting variance inflation factor (VIF) values did not surpass the threshold of 3.3. Furthermore, we used Liang *et al.'s* (2007) ULMC test based on the comparison of substantive and method variances. As per Appendix A3 (see: https://osf.io/upked), all substantive loadings were significant, whereas almost all method loadings were insignificant. Furthermore, the ratio of substantive variance to method variance was notably high (65:1), indicating that CMB poses no risk in this study.

Analysis methods

We employed a multi-analytic approach by examining the proposed relationships from a symmetric (PLS-SEM) and asymmetric (NCA) standpoint. The PLS-SEM method, which aims to maximize the explained variance of endogenous constructs, suits the explanatory purpose of this study. As Sarstedt, Hair, Nitzl, Ringle, and Howard (2020) noted, PLS-SEM is also effective for handling mediation effects. Since NCA relies on latent variable scores generated by PLS-SEM (Richter *et al.*, 2020), we found it appropriate to use the PLS-SEM technique utilizing the SmartPLS 3 software.

Both PLS-SEM and regression analysis assume symmetrical connections between variables (Richter *et al.*, 2020). However, this assumption may not capture the often asymmetrical causal relationships in the real world (Tho, 2019). Therefore, we assessed the role of three values (functional, emotional, social) and player satisfaction in shaping purchase intention for virtual goods from both asymmetric (NCA) and symmetric (PLS-SEM) perspectives.

The asymmetric perspective determines whether specific antecedents are necessary conditions for an expected outcome (Zhou & Wang, 2022). An NCA includes a scatter plot, effect size, and bottleneck table components. We combined two distinct procedures to create the scatter plot: ceiling envelopment-free disposal hull (CE-FDH) for discrete data and ceiling regression-free disposal hull (CR-FDH) for continuous data (Tóth, Dul, & Li, 2019). Regardless of the data type, the upper left zone of the scatter plot represents the effect size of a necessary condition (Sorjonen, Wikström Alex, & Melin, 2017). The effect size thresholds can be classified as small ($0 < d < 0.1$), medium ($0.1 \leq d < 0.3$), large ($0.3 \leq d < 0.5$), and very large ($d \geq 0.5$) effects (Dul, van der Laan, & Kuik, 2020).

To confirm that this effect size is not random, NCA calculates statistical significance through permutation testing (Tóth, Dul, & Li, 2019). The current literature applies approximate permutation testing with 10,000 resamples to show that necessary condition hypotheses are far from randomness (Dul *et al.*, 2020). Finally, the bottleneck table, a crucial component of NCA, illustrates the necessity for multiple necessary conditions for a desired outcome to occur (Richter *et al.*, 2020). We employed the NCA R package to test the necessary conditions using NCA (Dul, 2021).

Results

Measurement model assessment

The measurement model validated the proposed constructs. Table 1 depicts the measurement accuracy assessment. Composite reliability (CR) and Cronbach's alpha (α) for each construct exceed the 0.70 threshold, ensuring internal consistency (Hair *et al.*, 2021). All item factor loadings, except EV4 and SV2, surpassed the 0.70 cutoff. We kept EV4 and SV2 due to average variance extracted (AVE) values exceeding 0.50, indicating indicator reliability (Sarker, Mohd-Any, & Kamarulzaman, 2020). Lastly, we confirmed convergent validity with AVE values surpassing 0.50 (Mkedder & Bakır, 2023).

Furthermore, we tested the discriminant validity of the constructs utilizing the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio of correlation (Henseler, Ringle, & Sarstedt, 2015). According to the Fornell-Larcker criterion, the correlation of a construct with other constructs must be less than the square root of the AVE value of the same construct. Table 2 confirms that discriminant validity is achieved, with AVE square roots on the diagonal meeting this criterion. Second, we employed the more stringent HTMT measure (Benitez, Henseler, Castillo, & Schuberth, 2020). According to Table 3, discriminant validity was corroborated as the HTMT measure between all construct pairs remained below the threshold of 0.85 (Hair *et al.*, 2021).

Structural model assessment

After establishing the measurement model, we examined the structural model. Initially, the multicollinearity among exogenous variables was investigated through variance inflation factors (VIFs). According to Table 4, as VIFs ranged between 1.023 and 1.565, multicollinearity did not prevail in the dataset, which could have resulted in insignificant estimates (Benitez *et al.*, 2020; Mkedder, Bakir, & Lachachi, 2021). To test our hypotheses, we employed a Bias-Corrected and Accelerated (BCa) bootstrapping approach with 5,000

Construct	Items	Loadings	Cronbach's alpha(α)	CR	AVE
Functional value	FV1	0.723	0.779	0.856	0.599
	FV2	0.747			
	FV3	0.842			
	FV4	0.778			
Emotional value	EV1	0.700	0.705	0.814	0.523
	EV2	0.778			
	EV3	0.735			
	EV4	0.674			
Social value	SV1	0.754	0.726	0.830	0.551
	SV2	0.665			
	SV3	0.789			
	SV4	0.754			
Player satisfaction	SAT1	0.756	0.821	0.882	0.652
	SAT2	0.826			
	SAT3	0.795			
	SAT4	0.849			
Purchase intention	PI1	0.763	0.789	0.878	0.706
	PI2	0.875			
	PI3	0.878			

Table 1. Measurement model assessment

Note(s): FV – Functional value, EV – Emotional value, SV – Social value, SAT – Player satisfaction, PI – Purchase intention
Source(s): Own elaboration

resamples (Hair *et al.*, 2021). Table 4 and Figure 2 illustrate the results of hypothesis testing for each proposed path. Notably, both functional value ($\beta = 0.182$, $p < 0.01$) and emotional value ($\beta = 0.519$, $p < 0.01$) significantly predict player satisfaction, supporting H1a and H2a. However, this study failed to uncover a significant relationship between social value and player satisfaction ($\beta = 0.088$, $p = 0.075$), thus rejecting H3a. Next, functional value ($\beta = 0.105$, $p < 0.01$), emotional value ($\beta = 0.207$, $p < 0.01$), social value ($\beta = 0.201$, $p < 0.01$), and player satisfaction ($\beta = 0.475$, $p < 0.01$) all exert a significant influence on purchase intention, confirming H1b, H2b, H3b, and H4.

Next, we evaluated the in-sample prediction accuracy, corresponding to the model's explanatory power (Sarker *et al.*, 2020). As seen in Table 4, player satisfaction is responsible for 36.1% of the variance explained in the PLS path model ($R^2 = 0.361$), while purchase intention, the key endogenous variable, accounts for 53.2% of the explained variance ($R^2 = 0.532$). Given that R^2 values above 0.20 are significant in consumer research (Hair *et al.*, 2021), this study achieved satisfactory in-sample prediction power.

Construct	FV	EV	SV	SAT	PI
Functional value	*0.774*				
Emotional value	0.130	*0.723*			
Social value	0.103	0.243	*0.742*		
Player satisfaction	0.258	0.565	0.234	*0.807*	
Purchase intention	0.276	0.538	0.373	0.666	*0.840*

Note(s): FV – Functional value, EV – Emotional value, SV – Social value, SAT – Player satisfaction, PI – Purchase intention
Source(s): Own elaboration

Table 2. Discriminant validity: Fornell–Larcker criterion

Construct	FV	EV	SV	SAT	PI
Functional value					
Emotional value	0.170				
Social value	0.131	0.335			
Player satisfaction	0.312	0.713	0.300		
Purchase intention	0.342	0.692	0.492	0.828	

Note(s): FV – Functional value, EV – Emotional value, SV – Social value, SAT – Player satisfaction, PI – Purchase intention
Source(s): Own elaboration

Table 3. Discriminant validity: $HTMT_{0.85}$ criterion

Path	Std β	t-value	p-value	95% CI	Decision	R^2	VIF
H1a. FV → SAT	0.182	3.691	0.000	[0.083; 0.276]	Approved	0.361	1.023
H1b. FV → PI	0.105	2.680	0.007	[0.030; 0.182]	Approved	0.532	1.074
H2a. EV → SAT	0.519	10.255	0.000	[0.414; 0.615]	Approved		1.076
H2b. EV → PI	0.207	4.062	0.000	[0.105; 0.303]	Approved		1.498
H3a. SV → SAT	0.088	1.783	0.075	[−0.011; 0.182]	Rejected		1.069
H3b. SV → PI	0.201	4.317	0.000	[0.110; 0.293]	Approved		1.081
H4. SAT → PI	0.475	9.313	0.000	[0.377; 0.574]	Approved		1.565

Note(s): FV – Functional value, EV – Emotional value, SV – Social value, SAT – Player satisfaction, PI – Purchase intention
Source(s): Own elaboration

Table 4. Assessment of the structural model

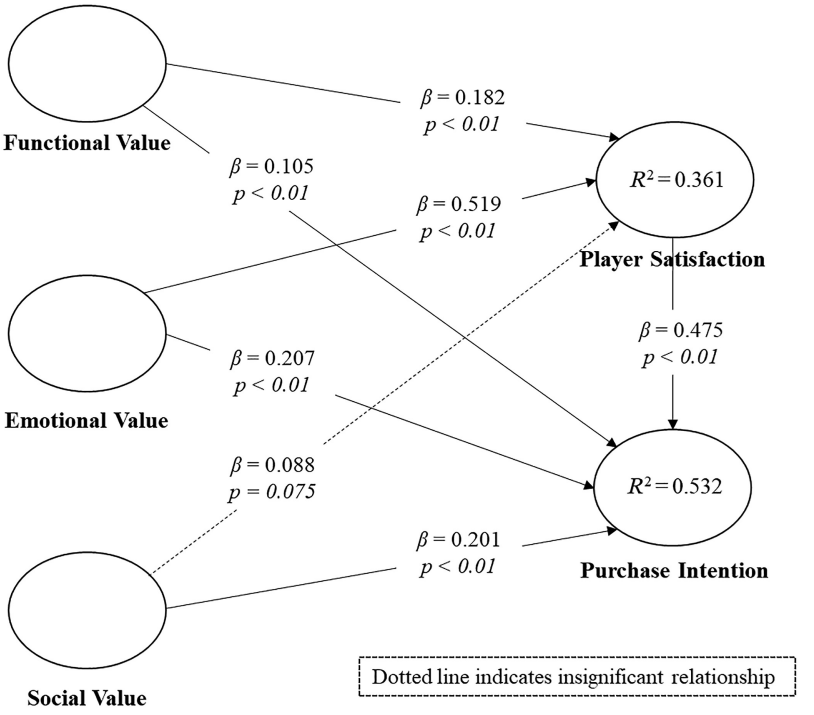


Figure 2.
Structural equation model results

Source(s): Own elaboration

In the final step, we quantified the model's out-of-sample predictive accuracy by applying the $PLS_{predict}$ procedure with a 10-fold cross-validation parameter (Shmueli *et al.*, 2019). As per Table 5, the $Q^2_{predict}$ value for purchase intention was greater than 0 ($Q^2_{predict}$ = 0.365). Furthermore, we compared the root mean squared error (RMSE) between the PLS model (PLS) and the linear model (LM) to quantify predictive accuracy at the item level (Sarker *et al.*, 2020). Table 5 shows that the RMSE values are lower than those of the LM model, indicating the model's strong out-of-sample predictive accuracy.

Mediation effect estimation

We conducted further analysis to investigate the mediating effects using the BCa bootstrapping procedure with 5,000 resamples. According to Table 6, player satisfaction significantly mediates the effect of functional value on purchase intention ($\beta = 0.086, p < 0.01$,

Endogenous constructs	Indicator	PLS RMSE	PLS $Q^2_{predict}$	LM RMSE	LM $Q^2_{predict}$	PLS-LM RMSE
PI (Q^2_predict–0.365)	PI1	1.515	0.242	1.519	0.238	−0.004
	PI3	1.329	0.269	1.348	0.248	−0.019
	PI2	1.303	0.258	1.305	0.255	−0.002

Table 5.
Assessment of the $PLS_{predict}$

Note(s): RMSE – root mean squared error, LM – linear regression model
Source(s): Own elaboration

95% CI [0.041; 0.137]). Similarly, the mediating role of player satisfaction in the effect of emotional value on purchase intention was maintained ($\beta = 0.247$, $p < 0.01$, 95% CI [0.183; 0.321]). Therefore, we confirmed H5a and H5b. However, we did not confirm H5c, which suggests the mediating effect of player satisfaction between social value and purchase intention ($\beta = 0.042$, $p = 0.088$, 95% CI [−0.003; 0.092]).

Robustness tests

This study rigorously assessed the robustness of the proposed model (Hair, Sarstedt, Ringle, & Gudergan, 2018; Sarstedt, Ringle, *et al.*, 2020). First, we applied Ramsey's (1969) RESET test, guided by Sarstedt and Mooi's (2019) recommendations, to identify potential nonlinearity. The outcomes indicated strong insignificance for the nonlinear effects concerning player satisfaction [$F(2, 326) = 1.422$; $p = 0.243$] and purchase intention [$F(2, 325) = 1.749$; $p = 0.176$]. Therefore, nonlinear effects were not an issue in the research model.

Next, we employed the finite mixture PLS (FIMIX-PLS) method, as per Matthews, Sarstedt, Hair, and Ringle (2016), with a one-segment assumption for a maximum of 5,000 iterations and 10 repetitions. Given the minimum sample size of 85 from the power analysis, we proceeded with the FIMIX-PLS method, maintaining these settings until reaching a maximum four-segment solution for the total sample size (Ringle, Sarstedt, Mitchell, & Gudergan, 2020). The fit indices comparing a one-segment solution to a four-segment solution indicate uncertainty (see Appendix A4, (see: https://osf.io/upked). According to existing literature, when AIC_3 and CAIC yield the same number of segments, it signifies the most suitable choice (Sarker *et al.*, 2020; Sarstedt *et al.*, 2020b). Furthermore, AIC_3 suggests a four-segment solution, while CAIC indicates a two-segment solution. Hair *et al.* (2018) recommended considering the number of segments indicated by AIC_3 and BIC. Unfortunately, AIC_3 consistently aligns with neither CAIC nor BIC. Thus, unobservable heterogeneity in the model is not a critical concern.

Lastly, we assessed potential endogeneity using the Gaussian copula analysis method, following Hult *et al.*'s (2018) systematic procedure. We used latent variable scores from PLS-SEM as input (Sarker *et al.*, 2020). First, we continued with Park and Gupta's (2012) Gaussian copula approach since latent variable scores of endogenous variables did not follow a normal distribution (Sarstedt *et al.*, 2020b). Results in Appendix A5 (see: https://osf.io/upked) show that Gaussian copulas are generally insignificant, except for models involving player satisfaction ($p > 0.05$). Moreover, we employed the control variable approach, which is a commonly used technique, to model gender ($\beta = 0.063$, $p = 0.107$), age ($\beta = 0.048$, $p = 0.237$), and income level ($\beta = 0.002$, $p = 0.962$) to validate the endogeneity potential (Hult *et al.*, 2018). The parameter estimates between the baseline model and the model with control variables did not show a significant change. Therefore, endogeneity was not a concern.

Necessary condition analysis

After applying PLS-SEM, we tested whether the specific antecedents (i.e. functional value, emotional value, social value, and player satisfaction) are necessary for the expected outcome

Effect	β	*t*-value	*p*-value	95% CI	Decision
H5a. FV → SAT → PI	0.086	3.496	0.000	[0.041; 0.137]	Approved
H5b. EV → SAT → PI	0.247	7.039	0.000	[0.183; 0.321]	Approved
H5c. SV → SAT → PI	0.042	1.705	0.088	[−0.003; 0.092]	Rejected

Note(s): FV – Functional value, EV – Emotional value, SV – Social value, SAT – Player satisfaction, PI – Purchase intention
Source(s): Own elaboration

Table 6.
Mediation assessment

(i.e. purchase intention) using NCA. We employed a contrarian case analysis, utilizing Cramer's V test to identify asymmetrical relationships between variables (Olya, 2020). Following the guidance of Pappas and Woodside (2021), we conducted cross-tabulations for suggested relationships (see Appendix A6 (see: https://osf.io/upked)). The results confirmed the presence of contrarian cases in bold cells, indicating the necessity of NCA for investigating asymmetrical relationships. Next, we used latent variable scores transferred from PLS-SEM to perform NCA (Richter *et al.*, 2020). Sorjonen *et al.* (2017) noticed that when the outcome variable (Y) is positively skewed and condition (X) is negatively skewed, a necessity effect size emerges. Thus, the NCA may be prone to data skewness, potentially deflating the effect size. There is no such risk of bias in the data, as the skewness values of the scores remained within ±3 (Olya, 2020).

We tested the significance of necessary condition hypotheses using permutation testing with 10,000 random resamples, as recommended by Dul *et al.* (2020). We used the CE-FDH ceiling line to avoid the assumption of a linear relationship between necessary conditions and outcomes (Zhou & Wang, 2022). Figure 3 displays scatter plots for all relationships examined using the NCA model. Moreover, Table 7 presents the results of the necessary condition analysis. The findings confirmed that functional value ($d = 0.092$, $p < 0.01$), emotional value

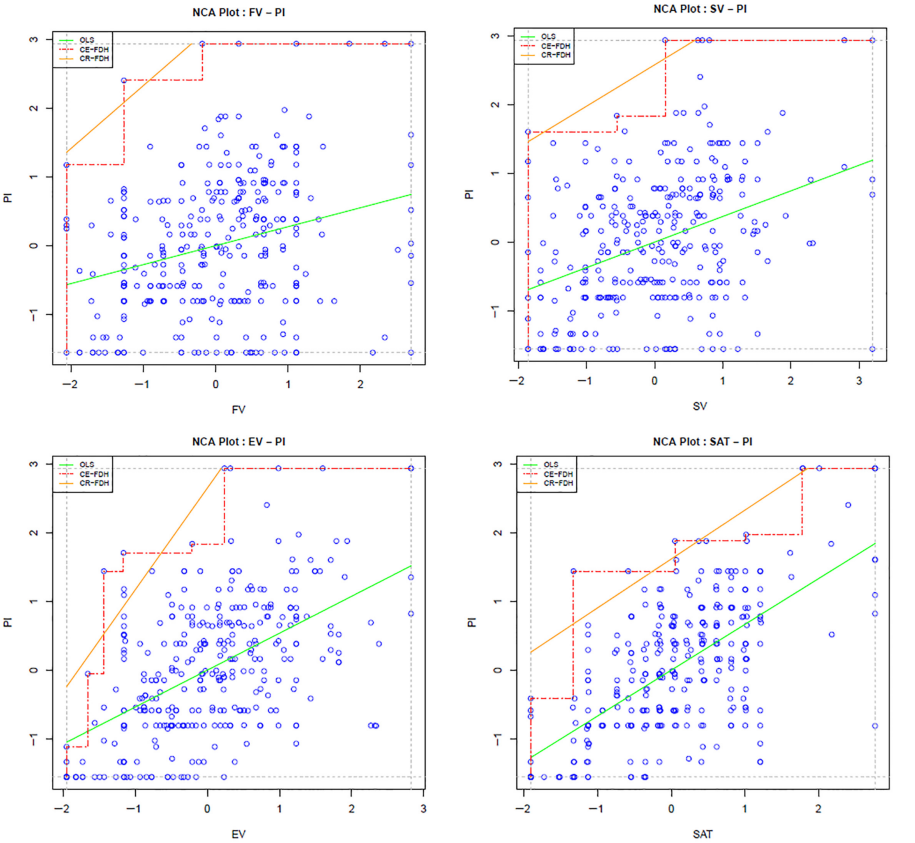


Figure 3.
Scatter plots for all necessary conditions

Source(s): Own elaboration

($d = 0.183$, $p < 0.01$), social value ($d = 0.111$, $p < 0.01$), and player satisfaction ($d = 0.275$, $p < 0.01$) are necessary conditions to generate purchase intention toward virtual goods. However, functional value generates a small effect size, while other necessary conditions exhibit a medium effect size. Sharma *et al.* (2022) argued that the small effect sizes in the NCA are nevertheless notable and that a certain condition must be present for the outcome to exist.

Finally, the bottleneck table examined the necessary condition levels for multiple necessary conditions to achieve a certain outcome. Table 8 represents the critical condition levels to accomplish the desired level of purchase intention for virtual goods. For example, to sustain a medium level of purchase intention (50%), the level of emotional value should not fall below 10.8% and player satisfaction – below 12.4%. Similarly, to generate a higher purchase intention (>80%), at least 16.7% of functional value, 45.8% of emotional value, 39.8% of social value, and 78.9% of player satisfaction must exist.

Conclusions

Discussion

Drawing upon the theory of consumption values Sheth *et al.* (1991), we posit that functional, emotional, and social values play pivotal roles in shaping player satisfaction and the intention to purchase virtual goods. First, we observed that both functional and emotional values positively affect player satisfaction and purchase intention for virtual goods. These findings

Construct	Ceiling zone	Scope	Effect size (d)	p-value
Functional value	1.981	21.423	0.092	0.006
Emotional value	3.935	21.468	0.183	0.000
Social value	2.518	22.705	0.111	0.005
Player satisfaction	5.783	21.046	0.275	0.000

Note(s): $0 < d < 0.1$ – small effect size, $0.1 \leq d < 0.3$ – medium effect size, $0.3 \leq d < 0.5$ – large effect size, $d \geq 0.5$ – very large effect size
Method: CE-FDH
Source(s): Own elaboration

Table 7.
Necessary condition analysis result

Y	X_1	X_2	X_3	X_4
PI (%)	FV	EV	SV	SAT
0	NN	NN	NN	NN
10	NN	6.2	NN	NN
20	NN	6.2	NN	NN
30	NN	6.2	NN	12.4
40	NN	10.8	NN	12.4
50	NN	10.8	NN	12.4
60	NN	10.8	NN	12.4
70	16.7	16.5	NN	41.9
80	16.7	45.8	39.8	78.9
90	39.4	45.8	39.8	78.9
100	39.4	45.8	39.8	78.9

Note(s): FV – Functional value, EV – Emotional value, SV – Social value, SAT – Player satisfaction, PI – Purchase intention
Method: CE-FDH
Source(s): Own elaboration

Table 8.
Bottleneck table

contradict prior research (Kim *et al.*, 2011), which found that functional value had no effect on purchase intention for virtual goods and emotional value did. These important findings can be attributed to shifts in player behavior, increased knowledge, and the widespread use of online games. Virtual goods have become popular and seen as highly useful and effective by players. This perception enhances satisfaction and motivates players to spend time and money acquiring virtual goods. Moreover, as game players learn new features that meet their functional needs, such as gaining power, enhancing skills through player competition, and elevating their status in online games, functional value begins to emerge (Li, Liu, Xu, Heikkilä, & Van Der Heijden, 2015; Mkedder & Zeynep, 2023). This proposition is further consistent with Poushneh (2021), who indicated that virtual consumption hinges on consumers' perceptions of closeness to virtual product attributes and performance in the virtual environment.

Conversely, as confirmed by previous studies (Kim *et al.*, 2011; Mäntymäki & Salo, 2015; Ramírez-Correa *et al.*, 2019; Hsiao *et al.*, 2020), emotional value signifies player satisfaction derived from using and purchasing virtual goods. It includes the feeling of happiness, entertainment, and enjoyment stemming from virtual goods, motivating players to continue purchasing these items, and engaging in online games. This study also noted that social value significantly affects purchase intention for virtual goods, corroborating previous studies (Kim *et al.*, 2011; Mäntymäki & Salo, 2015; Ling, Chen, Ho, & Hsiao, 2021). Individuals are concerned about what others think of them (Kim *et al.*, 2011; Mkedder & Zeynep, 2023). In the realm of online games, individuals are particularly concerned about how they are perceived by others, given the visibility of player avatars, profiles, and achievements (Chen & Chen, 2022). However, we did not find a direct link between social value and player satisfaction. Player dissatisfaction may stem from negative in-game experiences or instances of bullying during interactions with other players (Silva *et al.*, 2021).

Second, this study suggests that player satisfaction can mediate the interplay among functional, emotional, and social values and the intention to purchase virtual goods. Fulfillment of functional and emotional needs affects players' desire for virtual goods. When players have a favorable attitude and ample virtual goods experience, they are more satisfied and inclined to purchase. These findings align with prior research (Zhou, Jin, & Fang, 2014) and underline the importance of online games and virtual goods in meeting player needs (Mkedder & Zeynep, 2023). In contrast, findings show that players could not achieve satisfaction in terms of social value, which diminishes their desire to buy virtual goods based on satisfaction.

Finally, the present study extends the PLS-SEM findings by applying NCA, which reveals that all predictors in the model have significant necessary effects on the intention to purchase virtual goods. Specifically, emotional value is a must-have factor in achieving purchase intention, albeit with a modest effect size. For instance, a 10–20% purchase intention level requires a minimum of 6.2% emotional value. Furthermore, at the level of 6.2% to 10.8% emotional value and 12.4% satisfaction, 30% to 60% of purchase intention toward virtual goods would appear. As such, we should regard these two factors as key necessary conditions to generate purchase intention for virtual goods. Finally, to achieve a 90% level of purchase intention, all necessary conditions must exist: functional value at no less than 39.4%, emotional value at no less than 45.8%, social value at no less than 39.8%, and player satisfaction at no less than 78.9%.

Theoretical and managerial implication

The current study makes two key contributions to the expanding literature of online games related to the intention to purchase virtual goods in emerging nations such as Algeria. First, the interplay of three functional, emotional, and social values in shaping players' satisfaction

and intention to purchase virtual goods in emerging nations have yet to be explored. Drawing on consumption values theory, we demonstrate how these values affect purchase intention for virtual goods directly and indirectly through player satisfaction. Our findings suggest that player satisfaction could mediate the relationship between these values and the intention to buy virtual goods, which enhances the existing online gaming literature significantly.

Second, we contribute methodologically by integrating PLS-SEM and NCA approaches. Most previous research on online games primarily employed symmetrical approaches (e.g. CB-SEM, PLS-SEM) to elucidate causal effects between variables. However, such approaches do not discover the necessary conditions for expected outcomes. Therefore, we used NCA in this study with PLS-SEM to gain better insights into the necessary conditions for the formation of purchase intention toward virtual goods. With this comprehensive approach, we explored if functional, emotional, and social values, along with player satisfaction, play a role in influencing players' intention to purchase virtual goods. This methodological integration aims to strengthen our findings by enhancing their robustness. Consequently, this multi-analytic approach is anticipated to provide a holistic understanding of the intention to purchase virtual goods in online games, thus contributing to the online gaming literature.

This study offers essential insights for online game providers, highlighting the major impact of four key factors: functional, emotional, and social values, along with player satisfaction, on players' intention to buy virtual goods. To improve purchase rates, game developers should prioritize and enhance these factors. Interestingly, our research reveals that player satisfaction is linked solely to functional and emotional values, while social value provides no contribution. Thus, we suggest game providers prioritize these two elements, focusing on enhancing the game environment, fostering effective communication, and implementing regulations to protect players from harassment or bullying. As noted by Mkedder and Das (2024), privacy, security, and ethical considerations represent primary concerns for companies operating within virtual environments. Thus, ensuring the safety of children and teenagers, who are active participants in online games, is of paramount importance. Game providers should implement rigorous measures and guidelines to safeguard this demographic from potential abuse, exploitation, exposure to violence, and unsuitable content within gaming platforms. Safeguarding the well-being of young users should be a fundamental priority in the design and provision of these virtual spaces. Lastly, our NCA underscores that all proposed predictors for purchase intention are necessary conditions.

One of NCA's unique managerial contributions lies in guiding online game providers and marketers on the necessary conditions to achieve specific outcomes (Sharma *et al.*, 2022). This allows online game providers to pinpoint these necessary conditions precisely and take immediate steps to enhance them for better responses to their virtual goods offerings. For example, our study underscores the significance of emotional value and player satisfaction as crucial conditions of intention to purchase virtual goods. Thus, online game providers can invest resources to generate the desired level of two factors. However, exceeding the required thresholds for these factors does not yield additional benefits. To illustrate, only 38.9% of social value and 78.9% of player satisfaction are adequate to achieve the highest level of purchase intention for virtual products (>80%). Once you go beyond these levels, putting more resources does not offer significant advantages. In such situations, online game providers can smartly distribute their resources to create positive brand impressions in other areas. Therefore, the NCA outcome provides an effective roadmap for assessing the studied factors.

Limitations and future research

This study has limitations that future research can address. First, we evaluated players' intentions to purchase virtual goods in an emerging country (Algeria). Several previous studies (Kim *et al.*, 2011; Mäntymäki & Salo, 2015; Hsiao *et al.*, 2020) addressed this phenomenon primarily in developed countries, thus, we suggest that future research should

examine the players' intention to purchase virtual goods in a diverse culture (developed vs developing nations). Second, the study excluded certain dimensions based on seminal literature and methodological alignment, emphasizing critical aspects within its research scope. However, player behavior and opinions are subject to change, potentially influenced by epistemic and conditional values over time. Future research could replicate the model by incorporating these constructs and exploring player behavior across diverse geographical regions. Third, we combined an asymmetric perspective (NCA) along with a symmetric perspective (PLS-SEM) to examine the phenomenon. We suggest that future research examines purchase intention for virtual goods using different approaches, such as interpretive structural modeling (ISM) (Bakır & Mkedder, 2023), artificial neural network (ANN) (Mkedder & Bakır, 2023), or structural equation modeling (CB-SEM), and fuzzy set qualitative comparative analysis (fsQCA).

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Appendices

Table A1.
Demographic profile of players

Category	Characteristic	Frequency (n = 332)	Percentage (%)
Gender	Female	133	40.1
	Male	199	59.9
Age	Less than 20	60	18.1
	Between 21–30	153	46.1
	Between 31–40	87	26.2
	Between 41–50	26	7.8
	Over 50	6	1.8
Education	High school	123	37
	Bachelor's	102	30.7
	Master	86	25.9
	PhD	21	6.3
Income	Less than 15,000 DZD	111	33.4
	Between 15,000 and 25,000 DZD	48	14.5
	Between 25,001 and 35,000 DZD	58	17.5
	Between 35,001 and 45,000 DZD	47	14.2
	Between 45,001 and 60,000 DZD	30	9.0
	More than 60,000 DZD	38	11.4
How long are you playing the game per week?	3–6 hours	48	14.5
	6–9 hours	132	39.8
	9–12 hours	117	35.2
	More than 12 hours	35	10.5
The average cost of acquiring virtual goods?	Less than 1,000 DZD	175	52.7
	1,000–2,000 DZD	67	20.2
	2,001–4,000 DZD	22	6.6
	4,001–6.000 DZD	32	9.6
	More than 6,000 DZD	36	10.8

Note(s): DZD, Djazaïr Dinar (Algerian national currency)

Functional value adapted from Xiao *et al.* (2019)
FV1: virtual goods have good functions
FV2: virtual goods are reliable
FV3: virtual goods fulfill my needs well
FV4: virtual goods are well provided

Emotional value adapted from Rezaei and Ghodsi (2014)
EV1: I would adore purchasing virtual goods
EV2: virtual goods are one that I would feel relaxed about using
EV3: using virtual goods would make me feel wonderful
EV4: using virtual goods would bring me happiness

Social value adapted from Rezaei and Ghodsi (2014)
SV1: virtual goods would enable me to feel accepted
SV2: virtual goods would enhance how others see me
SV3: virtual goods would create a favorable impression on others
SV4: virtual goods would provide me with social acceptance

Player satisfaction adapted from Cheung *et al.* (2015)
SAT1: I am satisfied with the virtual goods
SAT2: I am satisfied with my decision to use virtual goods
SAT3: I believe that virtual goods are very good
SAT4: my choice to use these virtual goods is a smart decision

Purchase intention adapted from Guo and Barnes (2012)
PI1: I intend to purchase virtual goods for my characters in online games
PI2: my willingness to buy advanced virtual goods in online games is high
PI3: the likelihood that I would purchase advanced goods in online games is high

Table A2.
Measurement items

Construct	Item	Substantive factor loading (*R1*)	$R1^2$	Method factor loading (*R2*)	$R2^2$
Functional value	FV1	0.735**	0.540	−0.003	0.000
(FCT = 1.064)	FV2	0.784**	0.615	−0.038	0.001
	FV3	0.774**	0.599	0.068	0.005
	FV4	0.808**	0.653	−0.030	0.001
Emotional value	EV1	0.604**	0.365	0.081	0.007
(FCT = 1.165)	EV2	0.508**	0.258	0.270**	0.073
	EV3	0.880**	0.774	−0.123*	0.015
	EV4	0.916**	0.839	−0.223**	0.050
Social value (FCT = 1.046)	SV1	0.720**	0.518	0.035	0.001
	SV2	0.625**	0.391	0.038	0.001
	SV3	0.822**	0.676	−0.040	0.002
	SV4	0.789**	0.623	−0.024	0.001
Player satisfaction	SAT1	0.732**	0.536	0.022	0.000
(FCT = 1.379)	SAT2	0.792**	0.627	0.036	0.001
	SAT3	0.840**	0.706	−0.047	0.002
	SAT4	0.862**	0.743	−0.011	0.000
Purchase intention	PI1	0.644**	0.415	0.122	0.015
(FCT = 1.386)	PI2	0.934**	0.872	−0.062	0.004
	PI3	0.922**	0.850	−0.044	0.002
Average			0.610		0.010

Note(s): FCT, Full collinearity test

Table A3.
Analysis for common method biasness

	Segments			
	1	2	3	4
AIC	1501.713	1434.259	1454.762	*1398.027*
AIC3	1510.713	1453.259	1483.762	*1437.027*
AIC4	1519.713	*1472.259*	1512.762	1476.027
BIC	1535.959	*1506.556*	1565.111	1546.427
CAIC	1544.959	*1525.556*	1594.111	1585.427
HQ	1515.37	1463.091	1498.769	*1457.209*
MDL5	*1744.944*	1947.746	2238.506	2452.028
LnL	−741.856	−698.129	−698.381	*−660.013*
EN	Na	*0.876*	0.562	0.593
NFI	Na	*0.891*	0.546	0.543
NEC	Na	*41.274*	145.578	135.084

Note(s): AIC, Akaike's information criterion; AIC3, modified AIC with factor 3; AIC4, modified AIC with factor 4; BIC, Bayesian information criteria; CAIC, consistent AIC; HQ, Hannan Quinn criterion; MDL5, minimum description length with factor 5; LnL, LogLikelihood; EN, entropy statistic; NFI, non-fuzzy index; NEC, Normalized entropy criterion; Na, not available; Italic numbers indicate the best output per segment retention criterion

Table A4. Unobserved heterogeneity for one to four-segments solution

Table A5. Gaussian copula models

Construct	Model 1		Model 2		Model 3		Model 4		Model 5	
	Std. β	p-value	Std. β	p-value	Std. β	p-value	Std. β	p-value	Std. β	p-value
EV	0.205	0.000	−1.044	0.159	0.209	0.000	0.195	0.000	−1.116	0.131
FV	0.485	0.064	0.11	0.006	0.105	0.009	0.11	0.006	0.519	0.049
SV	0.195	0.000	0.198	0.000	0.237	0.552	0.198	0.000	0.192	0.000
SAT	0.490	0.000	0.474	0.000	0.475	0.000	1.078	0.000	0.489	0.000
^{c}EV			*1.304*	*0.090*					*1.375*	*0.074*
^{c}FV	*−0.387*	*0.146*							*−0.417*	*0.119*
^{c}SV					*−0.038*	*0.927*				
^{c}SAT							*−0.62*	*0.038*		

Construct	Model 6		Model 7		Model 8		Model 9		Model 10	
	Std. β	p-value	Std. β	p-value	Std. β	p-value	Std. β	p-value	Std. β	p-value
EV	0.205	0.000	0.191	0.000	−1.076	0.151	−1.118	0.128	0.195	0.000
FV	0.485	0.066	0.472	0.075	0.11	0.006	0.115	0.004	0.11	0.006
SV	0.186	0.638	0.193	0.000	0.329	0.409	0.195	0.000	0.264	0.493
SAT	0.490	0.000	1.077	0.000	0.473	0.000	1.098	0.000	1.079	0.000
^{c}EV					*1.338*	*0.085*	*1.366*	*0.073*		
^{c}FV	*−0.387*	*0.148*	*−0.369*	*0.170*						
^{c}SV	*0.01*	*0.981*			*−0.137*	*0.741*			*−0.068*	*0.865*
^{c}SAT			*−0.605*	*0.044*			*−0.643*	*0.033*	*−0.622*	*0.037*

Construct	Model 11		Model 12		Model 13		Model 14		Model 15	
	Std. β	p-value	Std. β	p-value	Std. β	p-value	Std. β	p-value	Std. β	p-value
EV	−1.137	0.128	−1.185	0.106	0.191	0.000	−1.159	0.118	−1.215	0.101
FV	0.515	0.052	0.507	0.057	0.47	0.078	0.115	0.004	0.501	0.062
SV	0.279	0.482	0.19	0.000	0.215	0.575	0.363	0.348	0.314	0.416
SAT	0.488	0.000	1.098	0.000	1.078	0.000	1.103	0.000	1.102	0.000
^{c}EV	*1.396*	*0.072*	*1.432*	*0.060*			*1.409*	*0.067*	*1.463*	*0.057*
^{c}FV	*−0.413*	*0.126*	*−0.399*	*0.140*	*−0.368*	*0.174*			*−0.393*	*0.149*
^{c}SV	*−0.091*	*0.826*			*−0.022*	*0.955*	*−0.174*	*0.665*	*−0.129*	*0.747*
^{c}SAT			*−0.628*	*0.038*	*−0.606*	*0.043*	*−0.648*	*0.031*	*−0.632*	*0.036*

Note(s): c denotes Copula term in the model. Values in italics only indicate beta coefficients for copulas

			Purchase Intention				
			1	2	3	4	5
Functional value (Cramer's V= 0.188, $p < 0.01$)		1	19	16	14	12	3
			5.7%	4.8%	4.2%	3.6%	0.9%
		2	7	22	24	12	8
			2.1%	6.6%	7.2%	3.6%	2.4%
		3	7	10	11	10	11
			2.1%	3.0%	3.3%	3.0%	3.3%
		4	11	13	11	26	21
			3.3%	3.9%	3.3%	7.8%	6.3%
		5	10	10	10	12	22
			3.0%	3.0%	3.0%	3.6%	6.6%
Emotional value (Cramer's V = 0.271, $p < 0.01$)		1	31	15	7	8	4
			9.3%	4.5%	2.1%	2.4%	1.2%
		2	13	19	21	11	10
			3.9%	5.7%	6.3%	3.3%	3.0%
		3	6	17	17	21	10
			1.8%	5.1%	5.1%	6.3%	3.0%
		4	3	13	15	14	16
			0.9%	3.9%	4.5%	4.2%	4.8%
		5	1	7	10	18	25
			0.3%	2.1%	3.0%	5.4%	7.5%
Social value (Cramer's V = 0.238, $p < 0.01$)		1	27	17	11	7	7
			8.1%	5.1%	3.3%	2.1%	2.1%
		2	7	18	15	15	7
			2.1%	5.4%	4.5%	4.5%	2.1%
		3	10	18	21	21	9
			3.0%	5.4%	6.3%	6.3%	2.7%
		4	2	8	7	18	12
			0.6%	2.4%	2.1%	5.4%	3.6%
		5	8	10	16	11	30
			2.4%	3.0%	4.8%	3.3%	9.0%
Player Satisfaction (Cramer's V = 0.366, $p < 0.01$)		1	38	21	6	3	1
			11.4%	6.3%	1.8%	0.9%	0.3%
		2	8	16	21	7	3
			2.4%	4.8%	6.3%	2.1%	0.9%
		3	2	20	19	26	10
			0.6%	6.0%	5.7%	7.8%	3.0%
		4	3	7	17	22	24
			0.9%	2.1%	5.1%	6.6%	7.2%
		5	3	7	7	14	27
			0.9%	2.1%	2.1%	4.2%	8.1%

Table A6.
Results of contrarian case analysis

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