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Seeing More, Wanting More? A TAM2-Based Consumer Psychology Analysis of 3D Product Visualization and Online Purchase Intention

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ABSTRACT **Original Research Article**

This study examines the factors influencing consumer adoption of 3D product visualization in online shopping by extending the Technology Acceptance Model 2 (TAM2). Survey data from 309 online shoppers were analyzed using regression techniques. The results show that subjective norm enhances both image and perceived usefulness, highlighting the continued relevance of social influence in digital purchase decisions. Task relevance and perceived ease of use also positively shape perceived usefulness, while both perceived usefulness and perceived ease of use strongly predict purchase intention. Conversely, the result demonstrates no significant effect, suggesting that experiential visualization tools may rely on mechanisms beyond functional clarity. Online shopping experience does not moderate the examined relationships, indicating consistent behavioral patterns across user groups. The study contributes to TAM2 by identifying boundary conditions relevant to interactive product visualization and offers practical insights for improving interface design, social proof strategies, and consumer engagement.

Keywords: 3D Product Visualization, Technology Acceptance Model 2 (TAM2), Social Influence, Cognitive Instrumental Factors, Perceived Usefulness, Perceived Ease of Use, Purchase Intention.

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1. Introduction

1.1 Research Background

With the rapid expansion of global e-commerce, online shopping has become one of the primary channels for purchasing for modern consumers. According to Statista (2023), global e-commerce revenue continues to rise and is expected to maintain strong growth in the years to come. In this context, how online platforms present product information—especially when consumers cannot physically inspect the products —has become a critical issue.

Traditional product presentations rely heavily on 2D images and textual descriptions; however, such formats often provide limited information, leading to expectation gaps that result in dissatisfaction, returns, or disputes. Government reports in Taiwan similarly indicate that “product not matching its description” remains a top complaint among online shoppers (Consumer Protection Committee, 2023). To address this issue, many platforms have begun adopting 3D product visualization technologies, enabling users to rotate, zoom, and inspect products from multiple angles.

Prior studies highlight the advantages of 3D visualization, including information richness, interactivity, presence, and uncertainty reduction (Li et al., 2020; Heller et al., 2021; Park & Kim, 2021). Despite these technological benefits, it remains unclear whether 3D product displays can truly enhance consumer acceptance and purchasing intention—especially when considering perceived usefulness, ease of use, and social influence. Moreover, although 3D visualization research has grown, few studies have applied an integrated theoretical model to explain consumers’ adoption of such technologies. The Technology Acceptance Model 2

(TAM2) provides a strong theoretical basis for addressing this gap (Venkatesh & Davis, 2000).

This study, therefore, adopts the Technology Acceptance Model 2 (TAM2) to examine how social influence, cognitive instrumental processes, and perceived ease of use shape perceived usefulness and purchase intention when consumers interact with 3D product displays.

1.2 Research Motivation

The motivation for conducting this study is threefold:

(1) Addressing the need for high-quality product presentation in e-commerce. In highly competitive online marketplaces, the way product information is displayed has a significant impact on conversion rates. Although 3D product displays offer advantages, their actual effectiveness requires empirical validation.

(2) Filling the theoretical gap in 3D display adoption research. Prior studies have explored the interactive features of 3D displays but have seldom explained consumer adoption mechanisms using the Technology Acceptance Model (TAM). This study employs the Technology Acceptance Model (TAM) to elucidate how social influence and cognitive processes influence adoption behavior.

(3) Examining the role of online shopping experience. Online shopping experience may influence consumers' acceptance of new display technologies. However, previous findings are inconsistent. This study incorporates online shopping experience as a moderator to clarify its role.

1.3 Research Objectives

This study aims to:

(1) Examine the effects of social influence factors (subjective norm and image) on perceived usefulness.

(2) Investigate the effects of cognitive instrumental factors (task relevance, result demonstrability, perceived ease of use) on perceived usefulness.

(3) Evaluate the impacts of perceived usefulness and perceived ease of use on purchase intention.

(4) Test whether online shopping experience moderates the relationships among subjective norm, perceived usefulness, and purchase intention.

(5) Develop an integrated adoption model for 3D product visualization based on TAM2.

2. Literature Review

This chapter reviews three major domains relevant to the study: the Technology Acceptance Model (TAM and TAM2), 3D product visualization technologies, and purchase intention.

2.1 Technology Acceptance Model (TAM, TAM2, and TAM3)

The Technology Acceptance Model (TAM), introduced by Davis (1989), is one of the most influential theories for explaining the adoption of technology. TAM posits that perceived usefulness (PU) and perceived ease of use (PEOU) are the two core determinants of user acceptance. Recent studies continue to validate TAM's predictive power and highlight its applicability across various domains, including e-commerce, mobile applications, and augmented reality (AR) (Mariani et al., 2022; Alalwan, 2022).

However, the original TAM underemphasized social influence and task-oriented cognitive factors. To address this limitation, Venkatesh and Davis (2000) proposed TAM2, which incorporates two additional mechanisms: (1) social influence processes—including subjective norm and image, and (2) cognitive instrumental processes—including task relevance and result demonstrability. Recent literature provides further support:

(1) **Subjective Norm**: Social pressure and expectations from significant others significantly shape users' adoption of new technologies (Tarhini et al., 2022).

(2) **Image**: If using a technology enhances one's social image, perceived usefulness increases accordingly (Zhang et al., 2021).

(3) **Task Relevance**: Technologies that help users accomplish their goals are more likely to be adopted (Al-Emran & Granić, 2023).

(4) **Result Demonstrability**: The degree to which outcomes of using a technology are observable influences perceived usefulness (Mariani et al., 2022).

Extensions of TAM, such as UTAUT, further emphasize that social influences and facilitating conditions interact with user experience to shape adoption behavior (Venkatesh et al., 2012).

TAM3 and Its Relevance to This Study

TAM3, proposed by Venkatesh and Bala (2008), extends the earlier TAM frameworks by providing a detailed explanation of how perceived ease of use (PEOU) is formed. While TAM focuses on PU and PEOU as core beliefs, and TAM2 strengthens the explanation of PU, TAM3 emphasizes a comprehensive set of PEOU antecedents, including:

(1) Computer self-efficacy (users' belief in their ability to perform tasks),

(2) Perceptions of external control (availability of resources and support),

(3) Computer anxiety (emotional discomfort when using technology),

(4) Computer playfulness (the degree of cognitive spontaneity during interaction),

(5) Objective usability and subjective usability (actual and perceived system efficiency).

These constructs make TAM3 particularly suitable for contexts in which the ease of using a system is central—such as ERP implementation, office software, workplace IT systems, and educational platforms. In such systems, users must frequently engage in complex tasks, making psychological comfort and system usability essential predictors of user satisfaction.

However, the present study centers on how consumers evaluate 3D product visualization in terms of usefulness, rather than analyzing the psychological origins of ease of use. Since TAM3 does not include task-related cognitive factors—such as task relevance and result demonstrability—that are critical in evaluating 3D product displays, TAM2 provides a more theoretically aligned model for this research. TAM2's emphasis on social influence and cognitive instrumental processes more directly captures how consumers assess the value of 3D visualization, making it the most appropriate framework for this study.

2.2 3D Product Visualization Technologies 3D Product Visualization Technologies

3D product visualization has become one of the most important presentation techniques in e-commerce. Through rotation, zooming, lighting simulation, and texture rendering, 3D displays enable consumers to inspect products in a manner closer to physical interaction. Key findings from recent studies include:

(1) Enhanced Information Richness. 3D visualization presents detailed information and multiple viewing angles, helping consumers better understand product attributes (Park & Kim, 2021). Higher information richness reduces evaluation risk and boosts decision confidence (Chen et al., 2023).

(2) Increased Interactivity and Immersion. Manipulable functions such as zooming, rotation, and material simulation create a greater sense of presence and involvement (Fan et al., 2022). These interactive features enhance the user experience and facilitate product evaluation (Huang & Liao, 2021).

(3) Reduction of Uncertainty. By providing accurate, multi-angle views, 3D displays reduce interpretation errors caused by static photos, thereby lowering perceived risk and psychological cost (Sun et al., 2022; Kim & Forsythe, 2020).

(4) Potential Cognitive Load Issues. When interfaces are overly complex, cognitive load increases, which can harm perceived ease of use and reduce user willingness (Wang et al., 2023).

In summary, 3D visualization offers substantial informational and experiential value; however, its effectiveness ultimately depends on users' cognitive assessments, making TAM2 a suitable framework for examining adoption.

2.3 Purchase Intention

Purchase intention refers to the likelihood that a consumer will purchase after evaluating a product. Recent studies emphasize several determinants:

(1) Technological Presentation Enhances Purchase Intention. Interactive technologies—such as AR and 3D visualization—help consumers develop stronger product understanding and positive emotional responses (Heller et al., 2021).

(2) Mediating Roles of PU and PEOU. When technologies are perceived as valuable and easy to use, consumers exhibit stronger purchase intentions (Alalwan, 2022).

(3) Influence of Mental Imagery and Immersion. 3D product experiences enhance mental imagery and emotional engagement, leading to higher purchase intention (Sun et al., 2022; Fan et al., 2022).

Based on these findings, this study posits that 3D visualization enhances purchase intention primarily by influencing perceived usefulness and perceived ease of use—aligned with the TAM2 framework.

3. Research Methodology

3.1 Research Framework

Based on TAM2 (Venkatesh & Davis, 2000), this study proposes a research framework that integrates subjective norm, image, task relevance, result demonstrability, perceived ease of use, perceived usefulness, and purchase intention, with online shopping experience serving as a moderating variable. The complete framework is illustrated in Figure 1.

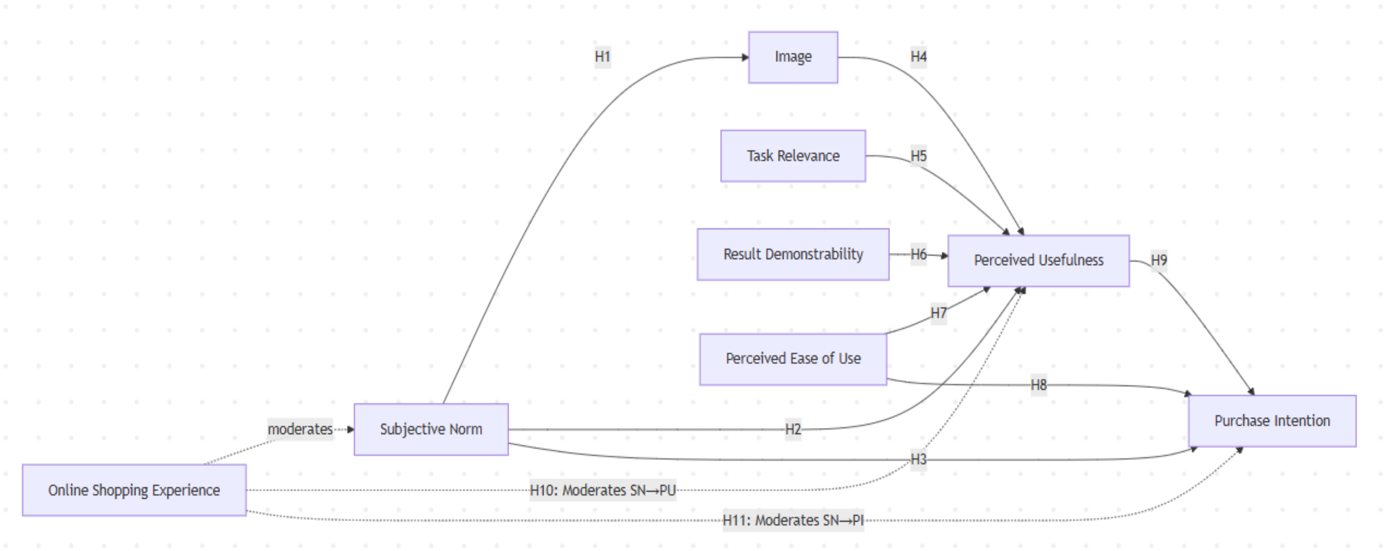

Figure 1. Research Framework Based on TAM2 for 3D Product Display Adoption

Note. H1–H11 represent hypothesized causal paths proposed in this study.

3.2 Hypotheses Development

Based on the Technology Acceptance Model 2 (TAM2), this study proposes eleven hypotheses regarding consumers' adoption of 3D product visualization. The hypotheses are drawn from two central TAM2 mechanisms—social influence processes and cognitive instrumental processes—and extend to core TAM relationships and their moderating effects. Each subsection provides theoretical justification supported by recent empirical findings.

Social Influence Process

Social influence in TAM2 comprises subjective norm (SN) and image (IMG). Subjective norm reflects perceived social pressure from important referents, while image represents the extent to which using a technology enhances one's social status.

Recent research indicates that the subjective norm has a strong influence on technology adoption, particularly in contexts where the technology is new or users are uncertain (Tarhini et al., 2022). When consumers believe that people who matter to them (e.g., friends, influencers, online communities) expect them to use 3D product displays, they are more likely to view such displays favorably. Moreover, the use of advanced visualization technologies often conveys innovativeness and competence, thereby enhancing users' social image (Zhang et al., 2021). These influences jointly contribute to shaping perceived usefulness.

H1: Subjective norm has a positive effect on image.
H2: Subjective norm has a positive effect on perceived usefulness.
H3: Subjective norm has a positive effect on purchase intention.
H4: Image has a positive effect on perceived usefulness.

Cognitive Instrumental Process

The cognitive instrumental route includes task relevance, result demonstrability, and perceived ease of use. These factors relate to how well consumers perceive the technology as supporting their goal-oriented product evaluations.

Task relevance (TR) refers to the degree to which 3D products align with consumers' shopping needs. When visualization tools provide meaningful, task-oriented information—such as size, texture, or viewing angles—users perceive the technology as more beneficial (Al-Emran & Granić, 2023).

Result demonstrability (RD) refers to the ease with which users can observe and articulate the benefits of using the technology. Prior studies show that when outcomes are clear and visible, perceived usefulness increases because users can more confidently justify their decisions (Mariani et al., 2022).

Perceived ease of use (PEOU) remains a critical determinant across technology adoption research. If 3D displays are intuitive and require minimal effort, users develop higher perceived usefulness and stronger behavioral intentions (Wang et al., 2023).

H5: Task relevance has a positive effect on perceived usefulness.
H6: Result demonstrability has a positive effect on perceived usefulness.
H7: Perceived ease of use has a positive effect on perceived usefulness.
H8: Perceived ease of use has a positive effect on purchase intention.

Core TAM2 Relationships

Perceived usefulness (PU) remains the strongest predictor of behavioral intention across decades of empirical TAM research. Contemporary findings confirm that when consumers believe 3D visualization enhances product understanding, reduces uncertainty, and improves decision confidence, they are significantly more likely to make a purchase (Alalwan, 2022; Park & Kim, 2021).

H9: Perceived usefulness has a positive effect on purchase intention.

Moderating Effect

The online shopping experience may influence how strongly subjective norm shapes user perceptions. TAM2 and later extensions (e.g., UTAUT2) suggest that experienced users rely less on normative pressure and more on independent evaluations (Venkatesh et al., 2012). Thus, moderation may strengthen or weaken the influence of the subjective norm, depending on users' familiarity with digital shopping environments.

H10: Online shopping experience moderates the relationship between subjective norm and perceived usefulness; the relationship is stronger for consumers with higher online shopping experience.
H11: Online shopping experience moderates the relationship between subjective norm and purchase intention; the relationship is stronger for consumers with higher online shopping experience.

3.3 Questionnaire Design

A five-point Likert scale (1 = strongly disagree, 5 = strongly agree) was used. All measurement items were adapted from validated TAM2 scales (Venkatesh & Davis, 2000) and modified to fit the context of 3D product visualization. The questionnaire contains seven constructs with multi-item scales.

Construct Definitions and Measurement Items

Below are construct definitions and example measurement items, each supported by TAM2 or related literature.

Subjective Norm (SN)

The degree to which individuals perceive that important others believe they should use the technology (Venkatesh & Davis, 2000).

SN1: People important to me think I should use 3D product displays.

SN2: People who influence my decisions encourage me to use 3D displays.
SN3: My peers believe using 3D displays is beneficial.

Image (IMG)

The degree to which using a system enhances one's status or social image (Venkatesh & Davis, 2000).
IMG1: Using 3D displays enhances my technological image.
IMG2: People who use 3D displays are perceived as innovative.
IMG3: Using 3D displays improves my social recognition.

Task Relevance (TR)

The extent to which a system applies to an individual's job or task (Venkatesh & Davis, 2000).
TR1: 3D displays provide information relevant to evaluating products.
TR2: 3D visualization supports essential product assessment tasks.
TR3: Using 3D displays helps me understand product attributes.

Result Demonstrability (RD)

The degree to which the benefits of using the system are observable and communicable (Venkatesh & Davis, 2000).
RD1: The benefits of using 3D displays are easy to observe.
RD2: The usefulness of 3D displays is apparent to me.
RD3: It is easy to demonstrate the advantages of 3D displays.

Perceived Ease of Use (PEOU)

The degree to which a person believes that using the system requires minimal effort (Davis, 1989).
PEOU1: Learning to operate 3D displays is easy for me.
PEOU2: I find 3D displays clear and understandable.
PEOU3: Interacting with 3D displays is easy.

Perceived Usefulness (PU)

The degree to which using the system enhances task performance (Davis, 1989).
PU1: Using 3D displays improves product understanding.
PU2: 3D visualization enhances my evaluation accuracy.
PU3: 3D displays increase my efficiency in online shopping.

Purchase Intention (PI)

The likelihood that a consumer intends to purchase after engaging with the system (Heller et al., 2021).
PI1: I am willing to purchase products with 3D displays.
PI2: 3D displays increase my intention to buy products.
PI3: I would consider purchasing products shown with 3D visualization.

Online Shopping Experience (EXP)

The extent of an individual's familiarity and prior usage of online shopping platforms.
EXP1: I frequently engage in online shopping.
EXP2: I am familiar with various online shopping technologies.
EXP3: I have extensive experience evaluating products online.

These items provide operational definitions for each construct and align with validated scales from TAM2 literature.

3.3 Questionnaire Design

A five-point Likert scale was used. Items were adapted from Venkatesh and Davis (2000) and revised to fit the 3D product display context. A pilot test was conducted before formal data collection.

3.4 Data Collection

A total of 309 valid responses were collected from individuals with online shopping experience. Most respondents were between 20 and 39 years old, with a slightly higher proportion of female participants.

3.5 Data Analysis

Data analysis included descriptive statistics, reliability testing, factor analysis, and regression modeling.

3.6 Ethical Considerations

This study adhered to standard ethical guidelines for research involving human participants. Participation was voluntary, and all respondents were informed of the study purpose, data usage, and confidentiality measures before completing the questionnaire. No personally identifiable information was collected, and all responses were analyzed in aggregate form. The study ensured anonymity and protected participants' rights in accordance with institutional ethical norms.

3.7 Statistical Tools

This study employed IBM SPSS Statistics (version 26) to conduct the primary analyses, including descriptive statistics, reliability assessment, exploratory factor analysis (EFA), and multiple regression analysis. The analytical procedures followed methodological guidelines recommended by Hair et al. (2019) and other contemporary quantitative research principles to ensure the robustness and validity of the statistical results.

3.8 Common Method Considerations

Although this study did not perform statistical tests for common method bias (such as Harman's single-factor test), several procedural remedies were implemented to minimize potential bias. First, all respondents were assured of anonymity and informed that there were no right or wrong answers, reducing evaluation apprehension. Second, the questionnaire items were derived from well-validated TAM2 constructs and distributed across different sections to reduce item-context-induced biases. Third, multiple constructs were measured using multi-item scales, decreasing the likelihood that a single factor would dominate the variance. These approaches align with recommendations by Podsakoff et al. (2020) for reducing standard method variance through research design.

3.9 Instrument Validation

Although no formal pilot test with statistical analysis was conducted, the measurement instrument underwent a rigorous content validation process. All questionnaire items were adapted from established scales in Venkatesh and Davis (2000) and related TAM2 literature. To ensure clarity and contextual appropriateness for 3D product visualization, the survey items were reviewed by three experts in e-commerce and consumer behavior. Revisions were made based on their feedback to improve wording precision and reduce ambiguity. This expert-based validation process ensured that the instrument possessed adequate face and content validity prior to data collection.

4. Results

This section presents the empirical results of the study, including sample characteristics, descriptive statistics, factor analyses, reliability and validity assessments, and hypothesis testing using regression analysis. All analyses were conducted using IBM SPSS Statistics 20.

4.1 Sample Characteristics

A total of 350 questionnaires were distributed to consumers with online shopping experience. After removing incomplete or invalid responses, 309 valid questionnaires were retained (effective response rate = 88%).

Demographic Information

Participants' demographic variables include gender, marital status, age, education level, occupation, monthly income, weekly computer-use hours, and years of online shopping experience. (see Table 1)

Table 1. Demographic Profile of Respondents

Variable	Category	Percentage (%)
Gender	Male	59.9
	Female	40.1
Marital Status	Unmarried	96.1
	Married	3.9
Age	19–25	81.9
	26–35	15.2
	36–45	2.3
	55+	0.6
Education Level	High school or below	14.2
	College/University	67.3
	Graduate school or above	18.4
Occupation	Agriculture/Mining	0.6
	Manufacturing	2.9
	Construction	0.6
	Finance/Insurance	3.2
	Service	6.1
	Media	0.6
	Public sector	1.6
	Student	83.8
	Others	0.3
Monthly Income (NTD)	≤10,000	53.4
	10,001–20,000	23.9
	20,001–30,000	11.0
	30,001–40,000	4.2
	40,001–50,000	4.9
	50,001–60,000	1.3
	≥100,000	1.3
Weekly Computer Use	≤2 hours	19.1
	3–6 hours	31.4
	7–10 hours	14.9
	≥11 hours	34.6
Online Shopping Experience	<1 year	33.7
	1–3 years	29.4
	3–6 years	27.5
	>6 years	9.4

4.2 Frequency Distribution of Measurement Items

This section presents the response distributions for each measurement item across all constructs. These distributions (see Table2) help identify general response tendencies, ensure there are no extreme floor or ceiling effects, and confirm that all items received valid responses. As shown in Table 2, the items measuring Subjective Norm chiefly fall within the neutral to agreement range, indicating moderate social influence perceptions among respondents. Similarly, Table 2 shows that responses for Image, Task Relevance, Result Demonstrability, Perceived Usefulness, Perceived Ease of Use, and Purchase Intention also cluster toward the mid-to-high end of the scale, suggesting generally positive evaluations across these constructs.

Table 2. Frequency Distribution Table (SN, IMG, TR, RD, PU, PEOU, PI)

Item	SD (Strongly disagree)	D (Disagree)	N (Neutral)	A (Agree)	SA (Strongly agree)
SN1	1.0%	4.2%	37.5%	35.6%	21.7%
SN2	1.9%	5.8%	36.2%	36.2%	19.7%
SN3	1.3%	8.4%	27.5%	37.5%	25.2%
IMG1	3.6%	10.7%	42.1%	25.6%	18.1%
IMG2	3.6%	10.4%	36.6%	30.7%	18.8%
IMG3	3.6%	8.1%	37.9%	36.6%	13.9%
TR1	1.0%	2.3%	12.9%	45.0%	38.8%
TR2	1.0%	3.6%	21.0%	46.6%	27.8%
TR3	1.9%	4.5%	26.2%	43.4%	23.9%
RD1	2.3%	7.1%	33.3%	37.5%	19.7%
RD2	1.9%	7.8%	33.7%	38.8%	17.8%
PU1	0.3%	3.6%	20.4%	48.5%	27.2%
PU2	1.6%	4.2%	19.1%	43.4%	31.7%
PU3	2.3%	7.4%	35.9%	33.3%	21.0%
PEOU1	1.3%	6.5%	23.6%	46.6%	22.0%
PEOU2	2.3%	6.5%	30.7%	37.5%	23.0%
PEOU3	2.6%	6.5%	31.4%	41.1%	18.4%
PI1	1.6%	2.3%	21.4%	39.8%	35.0%
PI2	1.6%	6.1%	32.0%	37.9%	22.3%
PI3	1.3%	3.9%	21.7%	45.6%	27.5%

4.3 Descriptive Statistics

This section presents descriptive statistics for each item, including the mean, standard deviation, skewness, and kurtosis. These statistics (Table 3) help evaluate normality assumptions and identify items with extreme distributions. As shown in Table 3, most items exhibit moderate skewness and acceptable kurtosis values, indicating approximate normality. However, TR1 and PI1 display higher mean scores, suggesting slightly stronger agreement tendencies compared with other items.

This section presents the descriptive statistics for all measurement items, including measures of central tendency and measures of distribution shape. These indicators help determine whether items exhibit abnormal patterns that might influence factor loadings or regression outcomes.

Table 3. Descriptive Statistics for All Items

Item	Min	Max	Mean	SD	Skewness	Kurtosis
Online shopping exp.	1	4	2.59	0.948	-0.233	-0.844
SN1	1	5	3.73	0.881	-0.156	-0.335
SN2	1	5	3.66	0.925	-0.316	-0.056
SN3	1	5	3.77	0.965	-0.443	-0.356
IMG1	1	5	3.44	1.020	-0.133	-0.345
IMG2	1	5	3.51	1.024	-0.286	-0.320
IMG3	1	5	3.49	0.952	-0.397	0.132
TR1	1	5	4.18	0.815	-1.040	1.476
TR2	1	5	3.97	0.848	-0.677	0.500
TR3	1	5	3.83	0.912	-0.638	0.415
RD1	1	5	3.65	0.950	-0.402	-0.051
RD2	1	5	3.63	0.930	-0.365	-0.069
PU1	1	5	3.99	0.806	-0.539	0.108
PU2	1	5	3.99	0.908	-0.851	0.694
PU3	1	5	3.97	0.950	-0.818	0.449
PEOU1	1	5	3.63	0.970	-0.308	-0.233
PEOU2	1	5	3.82	0.895	-0.615	0.253
PEOU3	1	5	3.72	0.963	-0.479	-0.036
PI1	1	5	4.04	0.895	-0.822	0.687
PI2	1	5	3.73	0.931	-0.390	-0.130
PI3	1	5	3.94	0.873	-0.711	0.552

4.4 Factor Analysis

Exploratory factor analysis was performed to verify the dimensionality of the measurement items. The initial rotated component matrix (Table 4) revealed that five items had loadings below 0.50 and were removed. After refinement, the revised factor structure (Table 5) showed clear loadings corresponding to each construct, with a KMO value of 0.849 and total variance explained of 71.31%, supporting sampling adequacy and strong construct validity.

Exploratory factor analysis was employed to evaluate the dimensionality of the measurement items and confirm their alignment with the theoretical constructs. Items with insufficient factor loadings were removed to improve construct clarity and model validity.

Table 4. Initial Rotated Component Matrix

Item	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7
SN1	—	—	0.807	—	—	—	—
SN2	—	—	0.885	—	—	—	—
IMG1	—	0.794	—	—	—	—	—
IMG2	—	0.838	—	—	—	—	—
TR1	—	—	—	—	0.832	—	—
TR2	—	—	—	—	0.662	—	—
PU1	—	—	—	0.755	—	—	—
PU2	—	—	—	0.788	—	—	—
PU3	—	—	—	0.643	—	—	—
PEOU1	0.842	—	—	—	—	—	—
PEOU2	0.686	—	—	—	—	—	—
PEOU3	0.682	—	—	—	—	—	—
PI1	—	—	—	—	—	—	0.804
PI2	—	—	—	—	—	—	0.530

KMO = 0.848; Total Variance Explained = 76.54%; $p < .001$

Table 5. Revised Rotated Component Matrix

Item	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6
SN1	0.811	—	—	—	—	—
SN2	0.873	—	—	—	—	—
IMG1	—	0.792	—	—	—	—
IMG2	—	0.836	—	—	—	—
TR1	—	—	0.723	—	—	—
TR2	—	—	0.763	—	—	—
PU1	—	—	—	0.792	—	—
PU2	—	—	—	0.767	—	—
PU3	—	—	—	0.562	—	—
PEOU1	—	—	—	—	0.822	—
PEOU2	—	—	—	—	0.711	—
PEOU3	—	—	—	—	0.630	—
PI1	—	—	—	—	—	0.584
PI2	—	—	—	—	—	0.750

KMO = 0.849; Total Variance Explained = 71.31%; $p < .001$

4.5 Reliability and Validity Analysis

Reliability and validity assessments were conducted to confirm measurement quality. As summarized in Table 6, Cronbach's α values generally exceeded acceptable thresholds for exploratory research, indicating reasonable internal consistency. Furthermore, convergent and discriminant validity results (Table 7) confirm that constructs share internal coherence while maintaining distinctiveness from one another.

Reliability analysis assesses the internal consistency of each construct, while validity analysis evaluates the adequacy of convergent and discriminant validity. These evaluations ensure that the measurement model is both theoretically coherent and statistically robust.

Table 6. Reliability Table (SN, IMG, TR, PU, PEOU, PI)

Construct	Cronbach's α	Item	Corrected Item–Total Correlation
Subjective Norm (SN)	0.717	**SN1**	0.560
		SN2	0.560
Image (IMG)	0.661	**IMG1**	0.495
		IMG2	0.495
Task Relevance (TR)	0.579	**TR1**	0.408
		TR2	0.408
Perceived Usefulness (PU)	0.712	**PU1**	0.566
		PU2	0.522
		PU3	0.514
Perceived Ease of Use (PEOU)	0.718	**PEOU1**	0.572
		PEOU2	0.506
		PEOU3	0.538
Purchase Intention (PI)	0.637	**PI1**	0.468
		PI2	0.468

Table 7. Convergent and Discriminant Validity (Fornell–Larcker Criterion)

Construct	α	AVE	SN	IMG	TR	PU	PEOU	PI
SN	0.717	0.710	0.843	0.350	0.356	0.206	0.316	0.218
IMG	0.661	0.814	0.350	0.902	0.395	0.289	0.332	0.324
TR	0.579	0.743	0.356	0.395	0.862	0.467	0.411	0.409
PU	0.712	0.707	0.206	0.289	0.467	0.840	0.485	0.558
PEOU	0.718	0.721	0.316	0.332	0.411	0.485	0.849	0.542
PI	0.637	0.667	0.218	0.324	0.409	0.558	0.542	0.816

4.6 Regression Analysis (Hypothesis Testing)

The regression analyses were conducted to evaluate the hypothesized relationships among the constructs. The results, summarized in Table 8, indicate that subjective norm significantly enhances image, and task relevance meaningfully contributes to perceived usefulness. Both perceived usefulness and perceived ease of use further exhibit strong positive effects on purchase intention.

Regarding the moderation models, the interaction terms involving online shopping experience are not significant, suggesting that experience does not alter the influence of subjective norm on perceived usefulness or purchase intention. Overall, the regression outcomes offer empirical support for most of the proposed pathways while highlighting a few relationships that did not receive statistical confirmation.

Table 8. Summary of Regression and Moderation Analyses for All Hypotheses

Hypothesis	Path	β	R^2	p-value	Result
H1	SN → IMG	0.465	0.216	< .001	Supported
H2	SN → PI	0.276	0.076	< .001	Supported
H3	SN → PU	0.241	0.058	< .001	Supported
H4	IMG → PU	0.315	0.099	< .001	Supported
H5	TR → PU	0.315	0.099	< .001	Supported
H6	RD → PU	—	—	n.s.	Not supported
H7	(SN × EXP) → PU	0.306	0.077	.391 (n.s.)	Not supported
H8	(SN × EXP) → PI	0.116	0.092	.744 (n.s.)	Not supported
H9	PEOU → PU	0.502	0.252	< .001	Supported
H10	PU → PI	0.584	0.341	< .001	Supported
H11	PEOU → PI	0.598	0.357	< .001	Supported

Note. n.s. = not significant.

4.7 Summary of Hypothesis Testing

A consolidated overview of the hypothesis testing results is presented in Table 8. Most proposed relationships were supported, including the effects of subjective norm, task relevance, perceived usefulness, and perceived ease of use. In contrast, the paths involving result demonstrability and the moderating influence of online shopping experience were not significant. This summary reinforces the robustness of the main TAM-based framework while highlighting areas that require further theoretical exploration.

5. Conclusion and Implications

5.1 Summary of Findings

This study constructed and empirically validated a TAM2-based model to explain consumer adoption of 3D product visualization in online shopping settings. The consolidated regression results (Table 8) reveal several key findings. Social influence remains a critical predictor in technology adoption: subjective norm significantly enhances both image and perceived usefulness, confirming the continued relevance of normative pressures even in individualized digital purchase environments.

Cognitive instrumental factors also demonstrated strong explanatory power. Task relevance and perceived ease of use both contribute meaningfully to perceived usefulness, indicating that consumers value 3D displays that provide task-relevant information and are easy to operate. In turn, perceived usefulness and perceived ease of use exert substantial positive effects on purchase intention, reaffirming core mechanisms proposed by TAM.

Several hypothesized relationships, however, were not supported. Demonstrability of results did not significantly influence perceived usefulness, suggesting that the benefits of 3D visualization may be perceived holistically rather than through discrete functional outcomes. Additionally, online shopping experience did not moderate any of the examined relationships, indicating that both novice and experienced users respond similarly to 3D visualization technologies.

Overall, the evidence from Table 8 supports most of the proposed hypotheses, while also highlighting meaningful boundary conditions for future TAM2-related research.

5.2 Theoretical Implications

The findings extend current understanding of technology adoption in several theoretical dimensions. First, the consistent influence of subjective norm and image confirms the centrality of social influence within TAM2 (Venkatesh & Davis, 2000), even in environments where decisions are ostensibly personal and private. This supports recent evidence that reputational considerations and perceived social expectations continue to shape digital behavior (Zhang et al., 2021; Tarhini et al., 2022).

Second, the strong effects of task relevance and perceived ease of use reinforce cognitive instrumental processes as central determinants of perceived usefulness (Fan et al., 2022; Mariani et al., 2022). These findings suggest that users evaluate visualization tools not only through experiential appeal but also through their contribution to evaluative efficiency, consistent with prior research on interactive and 3D product presentations (Park & Kim, 2021; Li et al., 2020).

Third, the non-significance of result demonstrability introduces a noteworthy deviation from TAM2 expectations. This suggests that experiential technologies—particularly 3D visualization—may require alternative explanatory constructs, such as immersion, mental imagery, or perceived diagnosticity (Heller et al., 2021; Sun et al., 2022). This divergence highlights opportunities to refine or extend TAM2 when applied to high-engagement digital interfaces.

Finally, the absence of moderation effects from online shopping experience suggests that experiential differences either do not meaningfully alter technology evaluations or that visualization technologies are sufficiently intuitive to minimize reliance on prior expertise. This outcome challenges assumptions within UTAUT-based models regarding habitual or experience-driven differences (Venkatesh et al., 2012). It underscores the need to revisit boundary conditions for experience-driven moderation in digital commerce.

5.3 Practical Implications

Several actionable insights emerge for practitioners seeking to enhance the adoption of 3D product visualization tools. First, the strong influence of subjective norm indicates that social proof mechanisms—such as influencer endorsements, user-generated content, and visible popularity cues—can enhance perceived usefulness. This aligns with growing industry evidence that social validation boosts engagement and purchase intention (Mariani et al., 2022).

Second, developers should prioritize usability and intuitive interface design, as perceived ease of use significantly shaped both perceived usefulness and purchase intention. Streamlined navigation, reduced cognitive load, and optimized loading performance are likely to strengthen user acceptance (Wang et al., 2023; Al-Emran &Granić, 2023).

Third, the strong role of task relevance suggests that marketing messages should emphasize how 3D visualization supports product evaluation—for instance, by enabling comparison, inspection, or trial-like product interaction (Kim & Forsythe, 2020; Chen et al., 2023). Practical demonstrations, guided walkthroughs, and context-specific prompts may compensate for the weak effect of result demonstrability.

Finally, since online shopping experience did not moderate key relationships, platforms may adopt uniform interface strategies across consumer segments, reducing the need for differentiated onboarding processes.

5.4 Limitations

This study exhibits several limitations that inform the interpretation of the results. First, the cross-sectional self-report design raises potential concerns regarding standard method bias, although procedural remedies were implemented (Podsakoff et al., 2020). Second, some constructs exhibited moderate reliability levels, suggesting a potential need for refinement of the measurement items. Third, the sample was heavily weighted toward younger consumers, which limits its generalizability to broader demographic groups. Fourth, the study focused solely on 3D product visualization, which may limit its applicability to related immersive technologies, such as AR or VR. Finally, the study did not incorporate behavioral data or experimental manipulations, limiting causal inference.

5.5 Future Research

Future studies may extend this work in several promising directions. First, the role of experiential constructs—such as immersion, flow, or perceived enjoyment—may provide deeper explanatory power for evaluating visualization technologies (Huang & Liao, 2021; Heller et al., 2021). Second, future research could explore moderating variables beyond online shopping experience, including product involvement, technology readiness, and cognitive style. Third, experimental and longitudinal designs may enhance causal inference and illuminate post-adoption trajectories. Fourth, comparative studies examining 2D, 3D, AR, and VR product presentation formats could clarify differential psychological and behavioral effects (Li et al., 2020; Park & Kim, 2021). Finally, integrating behavioral analytics—such as interaction intensity, dwell time, or eye-tracking data—may provide more objective insights into user engagement mechanisms.

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