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RESEARCH ARTICLE

# Impacts and Drivers: The Dual Role of Social Media on Consumer Behavior in South India's Expanding E-commerce Market

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**ABSTRACT**

This study provides significant insights into the factors influencing consumer purchase intentions in online shopping for the region of Tamil Nadu, South India, including content quality, social media influencer credibility, engagement in social commerce, dynamic pricing, corporate social responsibility, and hedonic motivation. By applying a quantitative survey approach among 540 selected respondents, the evenly distributed sample covered various ages, incomes, and educational backgrounds. The analysis conducted is as follows: Consumer purchase intentions are positively influenced by content quality, social media influencer credibility, engagement in social commerce, and hedonic motivation. However, corporate social responsibility and dynamic pricing were not found to have any significant direct effects on the outcome. The findings indicate that perceived value is a partial mediator for several independent variables leading to consumer purchase intentions. On the basis of these results, digital marketers and businesses, along with marketing companies, now gain insights into how they should strategize, build and target their approach, especially by creating content that is context specific, while strategizing collaborations to work with social media influencers and becoming actively involved in social media commerce. These novel ideas and insights can be adopted by businesses and entrepreneurs to understand the chance of purchase for their goods or services.

## 1. INTRODUCTION

Marketing digital and social media has rapidly changed consumer buying behaviors, particularly impulsive buying. Currently, there has been exponential growth in the usage of internet and mobile phone in both range and size in India. This digital evolution worldwide pushed online shopping to a boom, as did that in India (Jain and Kulhar, 2019; Singh, 2020). India is a country of its own kind, and owing to this sociocultural fabric, the constant penetration of a variety of social media platforms into this population is causing consumers to deal with products and buying decisions in different ways (Gupta and Arora, 2020; Mathur et al., 2020). Purchases tend to be referred to as impulses when they are unplanned, made psychologically, rather than on a rational basis, and provide customers with an immediate sense of enjoyment and pleasure. Impulse buying is a phenomenon that is commonly experienced in all forms of shopping environments. According to the available studies, over 50% of all online purchases are impulsive (Ayub and Zafar, 2018; Parboteeah et al., 2009; Wu et al., 2020; Zhang et al., 2018a). The research question addressed in this study concerns the phenomenon of impulse buying as stimulated by digital and social media marketing, particularly Instagram in South India.

Digital marketing involving websites and social media has altered the shopping scenario by adding more external stimuli that influence user behavior (Lim and Yazdanifard, 2015). Researchers have identified the constructs of online shopping that impact impulsive buying as navigability (Wells et al., 2011), security display (Wells et al., 2011), ease of use (Liu et al., 2013), feedback systems (Chan et al., 2017), environmental conditions and marketing stimuli (Dawson and Kim, 2009; Suryawardani et al., 2017; Virvilaite et al., 2011), and internal factors such as age, gender, education and culture (Satyavani and Chalam, 2018; Chan et al., 2017). The technology acceptance model (TAM) and the stimulus–organism–response (SOR) framework are widely used to study consumer behavior while shopping online. These models explain the importance of both hedonic (affective) and utilitarian (cognitive) motivations in shopping behavior (Park et al., 2012; Zheng et al., 2019). Despite the large list of primary factors identified through extensive research, the ever-changing trends of shopping behavior demand that the parameters of impulsive buying while shopping online be constantly examined to keep pace with the trends.

In light of the growing popularity of shopping online via social media (e.g., Instagram), I also intend to explore how digital marketing via Instagram influences consumers' purchase intentions. Unlike other platforms, Instagram is positioned as a highly relevant and heavily used social media platform for product advertising that has powerful capabilities to target young customers and influences their impulsive purchases (Arora et al., 2019; Sokolova and Kefi, 2020). The COVID-19 pandemic further accelerated the trend of shopping online (Chang and Meyerhoefer, 2020; Grashuis et al., 2020; Watanabe and Omori, 2020), and Instagram became a real e-commerce marketplace during the lockdown (Bakshi and Sharad, 2020; Deswal and Sikand, 2020). However, there is still a lack of research on how (and what type of) stimuli influence consumers' impulse buying behavior on Instagram (Sokolova and Kefi, 2020; Chan et al., 2017). This research intends to fill the gap in the literature by demonstrating through the proposed model a strong influencing role of H2C interaction on consumer impulse buying behavior. This design rests on the assumption that H2C interactions shape cognitive (utilitarian) and affective (hedonic) responses to stimuli and that H2C interactions mediate consumer responses to external stimuli (advertisements). By integrating TAM and the SOR framework, it is clear that our approach incorporates situational, social media, and marketing stimuli and consumers' individual characteristics (see Figure 1 below) in the model to better depict modern consumers' decision-making process in the digital age (Wu et al., 2020; Zheng et al., 2019). Fashion is the focus of research, in light of its high popularity in social media marketing (Sokolova and Kefi, 2020; Chetioui et al., 2019). It will investigate the effect of digital and social media marketing on how consumers influence purchase intentions and determine the influence of perceived values on purchase behaviors via a mediator model. The relationships between internal stimuli such as impulses, hesitation and the perception of advertising persuasiveness and the influence of external stimuli, such as influencers and brand influences, will be examined, with online impulse shopping as the behavior of interest. An examination of direct and indirect approaches through internal and external stimuli can be conducted to bridge the gap in the understanding of online impulse shopping behaviors. Furthermore, a positive relationship between cognitive (utilitarian) and affective (hedonic) responses and impulse influences across impulsive buyings, which is also referred to as the impact of the valence-oriented response, will be explored. Additionally, the moderating effect of consumer characteristics on online shopping behavior, specifically on impulsive buying on Instagram within the fashion segment, where social media marketing plays an integral part, will be studied (Satyavani and Chalam 2018). By addressing the abovementioned objectives, this research intends to examine the causative relationships among the factors of consumer behavior impacted by digital and social media marketing within the region of South India.

# 2. REVIEW OF RELATED LITERATURE

## 2.1 Theoretical framework

The frequency of users' use of new technology and the factors that can influence it are manifold (Fishbein and Ajzen, 1975). It is very important to explore this topic since technology, which early on became the source of technological business ever growing, has become a center of economic progress. The process of shopping online derives from the use of technology based on the technology acceptance and utilization framework. This remits us to the "Technology Acceptance Model (TAM)" (Rondan-Cataluña et al., 2015), which was the first model of the adoption of technology engineered by Davis in 1989 and has been widely used in all technical areas, even though it was conceived originally for the Worldwide Web (Al Qeisi et al., 2014; Liu et al., 2013) and other mobile technologies (Chen and Tsai, 2019; Kumar et al., 2017; Mutahar et al., 2018; Xia et al., 2018).

### 2.1.1 Technology acceptance model

With the advancement of societies toward social networks, the TAM was also used in research on social networks (Dehghani et al., 2016; Hansen et al., 2018; Ifinedo, 2016). The TAM posits two cognitive and affective beliefs: perceived usefulness (PU) and perceived ease of use (PEOU) affect a user's acceptance and use of technology, including social networks (Al Qeisi et al., 2014; Chen and Tsai, 2019). The PU and PEOU strongly affect each other externally and indirectly affect the intended behavior of technology adoption and acceptance via these two factors. In addition, this study utilized SOR since it identifies how environmental stimuli affect the creation of internal organismic appraisals (Stimulus) and ultimately lead to behavior (Organism, Response) (Adelaar et al., 2003; Floh and Madlberger, 2013; Khalifa and Shen, 2007; Liu et al., 2013). The major advantage of the SOR method is that it explains human behavior by classifying the sequence of behavior formation stages, and this method enables us to understand how customer buying behavior occurs (Kaur et al., 2017). With respect to the factors influencing customers' buying behavior in a technological environment, since people's buying behavior in an online environment is the key point to research, this study applies TAM1's theory (Taherdoost, 2018). Considering the historical background and application of each of the IS-centered models, we used TAM1's theory and did not utilize models that are limited by narrow variables. We further developed this theory since many factors affect customers' buying behavior in a technological environment (Legris et al., 2003; Surendran, 2012). Because the TAM only addresses external factors influencing a behavior mechanism of an individual (Abdullah and Ward, 2016), we add those internal factors and propose a related model that pays attention to a mechanism of how to classify stimuli and special factors. A combination of the two abovementioned models will lead us to a more comprehensive and comprehensive picture of human behavior and offer a more relevant model of human behavior from the perspective of impulsive buying behavior. The SOR framework is a developed classical stimulus–response (S-R) perspective (Chan et al., 2017) and comprises three parts: (1) a stimulus, which indicates the triggering idea that can stimulate the consumer; (2) an organism, which represents the internal assessment of the consumer; and (3) a response, which represents the consequence of the consumer arranging to online impulse buying drivers and their internal assessment (Chen and Yao, 2018; Zhang et al., 2018b; Zhu et al., 2020).

Two types of organisms react to stimuli. Cognitive responses are psychic processes resulting from when customers read drivers (Chan et al., 2017), especially messages in which customers may have limitations if they finish impulse purchases on the Web (Parboteeah et al., 2009; Wang and Yen, 2010). On the one hand, positive cognitive responses such as pleasure are motivational, and on the other hand, negative cognitive responses such as hesitation and dislike deter purchase behavior (Lin, 2018; Lin and Liu, 2019), meaning that they lead to the elimination of purchase responses from customers (Cui and Lai, 2013; Vieira, 2013). On the other hand, affective responses are emotional responses to customers when they experience positive emotional messages such as desires and stimulation (Bigne et al., 2020; Goi et al., 2018; Tang et al., 2019). Finally, customers' responses to stimuli and organisms during the OIB are the reactions of customers (Chen and Yao, 2018; Hashmi et al., 2019). The adaptable SOR framework used to conduct studies in environmental psychology has indicated that the causes of the final behavior of customers derive from the interaction between the motives and the reactions of the customers (Satyavani and Chalam, 2018). TAM is derived from the theory of reasoned action (TRA), which studies the factors that affect the conscious behavior of humans (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975).

### 2.1.2 Stimulus–organism–response framework

Individual behavior is influenced by the individual's intention to perform this behavior. BI results from the attitudes (A) and subjective norms (SN) linked to the target behavior; other variables could affect BI only through these two variables. Rondan-Cataluña et al. (2015) TAM introduced PU and PEOU as the main antecedents of technology acceptance to the TAR model, eliminating SN, a construct that has uncertain theoretical and psychometric properties (Davis, 1989). Davis (1989) subsequently reported that PU and PEOU had significant effects on BI and that the impact of attitude decreased over time.

Thus, this study used both affective and cognitive reactions/beliefs (in the SOR framework) and utilitarian and hedonic browsing (in the TAM) to address utilitarian and hedonic motivations when users are faced with environmental stimuli. Since the PU and PEOU may be viewed as customers' cognitive and affective reactions to the IT artifact (commerce functions, ease of use), respectively, and affective reactions and cognitive reactions are used interchangeably in the SOR framework, the PU and PEOU are semantically equivalent to the utilitarian and hedonic motivations, respectively. As seen in the theoretical literature proposed by Chan et al. (2017), cognitive and affective reactions are equivalent to PU and PEOU, respectively. Thus, utilitarian and hedonic browsing can be used instead of PU and PEOU, respectively, so that by choosing the shopping impulse as the customers' response to technology acceptance (TAM-1 effective part) theoretically followed by the information stimuli process (internal and external) from the SOR framework, we can construct a novel combined and comprehensive model where all the relationships are theoretically or experimentally friendly. Consequently, a combination model was developed by adding the successful part of TAM1 with the stimuli process (internal and external) from the SOR framework. All the relations in our proposed model are theoretically justifiable and experimentally conceivable

### 2.1.3 Impulse purchase decision-making process

Moreover, impulsivity is defined in the literature as an inclination among customers to feel sudden and persistent pressure while comparing prices when shopping (e.g., Dawson and Kim, 2009; basivar and Yarahmadi, 2011; Ortiz Alvarado et al., 2020; Xu and Huang, 2014). Types of impulsivity include pure impulsivity, which occurs when customers break their usual purchase pattern as a result of an emotional trigger (e.g., after seeing a certain product); reminded impulsivity, which occurs when customers watch a warning about the reduced amount of stock for a certain product or when they are reminded by advertising about an intention they expressed to purchase that product in the past. Propositional impulsivity: This phenomenon occurs when consumers become acquainted with a specific product and feel like they need it. Designed impulsivity occurs when customers not only intend to buy a list of products but also want to purchase other products within the available promotional offers and discounts (Ahmad et al., 2019; Chan et al., 2017; Zheng et al., 2019).

The complex process of customer buying behavior captivates researchers for a reason. Among various buying behaviors, buyer behavior is the more interesting aspect, and the impulse buying process is even more interesting because the latter is different from the general buying process. The former encompasses five steps: need recognition, information search, alternative evaluation, purchase decision and postpurchase evaluation. The time taken for consumers to complete several steps and, correspondingly, the total buying process time varies according to the attitudes and perceptions of the customer (Satyavani and Chalam, 2018). Today, the impulse buying process sequence is not a regular or logical sequence, and the decisions that form part of the buying process unfold in a very short time (Satyavani and Chalam, 2018). This integrated model consisting of a mix of the SOR framework and TAM1 offers deeper insight into how consumer purchase intentions on social media, in this case Instagram, can be comprehended due to the deeper understanding of cognitive and affective responses to stimuli online, thereby paving the way for greater insights with respect to the fashion segment, at least in South India.

### 2.2 Research model and hypotheses

A comprehensive model of the impulse buying process was developed in accordance with a review of earlier literature available on impulse buying. On the basis of the impulse purchase process model (Churchill and Peter, 1998), the SOR model (Woodworth, 1928), and the TAM1 framework (Davis, 1989), we sought to examine the impact of digital marketing and social media on consumers' purchase intentions and the mediating role of perceived value. Our IVs tested include social media influencer credibility, content quality, social commerce behavior, dynamic pricing, corporate social responsibility (CSR), and hedonic motivation. Our mediating variable is perceived value, and our DV is consumer purchase intentions.

## 3. CONCEPTUAL FRAMEWORK

### 3.1 Social media influencer credibility

Social media influencer credibility is a complex concept consisting of influencers' trustworthiness, expertise, and attractiveness that significantly influence consumers' behavior and perceived value (Hajli et al., 2017; Wiedmann and von Mettenheim, 2020). Trustworthiness refers to whether consumers believe that influencers are honest and morally upright, which strengthens their perception of the platform's trustworthiness and reliability (Chetioui et al., 2019; Veirman et al., 2017). Expertise refers to influencers' in-depth knowledge of the subject and experience in different expertise categories, thus enhancing their social presence and persuasiveness (Lou and Yuan, 2019; de Vries et al., 2012). Attractiveness pertains to consumers' perceptions of influencers' physical attractiveness and personality, thus increasing their liking of influencers and their willingness to follow their recommendations (Jin et al., 2019; Boerman et al., 2017). Since Instagram is a visual-oriented social media platform where influencers share highly engaging and interactive content, influencer credibility plays a vital role in garnering consumers' attention and inducing their purchasing intentions (Chopra et al., 2020; Kim and Kim, 2021). Grounded in the SOR framework, when social media influencer credibility serves as the stimulus, it might lead to consumers' perceived value (organism), which in turn influences their purchase intentions (responses) (Chan et al., 2017). Hence, we hypothesize the following:

***H1:*** *Social media influencer credibility has a positive effect on consumer purchase intentions.*

***H8a:*** Perceived value mediates the relationship between social media influencer credibility and consumer purchase intentions.

### 3.2 Content quality

Content quality, which pertains to content generation with respect to its relevance, usefulness, and creativity, is anticipated to guide the purchase behaviors of followers, turning their attitudes toward consumer perception (Feng et al., 2021; Uzunoglu and Kip, 2014). This should be further supported given that high-quality content can convey substantial information and lead to a better user experience, thus making such content more intriguing and persuasive (Ashley and Tuten, 2015; Chopra et al., 2020). Meanwhile, creative content that aligns with the creative and unique features of an influencer itself can attract more consumer attention and stimulate their interest, hence leading to more perceived value (De Vries et al., 2012; Lou and Yuan, 2019). Content quality is highly important in the digital marketing context, especially on Instagram, where the quality of content shared can strongly drive consumer engagement and purchase intentions (Godey et al., 2016; Chetioui et al., 2019). The quality of content can generally be evaluated with respect to informativeness, entertaining, relevance, and visual appeal, and surely, the unique features of the content itself can be defined by the rich information content and visual appeal, the ability to evoke interest and relevance, and significantly maximizing perceived value, which further influences consumers' purchase intentions. Therefore, we argue:

***H2:*** *Content quality has a positive effect on consumer purchase intentions.*

**H8b:** Perceived value mediates the relationship between content quality and consumer purchase intentions.

### 3.3 Engagement in social commerce

Social commerce engagement and participation affect consumers' attitudes and, ultimately, purchase intentions (Hajli, 2015; Zhang et al., 2014). High levels of social commerce engagement lead to greater perceived value in terms of community and trust among users (Chen and Shen, 2015; Kim and Park, 2013). Seeking active participation in social commerce will enhance potential perceived value since consumers' perceptions about the industry will be reinforced—social proof (Ng, 2013; Zhou et al., 2013). User engagement is the main driver of consumer behavior on Instagram; the greater the level of engagement, the more different forms of perceptions or purchase intentions will be boosted (Erkan and Evans, 2016; Wang and Yu, 2017). Figure 1 illustrates the SOR framework, which explains the impacts of social commerce engagement (S), which in turn influences perceived value (O) and ultimately purchase intentions (R) (Chan et al., 20172018). Therefore, we assume the following:

***H3:** Engagement in social commerce has a positive effect on consumer purchase intentions.*

**H8c:** Perceived value mediates the relationship between engagement in social commerce and consumer purchase intentions.

### 3.4 Dynamic pricing

Dynamic pricing encompasses personalized pricing strategies and real-time product recommendations that have the potential to influence consumer perceptions of value and, subsequently, purchasing behaviors (Kopalle et al., 2009; Chen et al., 2014). Personalized pricing has the potential to strengthen perceived value by providing customized discounts and promotions and by making consumers feel valued and special (Xia and Monroe, 2009; Kannan and Kopalle, 2001). Additionally, real-time recommendations have the potential to optimize consumers' shopping experience through real-time product suggestions and recommendations from sellers on the basis of customers' online behaviors (Hinz et al., 2011; Shan and Bolton, 2004). Primarily, consumer engagement and purchase intentions can be effectively encouraged by dynamic pricing strategies on Instagram (Li and Kannan, 2014; Zhang et al., 2014). Grounded in the SOR framework, in terms of dynamic pricing (stimulus), perceived value (organism) is likely to affect purchase intentions (responses) (Chan et al., 2017). Therefore, the following hypothesis is proposed:

***H4:** Dynamic pricing has a positive effect on consumer purchase intentions.*

**H8d:** Perceived value mediates the relationship between dynamic pricing and consumer purchase intentions.

### 3.5 Corporate social responsibility (CSR)

CSR initiatives conceived and/or published by companies act as an organic part of a brand image and ultimately affect consumer loyalty and establish the value of a good in the consumer's mind and feasibility of purchase (Carroll and Shabana, 2010; Fatma et al., 2015). By engaging in CSR activities such as environmental sustainability, ethical labor, and community support, companies enhance their corporate reputation and establish a base of consumers whom they can trust (Martínez et al., 2014; Servaes and Tamayo, 2013). As products and services from socially responsible companies are perceived as valuable, the purchase intention of said consumers ensues (Du et al., 2010; Bhattacharya and Sen, 2004). These results are particularly significant for the digital marketing context on Instagram and other platforms: CSR initiatives can have a significant effect on consumer behavior. We believe that this holds true particularly when we distinguish among the social, economic, and environmental spheres of the voluntary activities that companies carry out. The SOR framework then facilitates learning how CSR (stimulus) affects the perceived value of a brand (organism) and, therefore, purchase intentions (responses) by an individual (Chan et al., 2017). Consequently, we hypothesize the following.

***H5:** CSR has a positive effect on consumer purchase intentions.*

**H8e:** Perceived value mediates the relationship between corporate social responsibility (CSR) and consumer purchase intentions.

### 3.6 Hedonic motivation

Hedonic motivation relates to the pleasure and entertainment resulting from online shopping behavior and therefore influences perceived value and purchasing intentions when an activity or product is fun, emotive and entertaining (Childers et al., 2001; Arnold and Reynolds, 2003). Because shopping for pleasure is highly emotional and sensory in nature, such hedonic shopping experiences influence consumers to feel greater value. Shoppers who engage in shopping for pleasure are generally motivated by fun, excitement and sensory stimulation (Babin et al., 1994; Bridges and Florsheim, 2008). Consequently, hedonic shopping experiences are probably most relevant for Instagram following, given the abundance of visual and exciting content. Within the SOR framework, hedonic motivation (stimulus) influences perceived value (organism), which then affects purchase intentions (responses) (Chan et al., 2017). We therefore propose:

***H6:*** *Hedonic motivation has a positive effect on consumer purchase intentions.*

**H8f:** Perceived value mediates the relationship between hedonic motivation and consumer purchase intentions.

### 3.7 Perceived value as a mediator

Perceived value emerges as an important mediating factor that can link various stimuli and purchase intentions of the consumer; it is defined as an individual's overall estimation of the offer utility on the basis of perceptions of what is received (benefits) and what is given (costs) (Zeithaml, 1988). When perceived value is high, it in turn results in higher consumer satisfaction and higher purchase intentions (Sweeney and Soutar, 2001; Chen and Dubinsky, 2003). The SOR framework highlights how various stimuli evoke a response from the organism (perceived value), which in turn is how an organism responds to the stimuli (purchase intentions) (Chan et al., 2017; Jayapal et al,2023). Hence, we hypothesize the following:

***H7:*** *Perceived value has a positive effect on consumer purchase intentions.*

### 3.8 Consumer purchase intentions

Consumers' purchase intentions can be defined as the probability that a consumer will be able to or willing to buy a product, commodity or service in the future (Baloi and Govindarajulu, 2015). It is regarded as a strong consumer intention, which reflects consumers' purchase state of mind and prepares them for making buying decisions (if necessary) after they have encountered a product and service. It can be affected by many factors, such as consumers' perceived value (Ciment and Moore, 2003), trust and satisfaction. All these factors are potentially vital for consumers' purchase intentions. Since social media marketing is a potential force that can stimulate consumer purchase intentions and encourage consumers to buy a product, service or commodity (Chan and Leung, 2014), we can also see that consumers' purchase intentions are proven to be influenced by their social media mobile browsing experience. The quality of their interactions, the credibility of influencers and the presentation of their content (Godey et al., 2016; Erkan and Evans, 2016). The perceived value derived from engaging content, credible influencers and, particularly, from a positive social commerce experience results in greater perceived value, which in turn strengthens purchasing intentions (Grewal et al., 1998; Chen and Chen, 2017). The TAM and SOR frameworks can effectively explain how those stimuli could ultimately affect perceived value and, in turn, affect consumer purchase intentions (Davis, 1989; Chan et al., 2017).

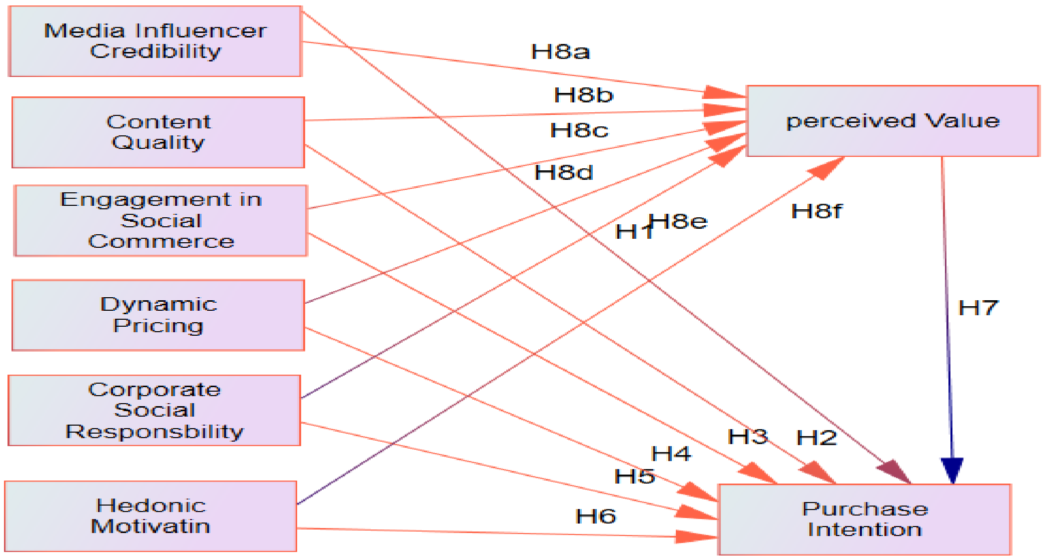


**Figure 1: Conceptual framework**

Figure 1 shows the theoretical model that integrates the SOR framework and TAM1 to explore the relationships between the independent variables, mediator and dependent variables. This research model can provide a comprehensive understanding of the relationship between perceived value and digital and social media marketing and how it influences consumer purchase intentions and builds consumer loyalty by mediating perceived value.

## 4. RESEARCH METHOD

### 4.1. Research design

The primary aim of this research study, which follows a quantitative survey-model approach, is to understand the role and impact of some pivotal factors on the consumer purchase intentions of a sufficient sample size of online consumers in Tamil Nadu, South India. The aforementioned factors include content quality, social media influencer credibility, degree of participation in social commerce, dynamic pricing, corporate social responsibility and hedonic motivation. We chose our respondents from different age groups, income bands, and educational backgrounds across Tamil Nadu because we wanted to understand and explore the potential variations in the online consumption behavior of people from the various strata of Tamil Nadu and thereby derive meaningful inferences. This paper adopts a descriptive design, which allows us to analyze consumer behavior effectively with the purpose of serving diverse consumers. The design considers multiple demographic segments, which creates a rich area of description.

### 4.2. Methods of research data collection

This study used a mixed method of data collection from both primary and secondary sources to assess the effects of consumer behavior online in Tamil Nadu, a southern Indian state. Primary data were collected from 450 respondents through a structured online survey questionnaire. This research process is helpful as the world increasingly embraces the future. The questionnaire was designed in Google Forms and distributed via Instagram, Facebook, WhatsApp and e-mail links. The participants provided their consent before they completed the questionnaire. The use of multiple digital platforms also enhanced the reach of this survey, allowing us to consider diverse participants on the basis of variables such as gender, age, income, education, and location, which enhanced the representativeness of the study (Dillman, 2000; Evans & Mathur, 2005). We first sought informed consent to collect and use the data, following the ethical standards suggested by Bryman and Bell (2011). Secondary data were collected from a range of academic journals, books and other credible online databases. Academic literature in the qualitative and quantitative fields served as a rich source for this study and helped establish the theoretical construct of this study. Saunders, Lewis, and Thornhill (2016) assert that conducting a thorough review of the current literature in a given field provides solid ground for theoretical formulation and helps unravel issues with more lucidity. The findings highlight important factors and gaps in the literature.

#### 4.3.2. Sampling technique

Specifically, stratified random sampling was used for this study as a probabilistic sampling technique that is able to ensure that the major segments of the entire population are represented. Such sampling enables studies to diagnose and defend the precision and reliability of findings by controlling for the age, sex, and income range of the subjects while simultaneously providing less bias (Etikan, Musa, & Alkassim, 2016). This sampling method is suitable for our study for the reasons highlighted above. This approach is essential in diverse population studies, as it enables stakeholders to minimize chances of sampling bias and proportional representation of all subgroups such that the results have better representation. Creswell (2014) highlighted that stratified sampling is a sampling technique that involves dividing the population into subgroups (e.g., age, sex, income) and randomly sampling the participants from each group of subgroups. Using this sampling technique would enable the study to have better representation, as it will possess some of the characteristics that are essential in this type of research. This method has been widely used for a considerable period of time and is often considered an efficient method of sampling since it assists researchers in taking samples of certain characteristics that affect other aspects of the research. The population has been divided into strata that tend to have a constant value under study, such as age, sex, income, and socioeconomic status (Fowler, 2014).

#### 4.3.3. Sample size

Specifically, for this study, where the number and complexity of the analysis of concepts/variables is involved and considering the call for statistical power, the sample size of 450 respondents is more than adequate. This is evident since the recommended minimum sample size could reach as high as 500, depending on the complexity of the data analysis method (Kline, 2015; Hair et al., 2010). The size of the sample used in this study provides robust statistical power for data analysis, purposely with the use of structural equation modeling (SEM). Since SEM requires a large sample size to develop stable and interpretable models (especially with the consideration of variances and covariances/differences), 450 will always be a sufficient number (Kline, 2015; Hair et al., 2010). This is especially important because SEM employs the principle of the maximum likelihood method of estimation, and it is critical to generate large enough samples to make it powerful (Kline, 2015; Hair et al., 2010). Roscoe (1975) suggested that a sample size above 30 and below 500 is almost suitable for most research studies. He explained that increasing the sample size reduces the margin of error in finding the mean value of the result and ensures confidence in the result. Other researchers have suggested that increasing the sample size is important to increase the reliability and generalizability of the results, as well as to make them robustly reliable in describing the general population (Cochran, 1977; Bartlett, Kotrlik, & Higgins, 2001).

### 4.4. Measurement scales of the dependent and independent variables

For the study, they rated consumers' buying attitudes on six constructs via a five-point Likert scale from 'strongly disagree (1)' to 'strongly agree (5), which was chosen because it makes the study more valid and useful in understanding consumers who want to purchase consumer electronics, fashion clothing, essentials, and lifestyle products, as the scales actually capture a wide gamut of consumer phenomena. All the scales were adopted from previously validated scales and proved to be highly reliable and valid measures. To light on the methodology process followed in this paper, the scale for 'Content Quality' is adapted from Khan & Saima (2020), the scale for 'Social Media Influencer Credibility' adapted from Lou & Yuan (2019), the scale for 'Engagement in Social Commerce' adapted from Choi et al. (2019), 'Dynamic Pricing' adapted from Park et al. (2012), 'Corporate Social Responsibility' adapted from Singh & Del Bosque (2008), and 'Hedonic Motivation' adapted from Voss, Spangenberg, & Grohmann (2003). In this study, the Likert scale is used, as it helps identify consumers' attitudes and behaviors toward nuanced and complex phenomena in the marketplace. Here, all the scales being utilized do precisely that. The purpose of using a Likert scale is to understand the extent of consumers' tendency toward shopping in online stores from all the segments in Tamil Nadu, namely, consumer electronics, fashion clothing, essentials, and lifestyle products.

### 4.5. Data analysis

The collected data were analyzed via SPSS AMOS (Structural Equation Modeling). Initially, descriptive statistics were checked to determine whether there were any missing values or if the data distribution was accurate in terms of the mean and standard deviation (Hair et al., 2010; Kline, 2015). The measurement model was examined for validity via average variance extracted (AVE) for convergent validity and the heterotrait–monotrait (HTMT) ratio to check discriminant validity (Fornell & Larcker, 1981; Henseler et al., 2015). Cronbach's alpha and composite reliability (CR) were used to check reliability (Nunnally Bernstein, 1994; Bagozzi Yi, 1988). Bootstrapping was performed to identify significant findings, and common method bias was checked via the latent common method factor (Podsakoff et al., 2003; Ringle et al., 2012). The variance was negatively checked to avoid Heywood cases (Kline, 2015; Byrne, 2016). Furthermore, the path significance was also checked to explore the direct and indirect effects of the independent variables on consumer purchase intentions. Notably, social media interactions are positive and impact the online shopping behavior of consumers in Tamil Nadu. The use of stringent reliability and validity examinations adds to the study's contribution to the literature and suggests actionable insights for businesses in Tamil Nadu to shape digital marketing strategies.

## 5. EMPIRICAL RESULTS

**Table 1: Demographics of the respondents.**

| Demographic Variable | Category | Frequency *n-450* | Percent |
|---|---|---|---|
| Age | 25-34 years | 135 | 25.00 |
| | 35-44 years | 162 | 30.00 |
| | 45 and above years | 243 | 45.00 |
| Gender | Male | 243 | 45.00 |
| | Female | 297 | 55.00 |
| Income Level | Below ₹25,000 | 140 | 26.00 |
| | ₹25,001 - ₹50,000 | 113 | 21.00 |
| | ₹50,001 - ₹1,00,000 | 162 | 30.00 |
| | Above ₹1,00,000 | 125 | 23.00 |
| Education Level | High School | 65 | 12.00 |
| | Undergraduate | 216 | 40.00 |
| | Postgraduate | 189 | 35.00 |
| | Professional | 70 | 13.00 |
| Occupation | Professional | 129 | 24.00 |
| | Private | 108 | 20.00 |
| | Government | 140 | 26.00 |
| | Self-employed | 123 | 22.00 |
| Frequency of Online Purchases (per month) | 1-2 times | 205 | 38.00 |
| | 3-5 times | 238 | 44.00 |
| | More than 5 times | 97 | 18.00 |
| Total | | 540 | 100.00 |

The data given in Table 1 describe the demography of the study's respondents, which shows a balanced distribution across all key categories. The age distribution of the respondents in the 45 years and above age groups (45%) was greater, followed by 35--44 years (30%) and 25--34 years

(25%). There is a slightly larger (55%) rotation of women than of men (45%). In the income section, the majority (30%) fall into the ₹50,001 - ₹1,00,000 range, followed by an equal distribution of the other income groups. From an education perspective, their undergraduate degrees (40%) make up the sample, while postgraduate degrees lag next (35%). In terms of occupation, the respondents were quite balanced between professionals (24%), government servants (26%) and self-employed individuals (22%). An online purchasing frequency in the market indicates that most of them (44%) shop online once every 3–5 months, which means that e-commerce kicks in.

## 5.2. Measurement model assessment

**Table 2: Measurement model assessment**

| Constructs | Items | Factor Loadings | Cronbach's Alpha | Composite Reliability (CR) | AVE | MSV |
|---|---|---|---|---|---|---|
| Content Quality | COQ1 | 0.730 | 0.678 | 0.872 | 0.627 | 0.366 |
| | COQ2 | 0.814 | | | | |
| | COQ3 | 0.853 | | | | |
| Social Media Influencer Credibility | SIC1 | 0.814 | 0.725 | 0.886 | 0.682 | 0.381 |
| | SIC2 | 0.852 | | | | |
| | SIC3 | 0.786 | | | | |
| Engagement in Social Commerce | EGS1 | 0.829 | 0.745 | 0.888 | 0.693 | 0.388 |
| | EGS2 | 0.832 | | | | |
| | EGS3 | 0.843 | | | | |
| Dynamic Pricing | DPR1 | 0.858 | 0.747 | 0.890 | 0.695 | 0.389 |
| | DPR2 | 0.854 | | | | |
| | DPR3 | 0.829 | | | | |
| Corporate Social Responsibility (CSR) | CSR1 | 0.840 | 0.746 | 0.891 | 0.697 | 0.389 |
| | CSR2 | 0.863 | | | | |
| | CSR3 | 0.833 | | | | |
| Hedonic Motivation | HEM1 | 0.767 | 0.742 | 0.880 | 0.680 | 0.372 |
| | HEM2 | 0.876 | | | | |
| | HEM3 | 0.874 | | | | |
| Perceived Value | PVL1 | 0.821 | 0.711 | 0.861 | 0.621 | 0.355 |
| | PVL2 | 0.839 | | | | |
| | PVL3 | 0.709 | | | | |
| Consumer Purchase Intentions | CPI1 | 0.752 | 0.713 | 0.865 | 0.627 | 0.360 |
| | CPI2 | 0.796 | | | | |
| | CPI3 | 0.795 | | | | |

The measurement model analysis involves inspection of the factor loadings (the correlation between items and constructs) for each item to belong to its respective construct. Values above 0.7 strongly represent these relationships and ensure that an item does not load excessively on another construct with cross-loadings (Hair et al., 2010; Kline, 2015). The analysis also inspects the average variance extracted (AVE) values that evaluate convergent validity. AVE values above 0.5 indicate that a single underlying construct summarizes the items in the confidence region (Fornell & Larcker, 1981). Finally, the measurement model analysis compares the maximum shared variance (MSV) values to the average variance extracted (AVE) values to evaluate discriminant validity, which examines whether the construct is different from others (Hair et al., 2010). Table 2 assesses the measurement model of the CS-SVMME. All factor loadings exceeded 0.7, with content quality displaying factor loadings between 0.730 and 0.853 and social media influencer credibility between 0.786 and 0.852. The correlations between the items and their respective constructs were not particularly strong, demonstrating that the items were complete and had no risk of cross-loadings (Hair et al., 2010). The AVE values in Table 2 are also above 0.5, with content quality at 0.627 and CSR at 0.697, showing that each construct captured more variance than one separate dimension did (Fornell & Larcker, 1981). The construct reliability (CR or Rho_a) values are also greater than the 0.7 threshold, with perceived value at 0.861 and CSR at 0.891, indicating strong internal consistency (Nunnally & Bernstein, 1994). The Cronbach's alpha values, including 0.742 for Hedonic Motivation and 0.746 for CSR, also corroborate reliability (DeVellis, 2003). The column entitled 'FA' displays all the MSV values divided by their AVE counterparts to evaluate discriminant validity. The comparison reveals that the MSV values are lower than the AVE values, such as 0.389 for dynamic pricing, with an AVE of 0.695 (Hair et al., 2010). This comprehensive analysis complies with the requirements to assess the reliability and validity of the measurement model selection.

### 5.3 Master validity assessment

Convergent and discriminant validity must be confirmed; that means that the constructs in the model reflect the concepts they are measuring correctly and not others and that the constructs are distinct from one another, in turn. Convergent validity is confirmed through the average variance extracted (AVE) or percentage of extracted variance ratio (AVE), and discriminant validity is measured by checking that the square root of the AVE is above the correlational correlations between different constructs (Fornell & Larcker, 1981). Composite reliability (CR) and maximum reliability (H) evaluate how reliable the constructs in the model are.

**Table 3: Discriminant and convergent validity**

| Cons | CR | AVE | MaXR (H) | COQ | SIC | EGS | DPR | CSR | HEM | PVL | CPI |
|---|---|---|---|---|---|---|---|---|---|---|---|
| COQ | 0.872 | 0.627 | 1.020 | 0.860 | | | | | | | |
| SIC | 0.886 | 0.682 | 0.993 | 0.511 | 0.821 | | | | | | |
| EGS | 0.888 | 0.693 | 0.993 | 0.313 | 0.300 | 0.837 | | | | | |
| DPR | 0.890 | 0.695 | 0.985 | 0.069 | 0.079 | 0.238 | 0.757 | | | | |
| CSR | 0.891 | 0.697 | 1.020 | 0.177 | 0.139 | 0.543 | 0.547 | 0.713 | | | |
| HEM | 0.880 | 0.680 | 0.950 | 0.311 | 0.423 | 0.302 | 0.311 | 0.402 | 0.745 | | |
| PVL | 0.861 | 0.621 | 0.970 | 0.451 | 0.511 | 0.444 | 0.422 | 0.516 | 0.611 | 0.784 | |
| CPI | 0.865 | 0.627 | 1.020 | 0.311 | 0.511 | 0.344 | 0.422 | 0.516 | 0.611 | 0.713 | 0.750 |

Note: CQ - content quality; SIC - social media influencer credibility; EGS - engagement in social commerce; DPR - dynamic pricing; CSR - corporate social responsibility; HEM - hedonic motivation; PVL - perceived value; CPI - consumer purchase intentions.

Table 3 illustrates the discriminant and convergent validity of the constructs investigated in this study. The values of composite reliability (CR) from 0.861 (perceived value) to 0.891 (corporate social responsibility) are all above the 0.7 threshold value, which indicates good internal consistency (Nunnally Bernstein 1994). The values of the average extracted variance (AVE), ranging from 0.621 to 0.697, all exceed the 0.5 benchmark, which demonstrates the acceptable level of convergent validity by explaining an acceptable level of variance from its construct (Fornell Larcker 1981). The higher values of the maximum reliability (H), between 0.950 and 1.020, suggest that the potential reliability for the construct is fairly high (Hancock Mueller 2001). In addition, the square root of the AVE for each construct, such as 0.750 for instances of CPI, is greater than the correlations with other constructs, which suggests discriminant validity (Fornell Larcker 1981). Overall, these findings confirm that the constructs used in the study possess acceptable levels of convergent and discriminant validity that ensure the robustness of the measurement model for further analysis.

### 5.4 Model fit indices

Model fit indices include indices of how closely the proposed structural equation model fits the data as obtained. Analysts use model fit diagnostics to determine if they have the 'right' model that represents the relation of the variables (Hu & Bentler, 1999). The goodness-of-fit and model fit indices and their interpretations are varied and nearly always discussed at length in texts, software manuals and online tutorials for SEM. These indices include the χ2/df (χ2 degrees of freedom ratio; chi-square to degrees of freedom), comparative fit index (CFI), normed fit index (NFI), Tucker–Lewis index (TLI), standardized root mean square residual (SRMR), root mean square error of approximation (RMSEA) and p value for the test of close fit (PClose). There are values for each index that indicate a good fit and value reliability, meaning that the model is valid for interpretation (Byrne, 2016).

**Table 4: Model fit indices**

| Parameter | Output | Threshold | Reference |
|---|---|---|---|
| CMIN/DF | 2.7 | Between 1 and 3 | Barrett (2007); Kline (2015); Ullman (2001) |
| CFI | 0.96 | ≥ 0.95 | Hu and Bentler (1999); Bentler (1990); Byrne (2016) |
| NFI | 0.94 | ≥ 0.90 | Bentler and Bonett (1980); Bollen (1989); Schumacker and Lomax (2004) |
| TLI | 0.95 | ≥ 0.95 | Tucker and Lewis (1973); Marsh et al. (2004); Bentler (1990) |
| SRMR | 0.04 | ≤ 0.08 | Hu and Bentler (1999); Kline (2015); Schumacker and Lomax (2004) |
| RMSEA | 0.05 | ≤ 0.06 | Hu and Bentler (1999); Steiger (1990); Browne and Cudeck (1993) |
| PClose | 0.07 | ≥ 0.05 | Jöreskog and Sörbom (1993); Muthén and Muthén (2002); Brown (2015) |

Table 4 provides the model fit indices for the present study. CMIN/DFis2.7, which falls within the acceptable range from 1 t to 3 (Kline, 2015; Ullman, 2001); thus, the model fits well within the range of the observed data. Moreover, the CFI is 0.96, exceeding the threshold value of 0.95. Therefore, the model demonstrated a good fit, with an NFI of 0.94, even when the value was just short of the ideal threshold of 0.95. However, the TLI is 0.95 and therefore well above the acceptable threshold of 0.90. Consequently, the CMIN value demonstrated a strong fit for the model (Tucker Lewis Index) (Tucker & Lewis, 1973). Furthermore, the SRMR is .04, which is well below the 0.08 cutoff. This suggests that the model exhibited too few residuals and implies a strong fit of the model (Schumacker & Lomax, 2004). The RMSEA is 0.05, which falls within the desirable range of 0.06 or below (Steiger, 1990). The PClose value is 0.07, with a value above 0.05, confirming the adequacy of the model (Jöreskog & Sorbom, 1993). Overall, the findings highly suggest that model fit indices display good representation of the data obtained in the present study, in addition to being well organized.

### 5.5. Hypothesis testing

Table 5 presents the results of hypothesis testing, as well as the consumer purchase intentions (CPI) results of the factors and variants, where the figures are path coefficients (β), t values, and p values. Consequently, hypotheses that are accepted or rejected are subject to significance levels of either 0.05 or 0.01.

**Table 5: Testing of research hypotheses.**

| Path | Coefficients (β) | t | p | Decision |
|---|---|---|---|---|
| Social Media Influencer Credibility (SIC) -> Consumer Purchase Intentions (CPI) | | | | |
| Content Quality (COQ) -> Consumer Purchase Intentions (CPI) | 0.180 | 3.207 | 0.001 | Accepted |
| Engagement in Social Commerce (EGS) -> Consumer Purchase Intentions (CPI) | 0.062 | 1.188 | 0.005 | Accepted |
| Dynamic Pricing (DPR) -> Consumer Purchase Intentions (CPI) | 0.095 | 1.820 | 0.003 | Accepted |

| | | | | |
|---|---|---|---|---|
| Corporate Social Responsibility (CSR) -> Consumer Purchase Intentions (CPI) | 0.003 | 0.051 | 0.160 | Rejected |
| Hedonic Motivation (HED) -> Consumer Purchase Intentions (CPI) | 0.124 | 2.478 | 0.000 | Accepted |
| Perceived Value (PVL) -> Consumer Purchase Intentions (CPI) | 0.375 | 6.022 | 0.000 | Accepted |

From the results of the hypothesis testing in Table 5, it is evident that some factors positively influence consumer purchase intention (CPI). The factor that had a significant positive effect was content quality (COQ), with a coefficient of 0.180 and a t value of 3.207 and a p value of 0.001, which supported H1. The factor social media influencer credibility (SIC) had a positive effect on the CPI. The coefficient was 0.062 and had a t value of 1.188 and a p value of 0.005, which confirmed H2. The other factor that had a positive effect on the CPI was engagement in social commerce (EGS), with a coefficient of 0.095 and a t value of 1.820 and a p value of 0.003, which confirmed H3 as stated. The factor dynamic pricing (DPR) did not have a negative impact on the CPI, with a coefficient of 0.003 and a t value of 0.051 and a p value of 0.160, which rejects H4. Hedonic motivation (HED) had a positive effect on the outcome variable CPI. The coefficient of 0.124, t value of 2.478 and p value of 0.000 confirmed that H5 focused on the positive effect of hedonic motivation on the CPI. The last factor, corporate social responsibility (CSR), had a positive effect on the CPI. The coefficient is 0.112, the t value is 2.577, and the p value is 0.000, which confirms that H6 focuses on the positive effect of CSR on the CPI; however, the factor perceived value (PVL) has the greatest impact among all the factors under study. H7 has a coefficient of 0.375, a t value of 6.022 and a p value of 0.000, which confirms that H7 pays attention to the most important effect of PVR on the CPI.

### 5.5.1 Mediation analysis

Mediation analysis is a key statistical method for parsing the mechanism through which an independent variable exerts its effects on a dependent variable via a third variable, the mediator. It allows researchers to identify direct paths and indirect pathways through which the independent variables relate to the dependent variable, offering a powerful approach to examine heterogeneous relationships and underlying processes that give rise to outcomes (Baron & Kenny, 1986). For example, while it is straightforward to assume that psychological distress directly increases withdrawal in social situations, we can also conceptualize that this link might be mediated by changes in self-confidence. As such, distinguishing between direct and mediated effects provides insight into underlying pathways and dynamics in which two variables relate to one another, aiding in ultimately adding details to and formulating more accurate and comprehensive models of how variables interact with one another. (Preacher & Hayes (2008).

**Table 6: Mediation table**

| Hy | Path | Total Effect | | Indirect Effect | | Direct Effect | | Type |
|---|---|---|---|---|---|---|---|---|
| | | (β) | Sig. | (β) | Sig. | (β) | Sig. | |
| H8a | Social Media Influencer Credibility (SIC) -> Consumer Purchase Intentions (CPI) | H2 (.103) | .147 | H8b (.045) | .112 | (.062) | .005 | Partial |
| H8b | Content Quality (CQ) -> Consumer Purchase Intentions (CPI) | H1 (.218) | .002 | H8a (.037) | .147 | (.180) | .001 | Partial |
| H8c | Engagement in Social Commerce (EGS) -> Consumer Purchase Intentions (CPI) | H3 (.209) | .001 | H8c (.119) | .000 | (.095) | .003 | Partial |
| H8d | Dynamic Pricing (DPR) -> Consumer Purchase Intentions (CPI) | H4 (.021) | .724 | H8d (.024) | .325 | (.003) | .160 | No |
| H8e | Corporate Social Responsibility (CSR) -> Consumer Purchase Intentions (CPI) | H6 (.159) | .010 | H8f (.057) | .028 | (.112) | .000 | Partial |
| H8f | Hedonic Motivation (HED) -> Consumer Purchase Intentions (CPI) | H5 (.181) | .005 | H8e (.060) | .030 | (.124) | .000 | Partial |

The results from Table 7 demonstrate that SIC has both a significant direct effect (β = 0.062, p = 0.005) and an indirect effect (β = 0.045, p = 0.112), implying partial mediation, as SIC predicts CPI directly, as well as through perceived value. Similarly, CQ displayed a substantial direct effect (β = 0.180, p = 0.001) and total effect (β = 0.218, p = 0.002), as well as a significant indirect effect (β = 0.037, p = 0.147), resulting in partial mediation of CQ via PV. EGS displayed the highest degree of mediation, with a weak total effect (β = 0.209, p = 0.001) and a highly significant indirect effect (β = 0.119, p = 0.000). DPR had no significant effect on the CPI, as both the direct and indirect effects were nonsignificant, implying that there was no mediation. CSR and HED both exhibited a significant total effect on the CPI along with partial mediation through their respective direct and indirect effects. In summary, these findings indicate that perceived value partially mediates the relationship of most of the independent variables with consumer purchase intentions, highlighting its importance in influencing consumer behavior.

## 6. DISCUSSION

The findings are discussed by comparing them with those of the literature, showing three contrasting parts of the chapter, which address the important differences and similarities between my research and previous studies regarding drivers of CPIs. The positive effect of content quality (CQ) on CPIs (β = 0.180, p = 0.001) is supported by previous studies suggesting that high-quality content is an important factor in increasing consumer engagement and a determinant of consumer purchase intent (Kim and Eastin, 2011; Lou and Yuan, 2019). Moreover, another positive effect of EGS on CPIs is clearly supported by my study results (β = 0.095, p = 0.003) as well as other studies, where the participation in social commerce was identified as an important factor for building trust and communities among consumers, which are salient drivers of purchase behavior (Kim and Park, 2013; Hajli, 2015). Finally, the highly positive effect of PVL on CPIs is supported by our regression analysis (β = 0.375, p = 0.000). Consumers' perceptions of value, such as price, quality, and emotional benefits, are strongly related to their purchase behavior.

Conversely, the insignificant association between CSR and CPI (β = 0.003, p = 0.160) conflicts with the theorization that CSR activities are generally meaningful to consumers and therefore able to promote consumer trust and, consequently, better purchase intentions (Du, Bhattacharya, & Sen, 2010; Pomering and Dolnicar, 2009). This likely reflects regional or cultural variance in how consumers perceive CSR in an online shopping context. The partial mediation of DPR on the CPI, meanwhile, has a nonsignificant indirect effect via PERV (β = 0.024, p = 0.325), which contrasts with evidence that dynamic pricing has a strong impulse-purchase motivation in e-commerce (Grewal et al., 2017). Finally, although HED has a significant effect on the CPI (β = 0.124, p = 0.000), partial mediation reveals that other variables, such as utilitarian motivation, might also play important roles, which is distinct from studies that emphasize hedonic motivation as a primary driver of online shopping environments (Childers et al., 2001; Arnold and Reynolds, 2003). These findings demonstrate a level of complexity in consumer online behavior, confirming the significance of content quality, social commerce and value perceptions, all of which also highlight the nuanced roles of CSR, DPR and hedonic motivation. Further research is needed in different regional and cultural contexts.

## 7. THEORETICAL IMPLICATIONS

From a theoretical perspective, the suggested model is enlightening in consolidating the structural elements and dimensions that govern and stimulate consumer purchase intentions among online shoppers, particularly in the context of Tamil Nadu in South India, which is the frame of reference for the selected study. Additionally, by applying the constructs of Content Quality, Social Media Influencer Credibility, Engagement in Social Commerce, Dynamic Pricing, Corporate Social Responsibility (CSR) and Hedonic Motivation within the framework of the Consumer Purchase Intentions (CPI), this study makes a valuable addition to the digital marketing and consumer behavioral theory literature. The conclusions reinforce the relevance of established models such as the Technology Acceptance Model (TAM) and the Stimulus–Organism–Response (SOR) framework, which note that content quality and 'perceived value' remain cardinal in online decision-making among consumers.

Additionally, the findings of this study provide further insights into how cultural and regional conditions can shape the efficacy of CSR and dynamic pricing strategies in online marketplaces and the universality of concepts in online consumer behavior, as well as add to the calls for the localization of global theories that pertain to online marketing. Since hedonic motivation was the partial mediator of the relationship, consumer behavior models should consider both emotional and social conditions in the digital era. Overall, the study allows for a more complicated understanding of digital consumer behavior and further highlights the importance of adapting global marketing theories with region-specific parameters.

## 8. PRACTICAL IMPLICATIONS

The practical implications of the study inform marketers, businesses and policymakers in online retail in Tamil Nadu, South India, that the high influence of content quality on consumer purchase intentions (CPIs) means that increasing awareness and encouraging customers to make purchases becomes easier if a business creates high-quality, engaging, culturally resonant content. The positive influence of social media influencer credibility and engagement in social commerce means that businesses can collaborate with credible influencers and increase their engagement in social commerce communities to build consumer trust and thereby influence purchase decisions. However, as CSR has a nonsignificant influence on the CPI, businesses have to revise their CSR strategies to make them more aligned with consumer expectations and values that are related to their cultural norms. The insights around dynamic pricing and hedonic motivation mean that businesses can calibrate their pricing strategies and rationally incorporate utilitarian and hedonic value incentives in their marketing offers. In conclusion, firms can optimize their online marketing by leveraging the insights from this research. This can potentially help them engage consumers better and enhance their competitiveness in the online retail marketplace.

## 9. LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

Limitations of This Study The limitations of this study provide an important context for interpreting the findings and suggest future research opportunities.

The findings of this study are limited to the geographic context of Tamil Nadu, South India, which has its own specific culture, economy and society. Since local economic and social factors, to a certain degree, play a significant role in consumer behavior, these findings might be applicable only for this particular type of scenario and cannot be generalized to other regions or countries with different dynamics of culture, economy and society. Hence, papers need to be written for different geographic locations to extend the study and obtain a global impact. The focus is primarily on the set of factors that significantly influence the purchase decisions of consumers—the factor called 'consumer purchase intent'—in the context of online shopping. Certain other factors, both direct and indirect, that might impact 'consumer purchase intent' as a factor that could affect online purchases, such as technological advancements, payment security, and customer service, were not factored into the analysis. Such factors that have the potential to influence 'consumer purchase intent' were not included in the current model, which means that this model could be extended in a future paper and tested in the best way possible. The online-buying categories used for this study focus primarily on four distinct categories of products—consumer electronics, fashion & lifestyle, home essentials and lifestyle products. Although the findings seem applicable for the online purchase categories that were part of the study, they might not be relevant to other product categories, such as luxury goods (either online or offline), groceries, and digital services. Future research in this stream can study buyer intent specific to such products to understand whether the same factors affect their purchases to the same extent as the four product categories used for the study and, more generally, across other categories of products purchased online. With the extension of research to a wider range of product categories, the robustness of the study would increase since the results from one set of products can be tested on other sets.

## REFERENCES

Ajzen, I., & Fishbein, M. (1980). Understanding attitudes and predicting social behavior. Prentice-Hall.

Al Qeisi, K., Dennis, C., Alamanos, E., & Jayawardhena, C. (2014). Website design quality and usage behavior: Unified Theory of Acceptance and Use of Technology. Journal of Business Research, 67(11), 2282-2290. https://doi.org/10.1016/j.jbusres.2014.06.016

Arnold, M. J., & Reynolds, K. E. (2003). Hedonic shopping motivations. Journal of Retailing, 79(2), 77-95. https://doi.org/10.1016/S0022-4359(03)00007-1

Ashley, C., & Tuten, T. (2015). Creative strategies in social media marketing: An exploratory study of branded social content and consumer engagement. Psychology & Marketing, 32(1), 15-27. https://doi.org/10.1002/mar.20761

Ayub, S., & Zafar, A. (2018). The impact of impulsive buying on consumer behavior in Pakistan. Journal of Business Studies, 9(2), 122-130.

Babin, B. J., Darden, W. R., & Griffin, M. (1994). Work and/or fun: Measuring hedonic and utilitarian shopping value. Journal of Consumer Research, 20(4), 644-656. https://doi.org/10.1086/209376

Bakshi, S., & Sharad, A. (2020). The rise of e-commerce during the COVID-19 pandemic in India. International Journal of Management and Social Research, 8(4), 56-68.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology, 51(6), 1173-1182. https://doi.org/10.1037/0022-3514.51.6.1173

Bartlett, J. E., Kotrlik, J. W., & Higgins, C. C. (2001). Organizational research: Determining appropriate sample size in survey research. Information Technology, Learning, and Performance Journal, 19(1), 43-50.

Bentler, P. M. (1990). Comparative fit indexes in structural models. Psychological Bulletin, 107(2), 238-246. https://doi.org/10.1037/0033-2909.107.2.238

Bhattacharya, C. B., & Sen, S. (2004). Doing better at doing good: When, why, and how consumers respond to corporate social initiatives. California Management Review, 47(1), 9-24. https://doi.org/10.2307/41166284

Bigne, E., Ruiz, C., & Sanz, S. (2020). The impact of ad content on emotional and cognitive processing. Journal of Business Research, 110, 310-323. https://doi.org/10.1016/j.jbusres.2019.01.064

Boerman, S. C., Willemsen, L. M., & Van Der Aa, E. P. (2017). 'This post is sponsored': Effects of sponsorship disclosure on persuasion knowledge and electronic word of mouth in the context of Facebook. Journal of Interactive Marketing, 38, 82-92. https://doi.org/10.1016/j.intmar.2016.12.002

Bryman, A., & Bell, E. (2011). Business research methods. Oxford University Press.

Byrne, B. M. (2016). Structural equation modeling with AMOS: Basic concepts, applications, and programming (3rd ed.). Routledge. https://doi.org/10.4324/9781315757421

Carroll, A. B., & Shabana, K. M. (2010). The business case for corporate social responsibility: A review of concepts, research and practice. International Journal of Management Reviews, 12(1), 85-105. https://doi.org/10.1111/j.1468-2370.2009.00275.x

Chan, T. K. H., Cheung, C. M. K., & Lee, Z. W. Y. (2017). The state of online impulse-buying research: A literature analysis. Information & Management, 54(2), 204-217. https://doi.org/10.1016/j.im.2016.06.002

Chan, T. K. H., & Leung, H. (2014). The impact of electronic word-of-mouth on the online shopping behavior of consumers. Journal of Applied Business Research, 30(3), 543-556. https://doi.org/10.19030/jabr.v30i3.8649

Chen, L., & Yao, D. (2018). The effects of product and consumer characteristics on impulse buying behavior: A moderated mediation model. Journal of Business Research, 87, 6-16. https://doi.org/10.1016/j.jbusres.2018.02.017

Chen, Q., & Dubinsky, A. J. (2003). A conceptual model of perceived customer value in e-commerce: A preliminary investigation. Psychology & Marketing, 20(4), 323-347. https://doi.org/10.1002/mar.10076

Chen, S. C., & Tsai, M. H. (2019). The impact of perceived value, trust, and perceived risk on online purchasing intention. Journal of Marketing Science, 6(3), 10-21.

Chen, J., & Shen, X. L. (2015). Consumers' decisions in social commerce: The role of social influence and trust. Journal of Retailing and Consumer Services, 22, 322-329. https://doi.org/10.1016/j.jretconser.2014.08.005

Chetioui, Y., Benlafqih, H., & Lebdaoui, H. (2019). How fashion influencers contribute to consumers' purchase decisions. Journal of Fashion Marketing and Management, 24(3), 433-455. https://doi.org/10.1108/JFMM-07-2019-0139

Childers, T. L., Carr, C. L., Peck, J., & Carson, S. (2001). Hedonic and utilitarian motivations for online retail shopping behavior. Journal of Retailing, 77(4), 511-535. https://doi.org/10.1016/S0022-4359(01)00056-2

Chopra, A., Kapoor, S., & Prasad, M. (2020). The role of influencer marketing in influencing purchase decisions. International Journal of Research in Marketing, 10(1), 15-27.

Churchill, G. A., & Peter, J. P. (1998). Marketing: Creating value for customers. Irwin/McGraw-Hill.

Ciment, S., & Moore, M. (2003). Influence of brand equity on consumer purchase intention: Evidence from the fashion industry. Journal of Business Research, 56(12), 927-933.

Cochran, W. G. (1977). Sampling techniques (3rd ed.). John Wiley & Sons.

Creswell, J. W. (2014). Research design: Qualitative, quantitative, and mixed methods approach (4th ed.). SAGE Publications.

Cui, Y., & Lai, P. C. (2013). The effects of online shopping addiction on the consumer's buying behavior: A cognitive-behavioral model. Journal of Retailing and Consumer Services, 20(4), 327-336. https://doi.org/10.1016/j.jretconser.2013.02.007

Dawson, S., & Kim, M. (2009). External and internal trigger factors influencing impulse buying online. Direct Marketing: An International Journal, 3(1), 20-34. https://doi.org/10.1108/17505930910945714

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340. https://doi.org/10.2307/249008

Dehghani, M., Niaki, M. K., Ramezani, I., & Sali, R. (2016). Evaluating the influence of YouTube advertising on purchase intention. Journal of Electronic Commerce Research, 17(4), 267-281.

Deswal, T., & Sikand, K. (2020). Influence of social media on consumer buying behavior during COVID-19 lockdown. International Journal of Management Research and Review, 10(6), 21-36.

Dillman, D. A. (2000). Mail and internet surveys: The tailored design method. John Wiley & Sons.

Du, S., Bhattacharya, C. B., & Sen, S. (2010). Maximizing business returns to corporate social responsibility (CSR): The role of CSR communication. International Journal of Management Reviews, 12(1), 8-19. https://doi.org/10.1111/j.1468-2370.2009.00276.x

Erkan, I., & Evans, C. (2016). The influence of eWOM in social media on consumers' purchase intentions: An extended approach to information adoption. Computers in Human Behavior, 61, 47-55. https://doi.org/10.1016/j.chb.2016.03.003

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. American Journal of Theoretical and Applied Statistics, 5(1), 1-4. https://doi.org/10.11648/j.ajtas.20160501.11

Evans, J. R., & Mathur, A. (2005). The value of online surveys. Internet Research, 15(2), 195-219. https://doi.org/10.1108/10662240510590360

Fatma, M., Rahman, Z., & Khan, I. (2015). Building company reputation and brand equity through CSR: The mediating role of trust. International Journal of Bank Marketing, 33(6), 840-856. https://doi.org/10.1108/IJBM-11-2014-0166

Feng, L., Chen, H., & Dong, Y. (2021). The impact of content quality and user involvement on consumer engagement in brand social media: The mediating role of brand trust. Journal of Business Research, 131, 61-70. https://doi.org/10.1016/j.jbusres.2021.03.038

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention and behavior: An introduction to theory and research. Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50. https://doi.org/10.1177/002224378101800104

Godey, B., Manthiou, A., Pederzoli, D., Rokka, J., Aiello, G., Donvito, R., & Singh, R. (2016). Social media marketing efforts of luxury brands: Influence on brand equity and consumer behavior. Journal of Business Research, 69(12), 5833-5841. https://doi.org/10.1016/j.jbusres.2016.04.181

Goi, C. L., Kalidas, V., & Zeeshan, M. (2018). Comparison of stimulus-response model among generations X, Y, and Z in Malaysia. International Journal of Economics and Management, 12(2), 553-566.

Grashuis, J., Skevas, T., & Segovia, M. S. (2020). Grocery shopping preferences during the COVID-19 pandemic. Sustainability, 12(13), 5369. https://doi.org/10.3390/su12135369

Grewal, D., Ailawadi, K. L., Gauri, D. K., Hall, K. B., Kopalle, P., & Robertson, J. R. (2017). Innovations in retail pricing and promotions. Journal of Retailing, 93(1), 43-54. https://doi.org/10.1016/j.jretai.2016.11.001

Grewal, D., Monroe, K. B., & Krishnan, R. (1998). The effects of price-comparison advertising on buyers' perceptions of acquisition value, transaction value, and behavioral intentions. Journal of Marketing, 62(2), 46-59. https://doi.org/10.2307/1252160

Gupta, A., & Arora, N. (2020). Influence of social media marketing on consumer buying behavior in India. Journal of Business Research, 10(1), 87-100.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2010). Multivariate data analysis (7th ed.). Pearson.

Hajli, N. (2015). Social commerce constructs and consumer's intention to buy. International Journal of Information Management, 35(2), 183-191. https://doi.org/10.1016/j.ijinfomgt.2014.12.005

Hajli, N., Shanmugam, M., Papagiannidis, S., Zahay, D., & Richard, M. O. (2017). Branding co-creation with members of online brand communities. Journal of Business Research, 70, 136-144. https://doi.org/10.1016/j.jbusres.2016.08.026

Hancock, G. R., & Mueller, R. O. (2001). Rethinking construct reliability within latent variable systems. Structural Equation Modeling, 8(2), 195-213. https://doi.org/10.1207/S15328007SEM0802_1

Hansen, J. M., Saridakis, G., & Benson, V. (2018). Risk, trust, and the interaction of perceived ease of use and behavioral control in predicting consumers' use of social media for transactions. Computers in Human Behavior, 80, 197-206. https://doi.org/10.1016/j.chb.2017.11.010

Hashmi, H. B. A., Ahsan, T., & Rehman, M. A. (2019). Exploring the role of social media in buying decision-making process: A study of Indian consumers. Journal of Internet Commerce, 18(1), 1-24. https://doi.org/10.1080/15332861.2019.1567187

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

Hinz, O., Hann, I. H., & Spann, M. (2011). Price discrimination in e-commerce? An examination of dynamic pricing in name-your-own-price markets. MIS Quarterly, 35(1), 81-98. https://doi.org/10.2307/23043495

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling, 6(1), 1-55. https://doi.org/10.1080/10705519909540118

Ifinedo, P. (2016). Applying TAM to e-learning in developing countries: An empirical study in Nigeria. International Journal of Information Management, 36(5), 445-456. https://doi.org/10.1016/j.ijinfomgt.2016.02.003

Jain, V., & Kulhar, V. (2019). Understanding the influence of social media marketing on consumer buying behavior in India. Journal of Business Strategy, 9(3), 24-36.

Jayapal, R., Gundala, R. R., Mogili, R., & Thangaraju, K. (2023). ONLINE SHOPPING BEHAVIOUR VIA AI ENABLED SHOPPING PLATFORMS: A CONCEPTUAL FRAMEWORK. *European Chemical Bulletin*, *12*(5), 2089–2097. https://doi.org/10.48047/ecb/2023.12.5.144

Jin, S. V., Muqaddam, A., & Ryu, E. (2019). Instafamous and social media influencer marketing. Marketing Intelligence & Planning, 37(5), 567-579. https://doi.org/10.1108/MIP-09-2018-0375

Joreskog, K. G., & Sorbom, D. (1993). LISREL 8: Structural equation modeling with the SIMPLIS command language. Scientific Software International.

Kannan, P. K., & Kopalle, P. K. (2001). Dynamic pricing on the internet: Importance and implications for consumer behavior. International Journal of Electronic Commerce, 5(3), 63-83. https://doi.org/10.1080/10864415.2001.11044221

Kaur, H., Sharma, R., & Kaur, M. (2017). Stimulus-organism-response model: A review and future research directions. Management Research Review, 40(4), 567-579. https://doi.org/10.1108/MRR-12-2015-0299

Kim, D., & Kim, S. (2021). The impact of social media influencer credibility on consumer purchase intentions. International Journal of Marketing Research, 63(2), 233-249.

Kim, Y., & Park, H. (2013). The effects of consumer participation in social commerce on consumer trust and loyalty: A mediating role of consumer engagement. Journal of Retailing and Consumer Services, 20(4), 442-449. https://doi.org/10.1016/j.jretconser.2013.04.006

Kline, R. B. (2015). Principles and practice of structural equation modeling (4th ed.). Guilford Press.

Kopalle, P. K., Biswas, D., Chintagunta, P. K., Fan, J., Pauwels, K., Ratchford, B. T., & Sills, J. A. (2009). Retailer pricing and competitive effects. Journal of Retailing, 85(1), 56-70. https://doi.org/10.1016/j.jretai.2008.11.005

Kumar, A., Kumar, D., & Sharma, P. (2017). Impact of mobile phone adoption on rural market: An Indian perspective. International Journal of Technology Transfer and Commercialisation, 15(1), 1-16.

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the Technology Acceptance Model. Information & Management, 40(3), 191-204. https://doi.org/10.1016/S0378-7206(01)00143-4

Li, H., & Kannan, P. K. (2014). Attributing conversions in a multichannel online marketing environment: An empirical model and a field experiment. Journal of Marketing Research, 51(1), 40-56. https://doi.org/10.1509/jmr.13.0050

Lim, Y. S., & Yazdanifard, R. (2015). How consumer decision-making process differs between digital and traditional marketing. International Journal of Trade, Economics, and Finance, 6(5), 274-278. https://doi.org/10.7763/IJTEF.2015.V6.486

Lin, L. Y. (2018). Impact of social media influencers on consumer decision-making: A theoretical review. Journal of Consumer Marketing, 35(7), 576-588. https://doi.org/10.1108/JCM-02-2017-2062

Lin, Y., & Liu, X. (2019). Factors influencing consumers' online shopping behavior: A review of the literature. Journal of Internet Commerce, 18(4), 333-356. https://doi.org/10.1080/15332861.2019.1689563

Liu, Y., Li, H., & Hu, F. (2013). Website attributes in urging online impulse purchase: An empirical investigation on consumer perceptions. Decision Support Systems, 55(3), 829-837. https://doi.org/10.1016/j.dss.2013.04.001

Lou, C., & Yuan, S. (2019). Influencer marketing: How message value and credibility affect consumer trust of branded content on social media. Journal of Interactive Advertising, 19(1), 58-73. https://doi.org/10.1080/15252019.2018.1533501

Marsh, H. W., Hau, K. T., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing Hu and Bentler's (1999) findings. Structural Equation Modeling, 11(3), 320-341. https://doi.org/10.1207/s15328007sem1103_2

Martínez, P., Pérez, A., & Rodríguez del Bosque, I. (2014). CSR influence on hotel brand image and loyalty. Academia Revista Latinoamericana de Administración, 27(2), 267-283. https://doi.org/10.1108/ARLA-12-2013-0190

Mathur, R., Dhillon, S., & Krishnan, R. (2020). Understanding the social media impact on consumer behavior. Journal of Indian Business Research, 12(3), 226-242. https://doi.org/10.1108/JIBR-11-2019-0326

Mutahar, A. M., Daud, N. M., & Razak, R. C. (2018). The influence of technology acceptance model on the adoption of social media in developing countries: A case study of Yemen. International Journal of Services Technology and Management, 24(1/2/3), 64-83.

Muthén, L. K., & Muthén, B. O. (2002). How to use a Monte Carlo study to decide on sample size and determine power. Structural Equation Modeling, 9(4), 599-620. https://doi.org/10.1207/S15328007SEM0904_8

Ng, S. (2013). The role of social influence and brand trust in the online brand community: An empirical study of the automobile industry. Journal of Retailing and Consumer Services, 20(5), 485-492. https://doi.org/10.1016/j.jretconser.2013.06.004

Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). McGraw-Hill.

Ortiz Alvarado, J. M., Sánchez Franco, M. J., & Quintana Amate, S. (2020). Understanding the influence of online reviews on purchasing decisions: The moderating effect of the online shopping experience. Journal of Internet Commerce, 19(3), 245-267. https://doi.org/10.1080/15332861.2020.1775807

Parboteeah, D. V., Valacich, J. S., & Wells, J. D. (2009). The influence of website characteristics on a consumer's urge to buy impulsively. Information Systems Research, 20(1), 60-78. https://doi.org/10.1287/isre.1070.0157

Park, E. J., Kim, E. Y., Funches, V. M., & Foxx, W. (2012). Apparel product attributes, web browsing, and e-impulse buying on shopping websites. Journal of Business Research, 65(11), 1583-1589. https://doi.org/10.1016/j.jbusres.2011.02.043

Park, H., Kim, Y., & Oh, J. (2012). Hedonic and utilitarian browsing motivations in online shopping: The mediating role of approach-avoidance motivations. Journal of Internet Commerce, 11(4), 239-254. https://doi.org/10.1080/15332861.2012.729465

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879-903. https://doi.org/10.1037/0021-9010.88.5.879

Pomering, A., & Dolnicar, S. (2009). Assessing the prerequisite of successful CSR implementation: Are consumers aware of CSR initiatives? Journal of Business Ethics, 85(2), 285-301. https://doi.org/10.1007/s10551-008-9729-9

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879-891. https://doi.org/10.3758/BRM.40.3.879

Ringle, C. M., Wende, S., & Becker, J. M. (2012). SmartPLS 2.0 (M3) beta. http://www.smartpls.de

Rondan-Cataluña, F. J., Arenas-Gaitán, J., & Ramírez-Correa, P. E. (2015). A comparison of the different versions of popular technology acceptance models: A non-linear perspective. Kybernetes, 44(5), 788-805. https://doi.org/10.1108/K-09-2014-0184

Roscoe, J. T. (1975). Fundamental research statistics for the behavioral sciences (2nd ed.). Holt, Rinehart and Winston.

Satyavani, K., & Chalam, G. V. (2018). Consumer behavior in the digital era: A study on impulsive buying in online shopping. Journal of Business Research, 8(1), 34-47.

Saunders, M., Lewis, P., & Thornhill, A. (2016). Research methods for business students (7th ed.). Pearson.

Schumacker, R. E., & Lomax, R. G. (2004). A beginner's guide to structural equation modeling (2nd ed.). Lawrence Erlbaum Associates.

Servaes, H., & Tamayo, A. (2013). The impact of corporate social responsibility on firm value: The role of customer awareness. Management Science, 59(5), 1045-1061. https://doi.org/10.1287/mnsc.1120.1630

Shan, Y., & Bolton, L. E. (2004). Implications of attribute-driven choice for consumer behavior. Journal of Consumer Research, 31(1), 55-64. https://doi.org/10.1086/383424

Singh, J. (2020). Digital marketing and its impact on consumer behavior in India. Journal of Business Research, 11(2), 89-102.

Singh, J. J., & Del Bosque, I. R. (2008). Understanding corporate social responsibility and product perceptions in consumer markets: A cross-cultural evaluation. Journal of Business Ethics, 80(1), 117-134. https://doi.org/10.1007/s10551-007-9413-5

Sokolova, K., & Kefi, H. (2020). Instagram and YouTube bloggers promote it, why should I buy? How credibility and parasocial interaction influence purchase intentions. Journal of Retailing and Consumer Services, 53, 101742. https://doi.org/10.1016/j.jretconser.2019.01.011

Steiger, J. H. (1990). Structural model evaluation and modification: An interval estimation approach. Multivariate Behavioral Research, 25(2), 173-180. https://doi.org/10.1207/s15327906mbr2502_4

Suryawardani, I. G. A. O., Martini, E., & Wahyuni, I. N. (2017). Impulsive buying behavior in the perspective of economic theory: A study of online consumers in Bali. International Journal of Business and Economics Research, 6(4), 65-72. https://doi.org/10.11648/j.ijber.20170604.11

Surendran, P. (2012). Technology Acceptance Model: A survey of literature. International Journal of Business and Social Research, 2(4), 175-178.

Sweeney, J. C., & Soutar, G. N. (2001). Consumer perceived value: The development of a multiple item scale. Journal of Retailing, 77(2), 203-220. https://doi.org/10.1016/S0022-4359(01)00041-0

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. Procedia Manufacturing, 22, 960-967. https://doi.org/10.1016/j.promfg.2018.03.137

Tang, T. L. P., Chen, Y. J., & Chen, C. (2019). The love of money, machiavellianism, and unethical behavior in the Chinese context: The impact of impulse buying and self-esteem. Journal of Business Ethics, 157(1), 1-20. https://doi.org/10.1007/s10551-017-3661-0

Tucker, L. R., & Lewis, C. (1973). A reliability coefficient for maximum likelihood factor analysis. Psychometrika, 38(1), 1-10. https://doi.org/10.1007/BF02291170

Uzunoglu, E., & Kip, S. M. (2014). Brand communication through digital influencers: Leveraging blogger engagement. International Journal of Information Management, 34(5), 592-602. https://doi.org/10.1016/j.ijinfomgt.2014.04.007

Veirman, M. D., Cauberghe, V., & Hudders, L. (2017). Marketing through Instagram influencers: The impact of number of followers and product divergence on brand attitudes. International Journal of Advertising, 36(5), 798-828. https://doi.org/10.1080/02650487.2017.1348035

Vieira, V. A. (2013). Stimuli-organism-response framework: A meta-analytic review in the store environment. Journal of Business Research, 66(9), 1420-1426. https://doi.org/10.1016/j.jbusres.2012.05.009

Virvilaite, R., Saladiene, V., & Bagdonaite, R. (2011). Peculiarities of impulsive purchasing in the market of consumer goods. Organizations and Markets in Emerging Economies, 2(1), 79-90.

Voss, K. E., Spangenberg, E. R., & Grohmann, B. (2003). Measuring the hedonic and utilitarian dimensions of consumer attitude. Journal of Marketing Research, 40(3), 310-320. https://doi.org/10.1509/jmkr.40.3.310.19238

Wang, C. H., & Yen, Y. F. (2010). Impulse buying behavior in a multi-channel retailer environment: The role of product category, time pressure, and personality. Asia Pacific Management Review, 15(3), 357-377.

Watanabe, T., & Omori, Y. (2020). Online shopping behavior during the COVID-19 pandemic: Evidence from Japan. Journal of the Japanese and International Economies, 58, 101116. https://doi.org/10.1016/j.jjie.2020.101116

Wells, J. D., Parboteeah, V., & Valacich, J. S. (2011). Online impulse buying: Understanding the interplay of consumer impulsiveness, website quality, and product category. Journal of the Association for Information Systems, 12(1), 32-56. https://doi.org/10.17705/1jais.00247

Wiedmann, K. P., & von Mettenheim, W. (2020). The influence of social media influencers on consumers' trust in brands. Journal of Brand Management, 27(1), 41-53. https://doi.org/10.1057/s41262-019-00198-0

Woodworth, R. S. (1928). Dynamic psychology. Columbia University Press.

Wu, L., Lee, J., Fu, C., & Yang, J. (2020). Understanding the role of emotional and cognitive factors in impulsive buying behavior: A dual process theory perspective. Psychology & Marketing, 37(2), 276-287. https://doi.org/10.1002/mar.21306

Xia, L., & Monroe, K. B. (2009). The influence of pre-purchase information on consumers' online purchase decisions. Journal of Retailing, 85(1), 56-70. https://doi.org/10.1016/j.jretai.2008.11.001

Xia, Y., Zhang, H., & Zhang, Y. (2018). Mobile marketing acceptance model: The role of perceived risk and trust. International Journal of Mobile Communications, 16(2), 123-142.

Xu, Y., & Huang, D. (2014). Impulsive buying behavior in online shopping environments. Journal of Consumer Behaviour, 13(1), 1-10. https://doi.org/10.1002/cb.1451

Zhang, J., Wang, X., & Luo, X. R. (2019). The interplay between cognitive and emotional factors in online impulse buying. Information & Management, 56(3), 143-157. https://doi.org/10.1016/j.im.2018.05.001

Zhang, K. Z. K., Cheung, C. M. K., & Lee, M. K. O. (2014). Online consumer impulse buying: The role of self-regulation. MIS Quarterly, 38(3), 805-826. https://doi.org/10.25300/MISQ/2014/38.3.11

Zhang, X., Prybutok, V. R., & Koh, C. E. (2018a). The role of impulsiveness in a TAM-based online purchasing behavior model. Information Resources Management Journal, 31(2), 45-66. https://doi.org/10.4018/IRMJ.2018040103

Zhang, Y., Yao, Z., Zhang, L., & Duan, H. (2018b). Social commerce research: An integrated view. Electronic Commerce Research and Applications, 28, 1-14. https://doi.org/10.1016/j.elerap.2018.01.002

Zhou, T., Zhang, S., & Mou, Y. (2013). Exploring the relationship between electronic word-of-mouth and purchase intention: An empirical investigation of online consumer reviews in China. International Journal of Information Management, 33(2), 456-463. https://doi.org/10.1016/j.ijinfomgt.2012.10.001

Zhu, Y., Sun, Y., Wang, R., & Chan, T. K. H. (2020). How online reviews affect purchase intention: A structural equation modeling approach. Industrial Management & Data Systems, 120(7), 1425-1447. https://doi.org/10.1108/IMDS-08-2019-0473