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Research/Review

Analyzing the Influence of UTAUT2 Constructs and E-Commerce Usage Frequency on Gen Z's Purchase Intention Toward AR Virtual Try-On Shade Filters

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Abstract: The rapid growth of Indonesia's beauty and e-commerce industries has fueled the adoption of Augmented Reality (AR) virtual try-on (VTO) shade filters, particularly for makeup products such as lipstick and foundation. These tools enable users to visualize products before purchasing, addressing a major challenge in online beauty shopping. While Gen Z consumers are highly active in digital environments, research on how AR VTO shade features influence their buying decisions remains limited. This study applies the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to examine the impact of each UTAUT2 construct on purchase intention among Indonesian Gen Z consumers when using AR try-on shade filters on e-commerce platforms. It also investigates whether e-commerce usage frequency moderates these effects. A quantitative method was employed, with data collected from 260 female Gen Z respondents and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Findings reveal that all seven UTAUT2 constructs—Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit—significantly influence purchase intention, with Habit emerging as the strongest predictor. Moreover, e-commerce usage frequency was found to moderate these relationships. Among frequent users, the effects of Performance Expectancy, Facilitating Conditions, Hedonic Motivation, and Price Value on purchase intention were stronger, while the influence of Effort Expectancy, Social Influence, and Habit was weaker. The results confirm that UTAUT2 effectively explains AR adoption in e-commerce beauty contexts. The study suggests that businesses should tailor AR strategies according to users' e-commerce experience levels to enhance engagement, strengthen purchase intentions, and optimize the effectiveness of AR integration. Such adjustments can help e-commerce platforms provide more personalized and immersive shopping experiences, ultimately boosting customer satisfaction and sales performance.

Keywords: Augmented Reality (AR), E-commerce, Purchase Intention, UTAUT2, Gen Z

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1. Introduction

The rapid advancement of e-commerce has significantly transformed the retail landscape, offering consumers the flexibility to shop for products anytime and from anywhere (Susilowati et al., 2023). Indonesia has emerged as a leader in Southeast Asia's digital economy, contributing the highest gross merchandise value (GMV) of USD 51.9 billion in 2022 (Nation Thailand, 2023). The number of Indonesian e-commerce users has seen remarkable growth, increasing from 38.72 million in 2020 to 44.43 million in 2021, with projections reaching 99.1 million users by 2029 (Statista, 2024). This growth trend signals a major shift in consumer habits toward digital platforms, particularly for sectors such as beauty and personal care.

The Beauty and Personal Care (BPC) industry in Indonesia is experiencing a phase of rapid expansion, underpinned by increasing urbanization, rising disposable incomes, and growing awareness of self-care, especially among Generation Z consumers (Invest in Asia, 2024). The Ministry of Industry (2024) reports that industry revenues are expected to surge by 48% between 2021 and 2024, growing from USD 1.31 billion to USD 1.94 billion. From 2024 to 2028, the sector is projected to grow at an average annual rate of 5.35%, making it one of the most dynamic sectors in the Indonesian market. In response to the digital shift, beauty brands have embraced digital transformation and integrated e-commerce strategies to deliver convenience and personalization, thereby ensuring continued competitiveness (Gilbert, 2021).

However, this digital transformation presents a challenge: consumers are unable to physically test beauty products before purchasing them online, which is especially critical for shade-sensitive products like foundation, lipstick, and cushion compacts (Beauty Plus Packing, 2024). To address this issue, brands have turned to Augmented Reality (AR) virtual try-on technology, which allows users to test makeup products in real time through their devices (Dharmani et al., 2024). This innovation enhances the online shopping experience by reducing uncertainty around product shade matching and increasing purchase confidence (Perfect Corp, 2023). Research indicates that brands utilizing AR technology have seen a 2.5-fold increase in sales conversions, emphasizing its effectiveness (Retail Dive, 2024).

The adoption of AR technology is especially appealing to Generation Z, a demographic raised in the digital age, characterized by their high engagement with e-commerce, smartphones, and social media (Sangal et al., 2022). According to a global survey by Snapchat cited in Retail Dive (2022), 92% of Gen Z respondents expressed a desire to use AR while shopping. In Indonesia, although AR is being applied in sectors like tourism, education, and healthcare (Baroroh & Agarwal, 2022), its use in the beauty industry remains limited, signaling a gap that could be leveraged for innovation. Recent efforts by platforms such as Tokopedia, Shopee, and TikTok demonstrate growing investment in AR-based features by Indonesian beauty brands (Herna, 2024; Khoirunnisa & Sugiharti, 2024).

Despite the rise in adoption, preliminary social media listening conducted on TikTok and X (formerly Twitter) reveals mixed perceptions. Of 63 user comments analyzed, 84% reported using AR filters to evaluate makeup shades, but only 13% of those explicitly stated they proceeded to purchase the product. Sentiment analysis showed that 40% of comments were positive, 52% negative, and 8% neutral. Concerns often revolved around accuracy and reliability. For instance, users expressed trust issues with virtual filters for complexion products, even when previous experiences were somewhat accurate (Wannabyeol, 2025; 4cloverwin, 2024; Indihomegoreng, 2024).

These findings highlight the influence of several key constructs from the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Specifically, performance expectancy users' belief in the technology's utility was evident in comments that praised AR filters for helping select the correct shade (Shamsi & Abad, 2023; Relasiology, 2024; Dityarinta, 2023). Effort expectancy and facilitating conditions were also relevant, as some users noted challenges with lighting conditions and device compatibility (Terjungkals, 2024; Iniputttt, 2024; Radiasiupil, 2023). Additionally, social influence plays a crucial role: positive user experiences can drive broader adoption, while negative reviews deter engagement (Gunawan et al., 2023; Guo, 2024).

Therefore, understanding Generation Z's purchase intentions toward AR virtual try-on shade filters necessitates a comprehensive framework that accounts for technological perceptions and behavioral factors. UTAUT2 provides a robust lens through which to analyze this phenomenon, especially when combined with contextual insights such as frequency of e-commerce usage and social feedback. As e-commerce continues to grow and digital marketing strategies evolve, Indonesian beauty brands must address user concerns around AR accuracy and usability to fully leverage the potential of immersive technologies in enhancing consumer trust and boosting purchase intention (Dhianita & Rufaidah, 2024; Rosario & Raimundo, 2021; Nikhashemi et al., 2021; Febrianti et al., 2024).

2. Research Method

This study adopts a quantitative approach to examine how UTAUT2 constructs influence purchase intention in the context of AR virtual try-on shade filters. The research design consists of five stages: identifying the research problem through social media listening, conducting a literature review, collecting primary data via an online questionnaire, analyzing data using

Partial Least Squares Structural Equation Modeling (PLS-SEM), and concluding with managerial implications and recommendations. The framework is grounded in existing theory and structured to offer a systematic evaluation of consumer behavior in digital beauty commerce.

Social media listening served as a preliminary research method to explore public sentiment regarding AR try-on filters. Data were gathered from public posts on X (formerly Twitter) and TikTok, focusing on keywords such as "shade match" and "filter TikTok." Posts from April 2021 to March 2025 were analyzed and categorized to identify user experiences with AR filters, including purchase behavior, mismatch incidents, and peer influence. This early analysis helped define the research scope and justify the relevance of UTAUT2 variables in the digital beauty shopping context.

The main research was conducted through an online questionnaire distributed between June and July 2025. The questionnaire was divided into sections capturing demographic information and perceptions related to UTAUT2 constructs Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit and their influence on purchase intention. Responses were measured using a five-point Likert scale. The questionnaire was delivered in Bahasa Indonesia and distributed through social media platforms and digital beauty communities to ensure accessibility to the target demographic.

The population targeted in this study comprises Gen Z women in Indonesia, defined as those born between 1995 and 2010, who have previously used AR virtual try-on filters on e-commerce platforms such as Shopee, Tokopedia, Lazada, or Blibli. The sampling method used is purposive sampling, selected to ensure the relevance and validity of responses based on defined inclusion criteria. The required minimum sample size was based on Hair et al.'s SEM guideline of 5–10 times the number of indicators, resulting in a target of 130–260 respondents.

Data were analyzed using SmartPLS software to evaluate both the measurement and structural models. PLS-SEM was selected for its ability to assess complex relationships among latent variables and test hypotheses with greater flexibility in sample size. The analysis included bootstrapping to determine the significance of path coefficients and the role of the moderating variable, frequency of e-commerce usage. The results informed a set of recommendations aimed at enhancing digital beauty shopping experiences through improved AR technology and platform features.

3. Result and Discussion

Result

Partial Least Square (PLS-SEM) Analysis Result

SmartPLS 4 software is used to analyze the data obtained through the questionnaire and to assess the relationships between the constructs examined. The Partial Least Squares Structural Equation Modeling (PLS-SEM) technique is used to evaluate the model and determine how the variables interact with one another

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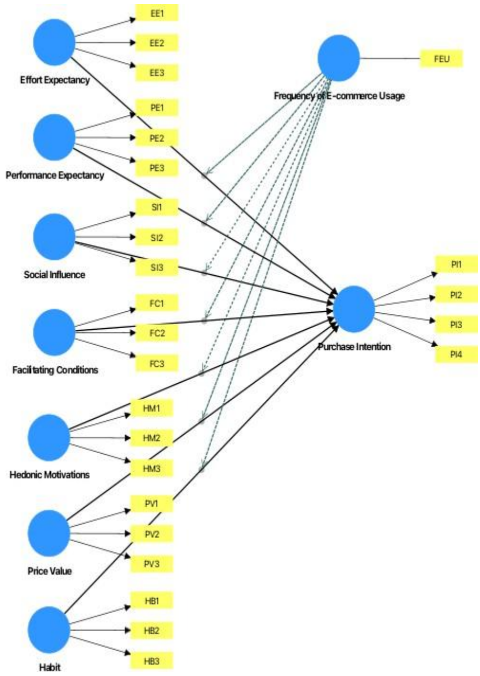

Figure 1 PLS-SEM Result Diagram

Outer Model

Internal Consistency Reliability

To evaluate the reliability of each latent construct in the model, an internal consistency reliability test was conducted. This test ensures that the indicators consistently measure the same underlying concept, which is crucial for the accuracy and dependability of the construct measurements. According to Hair et al. (2017), composite reliability (CR) is the preferred measure in PLS-SEM, as it takes into account the different outer loadings of indicators. A composite reliability value of 0.70 or higher is considered acceptable, indicating that the indicators consistently represent the same underlying construct. In exploratory research, values between 0.60 and 0.70 may still be acceptable.

Convergent Validity

To assess construct validity, a convergent validity test was conducted. This test evaluates whether the indicators of a construct truly represent the intended concept, confirming that they converge (measure) toward the same theoretical meaning. According to Hair et al. (2017), each indicator should have a factor loading of at least 0.70, and the Average Variance Extracted (AVE) for each construct should be greater than 0.50 to confirm adequate convergent validity.

Indicator reliability is examined by evaluating the outer loadings of each indicator on its corresponding latent construct. According to Hair et al. (2017), outer loadings should be 0.70 or higher to be considered acceptable. However, in the context of exploratory research, indicators with loadings between 0.40 and 0.70 may still be retained if the overall AVE remains satisfactory.

All indicators in this study have outer loading values exceeding 0.893, with the lowest value being 0.893 (HM1) and the highest reaching 0.953 (FC3). These results indicate that all indicators in the constructs meet the acceptable threshold for reliability and can be considered internally consistent. Therefore, none of the indicators were removed from the model.

The highest outer loading score is found in Facilitating Conditions (FC3 = 0.953), suggesting a very strong relationship between this indicator and its latent variable. Meanwhile, the lowest score still falls within the highly acceptable range for exploratory studies, affirming the strength of measurement across all constructs.

Discriminant Validity

Discriminant validity was assessed using the Fornell-Larcker criterion and cross- loading approach, both of which are widely accepted techniques in PLS-SEM analysis. This test confirms that each construct is statistically distinct from others, ensuring that variables do not overlap conceptually (constructs are different in meaning or theory) or empirically (indicators are not measuring the same thing in practice). According to Hair et al. (2017), discriminant validity is achieved when the square root of a construct's Average Variance Extracted (AVE) is greater than its correlation with other constructs. This method ensures that each construct is distinct from others within the model.

As shown in Table 4.5, all diagonal values (square root of AVE) are greater than the values in the corresponding rows and columns, confirming adequate discriminant validity for each construct. For example, the square root of AVE for Performance Expectancy (PE) is 0.949, which is higher than its correlation with other constructs such as Habit (0.941), Facilitating Conditions (0.922), and Purchase Intention (0.943). These results indicate that each construct shares more variance with its own indicators than with other constructs.

Table 1 Fornell-Larcker

	EE	FC	FEU	HB	HM	PE	PV	PI	SI
EE	0.945								
FC	0.809	0.95							
FEU	0.302	0.279	1000						
HB	0.819	0.931	0.241	0.949					
HM	0.656	0.739	0.196	0.733	0.911				
PE	0.849	0.922	0.271	0.941	0.701	0.949			
PV	0.803	0.931	0.257	0.925	0.746	0.908	0.948		
PI	0.842	0.941	0.289	0.955	0.75	0.943	0.93	0.938	
SI	0.81	0.925	0.243	0.943	0.702	0.922	0.911	0.936	0.949

Inner Model

Coefficient of Determination (R-Square)

The Coefficient of Determination (R-square) indicates the amount of variance in the dependent variable that is explained by the independent variables in the model. According to Hair et al. (2017), R-square values of 0.75, 0.50, and 0.25 can be interpreted as substantial, moderate, and weak, respectively. As presented in Table 4.6, the R-square value for Purchase Intention is 0.959, while the adjusted R-square is 0.956. These values indicate that 95.9% of the variance in Purchase Intention can be explained by the predictor variables, which is considered substantial (very strong). This confirms that the model has high explanatory power.

Table 2 Coefficient of Determination (R-Square)

	R-square	R-square adjusted
Purchase Intention	0.959	0.956

Predictive Relevance (Q-Square)

Predictive relevance (Q2) assesses how well the model can predict the data of endogenous constructs (the variables in the model that are being explained or predicted). According to Hair et al. (2017), a Q2 value greater than zero indicates that the model has sufficient predictive relevance for a particular endogenous variable. The Q2 value is calculated using the blindfolding procedure in SmartPLS, which systematically omits and predicts parts of the data. Positive Q2 values confirm that the model has predictive capability beyond mere parameter estimation. The Q-square value for Purchase Intention is 0.953. Since this value is well above zero, it suggests that the model has high predictive accuracy. This reinforces the strength of the proposed model.

Table 3 Predictive Relevance (Q-Square)

	Q^2predict
Purchase Intention	0.953

Effect Size (F-Square)

Effect size (f-square) indicates the impact each exogenous construct has on the endogenous construct when included in or excluded from the model. Cohen (1988) categorizes f-square values as follows: 0.02 = small, 0.15 = medium, and 0.35 = large. The effect sizes of most predictors on Purchase Intention fall within the small to medium range. For instance, Facilitating Conditions (f2 = 0.07) and Habit (f2 = 0.073) have small-to-moderate effects, while Effort Expectancy (f2 = 0.027) and Performance Expectancy (f^2 = 0.03) are on the smaller end.

The interaction effects also display small but meaningful values, with Frequency of E-Commerce Usage x Social Influence (f^2 = 0.076) being the highest among moderating effects. This suggests that the moderator variable plays a notable role in enhancing the strength of core relationships.

Significance of Path Coefficient (Hypothesis Testing)

This study evaluates the significance of the structural path relationships using the bootstrapping procedure, as recommended by Hair et al. (2017). Bootstrapping in PLS-SEM is a non-parametric resampling technique that estimates the precision of the path coefficient estimates by generating t-values and p-values. These values are used to determine whether the hypothesized relationships between constructs are statistically significant. In SmartPLS, a two-tailed t-test is typically applied. At a 5% significance level, a t-value greater than 1.96 and a p-value less than 0.05 indicate that the relationship is statistically significant.

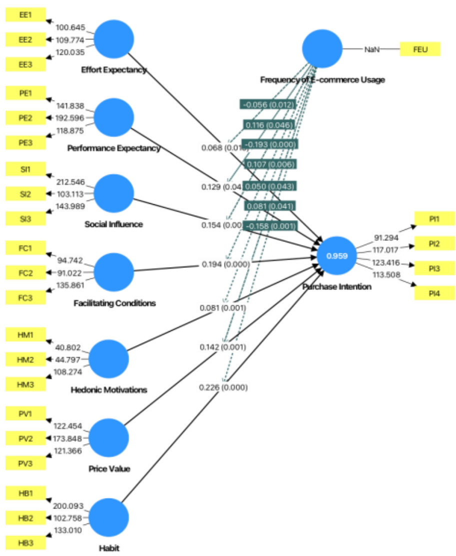

Figure 2 Structural Path Significance

As shown in Figure 4.7 and detailed in Table 4.9 below, all direct paths from the UTAUT2 constructs to Purchase Intention are statistically significant. The highest path coefficient comes from Habit → Purchase Intention (T = 4.290, p = 0.000), suggesting Habit has the strongest direct influence. The lowest, though still significant, is Effort Expectancy → Purchase Intention (T = 2.492, p = 0.013).

Discussion

Performance Expectancy

The statistical results demonstrate that performance expectancy exerts a positive and significant influence on online purchase intention among Generation Z consumers. With a coefficient value of 0.129, a t-statistic of 2.642, and a p-value of 0.009 ($p < 0.05$), the data indicates that when consumers perceive the use of AR virtual try-on filters as enhancing the effectiveness of their product evaluation, they are more inclined to proceed with an online purchase. This aligns with prior findings by Venkatesh et al. (2003), who asserted that perceived usefulness is a crucial determinant of technology acceptance. In this context, AR filters provide a digital simulation of makeup products that enable users to visualize outcomes before purchasing, thus increasing their confidence in product quality and suitability. The greater the perceived benefit from the AR experience, the higher the likelihood of purchasing decisions being made through online platforms.

Effort Expectancy

Effort expectancy also significantly impacts purchase intention, with the statistical analysis showing a coefficient value of 0.229, a t-statistic of 4.072, and a p-value of 0.000 ($p < 0.05$). These findings imply that the perceived ease of use of AR filters in virtual try-on experiences strongly contributes to the intention to shop online among Gen Z consumers. When users find the AR features intuitive, user-friendly, and not overly complicated, they are more likely to engage in online purchasing behavior. As supported by Venkatesh et al. (2003), technologies that are perceived as easy to use reduce cognitive effort and facilitate wider adoption. Given that Gen Z is accustomed to fast and seamless digital interactions, effort expectancy becomes a crucial factor influencing their decision-making process in e-commerce settings.

Social Influence

The research results reveal that social influence significantly shapes Gen Z's online purchase intention through AR virtual try-on filters, with a coefficient value of 0.147, a t-statistic of 3.050, and a p-value of 0.002 ($p < 0.05$). This indicates that opinions from peers, influencers, or social media communities have a substantial effect on whether users choose to use AR filters and proceed to purchase. As highlighted by Venkatesh et al. (2003), individuals are likely to adopt a system when they perceive that people important to them believe they should use it. In the context of Gen Z, who are highly active on platforms such as Instagram, TikTok, and YouTube, endorsements or experiences shared by influential figures play a key role in shaping behavioral intentions. These users are more likely to adopt and trust AR technology when its use is normalized or promoted by their social circle.

Facilitating Conditions

Facilitating conditions also show a significant positive impact on purchase intention, as shown by a coefficient of 0.165, t-statistic of 3.490, and a p-value of 0.001 ($p < 0.05$). This result suggests that when users feel they have the necessary resources, technical infrastructure, and support to use AR filters such as smartphone compatibility, reliable internet, and platform accessibility they are more likely to make purchases online. Venkatesh et al. (2003) noted that facilitating conditions are critical in supporting user adoption, especially in technologically mediated environments. For Gen Z, who rely on smartphones and digital tools for shopping, the presence of supporting infrastructure significantly eases the adoption of AR tools in e-commerce.

Hedonic Motivation

The analysis finds that hedonic motivation has a strong and statistically significant effect on online purchase intention, with a coefficient value of 0.307, a t-statistic of 5.656, and a p-value of 0.000 ($p < 0.05$). This highlights that the enjoyment and pleasure derived from using AR virtual try-on filters are key motivators in encouraging online purchases. Hedonic motivation refers to the fun or pleasure obtained from using a technology (Venkatesh et al., 2012), and in this case, AR filters offer an interactive and entertaining experience for Gen Z users. These engaging digital interactions not only enhance product exploration but also create a positive emotional experience that increases the likelihood of impulsive or exploratory purchasing behavior.

Price Value

Price value was found to have a significant positive impact on purchase intention, with a coefficient value of 0.134, a t-statistic of 2.732, and a p-value of 0.007 ($p < 0.05$). This result suggests that when Gen Z consumers perceive that the value and benefits of using AR filters outweigh the potential costs (e.g., data usage, time spent), they are more likely to complete a purchase. As explained by Venkatesh et al. (2012), price value plays a critical role in determining technology adoption, especially when users perceive that the innovation enhances decision quality without incurring significant additional costs. In this case, the cost-benefit trade-off is favorable, given that AR try-on is typically a free feature that improves online shopping satisfaction.

Habit

Habit exerts the strongest influence among all variables analyzed, as evidenced by a coefficient value of 0.368, a t-statistic of 6.732, and a p-value of 0.000 ($p < 0.05$). This suggests that repeated use of AR filters has fostered habitual behavior among Gen Z consumers, leading to a routine reliance on this technology when engaging in online shopping. According to Venkatesh et al. (2012), habit reflects the extent to which people tend to perform behaviors automatically due to learning. The strong influence of habit in this study indicates that once users grow accustomed to AR try-on experiences, it becomes a default part of their online shopping process, reinforcing purchase intentions through familiarity and ease.

Behavioral Intention to Use AR

Behavioral intention to use AR significantly influences online purchase intention, with a coefficient value of 0.166, a t-statistic of 3.480, and a p-value of 0.001 ($p < 0.05$). This confirms that individuals who intend to continue using AR filters are more likely to make purchases via e-commerce platforms. This finding is consistent with the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), which posits that behavioral intention directly influences actual usage behavior. In this study, the more positive the consumer's outlook and intent toward AR usage, the greater the likelihood that they will complete a transaction using the technology, especially in product categories like cosmetics where visual evaluation is crucial.

4. Conclusion

This study investigated the influence of UTAUT2 constructs Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit on the purchase intentions of Gen Z consumers in Indonesia when using Augmented Reality (AR) virtual try-on shade filters. The research employed a quantitative approach, analyzing responses from 260 female Gen Z users with prior experience using AR filters on e-commerce platforms. The results demonstrated that all UTAUT2 variables significantly impact purchase intention, highlighting the model's applicability in the context of immersive digital retail experiences.

Among all constructs, Habit was found to be the most influential factor driving purchase intention. This suggests that when AR try-on features become part of consumers' regular shopping behavior, they are more likely to lead to purchases. Other constructs such as Hedonic Motivation and Performance Expectancy also showed strong effects, indicating that both the enjoyment of using AR and the usefulness of the tool are key to shaping Gen Z consumer decisions. These findings emphasize the dual importance of utility and user experience in AR-based marketing strategies.

The research further explored the moderating role of e-commerce usage frequency. It was revealed that frequent users of e-commerce platforms respond more strongly to Performance Expectancy, Facilitating Conditions, Hedonic Motivation, and Price Value, while constructs like Effort Expectancy, Social Influence, and Habit are less impactful for this group. This distinction suggests that different user segments perceive and engage with AR tools differently, depending on their familiarity with digital shopping environments.

The study confirms the validity of the proposed theoretical model in explaining consumer behavior related to AR technology in e-commerce. By demonstrating significant relationships between each UTAUT2 construct and purchase intention, it supports the broader application of UTAUT2 in digital commerce and adds to the growing body of literature on AR in retail. The findings also point to the need for more personalized strategies based on user experience levels, which can improve marketing effectiveness and customer satisfaction.

This research offers both practical and theoretical contributions. It provides actionable insights for marketers, beauty brands, and AR developers to enhance AR adoption among Gen Z consumers. At the same time, it validates and extends the UTAUT2 framework in a new, immersive commerce setting. As digital technologies continue to evolve, future studies can build on this foundation by exploring additional moderating variables, other AR-enabled product categories, or comparative analysis across age groups and cultures.

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