UTAUT2 Determinants and User Engagement in a Freemium Game: A PLS-SEM Study of Love and Deepspace

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Abstract

Freemium mobile games rely heavily on optional in-app purchases, yet the factors driving purchase intentions among existing users may differ from those underlying general game use. This study investigates the relationships between Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) determinants, User Engagement (UEng), Purchase Intention (PurIn), and self-reported Use Behavior (UBhv) in Love and Deepspace. A quantitative cross-sectional survey was conducted with 374 adult active purchasers and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The structural model explains 50.3% of the variance in Purchase Intention (PurIn) and 54.0% in Use Behavior (UBhv). Price Value (PriVal) was the strongest predictor of Purchase Intention (PurIn) ($\beta = 0.342$, $p < 0.001$), while User Engagement (UEng) also showed a significant direct association with Purchase Intention (PurIn) ($\beta = 0.287$, $p < 0.001$). Facilitating Conditions (FaCo) and Habit (Hbt) were statistically significant but had negligible effects, whereas Performance Expectancy (PeEx), Effort Expectancy (EfEx), Social Influence (SoIn), and Hedonic Motivation (HeMo) were not significant. None of the User Engagement (UEng) moderation effects were supported. These findings highlight the stronger role of purchase-related value in explaining purchase intention and indicate that the retained, purchase-linked dimensions of User Engagement (UEng) were positively associated with purchasing outcomes but did not significantly moderate the examined relationships.

Keywords: Freemium Games, Love and Deepspace, Purchase Intention, UTAUT2, User Engagement

I. INTRODUCTION

In-app purchases have become an increasingly important monetization mechanism in the mobile gaming industry. In 2024, global mobile-game in-app purchase revenue reached approximately USD 82 billion, representing a 4% increase from the previous year [1]. One widely adopted approach is the freemium model, which allows players to access a game without an initial payment while offering optional premium content for purchase [2]. Despite its substantial revenue potential, monetizing freemium users remains challenging. Nguyen et al. [3] reported that only a small proportion of users in freemium social games make in-app purchases. In contrast, a relatively small group of high-spending players accounts for a substantial share of revenue. This pattern highlights the importance of understanding the factors associated with players' purchase intentions in freemium game environments.

The factors underlying purchase intention may be particularly complex in narrative-oriented games, where players' decisions can relate to both technology use and the experience premium content offers. Love and Deepspace is a relevant example, combining character-centered narratives with interactive features such as first-person 3D interactions, AR Snapshot, and AI-assisted face crafting. Its monetization mechanisms include the Wish system, paid Promise rewards, Aurum Pass, virtual currency, item packs, outfits, and accessories. Some premium Memories also provide character-specific stories beyond the main storyline [4]. As an otome game, Love and Deepspace centers on romantic interactions between a female protagonist and male characters [5]. In this context, Gong and Huang [6] found that romantic parasocial interaction was positively associated with in-game purchase intention among female otome-game players. These findings suggest that purchasing in narrative games may involve a combination of technology-related perceptions and players' involvement with the game's content and characters.

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) provides a framework for examining consumer technology use through seven constructs: Performance Expectancy (PeEx), Effort Expectancy (EfEx), Facilitating Conditions (FaCo), Social Influence (SoIn), Hedonic Motivation (HeMo), Price Value (PriVal), and Habit (Hbt) [7]. Prior studies have applied technology-acceptance frameworks to gaming contexts, including purchase intention and

continuance gaming intention [8], [9]. UTAUT2 has also been used to examine in-game purchasing behavior [10], while purchase intention has been investigated in other mobile-game settings [11]. However, these applications have mainly addressed general technology use or broad purchase intention and have not explicitly integrated players' engagement with the game experience into the UTAUT2 model in a narrative-oriented freemium context. This gap matters because the seven constructs may not operate the same way when premium content is tied to character relationships and story experiences. In addition, the study's behavioral focus differs from general intention to use: players can continue playing a freemium game without paying. Therefore, this study operationalizes Behavioral Intention as Purchase Intention (PurIn), referring specifically to willingness to make in-game purchases.

User Engagement (UEng) is considered as an additional construct because players' involvement with a digital experience may provide information beyond the perceived usefulness, ease, enjoyment, value, or habitual use captured by UTAUT2. UEng encompasses cognitive, affective, and behavioral involvement [12], whereas HeMo concerns the enjoyment derived from using a technology [7]. Although these concepts may be related, they represent distinct aspects of the player experience: users may enjoy a game without being deeply engaged with its narrative, characters, or activities. UEng is therefore included as a complementary construct, not as a replacement for UTAUT2 determinants. Prior research has examined engagement as a moderator in digital and consumer contexts [13], [14], and gaming studies have linked engagement with purchase-related intentions [12], [15]. Building on this work, the present study examines whether UEng moderates the relationships between selected UTAUT2 determinants and purchase intention, specifically SoIn, HeMo, PriVal, and Hbt, while also examining its direct associations with purchase intention and use behavior in a narrative-oriented freemium game. In narrative-driven games, players' involvement levels may shape how they interpret and prioritize social cues, enjoyment, perceived value, and habitual gameplay when making purchase decisions. Consequently, engagement may influence how strongly these factors translate into purchase intention. This moderation is examined without assuming that engagement necessarily strengthens these relationships.

Accordingly, this study investigates the relationships between the seven UTAUT2 constructs and PurIn, the association between PurIn and Use Behavior (UBhv), and the direct and moderating roles of UEng in Love and Deepspace using PLS-SEM. Its contribution lies in applying UTAUT2 to transaction-specific purchasing in an experience-driven mobile game while empirically examining both the direct and moderating roles of player engagement. The findings may provide mobile game developers and publishers with insights into factors associated with players' purchase intention and use behavior in narrative-oriented freemium environments.

II. RESEARCH METHODOLOGY

A. Research Model and Hypotheses

This study extends the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) by incorporating User Engagement (UEng) to examine purchase intention and use behavior among Love and Deepspace players. UTAUT2 comprises seven constructs, providing a theoretical basis for examining consumer technology use and behavioral intention [7]. Prior studies have applied technology acceptance frameworks in freemium and gaming contexts [8], [10].

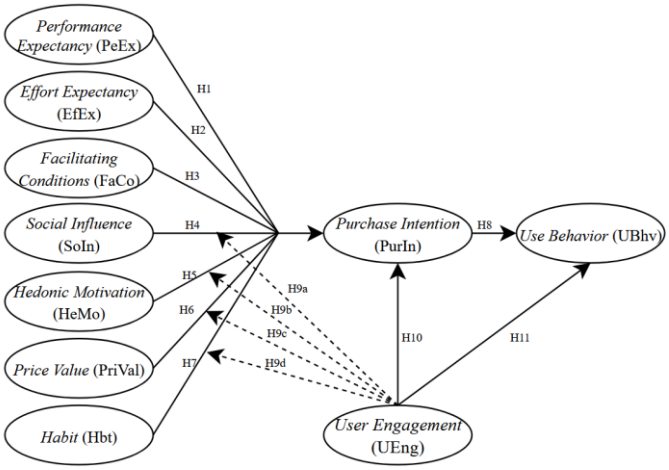

Figure 1. Research Model

The study first examines the direct effects of the seven UTAUT2 constructs on Purchase Intention (PurIn) and the effect of PurIn on Use Behavior (UBhv) as shown in Figure 1:

- H1: Performance Expectancy (PeEx) positively influences PurIn.
- H2: Effort Expectancy (EfEx) positively influences PurIn.
- H3: Facilitating Conditions (FaCo) positively influence PurIn.
- H4: Social Influence (SoIn) positively influences PurIn.
- H5: Hedonic Motivation (HeMo) positively influences PurIn.
- H6: Price Value (PriVal) positively influences PurIn.
- H7: Habit (Hbt) positively influences PurIn.
- H8: PurIn positively influences UBhv.

UEng is proposed to moderate the relationships of SoIn, HeMo, PriVal, and Hbt with PurIn. These four constructs capture social [16], experiential [17], economic [18], [19], and habitual [20], [21] dimensions that may be relevant to purchase decisions and provide distinct contexts in which user engagement may operate. In contrast, PeEx, EfEx, and FaCo are examined as direct predictors because they primarily reflect functional perceptions of usefulness, ease of use, and available resources. This approach focuses the moderation analysis on the social, experiential, economic, and habitual dimensions of gameplay. Prior findings also indicate that engagement's moderating role may differ across relationships [13], [14].

Finally, aligning with prior findings linking game engagement to purchase-related intentions [12], [15], UEng is

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hypothesized to exert direct positive effects on PurIn and UBhv. The complete set of hypotheses is structured as follows:

- H9a–d: UEng moderates the relationship between (a) SoIn, (b) HeMo, (c) PriVal, (d) Hbt, and PurIn.
- H10: UEng positively influences PurIn.
- H11: UEng positively influences UBhv.

B. Research Design and Measurement

This study employs a quantitative, cross-sectional survey design to examine the hypothesized relationships among the UTAUT2 constructs, User Engagement (UEng), Purchase Intention (PurIn), and Use Behavior (UBhv) in Love and Deepspace. Data were collected using a structured online questionnaire administered through Google Forms. All construct indicators were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Measurement items were adapted from prior studies on technology acceptance, digital-game behavior, purchase intention, and user engagement [2], [7], [8], [9], [10], [22], [23], [24], [25] and contextualized to Love and Deepspace. Before distribution, the research supervisor reviewed and approved the questionnaire. The instrument comprised 46 indicators across ten constructs: four indicators each for PeEx, EfEx, SoIn, FaCo, PriVal, and Hbt; five for HeMo; eight for UEng; five for PurIn; and four for UBhv.

All constructs were assessed using self-reported questionnaire responses. For UBhv specifically, the items captured respondents' reported purchasing frequency and tendency to make repeat in-game purchases; therefore, UBhv reflects self-reported purchasing behavior rather than objectively observed transaction behavior. This measurement approach may be subject to recall and response biases, and reported behavior may not fully reflect actual purchasing activity. Table 1 summarizes how the questionnaire measured the constructs.

Table 1. Operational Definitions and Indicators

Construct	Operational Description	Items
Performance Expectancy (PeEx)	Expected gameplay benefits from premium features or purchases.	PeEx1–PeEx4
Effort Expectancy (EfEx)	Perceived ease of using in-game purchasing systems or features.	EfEx1–EfEx4
Social Influence (SoIn)	Perceived social influence on in-game purchasing decisions.	SoIn1–SoIn4
Facilitating Conditions (FaCo)	Technical conditions and resources supporting in-game purchases.	FaCo1–FaCo4
Hedonic Motivation (HeMo)	Enjoyment and satisfaction experienced while playing the game.	HeMo1–HeMo5
Price Value (PriVal)	Perceived benefits of in-game purchases relative to monetary cost.	PriVal1–PriVal4
Habit (Hbt)	Habitual or automatic game use and in-game purchasing.	Hbt1–Hbt4
User Engagement (UEng)	Players' involvement with the game and its characters.	UEng1–UEng8
Purchase Intention (PurIn)	Intention to make current, future, or repeat in-game purchases.	PurIn1–PurIn5
Use Behavior (UBhv)	Self-reported in-game purchasing behavior.	UBhv1–UBhv4

C. Respondents, Sampling, and Data Collection

The study targeted active Love and Deepspace players registered on the game's global servers in Asia, North America, and Europe. Purposive sampling was employed based on three criteria: respondents had to (1) actively play Love and Deepspace, (2) be registered on a global server, and (3) have made at least one in-game purchase. These criteria ensured respondents were familiar with the game's monetization system, shared a relatively consistent gaming context in terms of available content and purchasing features, and had actual purchasing experience rather than relying on hypothetical intentions. Consequently, the study focuses on existing purchasers and their potential for continued purchasing rather than the initial conversion of free-to-play (F2P) players into paying users.

Given the non-probability sampling design, sample adequacy was evaluated using a PLS-SEM-based criterion rather than a population-based margin-of-error calculation. The minimum sample size was estimated using a two-tailed adaptation of the inverse-square-root approach proposed by Kock and Hadaya [26]. With a significance level of 0.05, statistical power of 0.80, and a minimum absolute path coefficient of 0.15, the calculation yielded a minimum sample size benchmark of 349 respondents. The final sample of 374 respondents exceeded this benchmark. However, the statistical power of moderation effects also depends on interaction effect sizes and measurement reliability. Thus, small interaction effects may not be adequately detected and should be interpreted with caution.

Data were collected between December 2025 and February 2026 through Discord, Facebook, WhatsApp, X (Twitter), Instagram, and TikTok, with additional distribution through sharing within the player community. Following data screening, responses from participants under 18 years of age were excluded, resulting in a final analytical sample of 374 adult respondents. Because we used purposive, non-probability sampling and included only existing purchasers, the findings are not statistically generalizable to all Love and Deepspace players, particularly non-paying users and players outside the sampled global-server communities. Nevertheless, the findings may offer theoretical insights into purchasing behavior in similar narrative-driven freemium games. However, further research is needed to examine their applicability across different games and player populations.

D. Data Analysis

Data analysis utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. Respondent characteristics were summarized using frequencies and percentages. The reflective measurement model was evaluated using indicator loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), and the heterotrait–monotrait (HTMT) ratio [27], [28]. Assessment criteria included a minimum loading of 0.70, reliability values of at least 0.70, AVE of at least 0.50, and HTMT below 0.90. The evaluation also examined bootstrapped HTMT confidence intervals. Indicators with loadings below 0.70 were evaluated for removal based on their measurement performance and theoretical relevance. The removal process was conducted iteratively, resulting in the exclusion of 16 indicators, including six of the eight original UEng indicators [28].

The analysis calculated descriptive statistics, including means and standard deviations, for the retained indicators. Common method bias (CMB) was assessed using the random dependent variable (RDV) technique, which tests whether latent constructs spuriously predict a randomly generated variable [29]. This technique was selected as an additional diagnostic to detect potentially spurious relationships arising from common method variance. Inner VIF values of 3.3 or lower served as the diagnostic threshold for low CMB concern [30], [31]. Structural model assessment evaluated collinearity (VIF), coefficient of determination (R^2 and adjusted R^2), effect size (f^2), and standardized root mean square residual (SRMR). The criteria required VIF values below 5 and SRMR values below 0.08, while classifying effect sizes of 0.02, 0.15, and 0.35 as small, medium, and large, respectively [28], [32].

Hypothesis testing used bootstrapping with 10,000 subsamples at a two-tailed 5% significance level. Percentile-based 95% confidence intervals served as the primary inference criterion alongside t-statistics and p-values [32], [33]. Moderating effects of UEng were examined using the Two-Stage Approach for the four interaction terms. This approach was selected based on simulation evidence of its parameter recovery performance and its flexibility in constructing interaction terms using latent variable scores in PLS-SEM [28], [33], [34]. Finally, predictive performance was evaluated using PLSpredict with 10 folds and 10 repetitions, comparing Q^2predict values and prediction errors (RMSE and MAE) against a linear benchmark model [33].

III. RESULTS AND DISCUSSION

A. Respondent Profile

The final sample consisted of 374 respondents. As shown in Table 2, the sample was predominantly female (96.26%) and aged 18–24 years (53.48%), with most respondents playing on the Asia server (88.77%). Most had played Love and Deepspace for more than one year (64.17%) and played daily (89.57%), indicating that the sample largely comprised experienced and active players. In addition, 48.66% reported spending more than USD 50, while 82.35% indicated being somewhat or very emotionally connected to the game.

Table 2. Respondent Profile ($N = 374$)

Category	Classification	Freq.	%
Gender	Female	360	96.26%
	Male	3	0.80%
	Prefer not to say	11	2.94%
Age	18-24 years	200	53.48%
	25-34 years	152	40.64%
	35-44 years	21	5.61%
	≥45 years	1	0.27%
Game Server	Asia	332	88.77%
	North America	16	4.28%
	Europe	26	6.95%
Playing Duration	<2 weeks	2	0.53%
	2 weeks–1 month	8	2.14%
	1–3 months	17	4.55%
	4–6 months	21	5.61%
	7–12 months	86	22.99%
	>1 year	240	64.17%
Playing Frequency	Daily	335	89.57%
	3–5 times/week	22	5.88%
	1–2 times/week	7	1.87%
	Less frequently	10	2.67%
Session Duration	<30 minutes	83	22.19%
	30–60 minutes	178	47.59%
	>1 hour	113	30.21%
Spending	<$3	21	5.61%
	$3–$9.99	53	14.17%
	$10–$29.99	73	19.52%
	$30–$50	45	12.03%
	>$50	182	48.66%
Emotional Connection	Not connected at all	1	0.27%
	Slightly connected	17	4.55%
	Neutral	48	12.83%
	Somewhat connected	124	33.16%
	Very connected	184	49.20%

B. Measurement Model Assessment

The measurement model was evaluated using the criteria described in the Research Method section. Following iterative refinement, 30 of the original 46 indicators were retained in the final model. Table 3 summarizes the deleted indicators, their initial outer loadings, and the reasons for their removal.

Table 3. Summary of Deleted Indicators

Const.	Deleted Indicators	Initial Outer Loadings	Reason
PeEx	PeEx3, PeEx4	0.697, 0.629	Low load.
FaCo	FaCo4	0.642	Low load.
Hbt	Hbt4	0.546	Low load.

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HeMo	HeMo5	0.574	Low load.
PriVal	PriVal1, PriVal2	0.602, 0.563	Low load.
SoIn	SoIn1	-0.630	Negative load.
UBhv	UBhv2, UBhv4	0.642, 0.816	Low load. (UBhv2); HTMT > 0.90 (UBhv4)
UEng	UEng1–UEng4, UEng7–UEng8	0.596, 0.508, 0.687, 0.389, 0.670, 0.509	Low load.

As detailed in Table 4, the retained indicators exhibited outer loadings ranging from 0.702 to 0.927. Cronbach's alpha values ranged from 0.701 to 0.859, composite reliability ranged from 0.846 to 0.899, and average variance extracted (AVE) values exceeded the 0.50 threshold (ranging from 0.603 to 0.798), thereby confirming satisfactory indicator reliability, internal consistency, and convergent validity.

Table 4. Reliability and Convergent Validity Assessment

Const.	Ind.	Load.	Alpha	CR	AVE
EfEx	EfEx1	0.729	0.787	0.858	0.603
	EfEx2	0.732			
	EfEx3	0.826			
	EfEx4	0.813			
FaCo	FaCo1	0.855	0.800	0.879	0.710
	FaCo2	0.762			
	FaCo3	0.904			
Hbt	Hbt1	0.813	0.731	0.846	0.648
	Hbt2	0.869			
	Hbt3	0.726			
HeMo	HeMo1	0.803	0.814	0.873	0.633
	HeMo2	0.818			
	HeMo3	0.840			
	HeMo4	0.716			
PeEx	PeEx1	0.895	0.734	0.883	0.790
	PeEx2	0.883			
PriVal	PriVal3	0.915	0.701	0.867	0.766
	PriVal4	0.833			
PurIn	PurIn1	0.814	0.859	0.899	0.643
	PurIn2	0.788			
	PurIn3	0.702			
	PurIn4	0.910			
	PurIn5	0.779			
SoIn	SoIn2	0.927	0.779	0.853	0.662
	SoIn3	0.781			
	SoIn4	0.719			
UBhv	UBhv1	0.888	0.747	0.888	0.798
	UBhv3	0.899			
UEng	UEng5	0.898	0.707	0.872	0.773
	UEng6	0.860			

Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT). As shown in Table 5, all final HTMT values were below 0.90. The highest value was observed between Purchase Intention and Use Behavior (HTMT = 0.883; 95% CI [0.812, 0.952]). During refinement, UBhv2 was first removed due to its low outer loading. Subsequently, the HTMT value between PurIn and UBhv increased from 0.889 to 0.925, leading to the removal of UBhv4. Following this adjustment, the final model met the specified HTMT point-estimate criterion, and all bootstrapped confidence intervals excluded 1.00.

Table 5. Heterotrait–Monotrait Ratio (HTMT)

Const.	Pair	HTMT
EfEx	FaCo	0.749
	Hbt	0.236
	HeMo	0.394
	PeEx	0.327
	PriVal	0.402
	PurIn	0.421
	SoIn	0.110
	UBhv	0.291
	UEng	0.270
FaCo	Hbt	0.230
	HeMo	0.360
	PeEx	0.346
	PriVal	0.448
	PurIn	0.435
	SoIn	0.040
	UBhv	0.348
	UEng	0.271
Hbt	HeMo	0.458
	PeEx	0.224
	PriVal	0.382
	PurIn	0.424
	SoIn	0.136
	UBhv	0.348
	UEng	0.528
HeMo	PeEx	0.443
	PriVal	0.581
	PurIn	0.439
	SoIn	0.125
	UBhv	0.443
	UEng	0.447
PeEx	PriVal	0.703
	PurIn	0.489
	SoIn	0.081
	UBhv	0.420
	UEng	0.509
PriVal	PurIn	0.761
	SoIn	0.100
	UBhv	0.742
	UEng	0.680
PurIn	SoIn	0.097
	UBhv	0.883
	UEng	0.708
SoIn	UBhv	0.065
SoIn	UEng	0.067
UBhv	UEng	0.761

For UEng, only UEng5 and UEng6 were retained from the original eight indicators, with outer loadings of 0.898 and 0.860, respectively. UEng5 reflects the integration of the game into players' routines and loyalty toward purchasing premium items, while UEng6 captures emotional attachment to in-game characters that motivates purchasing behavior. These indicators primarily capture behavioral and emotional aspects of engagement related to the study's outcomes. However, removing the other six indicators limits the construct's content coverage, particularly for cognitive engagement and broader behavioral engagement. Nevertheless, the retained indicators are closely related to purchase intention in narrative-driven freemium games, and the construct demonstrated acceptable reliability and convergent validity. Therefore, findings related to UEng should be interpreted in light of this narrower operationalization.

C. Construct Descriptive Statistics (CDS) and Common Method Bias (CMB) Assessment

Table 6 presents the construct-level descriptive statistics and CMB assessment. HeMo recorded the highest mean (4.44), followed by FaCo (4.40) and EfEx (4.34), indicating overall favorable respondent perceptions regarding enjoyment, facilitating conditions, and ease of use. In contrast, SoIn showed the lowest mean (2.36), suggesting that social influence played a relatively limited role. Regarding response variability, UBhv exhibited the highest standard deviation (1.09), indicating diverse patterns in reported use behavior, whereas HeMo showed the lowest variability (0.57), reflecting highly consistent responses regarding enjoyment. CMB was assessed using the random dependent variable (RDV) procedure described in Section II.D. Data Analysis, which tests whether latent constructs spuriously predict a randomly generated variable. The resulting VIF values ranged from 1.040 to 2.662, all below the 3.3 threshold. These results indicate that CMB is unlikely to pose a serious concern, suggesting that the estimated structural relationships are less likely to be substantially influenced by common method variance.

Table 6. CDS and CMB Assessment

Const.	Mean	SD	CMB VIF (RDV)
PeEx	3.86	0.88	1.421
EfEx	4.34	0.59	1.769
SoIn	2.36	1.05	1.040
FaCo	4.40	0.63	1.778
HeMo	4.44	0.57	1.514
PriVal	3.71	0.85	2.039
Hbt	4.04	0.87	1.277
UEng	3.72	0.98	1.762
PurIn	3.77	0.86	2.662
UBhv	3.45	1.09	2.270

D. Structural Model Assessment

The structural model was evaluated for model fit, collinearity, explanatory power, effect sizes, hypothesis testing, moderation, and predictive performance. The SRMR was 0.070 for both the saturated and estimated models, below the specified threshold of 0.08. Structural VIF values ranged from 1.041 to 1.824, indicating no evidence of problematic collinearity among the predictor constructs.

The model explained 50.3% of the variance in PurIn (R^2 = 0.503; adjusted R^2 = 0.487) and 54.0% of the variance in UBhv (R^2 = 0.540; adjusted R^2 = 0.538). These values indicate moderate explanatory power, suggesting that the model explains a substantial proportion of the variance in both purchase intention and use behavior. At the same time, other factors may also contribute to these outcomes.

Hypothesis testing was conducted using 10,000 bootstrap resamples. As shown in Table 7, FaCo (H3), PriVal (H6), Hbt (H7), PurIn (H8), and the direct effects of UEng on PurIn (H10) and UBhv (H11) were supported based on the 95% percentile bootstrap confidence intervals. However, statistical significance did not necessarily indicate a meaningful practical effect. FaCo (f^2 = 0.016) and Hbt (f^2 = 0.012) had negligible effects, while PriVal (f^2 = 0.133), UEng → PurIn (f^2 = 0.108), and UEng → UBhv (f^2 = 0.079) had small effects. PurIn → UBhv showed a large effect (f^2 = 0.506), indicating its substantial contribution to use behavior. PeEx (H1), EfEx (H2), SoIn (H4), and HeMo (H5) were not supported, indicating that these constructs did not significantly explain PurIn in the present sample, with all corresponding effect sizes remaining negligible (f^2 = 0.000–0.012).

Table 7. Structural Path and Hypothesis Testing Results

Hyp.	Relationship	β	T	p	95% CI	f^2	Result
H1	PeEx → PurIn	0.053	1.001	0.317	[-0.050, 0.157]	0.004	Not supported
H2	EfEx → PurIn	0.076	1.396	0.163	[-0.028, 0.187]	0.006	Not supported
H3	FaCo → PurIn	0.118	2.233	0.026	[0.015, 0.224]	0.016	Supported
H4	SoIn → PurIn	-0.079	1.722	0.085	[-0.162, 0.025]	0.012	Not supported
H5	HeMo → PurIn	0.005	0.119	0.905	[-0.080, 0.098]	0.000	Not supported
H6	PriVal → PurIn	0.342	6.010	<0.001	[0.227, 0.448]	0.133	Supported
H7	Hbt → PurIn	0.089	1.963	0.050	[0.003, 0.182]	0.012	Supported
H8	PurIn → UBhv	0.582	13.377	<0.001	[0.493, 0.662]	0.506	Supported
H9a	UEng × SoIn → PurIn	0.005	0.106	0.916	[-0.083, 0.088]	0.000	Not supported
H9b	UEng × HeMo → PurIn	0.010	0.245	0.807	[-0.080, 0.088]	0.000	Not supported
H9c	UEng × PriVal → PurIn	-0.020	0.456	0.648	[-0.107, 0.067]	0.001	Not supported
H9d	UEng × Hbt → PurIn	-0.031	0.663	0.507	[-0.119, 0.066]	0.002	Not supported
H10	UEng → PurIn	0.287	5.450	<0.001	[0.179, 0.387]	0.108	Supported
H11	UEng → UBhv	0.230	5.115	<0.001	[0.144, 0.321]	0.079	Supported

None of the four interaction effects involving UEng were statistically significant, as all corresponding 95% confidence intervals included zero. Accordingly, H9a–H9d were not supported, indicating that UEng did not significantly moderate the relationships of SoIn, HeMo, PriVal, or Hbt with PurIn in the present sample.

Out-of-sample predictive performance was subsequently assessed using PLSpredict. As shown in Table 8, all indicator-level Q^2_predict values were positive, ranging from 0.180 to 0.389. The PLS-SEM model produced lower RMSE values than the linear model benchmark for all seven indicators. For MAE, the PLS-SEM model showed lower prediction errors for

five of the seven indicators. Overall, the PLS-SEM model produced lower prediction errors than the linear model benchmark, particularly for RMSE.

Table 8. PLSpredict Results

Ind.	Q^2_predict	RMSE		MAE	
		PLS-SEM	LM	PLS-SEM	LM
PurIn1	0.316	0.893	0.903	0.692	0.688
PurIn2	0.277	0.912	0.950	0.705	0.732
PurIn3	0.180	1.120	1.161	0.887	0.918
PurIn4	0.389	0.794	0.818	0.606	0.620
PurIn5	0.300	0.850	0.853	0.676	0.662
UBhv1	0.299	1.026	1.061	0.795	0.813
UBhv3	0.299	1.016	1.041	0.813	0.821

E. Discussion

The findings indicate that the UTAUT2 determinants had differing levels of association with Purchase Intention (PurIn) among existing purchasers of Love and Deepspace. Price Value (PriVal) showed the strongest association with PurIn, whereas Facilitating Conditions (FaCo) and Habit (Hbt) were statistically significant but had negligible effects. User Engagement (UEng) also showed significant direct associations with both PurIn and Use Behavior (UBhv). This pattern suggests that, in a narrative-driven freemium game, purchase-related perceptions may be more relevant to purchasing outcomes than several broader technology acceptance determinants.

PriVal emerged as the most prominent determinant of PurIn. In the refined measurement model, PriVal was represented by willingness to spend on in-game content and satisfaction derived from purchases, indicating that the finding reflects a retained purchase-related value dimension rather than the full original price-value domain. This differs from [35], which found PriVal nonsignificant for Behavioral Intention in a gacha-gaming context. The stronger role of PriVal in the present study suggests that value perceptions tied specifically to purchasing may be particularly relevant when applying UTAUT2 to transaction-specific outcomes.

FaCo and Hbt showed positive but negligible effects, indicating that their statistical significance translated into limited practical contribution. The retained FaCo indicators emphasize accessible payment systems, payment-method availability, and purchasing-interface simplicity, consistent with the role of facilitating conditions in UTAUT2 [7]. Hbt reflects regular and automatic gameplay rather than habitual purchasing. Its positive direction is consistent with previous gaming research identifying habit as relevant to continuance intention or purchase-related behavior [9], [10], [35], although these studies examined outcomes different from PurIn. Thus, convenient transaction conditions and regular gameplay may be relevant to purchasing, but neither appears to be a major factor differentiating purchase intention in this sample.

In contrast, PeEx, EfEx, SoIn, and HeMo were not significantly associated with PurIn. The findings for PeEx and EfEx differ from [8], which reported significant relationships with PurIn in freemium mobile games, while [35] likewise found EfEx nonsignificant. For the present refined measures, PeEx captures experiential benefits associated with purchases, whereas EfEx reflects ease of navigation and feature use. Among predominantly frequent and experienced players, these aspects may have become established characteristics of the gaming experience rather than salient considerations in purchase decisions. SoIn also showed the lowest construct mean, with retained indicators concerning community pressure, social media trends, and others' opinions. Its nonsignificant relationship is consistent with [8], [35], although social influence may still operate through peer activity and community interaction in freemium games [16]. HeMo showed the highest mean (M = 4.44) and lowest variability (SD = 0.57), yet its association with PurIn was essentially zero. This differs from [9], which linked HeMo with continuance gaming intention. This contrast suggests that enjoyment may matter more for continued game use than for additional purchasing, consistent with the distinction between continued use and purchase intentions in freemium services [2].

PurIn showed a large effect on self-reported UBhv, supporting the intention–behavior relationship in this transaction context and consistent with prior gaming research [10]. However, UBhv measured reported purchasing frequency and repurchase tendencies rather than objectively recorded transactions. UEng was also positively associated with PurIn and UBhv, consistent with evidence linking video-game engagement with purchase-related intentions [12], [15]. The interpretation of these effects requires particular caution because the refined UEng construct retained indicators concerning routine involvement, loyalty toward purchasing premium items or features, and character attachment that encourages purchases. These indicators therefore represent narrower, purchase-linked engagement dimensions rather than the full multidimensional construct of user engagement. Their conceptual proximity to PurIn and UBhv may also have contributed to the observed direct associations. Accordingly, the findings support the relevance of the retained engagement dimensions within this model, rather than demonstrating that broad UEng independently explains purchasing outcomes.

None of the proposed UEng moderation effects were significant. Thus, the measured UEng did not significantly alter the relationships of SoIn, HeMo, PriVal, or Hbt with PurIn. Although engagement has been examined as a moderating mechanism in other digital contexts [13], [14], the present findings provide no evidence of such a conditional role in this setting. Instead, UEng was more clearly represented through its direct associations with purchasing outcomes than through moderation. Given UEng's reduced representation, these non-significant interaction effects should be interpreted as an absence of moderation in the present model and sample, rather than evidence that UEng cannot function as a moderator in other contexts.

The respondent profile provides an important boundary condition for these findings. The sample was predominantly female, concentrated on the Asia server, and largely composed of daily and experienced players with prior

purchasing experience. The findings therefore primarily characterize active existing purchasers rather than the broader freemium-game population. PLSpredict further showed positive Q^2_predict values and generally lower prediction errors than the linear-model benchmark, indicating useful out-of-sample predictive performance.

Purchase-related value, the retained purchase-linked engagement dimensions, and transaction-specific intention appear more relevant to purchasing outcomes in this narrative-oriented freemium context than several broader UTAUT2 determinants. These conclusions should not be generalized to free-to-play users who have not purchased, casual players, or other regional and demographic populations. Finally, because the study used cross-sectional and self-reported data, the observed relationships should be interpreted as associations rather than causal effects.

IV. CONCLUSION

This study examined the associations of UTAUT2 determinants and User Engagement (UEng) with Purchase Intention (PurIn) and self-reported purchasing behavior (UBhv) among existing adult purchasers of Love and Deepspace. Price Value (PriVal) showed the strongest association with PurIn and a small practical effect, while Facilitating Conditions (FaCo) and Habit (Hbt) were statistically significant but had limited practical effects. Performance Expectancy (PeEx), Effort Expectancy (EfEx), Social Influence (SoIn), and Hedonic Motivation (HeMo) were not significantly associated with PurIn. PurIn showed a large effect on UBhv, while UEng was positively associated with both PurIn and UBhv. None of the proposed UEng moderation effects were supported.

Theoretically, these findings indicate that the relative relevance of UTAUT2 determinants may differ when the behavioral target is contextualized as purchase intention rather than general technology-use intention. The findings also suggest that UEng may complement UTAUT2 through direct associations with purchasing outcomes rather than through moderation in this setting. However, the final UEng construct was empirically reduced to two purchase-linked indicators; therefore, its findings should be interpreted as applying to these retained engagement dimensions rather than to the broader multidimensional construct of user engagement.

From a practical perspective, purchase-related value appears more relevant to purchasing outcomes than general enjoyment or ease of use among active purchasers, while facilitating transaction conditions may play a supporting role. These findings are limited to a predominantly female, Asia-server sample of active purchasers and should not be generalized to non-purchasing or casual players. The cross-sectional and self-reported design also limits causal interpretation, particularly because UBhv reflected reported rather than objectively recorded purchasing behavior. Future research should examine broader player populations, use objective transaction data where feasible, and employ more comprehensive measures of UEng.

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