Creating Purchase Intention through Social Media: The use of AR enabled Social Media Filters

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ABSTRACT

Purpose –The primary objective is to uncover the role of AR-enabled filters provided through Social Media platforms in stimulating purchasing intent for cosmetic products.

Design/methodology/approach – This study tests the hypothesized relationships using UTAUT2 with the help of 297 responses. The study employed SPSS 28 and AMOS 28 for the data analysis. The moderation effect of SMU was studied with the help of Process Macro 4.1.

Findings – The results declare performance expectancy, social influence, price value, and hedonic motivation significantly influence purchase intention, while effort expectancy, habit, and facilitating conditions do not.

Practical implications – This research provides implications for marketers suggesting that SM communication channels should be complemented with new-age technologies, such as AR. Furthermore, AR as a promotional tool should be endorsed due to its ability of virtually representing the real product benefits to users that may eventually lead to high product awareness and purchases.

Originality/value – AR-enabled SM filters are underexplored through the lens of marketing communication; this research extends body of knowledge by broadening the scope of SM as a channel of marketing communication.

Keywords: Social Media, Communication Channel, Augmented Reality, UTAUT2, Purchase Intention.

1. Introduction

Since the advent of humans on this planet, communication has been a key for transferring ideas, information, and knowledge. Communication has been identified as a crucial element in the advancement of human civilization (Heintz & Scott-Phillips, 2023). However, communication channels have been used differently in different times, places, and situations. The impact of communication is significantly affected by the channels employed to convey information (Murphy et al., 1997). The efficiency of information delivery and reception is contingent upon the mode of communication employed (Ren & Zhao, 2023). The effectiveness of a message in terms of its clarity, relevance, and accuracy can exhibit significant variability based on the mode of transmission (Miller, 2014). *An appropriate selection of communication channels* helps convey the desired message and elicit the desired response (Shiva et al., 2021). Communication channels have evolved drastically during the last two decades (Kaufman et al., 2015). In the present scenario, communication channels are not limited to merely print, broadcast, and telecommunication but also include an array of digital platforms that were unimaginable few decades ago. Among the digital platforms, social media is prominent as there are approximately 5.16 billion individuals who use the internet, of which approximately 4.76 billion individuals use social media platforms (*Internet and Social Media Users in the World 2023*, 2023) for not just building communities but also for communication needs. *Social media platforms have become an essential channel of communication because they offer a number of unique advantages. They allow users to* engage with others in new and innovative ways, such as through multimedia content like photos, videos, and live streams. This functionality facilitates the exchange of personal experiences and viewpoints among users in a more immersive and engaging way that builds and maintains personal and professional relationships (Flynn, 2012). Furthermore, *social media platforms also allow for targeted communication, enabling businesses to tailor their messages to specific audiences* (Dahl, 2015). Prior studies have established the crucial role of SM in promoting sustainable consumption (Shamsi et al., 2022), investor behavior (Shiva et al., 2021), tourist decision-making (Tanković et al., 2022), luxury jewelry purchase intention (Shayeb & Deeb, 2023), E-commerce behavior (Bawack et al., 2023) and so on. The popularity of social media is growing by leaps and bounds globally. As per reports, the global social media users count has reached 4.76 Billion as on January 2023 with a worldwide penetration of 59.4% (*Internet and Social Media Users in the World 2023*, 2023) and is projected to reach approximately 6 billion by 2027 (*Number of Worldwide Social Network Users 2027*, 2022). In 2022, China accounted for the most users, with 1.02 billion people, while India stood in the second spot with 0.75 billion (*Social Network Users in Leading Markets 2027*, 2022). By 2027, these figures are expected to reach 1.21 billion for China and 1.17 billion for India, with an average growth rate of 18.62% and 56%, respectively (*Social Network Users in Leading Markets 2027*, 2022). The popularity of social media is phenomenal among marketers too. Due to the presence of a huge worldwide population on social media platforms, marketers have been consistently directing their marketing efforts on SM platforms. *Thus, the functional benefits, as well as the promising statistics, make social media an inevitable communication channel to be included in marketing strategies.*

The integration of novel technological advancements, such as augmented reality (AR), virtual reality (VR), artificial intelligence (AI), chatbot, live streaming, and 360-degree video, is enhancing the appeal of social media platforms for users (Safko, 2012). SM platforms like Facebook, Instagram, and Snapchat leverage AR to create amusing, interactive filters, masks, and lenses (Kriegel et al., 2023). AR-enabled filters and lenses are quite popular on social media platforms which empower users to virtually transform their appearance. Brands like Kylie Cosmetics, Air Matte, MAC Cosmetics, Lakme, L'Oréal Paris, Maybelline, etc., have been using filters on social media platforms like Instagram and Snapchat wherein users may try the cosmetic products on themselves virtually (Kite-Powell, 2021; Nast, 2016). However, despite its popularity and usage, AR-enabled SM filters have not been explored by researchers. We, thus, found this gap in the existing literature and tried to mend it through this study with the objective of revealing the influence of AR-enabled SM filters on the purchase intention of cosmetic products. For this purpose, we use the UTAUT2 model as it is intended to study the technology adoption (Venkatesh et al., 2012). Furthermore, different behavior may be exhibited by users depending on their social media usage (Roberts & David, 2022). Hence, the moderating role of SMU is also explored.

This gives us the following research questions:

RQ1. Do AR-enabled SM filters create purchase intention of cosmetic products?

RQ2. Does the level of SMU functions as a moderator in the interaction between UTAUT2 variables and purchase intent?

The paper henceforth is divided into the following sections: Section 2 provides a comprehensive survey of literature, while Section 3 enlists the hypothesized relationships. Further, section 4 provides a detailed research methodology; section 5 gives a detailed analysis, and section 6 discusses the results of the hypothesis testing, followed by implications in section 7. Lastly, the conclusion, limitations, and future research prospects are presented in section 8.

2. Review of literature

2.1 Social Media as a Communication Channel

Social media is a digital platform that facilitates interactive communication and collaboration among individuals, allowing them to generate, distribute, and exchange information, viewpoints, or concepts within virtual communities and networks (Tuten, 2017). Its addiction is widely observed among individuals and it has occupied a place in their daily life (Hussenoeder, 2023). It has gained widespread usage across the world, with a significant proportion of the global population engaging with these platforms. The underlying reasons for this widespread adoption can be attributed to various factors as it provides self-presentation, entertainment, social connection, and information seeking in just a few clicks (Hoffman & Novak, 2012). Consumers can engage with brands through social media platforms by producing or modifying information about a company and sharing it with their contacts. (Gilfoil, 2011). Social media has become a strong and popular communication channel to reach consumers (Safko, 2012). The apparent role of social media channels in facilitating efficient and effective business communication has been observed across various industries, for instance, *sustainable consumption* (Shamsi et al., 2022), *investor behavior* (Shiva et al., 2021), *tourist decision-making* (Tanković et al., 2022), *luxury jewelry purchase intention* (Shayeb & Deeb, 2023), *and E-commerce behavior* (Bawack et al., 2023).

2.2 *UTAUT2*

The Unified Theory of Acceptance and Use of Technology was introduced integrating eight major theories: Theory of Reasoned Action, Technology Acceptance Model, Motivational Model, Theory of Planned Behavior, combined TAM-TPB, Model of PC utilization, Innovation Diffusion Theory, and Social Cognitive Theory (Venkatesh et al., 2003). It is widely utilized to assess technology adoption and application, including virtual reality and healthcare technologies (Huang, 2023; Pal et al., 2018). As per this theory, performance expectancy, effort expectancy, social influence, and facilitating conditions directly affect behavioral intentions (Venkatesh et al., 2003). The theory had strong explanatory power, but experts faulted it for overlooking crucial determinants that might cause incompatibilities with novel factors. It did not anticipate consumer-grade innovations since it primarily assessed criteria related to employees' behavioral desire to adopt new technology in organizational contexts. Thus, UTAUT model was expanded from being organization centric to customer centric. This revised model incorporates price value, hedonic motivation, and habit into the analysis of customers' adoption and usage of technology in addition to the four previously included factors (Venkatesh et al., 2012). Previous studies verified the fact that UTAUT2 is a superior customer use prediction model (Wu & Liu, 2023; Rondan-Cataluña et al., 2015). The application of augmented reality in SM apps is relatively new, and this study utilized UTAUT2 because it will presumably act like a superior model with respect to new technology.

2.3 Purchase Intention (PI)

It predicts usage behavior by indicating a person's anticipation to embrace or purchase new technology. Behavior is "the visible, observable response to a given goal in a particular environment" (Venkatesh et al., 2012). IT acceptance studies reveal that behavioral intention to purchase greatly influences actual purchase (Venkatesh et al., 2012). Previous researches found a significant association among behavioral intention, purchase, and actual usage in virtual reality, online and mobile payment cases, and online delivery apps (Huang, 2023; Lu et al., 2011; Vărzaru et al., 2021).

3. Hypotheses development

3.1. Performance Expectancy (PE)

"The degree to which any technology provides benefit to consumers while performing any activities" (Venkatesh et al., 2012). The focus of users is always on what is the outcome of the technology rather than the type of technology (Kang & Shao, 2023). In tourism and travel, performance expectancy is a significant determinant that influences buying intentions (Coves-Martínez et al., 2023). Performance expectancy significantly affects mobile learning (Chao, 2019), paid course available on the Internet (Chen et al., 2023), and also act as a precursor of technology use in the tourism context (Kala & Chaubey, 2023).

So, we hypothesize -

H_1: PE significantly influences PI.

3.2. Effort Expectancy (EE)

"It is simply ease of use" (Venkatesh et al., 2012). Users like technology that is easy to operate (Chocarro et al., 2023). Past literature suggests that less complex technology has a high adoption rate (K. P. Gupta & Bhaskar, 2023). Effort expectancy significantly impacts the purchase of E-commerce applications (Octalina et al., 2023), mobile learning (Chao, 2019), and tourism and travel (Li et al., 2023).

So, we hypothesize-

H_2: EE significantly influences PI.

3.3. Social Influence (SI)

It is the "extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology" (Venkatesh et al., 2012). Social influence explains the contribution of family, friends, and peer groups in technology adoption (Tian et al., 2023). Prior studies have demonstrated that SI holds a significant place in shaping individuals' behavioral intentions (Kusumawardani et al., 2023). It has been looked at from various perspectives, such as augmented reality in education (Papakostas et al., 2023), destination selection (Sharma et al., 2023) and mobile apps (Axcell & Ellis, 2023).

So, we hypothesize the following –

H_3: SI significantly influences PI.

3.4. Facilitating condition (FC)

Facilitating conditions are how much a person thinks new technology is aided by enabling conditions (Venkatesh et al., 2012). It may include internet access, smartphone compatibility, and understanding of technology. The extant literature indicates that FC have a sound influence on the adoption of healthcare technology (Beh et al., 2021), mobile wallet solutions (Owusu Kwateng et al., 2019), as well as shopping through m-apps (Tak & Panwar, 2017). Therefore, it is evident that FC have a crucial role in creating the usage intention. That is why we propose the following hypotheses -

H_4: FC significantly influences PI.

3.5. Price Value (PV)

It is the difference between expected and real benefits of the technology with respect to its price (Venkatesh et al., 2012). If a person believes technology's benefits outweigh its costs, price value increases behavioral intention (Venkatesh et al., 2012). Numerous past studies focus on PV and technology usage intention (Beh et al., 2021; Owusu Kwateng et al., 2019; Tak & Panwar, 2017). PV of new technology influences its usage intention and adoption (Venkatesh et al., 2012). Hence, we propose the following hypotheses -

H_5: PV significantly influences PI

3.6. Hedonic motivation (HM)

It can be comprehended as the fun and joy users experience in using new technology (Venkatesh et al., 2012). Personal qualities or cognitive states can inspire hedonic motivation that eventually affects the adoption of new technology (Kusumawardani et al., 2023). Previous research has established a strong association between hedonic motivation and patterns of usage behaviour (Axcell & Ellis, 2023; Octalina et al., 2023; Tak & Panwar, 2017). Hedonic motivation affects the digital healthcare domain (S. Gupta et al., 2021), mobile health apps (Octavius & Antonio, 2021), and smartwatches (Beh et al., 2021). If users derive pleasure from a new technology's attributes they'll naturally incline towards it. Hence, we propose the following hypotheses –

H_6: HM significantly influences PI

3.7. Habit (HB)

Habits are formed behaviour that results from a consistent pattern, and is usually integrated without much effort on the part of the user (Venkatesh et al., 2012). A clear repetition of the behaviour over a period of time turns out to be a repetitive activity, strengthening the ability to try new things. Previous research revealed habit is a significant component of technology acceptance (Taherdoost, 2018) in diverse areas such as mobile apps (Rafique et al., 2020), tourism destination selection (Sharma et al., 2023), teaching (Chávez Herting et al., 2023), and so on.

So, we hypothesize the following –

H_7: HB significantly influences PI.

3.8 SMU as a moderator

People use social media differently. The usage level of users may differ based on their purpose of use, level of engagement as well as time invested (Bolton et al., 2013). Existing literature points out that SMU may range from occasional usage to addictive or compulsive usage (Andreassen et al., 2017; Atske, 2021). People with different SMU exhibit different behavior (Bányai et al., 2017). SMU level bears an impact on the engagement level of users as well as on time spent on other activities (Junco, 2012). It is also attributed to support customer relationship management activities of the business as it connects them to different set of users (Trainor et al., 2014). According to existing studies, SMU is a significant factor in shaping consumers' purchasing intentions (Renu et al., 2020; Wang et al., 2012). Hence, we propose the following hypotheses –

H_8: SMU significantly moderates the relationship (H_{8a}) PE; (H_{8b}) EE; (H_{8c}) SI; (H_{8d}) FC; (H_{8e}) PV; (H_{8f}) HM; and (H_{8g}) HB of AR enabled SM filters with PI of cosmetic products.

The conceptual framework formed on the bases of the hypothesized paths is presented in Figure 1.

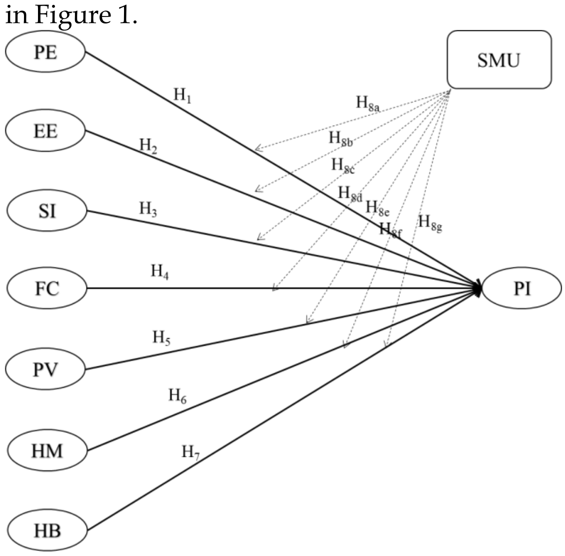

Figure 1 Conceptual Framework

4. Research Methodology

The present study follows descriptive design as it is an attempt to describe the effectiveness of SM as a marketing communication channel. The AR-enabled SM filters are quite popular among the youth across different SM platforms. Several brands have recognized this user association, thereby launching their own filters on the SM to ensure increased consumer engagement. In this context, cosmetic brands are not left behind. Brands like Kylie Cosmetics, Air Matte, MAC Cosmetics, Lakme, L'Oréal Paris, Maybelline, etc., have launched filters on SM through which the users can virtually experience the cosmetic beauty products themselves. Thus, providing them the opportunity to experience immersive entertainment on SM but also empowering them to make informed decisions. The present study has been taken up by observing the huge number of SM users and the growing usage of SM as a marketing communication channel.

4.1. Sampling & Data Collection

A preliminary observation on Instagram and Snapchat suggested that AR-enabled SM filters of cosmetic brands are majorly used by females. Further, a detailed look into these filters exhibited that those powering these filters are female cosmetic brands. Thus, females who use AR filters on SM promoted by cosmetic brands were selected as the sampling element for this study. For collecting the data, an online questionnaire was prepared using Google Forms. The items were derived from previous research studies (Beh et al., 2021; Venkatesh et al., 2012) and changes were made according to the present need (Table 2).

For a representative sample, the researchers used a 2 tier sampling process utilizing purposive and snowball sampling. Firstly, purposive sampling was used as the sampling element had to qualify a criterion (Etikan et al., 2016) of being a female as well as the user of AR enabled SM filters. The researchers' connections on SM who use such filters were contacted, and an online questionnaire via Google Forms was shared with them. Secondly, people sampled formerly were asked to get their SM connections, who use such filters, to fill out the questionnaire so as to reach more actual users of AR enabled filters (Emerson, 2015). A target of 400 was attempted, but only 297 useful responses were attained, which may be due to the very specific requirement of the sampling element.

A sample of at least 153 was needed (Faul et al., 2009) as calculated by G*Power software (Appendix A), while we got the sample of 297 which is quite satisfactory. The study's inclusion criteria mandated that only female participants were eligible to participate in the survey. The study found that 72% of the participants fell within the age range of 20 to 40 years, while 22.9% of the participants were under the age of 20 and 5.1%, were aged 40 years or older (Table 1). Table 1 also show that 47.8%, 24.2%, 23.6%, and 4.4% of respondents have education levels equivalent to the post-graduate, intermediate, graduate degree, and high school, respectively. As social media usage (SMU) is concerned, 44.8% of the respondents were heavy users, 37.7% were compulsive users, 16.2% were regular users, and 1.3% were occasional users (Table 1). Conclusively, respondents are female, educated, young, and spending a lot of time on social media.

A diverse population was targeted, achieving a mix of samples belonging to different age groups and qualifications and having different social media usage levels. The SMU was defined for respondents to ensure the accuracy of responses. Those who use SM sporadically as needed are classified under occasional users; regular users are those who interact with SM platforms on an almost daily basis; heavy users are the ones who use SM several times a day; whereas compulsive users are the impulsive ones who cannot control their desire to engage with SM platform several times a day. The data was collected from Indian users from October 2022 to January 2023.

5. Analysis

For the purpose of analyzing the data, SPSS 28 and AMOS 28 were used. Exploratory Factor Analysis, Cronbach's Alpha, and Common Method Bias were performed using SPSS, while Confirmatory Factor Analysis, Validity, and Structural assessment were done through AMOS. The moderation effect of SMU was studied with the help of Process Macro 4.1.

Table 1 Respondents' Demographic Description

Factor		*Frequency*	*Percentage*
Age	*Below 20*	68	22.9%
	20 – 40	214	72.05%
	Above 40	15	5.05%
Qualification	*High School*	*13*	*4.4%*
	Intermediate	*72*	*24.2%*
	Graduate	*70*	*23.6%*
	Post Graduate	*142*	*47.8%*
Social Media Usage	*Occasional User*	*4*	*1.3%*
	Regular User	*48*	*16.2%*
	Heavy User	*133*	*44.8%*
	Compulsive User	*112*	*37.7%*
Total		*297*	*100%*

Source: Author's own.

5.1. Data Normality

Before starting the statistical analysis of the data, normality must be satisfied. The data was firstly checked for any missing values, and then skewness and kurtosis values were considered, which were found within the allowed range of ±2 & ±7, respectively (Hair et al., 2019).

5.2. Common Method Bias

CMB must be checked to ensure there is no bias in the data when it is gathered from a single source. Harman's single-factor test was used to confirm the absence of CMB. The total variance explained by a single factor was 26.479%, significantly below 50%, hence, acceptable (Podsakoff et al., 2012).

Table 2 Item description and factor loadings

Construct	Cronbach Alpha	Items	EFA Loadings	CFA Loadings	Source
Effort Expectancy	0.829	Learning how to use AR enabled SM filters is easy for me [EE1]	.841	0.76	(Venkatesh et al., 2012)
		AR enabled SM filters are easy to use [EE2]	.828	0.85	
		It is easy for me to become skillful in using AR enabled SM filters [EE3]	.827	0.76	
Performance Expectancy	0.771	I find AR enabled SM filters useful for understanding the benefits of cosmetic products [PE1]	.740	0.72	(Beh et al., 2021)
		Using AR enabled SM filters helped me to see the effect of cosmetic products on me. [PE2]	.767	0.61	
		Using AR enabled SM filters is helpful in deciding which cosmetic product to buy. [PE3]	.841	0.89	
Social Influence	0.695	People who are important to me would think that I should use AR enabled SM filters to know the effect	.706	0.62	(Beh et al., 2021; Venkatesh et

		of cosmetic products. [SI1] People who influence me would think that I should use AR enabled SM filters. [SI2] People whose opinions I value would prefer that I should use AR enabled SM filters to visualize cosmetic products [SI3]	.747 .731	0.76 0.56	al., 2012)
Facilitating Conditions	0.701	I have the resources necessary to use AR enabled SM filters. [FC1] I have the knowledge necessary to use AR enabled SM filters [FC2] AR enabled SM filters are compatible with other technologies I use. [FC3]	.772 .757 .753	0.61 0.68 0.70	
Hedonic Motivation	0.865	Using AR enabled SM filters is fun. [HM1] Using AR enabled SM filters is enjoyable [HM2] I feel content in using AR enabled SM filters [HM3]	.767 .836 .803	0.74 0.88 0.86	
Price Value	0.693	AR enabled SM filters are reasonably priced. [PV1] AR enabled SM filters are good value for money. [PV2] At the current price, AR enabled SM filters are providing good value [PV3]	.759 .677 .678	0.77 0.78 0.50	
Habit	0.858	The use of mobile Internet has become a habit for me. [HB1] I am addicted to using AR enabled SM filters [HB2] I must use AR enabled SM filters. [HB3]	.870 .829 .737	0.86 0.90 0.70	(Venkatesh et al., 2012)
Purchase Intention	0.801	I would be willing to use cosmetic products to feel good. [PI1] I would be willing to use cosmetic products based on SM filter results [PI2] I would be willing to use cosmetic products to enhance my beauty [PI3] I am planning to use cosmetic products in the future. [PI4]	< .5 (Dropped) .661 .854 .844	- 0.72 0.72 0.94	(Beh et al., 2021)

5.3. EFA & CFA

An exploratory factor analysis (EFA) was conducted as a preliminary step to examine the factor loadings of the items utilized in the present investigation. All the items with loading more than 0.5 (Hair et al., 2019) were retained, while an item PI1 not confirming the threshold was removed from further analysis (Table 2). KMO sample adequacy test revealed a value of 0.816, and Bartlett's test of sphericity was found with p=0.00, confirming sample adequacy as well as sphericity norm (Hair et

Table 3 Reliability and Validity

	α	CR	AVE	HB	PE	EE	SI	FC	PV	HM	PI
HB	0.858	0.868	0.690	**0.830**							
PE	0.829	0.790	0.563	0.356	**0.750**						
EE	0.771	0.831	0.622	0.294	0.269	**0.789**					
SI	0.695	0.699	0.498	0.440	0.246	0.473	**0.705**				
FC	0.701	0.700	0.502	0.258	0.182	0.291	0.283	**0.708**			
PV	0.865	0.716	0.510	0.372	0.275	0.329	0.355	0.630	**0.714**		
HM	0.693	0.869	0.689	0.432	0.518	0.310	0.296	0.317	0.547	**0.830**	
PI	0.801	0.839	0.639	0.278	0.438	0.166	0.399	-0.001	0.009	0.402	**0.799**

al., 2019). Further, a measurement model was formulated using AMOS 28, and CFA was conducted. The CFA produced acceptable model fit indices (CMIN/DF= 2.38, CFI= 0.9, RMR= 0.05, GFI= 0.9, TLI= 0.88, RMSEA= 0.06) (Hair et al., 2019; Hu & Bentler, 1998; Kline, 2015).

5.4 Reliability & Validity

To ensure internal consistency, Cronbach's Alpha and composite reliability were used. The values of alpha and CR (Table 3) were attained as acceptable, above (or approx. equal to) 0.7 (Hair et al., 2019). The convergent validity and divergent validity also need to be explored to ensure the items define the construct that they are intended for (Byrne, 2010). The average variance extracted (AVE) for all variables was found above 0.5, and CR was above 0.7 (Table 3), thus ensuring convergent validity (Hair et al., 2019). For DV, the square root of AVE for each construct was compared with the correlation among the constructs (Hair et al., 2019). The results for DV were also satisfactory, as shown in table 3.

Table 4 Results of Hypothesis Testing

Hypothesis	Path	Estimate	Significance	Status
H_1	PI <--- PE	0.270	< 0.001	Accepted
H_2	PI <--- EE	-0.084	0.255	Rejected
H_3	PI <--- SI	0.393	< 0.001	Accepted
H_4	PI <--- FC	-0.026	0.783	Rejected
H_5	PI <--- PV	-0.372	0.002	Accepted
H_6	PI <--- HM	0.372	< 0.001	Accepted
H_7	PI <--- HB	0.016	0.820	Rejected

5.5. Hypothesis Testing

For the purpose of testing the hypothesis, SEM has been used. The regression weights for each hypothesized relationship have been obtained and results are presented in Table 4. The outcomes show that PE (β=0.27, p= 0.00), SI (β= 0.393, p= 0.00), PV (β= -0.372, p=0.002) and HM (β= 0.376, p= 0.000) have a significant impact on PI, while EE (β= -0.084, p=0.255), FC (β= -0.026, p= 0.783) and HB (β= 0.016, p= 0.82) doesn't. Thus accepting H1, H3, H5, H6, while rejecting H2, H4 and H7.

5.6. Moderation

Moderating effect of SMU was investigated on the relationship between the AR enabled SM filters and purchase intention using Model 1 of process macro 4.1. Table 5 shows the moderation analysis output. It is clear from the values obtained that SMU has a significant influence on the relationships of EE, FC with PI, accepting H_{8b} and H_{8d}. However, for all the other relationships, no moderating effect was visible, rejecting H_{8a}, H_{8c}, H_{8e}, H_{8f}, and H_{8g}. Figure 2 demonstrates that SMU intensifies the positive relationship between EE and PI, which translates that for higher-degree users, the ease of use of AR enabled SM filters plays a prominent role in shaping their purchase intention. Likewise, figure 3 demonstrates a similar interaction effect of SMU on the association between FC and PI. This means that the more the user engages with SM, the role of supporting infrastructure and conditions becomes crucial. As the user becomes more accustomed to the SM, they place more emphasis on the facilitating conditions provided by the brands on SM to make up their purchase intention for the cosmetic products.

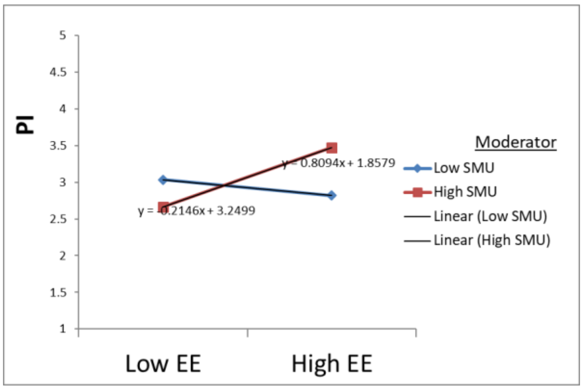

Figure 2 Moderating effect of social media use on the relationship between Effort expectancy and purchase intention.

Table 5 Moderation Analysis

Moderator: Social Media Usage (SMU)										
Hypothesis	Path			β	se	t	p	LLCI	ULCI	Moderation?
H_{8a}	PE	→	PI	.0577	.0517	1.1149	.2658	-0441	.1595	No
H_{8b}	EE	→	PI	.2566	.0702	3.6548	.0003	.1184	.3948	Yes
H_{8c}	SI	→	PI	.1199	.1040	1.1529	.2499	-0848	.3246	No
H_{8d}	FC	→	PI	.2253	.0954	2.3606	.0189	.0375	.4131	Yes
H_{8e}	PV	→	PI	-.0180	.0919	-.1961	.8447	-.1989	.1629	No
H_{8f}	HM	→	PI	.0331	.0585	.5655	.5721	-.0820	.1482	No
H_{8g}	HB	→	PI	.0502	.0859	.5845	.5593	-.1188	.2192	No

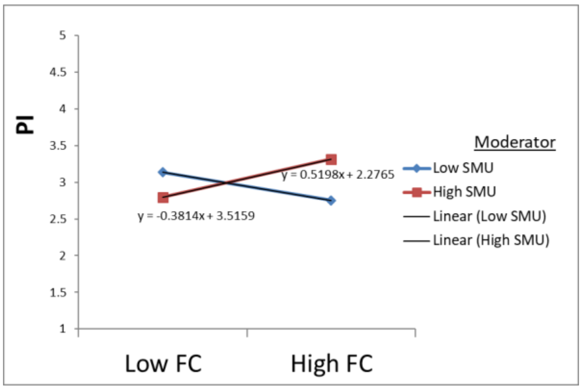

Figure 3 Moderating effect of social media use on the relationship between Facilitating conditions and purchase intention.

6. Discussion

The purpose of this research was to investigate the influence of augmented reality (AR) enabled social media (SM) filters on consumers' purchase intentions for cosmetic products. The study is unique as it examined whether PE, EE, SI, FC, PV, HM, and HB influence PI or not, in context of SM being used as a marketing communication channel. The results indicate that PE, SI, PV, and HM significantly influence PI for cosmetic products. Contrarily, EE, HB, and FC do not influence PI for cosmetic products. The research model explains a 41% variance in purchase intention.

Acceptance of H1 indicates that PE significantly influences PI. The findings are consistent with existing research too (Coves-Martínez et al., 2023; Chen et al., 2023). SM is used as a prominent communication channel among consumers as it provides numerous benefits to its users. As a result, diverse set of potential consumers are available on SM platforms; thus, marketers try to utilize these channels to market their products and services. Companies using AR to provide filters on SM allow users to show the instant virtual benefit of their products. The significant influence of PE on PI explains that if brands provide AR enabled filters through SM to show the benefits of their products to users virtually, it will eventually lead to significant purchases from the users' side.
Rejection of H2 indicates that EE does not have any significant impact on PI. Whereas previous studies found EE as a significant influencer for technological adoption (K. P. Gupta & Bhaskar, 2023) and intangible products such as mobile learning (Chao, 2019) and tourism & travel (Li et al., 2023). However, some studies find EE as an insignificant precursor in moderating PI, for instance, with context to E-commerce applications (Octalina et al., 2023). EE is an insignificant precursor for PI as EE is just the ease of use of AR enabled SM filters. Moreover, cosmetics are tangible product and not technological product, and as previous studies suggested, EE influence technology adoption and online applications, such as SM, not the purchase of tangible products like cosmetics.

Acceptance of H3 indicates that SI significantly influences PI. This claim is in line with past literature (Axcell & Ellis, 2023; Kusumawardani et al., 2023; Sharma et al., 2023). Peer pressure motivates users to try new technologies. Users are trying AR enabled filters because of herd behavior or to find the social attention of other individuals who are important to them. Similarly, users also initiate a purchase if the peer group purchases cosmetics using the AR enabled filter. SI also exerts the benefit of word of mouth for cosmetics as SM allows the users to try the cosmetic product virtually, and if users find conformance between virtual and actual results of these products, then they will create a positive word of mouth (Kusumawardani et al., 2023) for AR enabled filters as well as for cosmetic brands.
Rejection of H4 indicates that FC does not influence PI for cosmetic products. Users do not need FC to use AR enabled filters for cosmetics. Although previous literature suggests that FC influences the intention to adopt healthcare technology (Beh et al., 2021), mobile wallet solutions (Owusu Kwateng et al., 2019), etc. However, past literature is centered around the adoption of complex technologies, not on the technology having a friendly user interface, like SM. Using SM features, including AR enabled filters, does not require much technical support. A user can even try the AR enabled filters on SM without requiring anyone's help or assistance. Therefore, FC is not a requisite for PI of cosmetic products.

Acceptance of H5 indicates that PV significantly influences PI. Past studies also indicate that PV significantly influences technology usage intention (Owusu Kwateng et al., 2019; Tak & Panwar, 2017). AR enabled

SM filters are freely available on the companies' SM pages or apps, and anyone can try cosmetics filters virtually. This will give them an idea of whether to purchase the actual product or not. So in the context of AR enabled filters, the user is not incurring any additional cost, therefore, these filters are more than value for money (Venkatesh et al., 2012). This, in turn, increases the usage of these filters and influences significant PI as users find it interesting, and if they like one or more filters, they are most likely to purchase the tangible product.

Acceptance of H6 indicates that HM significantly influences PI. This result is also verified in prior literature (Beh et al., 2021; Octalina et al., 2023; Tak & Panwar, 2017). This reflects that the more fun and enjoyment users feel in using AR enabled filters on SM for cosmetics, the more likely they make a purchase. The more enthusiasm users feel in using these filters, the more they try to explore new filters, which exposes and demonstrates different cosmetics products to them, and after trying these products virtually, the excitement of users will lead to actual purchases.

Rejection of H7 indicates that HB does not have a significant influence on PI. Previous researches revealed habit as a significant constituent of tech-acceptance (Chávez Herting et al., 2023; Rafique et al., 2020; Taherdoost, 2018). Habits are formed behavior that is resulted from a consistent pattern. Users who habitually use SM allow them to try new technology such as AR enabled filters, but getting habitual of these filters will not inculcate PI. This may be because they consider AR enabled cosmetic filters just any other features added, and they take benefit from these filters virtually, but they do not purchase these cosmetics. Habitual SM users usually attribute the usage of SM to their engagement with the virtual world and are thus satisfied with just using the product virtually.

The research also enquired about the interaction effect of SMU over the association between UTAUT2 factors and PI of cosmetic products. The findings are quite interesting as they demonstrate a significant moderation by SMU over the association between (i) EE and PI and (ii) FC and PI accepting H8b and H8d, respectively. These outcomes are in confirmation with existing researches (Renu et al., 2020; Wang et al., 2012). This may be because increased SMU make users accustomed to the interface of SM, and they feel a strong belonging to the platform. If efforts are required to use filters or the required facilitating conditions change or become complex, these users may not be comfortable with the technology. Thus, the increased ease of using these technologies motivates the users to attach themselves more to it. It may also add to their purchase intention by increasing their engagement with the SM and, ultimately, with the brand.

7. Implications

7.1. Theoretical Implications

The current investigation adds some significant theoretical additions to the existing literature. To begin with, this is an empirical study of AR enabled cosmetic filters available on SM channels. AR enabled SM filters are underexplored through the lens of marketing communication; this investigation contributes to the existing body of literature as it opens the gateway for treating SM as a crucial and independent marketing communication channel. Secondly, this study adds to the literature in a way that points out the importance of technology-enabled promotional tools through social media, such as AR enabled filters. Academicians may take up such tech-enabled activities as an important integration in sales promotion techniques. Thirdly, as far as we know, UTAUT2 is not looked at to gauge the SM effectiveness as a marketing communication channel for cosmetics. This expands opportunities and scope for similar future researches. The next contribution of this study is that it confirms moderating effect of SMU on FC and EE with respect to PI. SMU can be considered by researches related to effectiveness of SM as a marketing communication channel. SMU can also be taken into consideration while studying the behavioral differences among SM users. This study also creates opportunities for research concerning Metaverse as SM and AR are deemed to be part of Metaverse infrastructure. Finally, this work contributes to the available body of knowledge in domains like promotion management, technology adoption, communication, and consumer behavior.

7.2. Practical Implications

This research has several consequences for marketers. First, in order to be effective, SM should be used as a channel of communication for marketing and promotional activities. The study also suggests that SM communication channels should be complemented with new-age technologies, such as AR. Furthermore, AR as a promotional tool should be endorsed due to its ability to give the idea of real product benefits to users. AR will help marketers to make users aware of the real effect of their products virtually (e.g., cosmetic filters), which may eventually lead to higher product awareness and successful purchases. While introducing AR enabled filters on SM, marketers should keep in mind that just like the SM, the AR filters should be designed with a user-friendly interface. Moreover, the virtual results displayed by AR enabled filters should be in conformance with the real product results. If users find a conformity between the virtual and real product results, then they will create positive word of mouth and vice-versa. Therefore, AR filters should be easy to use and provide efficient and realistic results.

Marketers may also initiate upselling activities by suggesting filters of better or premium variants of the product tried by the users. This eventually helps marketers to make users try more and more AR enabled filters for cosmetics. Marketers should take advantage of cross-selling by gradually introducing more product categories through AR enabled filters on SM. Additionally, the other concern for marketers to look at is trust. As trust is a main concern for anything on SM due to the prevalent cases of fraud and misleading information, that is why marketers should make strategies to build trust for AR enabled filters among those users who hesitate to use these filters or have trust issues regarding SM.

Marketers should focus on increasing SM engagement for the masses so that they can target more and more users. This can be done by introducing newness in existing AR filters and making these filters more realistic. Brand communities should be created for users that actively try AR enabled filters on social media. This will help not only contribute in creating a good brand image but also in creating positive word of mouth. Users get to know about the AR filters through SM itself, but still, there are potential customers who are not on SM. Marketers can utilize traditional media channels to create awareness for AR enabled filters available on SM channels.

8. Conclusion, Limitations, and future research prospects

8.1. Conclusion

The objective of the investigation was to examine SM as a marketing communication channel, using UTAUT2 as a theoretical foundation. This research work seeks answers to two research questions. The first research question is clearly answered as PE, SI, PV, and HM significantly influence PI for cosmetic products. Contrarily, EE, HB, and FC do not have a significant influence on PI for cosmetic products. This reflects that AR enabled SM filters contribute to creating PI for cosmetic products.

RQ2 is clearly answered as well, as the present investigation has revealed a noteworthy moderating impact of SMU on the association of specific factors of the UTAUT2, namely FC, EE, with PI. However, no moderation is found in other factors of UTAUT2. We conclude that SM as a marketing communication channel is exceptionally effective, and if complemented with AR it will produce desirable marketing results for brands. Specifically, for cosmetics brands, AR enabled SM filters will act as a boon for creating PI. Finally, the study yielded theoretical implications for researchers and practical implications for marketers.

8.2. Limitations and Future Research Prospect

The sample in this investigation is just confined to females due to the availability of female-centric cosmetics AR filters only. Moreover, this study is cross-sectional in nature. In future studies, longitudinal research or cross-sectional research with more product categories can also be conducted. The current study's model accounts for 41% of the variance observed in the endogenous variable. Thus more factors can be integrated with the present model to explain the outcome variable in more detail. AR filters are currently not available for male cosmetic products.

The study could have been more comprehensive if the same was administered to the male population as well. In future studies, more product categories with different demographic dynamics can be studied.

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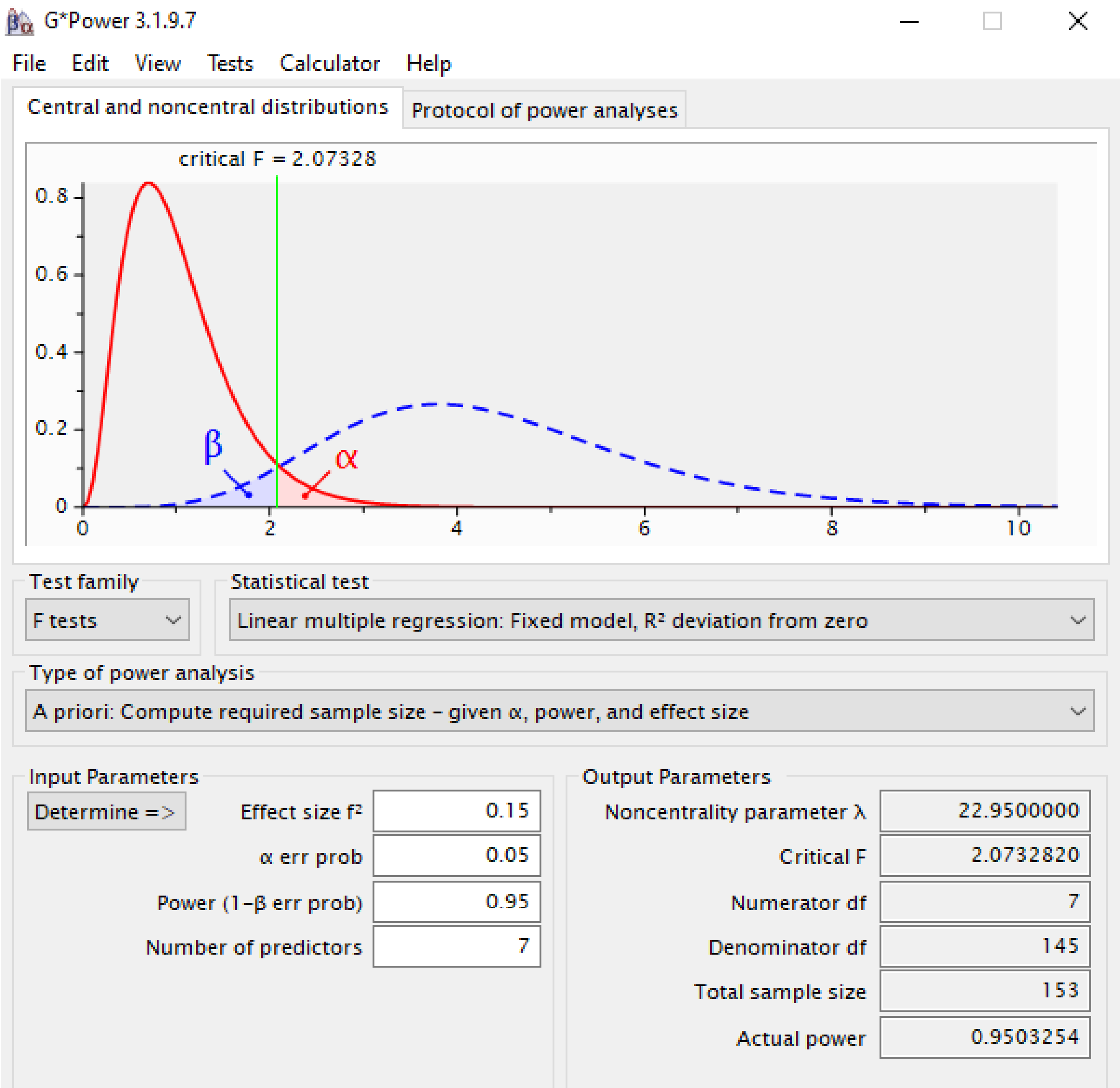
Appendix A: Minimum Sample Required by G*Power Software



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