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FROM DIGITAL-EXPOSURE TO PURCHASE-INTENTION: MODELING CONSUMER RESPONSES THROUGH AFFECTIVE, COGNITIVE, AND BEHAVIORAL MECHANISMS

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ABSTRACT

The rapid expansion of digital marketing has fundamentally transformed the ways in which consumers interact with brands and make purchasing decisions. Understanding the psychological mechanisms that connect digital marketing stimuli with consumer behavior has therefore become increasingly important. This study investigates how the digital marketing environment and brand communication strategy influence purchase intention through affective, cognitive, and behavioral consumer responses. Drawing upon the Stimulus–Organism–Response (S-O-R) framework, this research proposes an integrated model explaining how marketing stimuli shape consumer decision-making processes in digital contexts. A quantitative research design was employed using survey data collected from digital consumers in East Java, Indonesia who actively interact with marketing content on social media and online platforms. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the relationships among the constructs. The results reveal that both digital marketing environment and brand communication strategy significantly influence affective response, cognitive evaluation, and behavioral engagement. Furthermore, these consumer responses positively affect purchase intention, indicating that emotional experiences, rational evaluations, and active engagement jointly shape consumer purchasing decisions. The findings contribute to digital marketing literature by empirically validating the affective–cognitive–behavioral mechanism within an integrated marketing stimulus framework in an emerging market context. The study also provides practical insights for marketers seeking to design more effective digital marketing strategies that foster consumer engagement and strengthen purchase intentions.

Keywords : Affective Response; Behavioral Engagement; Brand Communication Strategy; Cognitive Evaluation; Digital Marketing Environment; Purchase Intention

ABSTRAK

Ekspansi pemasaran digital yang cepat secara fundamental telah mengubah cara konsumen berinteraksi dengan merek dan membuat keputusan pembelian. Oleh karena itu, memahami mekanisme psikologis yang menghubungkan rangsangan pemasaran digital dengan perilaku konsumen menjadi semakin penting. Studi ini menyelidiki bagaimana lingkungan pemasaran digital dan strategi komunikasi merek memengaruhi niat pembelian melalui respons konsumen yang afektif, kognitif, dan perilaku. Berdasarkan kerangka kerja *Stimulus-Organism-Response* (S-O-R), penelitian ini mengusulkan model terintegrasi yang menjelaskan bagaimana stimulus pemasaran membentuk proses pengambilan keputusan konsumen dalam konteks digital. Desain penelitian kuantitatif digunakan menggunakan data survei yang dikumpulkan dari konsumen digital di Jawa Timur, Indonesia yang aktif berinteraksi dengan konten pemasaran di media sosial dan platform online. Data dianalisis menggunakan *Partial Least Squares Structural Equation Modeling* (PLS-SEM) untuk memeriksa hubungan antar konstruk. Hasilnya mengungkapkan bahwa lingkungan pemasaran digital dan strategi komunikasi merek secara signifikan mempengaruhi respons afektif, evaluasi kognitif, dan keterlibatan perilaku. Selain itu, respons konsumen ini secara positif memengaruhi niat pembelian, menunjukkan bahwa pengalaman emosional, evaluasi rasional, dan keterlibatan aktif bersama-sama membentuk keputusan pembelian konsumen. Temuan ini berkontribusi pada literatur pemasaran digital dengan memvalidasi secara empiris mekanisme afektif-kognitif-perilaku dalam kerangka kerja stimulus pemasaran terintegrasi dalam konteks pasar yang sedang berkembang. Studi ini juga memberikan wawasan praktis bagi pemasar yang ingin merancang strategi pemasaran digital yang lebih efektif yang mendorong keterlibatan konsumen dan memperkuat niat pembelian.

Kata Kunci : Affective Response; Behavioral Engagement; Brand Communication Strategy; Cognitive Evaluation; Digital Marketing Environment; Purchase Intention.

INTRODUCTION

The rapid transformation of the digital economy has fundamentally reshaped the mechanisms through which firms interact with consumers and influence purchasing behaviour. Digital platforms, social media ecosystems, and data-driven marketing technologies have created new environments in which consumer decisions are increasingly formed through complex interactions between marketing stimuli and psychological responses. In this context, marketing effectiveness no longer depends solely on the functional attributes of products or services but increasingly on how consumers perceive, interpret, and emotionally respond to marketing messages delivered through digital channels (Kumar, 2021; Lemon & Verhoef, 2016). Consequently, understanding the psychological mechanisms that translate marketing exposure into behavioural outcomes has become a central concern in contemporary marketing research.

One influential perspective for explaining consumer responses to marketing stimuli is the affective–cognitive–behavioral (ACB) framework, which conceptualizes consumer reactions as a multi-stage psychological process. Within this perspective, marketing stimuli first shape consumers’ cognitive evaluations and emotional responses, which subsequently influence behavioural intentions and decision outcomes (Bagozzi, Gopinath, & Nyer, 1999; Hollebeek & Macky, 2019). This framework is closely aligned with the broader Stimulus–Organism–Response (S-O-R) theory, where marketing communications, digital environments, and brand-related signals serve as stimuli that trigger internal psychological processes before culminating in observable behavioural outcomes such as purchase intentions, loyalty, or engagement (Denizgil, Dayioğlu, & Evre, 2024; Jang & Namkung, 2009). Despite its theoretical relevance, the integration of affective, cognitive, and behavioural mechanisms within digital marketing contexts remains relatively underexplored, particularly in emerging economies where digital ecosystems and consumer behaviour may differ substantially from those observed in developed markets.

The rise of digital marketing has significantly expanded the scope of consumer–brand interactions. Firms now operate in environments characterized by continuous information flows, algorithmic content distribution, interactive communication, and user-generated content. These developments have transformed marketing from a one-directional communication process into an interactive and dynamic exchange between brands and consumers (Hennig-Thurau, Hofacker, & Bloching, 2013; Kannan & Li, 2017). Social media platforms such as Instagram, TikTok, and Facebook allow consumers to simultaneously act as audiences, content creators, and brand advocates, thereby amplifying the influence of peer communication and digital visibility on consumer decision-making. As a result, digital marketing environments increasingly function not merely as communication channels but as complex ecosystems that shape consumer perceptions, emotions, and engagement behaviours (Y. K Dwivedi, 2023a; Stephen, 2016).

Within Indonesia, East Java represents one of the most dynamic regional markets characterized by rapid urban development, growing digital adoption, and a diverse consumer base. As the second most populous province in the country and an important economic hub, East Java provides a compelling context for examining consumer responses to digital marketing. Cities such as Surabaya, Malang, and Sidoarjo have witnessed significant expansion in e-commerce activities, digital entrepreneurship, and social media-based marketing practices. At the same time, consumer behaviour in this region reflects a unique combination of modern digital engagement and local socio-cultural influences, which may shape how marketing messages are interpreted and internalized by consumers.

From a theoretical perspective, integrating digital marketing environment and brand communication strategy within the affective–cognitive–behavioral framework offers an opportunity to advance the understanding of consumer decision formation in digital contexts. The digital marketing environment can be conceptualized as a structural stimulus encompassing elements such as interactivity, personalization, algorithmic visibility, and social proof that shape consumers' exposure to marketing content (Yogesh K. Dwivedi et al., 2021; Kannan & Li, 2017). Meanwhile, brand communication strategy represents a strategic stimulus involving the design of marketing messages and narratives intended to influence consumer perceptions and emotions (Keller, 2012; Keller et al., 2016). Together, these stimuli may activate internal psychological responses that ultimately lead to behavioural outcomes such as purchase intentions.

Literature Review

Consumer Response Formation in Digital Marketing

The rapid digitalization of markets has significantly transformed the mechanisms through which consumers interact with brands and make purchasing decisions. Digital platforms, social media ecosystems, and algorithm-driven information flows have reshaped the contemporary marketing environment, enabling firms to engage with consumers in ways that were previously impossible through traditional communication channels. In this evolving landscape, marketing effectiveness increasingly depends not only on the quality of products or services but also on how consumers perceive, interpret, and emotionally respond to marketing stimuli delivered through digital environments (Kumar Das, 2021; Lemon & Verhoef, 2016). Modern consumers are exposed to vast amounts of marketing information through online platforms, where product reviews, social media interactions, influencer endorsements, and brand-generated content collectively shape consumer perceptions and decisions. Consequently, consumer decision-making has become more complex and multidimensional, involving the interaction of cognitive evaluations, emotional responses, and behavioral tendencies (Stephen, 2016). Understanding these internal processes is therefore critical for explaining how marketing stimuli influence consumer behavior in digital contexts.

Digital Marketing Environment

The digital marketing environment refers to the technological and social context in which consumers interact with marketing content through digital platforms. This environment includes various elements such as social media platforms, online marketplaces, mobile applications, and algorithm-based content distribution systems that facilitate interactions between firms and consumers (Kannan & Li, 2017).

One of the defining characteristics of the digital marketing environment is its interactive nature. Unlike traditional marketing channels that primarily rely on one-way communication, digital platforms enable two-way and multi-directional communication between brands and consumers. Consumers can provide feedback, share content, and participate in discussions about products or services, thereby influencing the perceptions of other potential customers (Hennig-Thurau et al., 2013).

In addition, digital platforms rely heavily on algorithmic visibility, where algorithms determine, which content is shown to users based on engagement metrics and user behavior. This mechanism significantly influences the exposure of consumers to marketing content and shapes their perceptions of brands and products (Y. K Dwivedi, 2023b).

Brand Communication Strategy

In addition to the digital environment, brand communication strategy represents a crucial stimulus that shapes how consumers perceive and evaluate brands. Brand communication refers to the strategic process through which firms convey brand identity, values, and messages to consumers using various communication channels (Keller, 2012). In contemporary marketing, brand communication increasingly emphasizes emotional resonance and storytelling. Brand storytelling enables firms to communicate messages in a narrative format that resonates with consumers' experiences and values, thereby enhancing the memorability and impact of marketing messages (Lundqvist et al., 1998). Through storytelling, brands can create meaningful connections with consumers by framing products within broader narratives related to lifestyle, identity, or social values.

Affective Consumer Response

Affective response refers to the emotional reactions experienced by consumers when they encounter marketing stimuli or interact with brands. Emotions play a central role in consumer decision-making because they influence how individuals interpret information and form attitudes toward products or services (Bagozzi et al., 1999). In digital marketing contexts, affective responses may arise from visually appealing content, engaging narratives, or positive interactions within online communities. Emotions such as enjoyment, excitement, and trust can strengthen consumers' attachment to brands and increase their willingness to engage with marketing content (Hollebeek & Macky, 2019). Research has shown that emotional responses often act as mediating mechanisms that link marketing stimuli to behavioral outcomes. When consumers experience positive emotions toward a brand, they are more likely to develop favorable attitudes and intentions toward that brand (Thomson et al., 2020).

Cognitive Consumer Evaluation

Cognitive evaluation refers to the rational process through which consumers assess product attributes, brand credibility, and perceived value. This evaluation is based on the information consumers obtain from marketing communications, product descriptions, and third-party sources such as reviews or recommendations (Wirtz et al., 2021). In digital environments, consumers have access to extensive information that enables them to conduct detailed evaluations before making purchasing decisions. Online reviews, comparison tools, and informational content provide consumers with the knowledge necessary to assess product quality and reliability. Positive cognitive evaluations can increase consumers' confidence in their purchasing decisions and strengthen their perceptions of brand value. Therefore, cognitive evaluation plays a critical role in shaping consumer intentions and behaviors.

Behavioral Engagement

Behavioral engagement represents the observable actions taken by consumers when interacting with brands or marketing content. These actions may include liking, sharing, commenting on social media posts, visiting brand websites, or participating in brand-related activities (Hennig-Thurau et al., 2013). Consumer engagement is increasingly recognized as a key indicator of marketing effectiveness in digital environments. Engaged consumers not only interact with brands more frequently but also contribute to the dissemination of brand-related information within their social networks. Higher levels of consumer engagement often lead to stronger relationships between consumers and brands, which can ultimately increase purchase likelihood and brand loyalty.

Conceptual Framework and Hypotheses Development

Based on the literature discussed above, this study proposes an integrated framework that explains how marketing stimuli influences consumer purchase intentions through affective, cognitive, and behavioral responses. Within this framework, digital marketing environment and brand communication strategy function as external stimuli that shape internal consumer responses. These responses are represented by three key constructs: affective response, cognitive evaluation, and behavioral engagement. These constructs subsequently influence purchase intention, which represents the final behavioral outcome.

Digital Marketing Environment and Consumer Responses

Digital marketing environments shape how consumers interact with marketing content and influence their perceptions of brands. Interactive and user-friendly digital platforms can create enjoyable experiences that generate positive emotional responses among consumers. When consumers perceive digital environments as engaging and convenient, they are more likely to develop positive feelings toward brands. Furthermore, digital platforms provide consumers with information that facilitates rational evaluation of product attributes and brand credibility. Access to reliable information can enhance consumers' cognitive assessments and increase their confidence in the brand. Interactive digital environments also encourage consumers to actively engage with marketing content by liking, sharing, or commenting on brand-related posts. These engagement behaviors strengthen the relationship between consumers and brands and contribute to the diffusion of marketing messages. Therefore, the following hypotheses are proposed:

H1: Digital marketing environment positively influences affective consumer response.
H2: Digital marketing environment positively influences cognitive consumer evaluation.
H3: Digital marketing environment positively influences behavioral engagement.

Brand Communication Strategy and Consumer Responses

Effective brand communication strategies can significantly influence consumer perceptions and emotions. Through storytelling, visual identity, and consistent messaging, brands can create meaningful narratives that resonate with consumers and enhance emotional connections. When consumers perceive brand communication as authentic and engaging, they are more likely to develop positive emotional responses toward the brand. These emotional responses strengthen consumers' attachment to the brand and increase their willingness to interact with brand-related content. Brand communication also provides consumers with information that helps them evaluate the credibility and value of products. Clear and consistent communication can improve consumers' understanding of brand attributes and reinforce positive cognitive evaluations. In addition, compelling brand communication can encourage consumers to interact with marketing content, thereby increasing their engagement with the brand. Accordingly, the following hypotheses are proposed:

H4: Brand communication strategy positively influences affective consumer response.
H5: Brand communication strategy positively influences cognitive consumer evaluation.
H6: Brand communication strategy positively influences behavioral engagement.

Consumer Responses and Purchase Intention

Consumer responses in the affective, cognitive, and behavioral domains play important roles in shaping purchase intentions. Emotional responses toward brands can increase consumers' desire to experience the brand through product consumption. Positive emotions such as trust, enjoyment, and attachment often strengthen consumers' willingness to purchase products associated with the brand. Cognitive evaluations also influence purchase intentions by shaping consumers' perceptions of product value and reliability. When consumers believe that a product offers superior quality or value, they are more likely to consider purchasing it. Behavioral engagement further strengthens the relationship between consumers and brands. Consumers who actively interact with brands are more likely to develop familiarity and trust, which increases the likelihood of purchase. Therefore, the following hypotheses are proposed:

H7: Affective response positively influences purchase intention.
H8: Cognitive evaluation positively influences purchase intention.
H9: Behavioral engagement positively influences purchase intention.

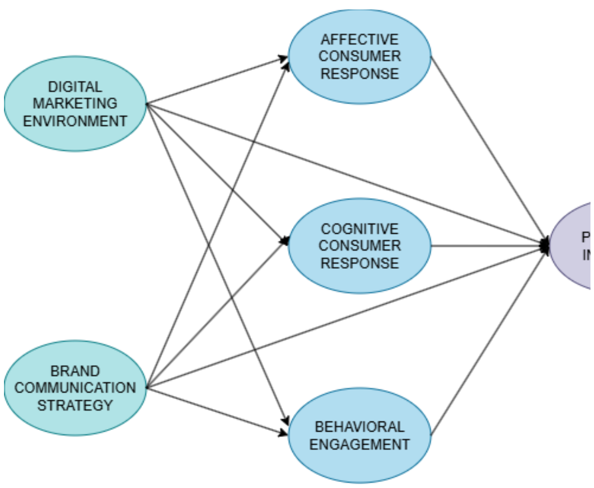

Figure 1. Proposed Research Framework

(Source: Author, 2021)

RESEARCH METHOD

Research Design

This study adopts a quantitative research design to examine the relationships between digital marketing stimuli and consumer purchase intentions through affective, cognitive, and behavioral mechanisms. The research model integrates constructs from digital marketing literature and consumer psychology within the Stimulus–Organism–Response (S-O-R) framework. The study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the proposed hypotheses. PLS-SEM is particularly suitable for exploratory and predictive research involving complex models with multiple constructs and indicators (Hair et al., 2022). In addition, PLS-SEM performs well with non-normal data distributions and is appropriate for studies focusing on consumer behavior and marketing relationships. The model evaluates both direct effects and mediating relationships among these constructs. The research framework consists of six latent constructs:

1. Digital Marketing Environment (DME)
2. Brand Communication Strategy (BCS)
3. Affective Response (AR)
4. Cognitive Evaluation (CE)
5. Behavioral Engagement (BE)
6. Purchase Intention (PI)

Research Context

The empirical context of this study focuses on consumers in East Java, Indonesia, a region characterized by rapid digital adoption and dynamic consumer markets. East Java is one of the most economically active provinces in Indonesia and represents an important digital consumer ecosystem with increasing use of social media, e-commerce platforms, and digital marketing communications. Major urban areas such as Surabaya, Malang, Sidoarjo, and Gresik exhibit high internet penetration and active social media usage, making them suitable contexts for examining consumer responses to digital marketing activities. Consumers in this region frequently interact with brands through platforms such as Instagram, TikTok, Shopee, and Tokopedia, where marketing content, influencer promotions, and user-generated reviews significantly influence purchasing decisions.

Population and Sampling

The population of this study consists of digital consumers in East Java who actively interact with marketing content through social media or e-commerce platforms. To ensure respondents possess relevant experience with digital marketing interactions, the following screening criteria are applied:

1. Respondents must reside in East Java.
2. Respondents must actively use at least one social media platform.
3. Respondents must have purchased a product online within the last six months.

Data Collection Procedure

Primary data are collected using a structured online questionnaire distributed through digital platforms, including social media networks and online communities in East Java. The questionnaire consists of three sections:

1. Screening questions
2. Measurement items for research constructs
3. Demographic information

Respondents evaluate each statement using a five-point Likert scale, ranging from:
1 = strongly disagree
2 = disagree
3 = neutral
4 = agree
5 = strongly agree

Prior to full data collection, a pilot test involving approximately 30 respondents is conducted to assess questionnaire clarity, reliability, and validity.

Measurement Development

All measurement items are adapted from validated scales in prior marketing and consumer behavior research to ensure content validity and construct reliability. The constructs are operationalized as follows:

1. Digital Marketing Environment adapted from digital experience literature
2. Brand Communication Strategy adapted from brand communication and storytelling research
3. Affective Response adapted from consumer emotion literature
4. Cognitive Evaluation adapted from perceived value and brand credibility studies
5. Behavioral Engagement adapted from customer engagement research
6. Purchase Intention adapted from consumer behavior studies

Minor wording adjustments are made to ensure relevance to the context of digital marketing interactions.

Measurement Items Table (Survey Indicators)

The measurement items used in this study were adapted from established scales in the marketing and consumer behavior literature and operationalized using multiple indicators to ensure construct validity and reliability within the context of digital marketing interactions among consumers in East Java, as seen in Table 1.

Table 1. Measurement Items Table (Survey Indicators)

Construct	Code	Measurement Item
Digital Marketing Environment (DME)	DME1	Digital platforms make it easy for me to find product information
	DME2	Marketing content on social media is visually attractive
	DME3	Digital platforms allow interactive communication with brands

	DME4	Online platforms provide personalized product recommendations
	DME5	I frequently see marketing content through digital platforms
	DME6	Digital platforms provide useful product reviews and ratings
Brand Communication Strategy (BCS)	BCS1	The brand communicates its message clearly
	BCS2	The brand tells interesting stories about its products
	BCS3	Brand messages are consistent across digital platforms
	BCS4	The brand communication feels authentic
Affective Response (AR)	AR1	I feel positive emotions when I see this brand
	AR2	This brand makes me feel excited
	AR3	I enjoy interacting with content from this brand
	AR4	I feel emotionally connected to this brand
Cognitive Evaluation (CE)	CE1	This brand offers high-quality products
	CE2	The brand provides good value for money
	CE3	The brand is credible and trustworthy
	CE4	The brand provides useful information
	CE5	I believe the brand performs better than competitors
	CE6	I consider the brand to be reliable
Behavioral Engagement (BE)	BE1	I often like or react to the brand's social media posts
	BE2	I comment on the brand's social media content
	BE3	I share brand content with others
	BE4	I follow the brand on social media
	BE5	I actively search for information about this brand
	BE6	I participate in brand campaigns or promotions
Purchase Intention (PI)	PI1	I intend to purchase products from this brand
	PI2	I will likely buy products from this brand in the future
	PI3	I prefer this brand over other brands
	PI4	I would recommend this brand to others
	PI5	I would consider buying this brand when I need the product

Source: Author (2026)

Data Analysis Technique

The data analysis in this study was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the assistance of SmartPLS software. PLS-SEM was selected due to its suitability for analyzing complex predictive models involving multiple latent constructs and mediating relationships. In addition, PLS-SEM is particularly appropriate for research that focuses on theory development and prediction, as well as for datasets that may not fully satisfy the assumptions of multivariate normality (Hair, 2022). The analysis followed a two-step approach, consisting of the evaluation of the measurement model (outer model) and the structural model (inner model). This procedure is widely recommended in structural equation modeling to ensure that the constructs are both reliable and valid before testing the proposed theoretical relationships.

Measurement Model Assessment

The measurement model was first evaluated to examine the reliability and validity of the constructs. Indicator reliability was assessed by examining the standardized factor loadings of each measurement item. According to recommended thresholds, factor loadings should exceed 0.70, indicating that the indicators adequately represent their respective latent constructs. Internal consistency reliability was evaluated using

Cronbach's Alpha and Composite Reliability (CR). Values greater than 0.70 indicate acceptable reliability and demonstrate that the indicators consistently measure the underlying constructs.

Structural Model Assessment

After establishing the reliability and validity of the measurement model, the structural model was evaluated to test the hypothesized relationships among constructs. The structural model assessment included the examination of path coefficients, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and overall model fit. Hypothesis testing was conducted using the bootstrapping procedure with 5,000 resamples, which provides robust estimates of the significance of path coefficients. The statistical significance of each relationship was determined based on t-values and p-values.

The coefficient of determination (R^2) was used to assess the explanatory power of the model for endogenous constructs. Higher R^2 values indicate greater predictive capability of the model. To evaluate the contribution of each exogenous construct to the endogenous variables, effect size (f^2) was calculated. Effect size values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. Predictive relevance of the model was examined using the Stone–Geisser Q^2 statistic, obtained through the blindfolding procedure. Q^2 values greater than zero indicate that the model has predictive relevance for the endogenous constructs.

RESULT AND DISCUSSIONS

The survey is carried out to obtain the facts of the symptoms that exist and look for information factually. In research, data was collected from respondents using a questionnaire. The PLS-SEM method was utilized to evaluate the theoretical framework in this study, which was carried out in phases over a period of many months. In the initial stage, the estimation framework is analyzed and after that the conceptual framework is tested. The entire sample was formed into datasets and then a further assessment was carried out on these datasets to see if there were variations in entrepreneurial mindsets and entrepreneurial intentions.

Model Measurement

The testing method in this research is carried out based on four metrics which include convergent validity, discriminatory validity, internal consistency and item reliability. Appropriate latent construct survey object weights were also tested to measure item reliability. The size of the products' standardized loadings must be greater than 0.7. Table 2 shows that the factor loadings of the two elements meet the criteria if the value of the factor loadings is greater than 0.7. The criteria described in the previous section measure how closely the survey objects have the potential to correlate with each other and are in fact related.

Table 2. Overview of Quality Criteria

Constructs/Items	Cronbach's Alpha	Composite Reliability	AVE	Factor Loadings	Mean	SD
Affective Response (AR)	0.963	0.973	0.900			
AR1				0.963	4.001	0.703
AR2				0.946	4.005	0.700
AR3				0.955	3.991	0.688
AR4				0.931	3.9	0.6

Constructs/Items	Cronbach's Alpha	Composite Reliability	AVE	Factor Loadings	Mean	SD
					68	92
Behavioral Engagement (BE)	0.979	0.983	0.907			
BE1				0.977	4.001	0.705
BE2				0.960	4.004	0.695
BE3				0.947	3.989	0.689
BE4				0.915	3.963	0.692
BE5				0.966	4.023	0.712
BE6				0.948	4.016	0.707
Cognitive Evaluation (CE)	0.977	0.981	0.897			
CE1				0.974	4.000	0.702
CE2				0.957	3.995	0.694
CE3				0.951	4.004	0.688
CE4				0.916	3.972	0.693
CE5				0.946	4.023	0.712
CE6				0.937	4.0	0.7

Constructs/Items	Cronbach's Alpha	Composite Reliability	AVE	Factor Loadings	Mean	SD
					16	07
Digital Marketing Environment (DME)	0.980	0.983	0.908			
DME1				0.979	3.971	0.701
DME2				0.969	3.974	0.694
DME3				0.954	3.971	0.690
DME4				0.924	3.946	0.689
DME5				0.951	3.985	0.708
DME6				0.940	3.984	0.700
Brand Communication Strategy (BCS)	0.964	0.974	0.903			
BCS1				0.951	3.914	0.682
BCS2				0.957	3.919	0.683
BCS3				0.941	3.890	0.685
BCS4				0.950	3.895	0.674
Purchase Intention (PI)	0.969	0.976	0.892			

Constructs/Items	Cronbach's Alpha	Composite Reliability	AVE	Factor Loadings	Mean	SD
PI1				0.975	4.000	0.704
PI2				0.958	4.009	0.703
PI3				0.961	4.004	0.714
PI4				0.963	3.999	0.712
PI5				0.862	3.911	0.684

Source: Calculated Data, Author (2026)

In addition, the convergent validity of each latent construct was also tested by looking at the Average Variance Extracted (AVE) and composite reliability from every underlying concept. On the other hand, composite reliability is utilized to measure the internal consistency of the latent model. When the composite reliability rating is more than 0.70, it implies that a build is internally reliable. The minimum criterion of composite reliability has been validated by the model in this research, as shown in Table 2. While the AVE is the number of variants of the latent construct obtained from the metric compared to the number of variances associated with calculation errors. If an AVE value of 0.50 indicates that at least half of the variation in the metric can be clarified. The results of the model analysis in this research show that the AVE of the latent construct is considered eligible if the AVE value is at least 0.50, as shown in Table 3.

Table 3. Standardized Loading Factors

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
AR1 ← AR	0.963	0.963	0.002	484.812	0.000
AR2 ← AR	0.946	0.946	0.003	328.406	0.000
AR3 ← AR	0.955	0.955	0.003	293.235	0.000
AR4 ← AR	0.931	0.931	0.004	215.670	0.000
BE1 ← BE	0.977	0.977	0.002	634.058	0.000
BE2 ← BE	0.960	0.960	0.002	459.387	0.000
BE3 ← BE	0.947	0.947	0.004	254.487	0.000
BE4 ← BE	0.915	0.915	0.005	170.269	0.000
BE5 ← BE	0.966	0.966	0.003	348.705	0.000
BE6 ← BE	0.948	0.948	0.004	255.281	0.000
CE1 ← CE	0.974	0.974	0.002	563.769	0.000
CE2 ← CE	0.957	0.957	0.003	362.569	0.000
CE3 ← CE	0.951	0.951	0.003	288.491	0.000
CE4 ← CE	0.916	0.916	0.005	173.319	0.000
CE5 ← CE	0.946	0.946	0.004	254.571	0.000
CE6 ← CE	0.937	0.937	0.004	239.418	0.000
DME1 ← DME	0.979	0.979	0.001	868.831	0.000
DME2 ← DME	0.969	0.969	0.002	554.044	0.000
DME3 ← DME	0.954	0.954	0.003	301.578	0.000
DME4 ← DME	0.924	0.924	0.005	178.007	0.000

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DME5 ← DME	0.951	0.951	0.004	269.916	0.000
DME6 ← DME	0.940	0.940	0.004	234.394	0.000
BCS1 ← BCS	0.951	0.951	0.003	322.412	0.000
BCS2 ← BCS	0.957	0.957	0.003	362.593	0.000
BCS3 ← BCS	0.941	0.941	0.003	270.702	0.000
BCS4 ← BCS	0.950	0.950	0.003	312.819	0.000
PI1 ← PI	0.975	0.975	0.002	606.585	0.000
PI2 ← PI	0.958	0.958	0.003	345.474	0.000
PI3 ← PI	0.961	0.961	0.003	339.679	0.000
PI4 ← PI	0.963	0.963	0.003	364.066	0.000
PI5 ← PI	0.862	0.862	0.008	112.150	0.000

Source: Calculated Data, Author (2026)

The estimation model as a tool to measure the relationship between constructs and indicators, which is carried out through two stages includes the measurement of Convergent Validity and Discriminant Validity because the initial evaluation of this measurement model is reflective. Measurement model evaluation is carried out by measuring Composite Reliability, Validity and AVE. Convergent Validity evaluation is obtained by measuring the reliability items that produce the Loading Factor value. Indicator validity with a Loading Factor value less than 0.5 is removed from the model. It can be assessed that this research instrument has good validity since all Loading Factor values for each construct are greater than 0.5.

Table 4. Discriminant Validity with Cross-Loading

	AC	BC	CC	EEd	EEn	EI
AR1	**0.963**	0.952	0.940	0.904	0.817	0.954
AR2	**0.946**	0.934	0.936	0.904	0.836	0.940
AR3	**0.955**	0.913	0.913	0.870	0.827	0.892
AR4	**0.931**	0.877	0.873	0.850	0.822	0.853
BE1	0.941	**0.977**	0.952	0.923	0.810	0.950
BE2	0.940	**0.960**	0.955	0.926	0.848	0.952
BE3	0.930	**0.947**	0.928	0.902	0.821	0.885
BE4	0.909	**0.915**	0.888	0.881	0.822	0.856
BE5	0.928	**0.966**	0.946	0.907	0.801	0.930
BE6	0.893	**0.948**	0.937	0.902	0.788	0.946
CE1	0.922	0.940	**0.974**	0.889	0.797	0.941
CE2	0.921	0.921	**0.957**	0.886	0.832	0.930
CE3	0.930	0.916	**0.951**	0.879	0.817	0.896
CE4	0.893	0.882	**0.916**	0.856	0.808	0.855
CE5	0.928	0.926	**0.946**	0.907	0.801	0.930
CE6	0.893	0.928	**0.937**	0.902	0.788	0.926
DME1	0.893	0.920	0.902	**0.979**	0.845	0.914
DME2	0.906	0.925	0.912	**0.969**	0.870	0.911
DME3	0.888	0.898	0.881	**0.954**	0.853	0.859
DME4	0.884	0.891	0.864	**0.924**	0.860	0.842
DME5	0.880	0.911	0.903	**0.951**	0.831	0.901
DME6	0.867	0.897	0.890	**0.940**	0.828	0.904
BCS1	0.829	0.822	0.807	0.868	**0.951**	0.817
BCS2	0.846	0.835	0.827	0.865	**0.957**	0.830
BCS3	0.799	0.791	0.796	0.816	**0.941**	0.816
BCS4	0.832	0.801	0.808	0.831	**0.950**	0.832
PI1	0.945	0.956	0.960	0.909	0.818	**0.975**
PI2	0.908	0.937	0.935	0.890	0.800	**0.958**

	AC	BC	CC	EEd	EEn	EI
PI3	0.908	0.912	0.922	0.878	0.786	**0.961**
PI4	0.923	0.916	0.919	0.883	0.787	**0.963**
PI5	0.848	0.837	0.833	0.845	0.813	**0.862**

Source: Calculated Data, Author (2026)
Note: The loadings of every detail on its latent construct are shown by the bolded numbers in the table.

Assessment of the estimation model with Discriminant Validity is done in two phases, to be specific estimating the Value of Cross-Loadings and looking at the Square of the Correlation between Constructs with AVE values or the Correlation between Constructs with Roots of AVE. Concerning the standards in Cross-Loadings estimated on every Indicator that quantifies the Construct must have a higher Correlation with the Construct itself contrasted with different Constructs. The Cross-Loadings yield esteem appeared in Table 4.

Structural Model

The significance level of the path coefficient and the explanatory ability described by R^2 from composite reliability are used to evaluate the conceptual framework in this research. The results of the verification of the conceptual framework considered in this research can be seen in Figure 2.

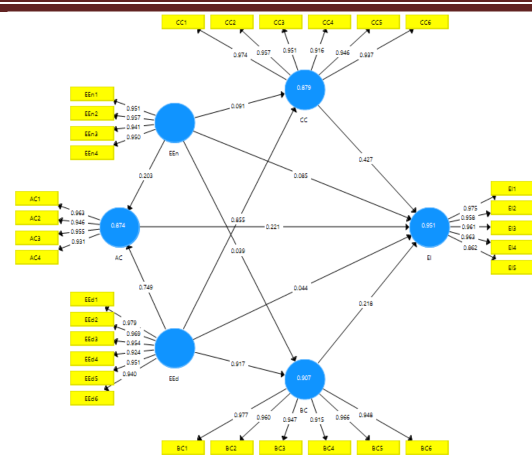

Figure 2. Structural Model

Since PLS-SEM does not depend on the expected distribution, statistically significant differences in the path coefficients in the conceptual framework were evaluated using a bootstrap assessment because the significance threshold could not be assessed using parametric methods. The results of the bootstrap test can be seen in Table 5. The research results show that AR, CE, BE, DME and BCS explain all the components of PI significantly, so this finding can prove hypotheses H1 to H11. Aside from that, the two independent factors both have a positive impact on the dependent variable. The confidence interval of the endogenous latent variable is considered as the main criterion to determine the consistency of the estimation method because PLS-SEM seeks to maximize the variance described in the endogenous variables.

Table 5. Path Coefficient

	Original Sample (O)	**T Statistics (|O/STDEV|)**	**P Values**	**Decision**
AR → PI	0.221	6.279	0.000*	Supported
CE → PI	0.218	4.848	0.000*	Supported

	Original Sample (O)	T Statistics (|O/STDEV|)	P Values	Decision
BE → PI	0.427	8.453	0.000*	Supported
DME → AR	0.749	40.677	0.000*	Supported
DME → BE	0.917	105.396	0.000*	Supported
DME → CE	0.855	54.301	0.000*	Supported
DME → PI	0.044	1.846	0.065*	Supported
BCS → AR	0.203	11.299	0.000*	Supported
BCS → BE	0.039	4.932	0.000*	Supported
BCS → CE	0.091	5.838	0.000*	Supported
BCS → PI	0.085	6.774	0.000*	Supported

Source: Calculated Data, Author (2021)
Note: **Significant at 1% level*

This research framework is considered to have a significant explanatory capacity because R^2 of the EI is worth 0.951 so it can be said that the prediction accuracy of the conceptual framework is quite satisfactory. On the other hand, the Goodness-of-Fit (GoF) metric which has a range of values between 0 and 1 is another approach to assess the consistency of the PLS-SEM procedure. This research also found that the significance value of the GoF conceptual framework is 0.039, which is called the significant value at 1% level. The validity of the conceptual framework and reliability have been measured and proven to meet the criteria that have been set based on the results obtained.

Table 6 shows the results of measuring the indirect effect of the mediating variables in this research. This research examines the mediating effect of AR, BE and CE in the relationship between PI with DME and BCS. Table 6 shows that AR, BE and CE have a mediating effect on the relationship between PI with DME and BCS as evidenced by the significant P Values at the 1% level. It has been shown that AR, BE, and CE have a substantial mediating impact on the connection between PI and both DME as well as BCS. The mediation effect is partial because DME and BCS also have a significant direct effect on PI.

Table 6. Specific Indirect Effect

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Decision
DME → AR → PI	0.166	0.164	0.025	6.683	**0.000***	**Supported**
DME → CE → PI	0.365	0.366	0.042	8.616	**0.000***	**Supported**
DME → BE → PI	0.200	0.200	0.041	4.831	**0.000***	**Supported**
BCS → AR → PI	0.045	0.045	0.01	4.612	**0.000***	**Supported**
BCS → CE → PI	0.009	0.009	0.002	3.729	**0.000***	**Supported**
BCS → BE → PI	0.039	0.039	0.009	4.341	**0.000***	**Supported**

Source: Calculated Data, Author (2021)
Note: *Significant at 1% level

Discussion

The objective of this study was to examine how digital marketing influence consumer purchase intentions through affective, cognitive, and behavioral mechanisms within the context of digital consumers in East Java. The empirical findings provide strong support for the proposed conceptual framework, demonstrating that both digital marketing environment and brand communication strategy significantly shape consumer responses across affective, cognitive, and behavioral dimensions, which subsequently influence purchase intention. Overall, the results reinforce the relevance of the Stimulus–Organism–Response (S-O-R) framework in explaining consumer decision-making processes in contemporary digital marketing environments.

Digital Marketing Environment and Consumer Responses

The results indicate that the digital marketing environment positively influences affective consumer responses, supporting Hypothesis 1. This finding suggests that interactive and visually engaging digital platforms play an important role in shaping consumers' emotional experiences when interacting with brands. When consumers perceive digital marketing environments as dynamic, informative, and user-friendly, they tend to experience positive emotions such as enjoyment, excitement, and trust toward the brand. This finding aligns with prior studies emphasizing that digital environments can generate emotional engagement through immersive and interactive marketing experiences (Y. K Dwivedi, 2023b; Lemon & Verhoef, 2016). In the context of East Java, where consumers increasingly rely on social media and digital platforms to discover and evaluate products, the emotional appeal of digital marketing content appears to be a crucial factor in shaping brand perceptions.

The analysis also reveals that the digital marketing environment positively influences cognitive consumer evaluation, supporting Hypothesis 2. This result highlights the role of digital platforms as important sources of information that facilitate rational evaluation during the consumer decision-making process. Online reviews, product descriptions, ratings, and algorithm-based recommendations enable consumers to assess product quality, reliability, and value more effectively. Consequently, a well-structured digital marketing environment can strengthen consumers' cognitive perceptions regarding brand credibility and product performance. This finding is consistent with previous research suggesting that digital platforms significantly enhance consumers' access to information, thereby influencing their evaluation processes (Kannan & Li, 2017).

Brand Communication Strategy and Consumer Responses

The results demonstrate that brand communication strategy positively influences affective response, supporting Hypothesis 4. This finding indicates that emotionally resonant and authentic brand messages can evoke positive emotional reactions among consumers. Storytelling, consistent messaging, and visually appealing communication contribute to creating meaningful brand experiences that strengthen emotional attachment to the brand. These results align with previous studies emphasizing the importance of narrative-driven brand communication in shaping consumer emotions and brand attachment (Lundqvist et al., 1998). In digital contexts, where consumers are frequently exposed to large volumes of marketing messages, emotionally engaging brand communication appears to be essential for capturing consumer attention and fostering positive affective responses.

Consumer Responses and Purchase Intention

The results further indicate that affective response positively influences purchase intention, supporting Hypothesis 7. Emotional reactions toward brands appear to play a crucial role in shaping consumers' willingness to purchase products. When consumers experience positive emotions such as enjoyment, trust, or excitement in response to brand interactions, they are more likely to develop favorable attitudes and intentions toward purchasing the brand's products. This finding supports earlier research suggesting that emotional attachment can significantly influence consumer loyalty and purchase decisions (Thomson et al., 2020).

Finally, the analysis demonstrates that behavioral engagement positively influences purchase intention, supporting Hypothesis 9. Consumers who actively interact with brands on digital platforms tend to develop stronger familiarity and trust toward those brands. Engagement behaviors such as following brand accounts, sharing content, or participating in marketing campaigns create repeated interactions that strengthen consumer–brand relationships. As a result, highly engaged consumers are more likely to translate their interactions into actual purchasing intentions. This finding is consistent with the growing body of literature emphasizing the importance of customer engagement as a key driver of marketing performance in digital environments (Hennig-Thurau et al., 2013).

CONCLUSSION

This study investigated how digital marketing stimuli influence consumer purchase intentions through affective, cognitive, and behavioral mechanisms. Drawing upon the Stimulus–Organism–Response framework, the study proposed and tested an integrated conceptual model in which digital marketing environment and brand communication strategy function as external stimuli that shape internal consumer responses.

The empirical findings provide strong support for the proposed framework. Both digital marketing environment and brand communication strategy were found to significantly influence consumers' affective responses, cognitive evaluations, and behavioral engagement. These internal responses, in turn, were shown to significantly affect purchase intention. The results highlight the importance of considering consumer decision-making as a multidimensional process involving emotional, rational, and behavioral elements. In digital marketing environments, effective marketing strategies must therefore go beyond delivering product information and focus on creating engaging experiences that stimulate positive emotions, strengthen cognitive perceptions, and encourage active consumer participation.

By providing empirical evidence from consumers in East Java, this study contributes to the growing literature on digital marketing and consumer behavior in emerging economies. The findings suggest that integrated marketing strategies that combine digital platform design, effective brand communication, and consumer engagement initiatives can significantly enhance marketing outcomes in rapidly evolving digital markets. Overall, the study demonstrates that understanding the psychological mechanisms underlying consumer responses is essential for designing effective marketing strategies in the digital era. As digital technologies continue to reshape the marketing landscape, future research and managerial practices should increasingly focus on integrating technological innovation with deeper insights into consumer behavior.

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