The Impact of AI-Enhanced Digital Marketing Strategies on Consumers' Purchase Behavior for Lifestyle Products

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***Abstract*—The impact of Artificial intelligence (AI)-powered digital marketing practices on consumer purchase intention toward lifestyle goods is the focus of this research and aims at analyzing the mediating role of consumer motivation (CM) in the relationship between consumer attitude (CA) and purchase behavior (PB) toward lifestyle products. The study uses descriptive research design to understand CA, motivation, and PB. The study is based on 577 responses collected from Uttar Pradesh state (India). Structural equation modeling was carried out with the help of SmartPLS. Evidence shows a robust relationship between consumers' attitude, motivation and PB, and an optimistic outlook on AI-driven marketing campaigns is likely to inspire more action, given the robust positive correlation between customer attitude and motivation. The study also emphasizes the importance of CM as a mediator in the relationship between CA and PB. It emphasizes the strategic tools for improving PB in the dynamic digital marketing landscape, which include cultivating a positive CA. The study contributes to the theory by highlighting CM as a critical mediator linking CA s to PB for lifestyle products, advancing understanding of the attitude-behavior relationship in consumer behavior models. Managerially, it underscores the importance of designing marketing strategies that enhance CM, such as personalized engagement, value-driven messaging, and emotional appeal. By fostering motivation, brands can effectively translate positive attitudes into stronger PB, driving sales and long-term consumer loyalty in the lifestyle segment.**

***Keywords*—Consumer attitude, Consumer behavior, Consumer motivation, Digital marketing strategies, Lifestyle products.**

I. Introduction

In today's fast-paced society, productivity is prioritized, with electronic devices increasing data generation. Technology research is focused on the Internet of Things, Data Science, computational analysis, and computer vision. Artificial intelligence (AI) is a prominent innovation in these fields (Yang et al., 2021). Contemporary AI-driven investigations integrate diverse data sources, such as text, passive and behavioral data, sales figures, and social media inputs. A survey in 2020 revealed that 13% of sales and business development respondents consider AI the most crucial skill, while 8% in procurement roles highlighted their ability to synthesize data from multiple origins (Dwivedi et al., 2021 and Lee et al., 2021). Technological advancements significantly impact AI, attracting clients and providing competitive advantages to businesses. AI facilitates real-time data tracking, enabling swift responses to diverse customer needs. By anticipating customer behavior, AI transforms the user experience and guides decision-making processes (Kulkov, 2021). However, it is crucial to acknowledge the limitations of AI technology. Researchers in cognitive theory and self-awareness are actively addressing constraints and challenges faced during AI implementation (Huntinghouse et al., 2021).

A lot of focus has been on how consumers feel about digital marketing that uses AI as AI has progressed in recent years, enabling marketers to enhance consumer experiences through personalization (PRS) and optimization (Smith, 2020). Personalized recommendations and tailored content are examples of AI marketing features that clients like (Smith, 2020), but there is a fine line to walk. Educating consumers is a crucial part of creating positive attitudes toward AI in marketing. In a 2019 study, Li et al. Kim et al. (2022) also pointed out that customers want to feel like they can influence AI-driven interactions. Concerns about algorithmic manipulation and data privacy (DP) stand in contrast to these generally positive tendencies (Chen et al., 2021). Customers like AI-driven marketing for its relevance and ease, but they also want companies to be honest about how they use their

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data and how ethically they use AI (Hargittai and Marwick, 2020). Striking a balance between the advantages of AI-enhanced marketing and addressing these consumer concerns is critical for shaping the future of digital interactions between brands and customers (Smith, 2020).

The Indian market for lifestyle products has expanded greatly. A total of US$ 48.42 million will be generated by the Lifestyle market in 2022, as reported by Statista. At a CAGR of 9.23% from 2022 to 2027, the market is expected to reach US$ 77.85 million in sales by 2027. For AI-enabled marketing initiatives to hit the point and get people interested in the offered products, there has to be a careful balance between being open and being personalized.

The advent of AI in digital marketing has revolutionized how businesses interact with consumers, particularly in the lifestyle product segment (Massoudi et al., 2024). AI-driven technologies, such as personalized recommendations, predictive analytics, chatbots, and sentiment analysis, have enabled marketers to craft tailored experiences that resonate with individual consumer preferences and behaviors. Despite the rapid adoption of AI-enhanced strategies, there remains a gap in understanding how these advancements directly influence consumers' purchase behavior (PB) in the lifestyle product category. This study seeks to address this gap by examining the effectiveness of AI-enabled digital marketing in shaping consumer decision-making, the research question here arises whether AI-driven marketing strategies build positive attitude, motivate consumer, and have an effect in the PB of lifestyle product? To answer the research question, the primary objective of the study is to explore the relationship between AI-enhanced digital marketing strategies and their influence in building consumer attitude (CA) and consumers' PB in the lifestyle product segment. Specifically, the study aims to:

1. Analyze the impact of AI-driven Marketing practice in building CA in favor of lifestyle products.
2. To investigate the role of CA in influencing consumer motivation (CM) and PB toward the purchase of lifestyle products.
3. Evaluate the mediating role of CM in the relationship between CA and PB toward lifestyle products.

II. Theoretical Background and Hypotheses Development

A. Convenience and Usefulness

As per Smith et al. (2018) and Chen and Shen (2020), customers highly value functionality and user-friendliness. Novak et al. (2000) Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D (2003) found that the effectiveness and simplicity of a tech item greatly influence its acceptance and usage plans. When equipped with easy-to-use interfaces, speedy delivery services, and seamless buying processes, lifestyle products tend to be better received by consumers. Based on these arguments, we can infer the following hypothesis.

H_1: Convenience has a significant effect on consumers' PB for lifestyle products.

B. Customization (CUST)

Today, PRS is super popular! People love making things that show off what they like. This gives them a feeling of achievement and the joy of having something special. Some research by Li et al. (2018) found that when people customize products to match their own tastes, they feel more involved and happier with what they own. In fact, a later study by Li et al. (2019) showed that when shoppers get more choices to personalize their stuff, they really want lifestyle items even more. When these connections grow stronger, it leads to more enjoyment and motivation. In addition, the study by Li et al. (2018) points out how consumers feel more attached to brands when they get products made just for them. CUST really helps boost customer satisfaction, motivation, and loyalty. It's all about creating that special bond.

H_2: CUST has a significant effect on consumers' PB for lifestyle products.

C. PRS

CUST makes things more interesting and to use. It really changes how people see products. For example, a study by Li et al. (2020) found that when content is personalized, people feel better about what they buy. Liao and Lu (2019) along with Chen and Chou (2019) say that when stuff is made just for you, it makes customers more involved and happier; they think it's worth more too! You know, lifestyle products become really popular when they fit just right with what people like. This idea comes from all those points mentioned earlier.

H_3: PRS has a significant effect on consumers' PB for lifestyle products.

D. DP

In a study by Chen et al. (2021), researchers discovered something interesting. Customers really care about data security, and this affects whether they want to buy a lifestyle. There's been a lot of research into how DP connects with users' trust and their willingness to respond to ads driven by AI. The trust that people feel and how ready they are to share their information can really change based on clear data collection methods and strong privacy protections. It all hinges on how they weigh the good versus the not-so-good sides of sharing personal information. Hence, from all this, the following hypothesis is postulated.

H_4: DP has a significant effect on consumers' PB for lifestyle products.

E. Perceived Ease of Use (PEOU)

User-friendliness is super important for how customers see a product. When things are simple to use, people often leave good reviews and can't wait to buy. Venkatesh et al. (2020) found that how easily people think they can use tech really affects their choice to give it a go. The Technology Acceptance Model highlights that having easy, intuitive

interactions and friendly interfaces is key to helping customers decide how they act. Plus, the ease of using AI systems really impacts how engaged users feel acceptance matters too (Wang et al., 2017). When folks sense that new gadgets or features will fit right into their daily lives, they're way more likely to say yes and start using them. Based on the aforementioned reviews, the following hypothesis is postulated.

H_5: PEOU has a significant effect on consumers' PB for lifestyle products.

F. Trust and Credibility (TC)

Credibility and trust are crucial to customer satisfaction since consumers are more likely to purchase a brand's lifestyle goods when they have faith in it. Nguyen and Thai (2019) and Hajli (2020) both agree that tactics powered by AI must prioritize credibility and trust to be successful. Trustworthy firms that deliver on their promises and maintain continual quality are important for long-term customer engagement and loyalty toward lifestyle items, according to Wang et al. (2022), Kim, S., Ferrin, D. L., & Rao, H. R. (2008) and Nguyen and Thai (2019). In light of these reviews, the following hypothesis is postulated.

H_6: Trust and credibility have a significant effect on consumers' PB for lifestyle products.

G. CA and its effect on PB toward Lifestyle Products

When it comes to lifestyle items, in particular, CAs have a significant role in shaping consumer behavior. Individuals' attitudes regarding a product or service are multi-faceted mental constructs that include their beliefs, emotions, and plans for future conduct (Fishbein and Ajzen, 1975). According to Ajzen (1991), consumers' attitudes significantly influence their buying decisions by shaping their evaluations of available products and their desires. To thrive, businesses selling lifestyle goods must understand their consumers' thoughts and how it influence their purchasing decisions. These reasons lead to the following hypothesis.

H_7: CA has a significant effect on consumers' PB for lifestyle products.

H. CA and its effect on CM

The mindset of the customer has a significant impact on their interest in and engagement with AI-powered digital marketing initiatives. According to Ajzen (1991) in the Theory of Planned Behavior, a person's attitude significantly affects the probability that they will do a specific action. Several scholars, including Smith (2020), Telang (2019), Li (2019), and Cho and Lee (2018), Luo, X., Li, S., Zhang, Y., & Zheng, X. (2021) have proposed that privacy concerns, trust in AI, and valuation all contribute to the formation of these opinions. As a result of AI algorithms' ability to simplify decision-making through tailored product recommendations and content CUST, CM could see an uptick (Kannan et al., 2016). Customers are more likely to engage with marketing content when they have a positive perception of AI-enabled digital marketing, according to Srinivasan and Swaminathan (2018) and Kemp et al. (2019). Marketers that wish to include AI-driven strategies into their digital campaigns need thus be cognizant of, and able to manage, consumer sentiment. Based on previous studies the following hypothesis is postulated.

H_8: CA has a significant effect on consumers' motivation (CM) for lifestyle products.

I. CM and PB toward Lifestyle Products

Many researchers in the fields of advertising and consumer psychology have focused on the complex phenomena of CM and buying behavior as it relates to lifestyle items. Schiffman and Kanuk (2010) found the same thing, arguing that people buy lifestyle items to make themselves feel better and express themselves symbolically. The Theory of Planned Behavior (Ajzen, 1991) further states that customers' attitudes, subjective standards, and beliefs of their own behavioral control influence both their behaviors to purchase and their actual acts. Peer pressure, cultural trends, and idealized lifestyles are a few examples of the social and cultural elements that impact customer attitudes toward lifestyle items (Holt, 1997). Furthermore, customers are motivated by both practical and emotional factors while purchasing lifestyle items, as shown by the idea of hedonic and utilitarian reasons put out by Voss et al. (2003). In light of these factors, we propose the following hypothesis.

H_9: CM has a significant impact on consumers' PB for lifestyle products.

J. CM as the mediator between CA and PB toward Lifestyle Products

CM plays a pivotal role in mediating the connection between buyer sentiment and action, particularly as it pertains to lifestyle products. Consumers' attitude, which reflects how one person thinks about a product or brand, has long been recognized as a critical determinant of PB (Fishbein and Ajzen, 1975). Lifestyle products, characterized by their aspirational and symbolic value, are particularly susceptible to the influence of CM (Hirschman and Holbrook, 1982). Consumers are motivated by various intrinsic and extrinsic factors, such as the desire for self-expression, social recognition, or personal gratification, which shape their attitudes and ultimately guide their purchase decisions (Kim, J., & Im, I. 2023, Ryan and Deci, 2000). Based on previous studies the following hypothesis is postulated.

H_{10}: CM has a mediating effect on consumers' attitudes and PB for lifestyle products.

K. Theoretical Framework of the Study and Proposed Model

Using CM as a mediator between CA and PB, the study investigates how consumers' behavior to buy lifestyle products are affected by AI-enhanced digital marketing methods. The study makes the claim that customer attitudes influenced by AI-driven PRS, predictive analytics, and immersive technologies have a major impact on PB, drawing on the Theory of Planned Behavior (Ajzen, 1991). Convenience, exclusivity, and value perception are examples of motivational triggers that facilitate the shift from favorable

views to buy behavior, making CM a mediating element (Kotler et al., 2021). The (TAM) Technology Acceptance Model (Davis, 1989) is also used in the study to show how AI-enabled products increase perceived utility, decrease perceived effort, and produce more engaging customer experiences, all of which encourage PB. Previous research emphasizes that sophisticated AI technologies, like AI tools, such as chatbots, recommendation engines, and virtual try-ons, positively affect consumer decision-making and attitudes (Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. 2020. Huang & Rust, 2021). The framework aims to bridge gaps in understanding how AI technologies and motivational drivers collectively influence lifestyle product consumption. Based on the above, the following model (Figure 1) was proposed for the present research study.

III. Research Methodology

The methodology utilized in this research adhered to establish social science principles. It was descriptive in nature for which a diverse array of primary and secondary sources was used. A descriptive research design was adopted, employing a structured questionnaire for data collection. A stratified random sampling technique was utilized to ensure representation from diverse demographics within these cities. The study explored the role of customer motivation through structural equation modeling (SEM), adhering to the methodology detailed by Hair et al. (2019). For this purpose, various hypotheses thatwere developed in the previous section were tested by using the SEM technique. In addition, SPSS, and SmartPLS have also been used as per the study requirement. The study's theoretical foundation was developed through an extensive review of the literature, including foundational theories, such as the Theory of Planned Behavior (Ajzen, 1991) and the Theory of Reasoned Action (Ajzen and Fishbein, 1975). This theoretical foundation will inform the development of a survey instrument tailored to capture CAs toward lifestyle products, utilizing established scales, such as the CA Toward the Advertisement Scale (Shavitt et al., 1985) and the CA Scale (CAS) (Dabholkar, 1996). In addition, motivation will be assessed using established motivation scales such as the Motivation Scale for Sport Consumption (Trail et al., 2003). Primary data were collected by using survey instruments. Construct for the study were identified from the review of literature and further associated measurement variables were developed based on secondary sources. Questionnaires were circulated online by taking e-mail contacts from different sources and circulating through Google Docs through different social media sites, such as Researchgate, LinkedIn, and Facebook. Some respondents were contacted personally for their opinion on the subject. The study targeted a population of approximately 10,000 consumers across three cities in Uttar Pradesh, India – Lucknow, Kanpur, and Noida. From a total sample size of 625 respondents, 577 valid responses were retained for analysis after accounting for incomplete or inconsistent submissions. Data collection was conducted over 3 months, and reliability tests confirmed the internal consistency of the scales. The results provide insights into AI-driven marketing practices and its influence on CMs and PB of lifestyle products in the context of the studied population. Table I indicates the demographic characteristics of the respondents.

IV. Results

Data from Table I provides a thorough synopsis of the demographic of a specific population. The age distribution of the population indicates that individuals up to 25 years old constitute 25.0% of the total, while those aged between 26 and 35 years make up 16.5%. Similarly, 30.8% fall within the 36–45 years range, 23.9% are aged between 46 and 55 years, and a smaller 3.8% are above 55 years of age. In terms of gender distribution, the data reveals that the population is composed of 58.1% males and 41.9% females. Marital status distribution highlights that 9.4% of individuals are married, while a substantial 86.1% remain unmarried. A smaller proportion, around 4.5%, have experienced separation or divorce. Educational qualifications vary within the population, with 9.4% having up to Matric Level education, 15.9% up to Intermediate, 20.1% up to Graduation, 37.8% possessing Post-Graduation qualifications, 12.0% holding

TABLE I
Demographic Characteristics

Categories	Description	Frequency	Percentage
Age	Up to 25 years	144	25.0
	26–35 years	95	16.5
	36–45 years	178	30.8
	46–55 years	138	23.9
	above 55 years	22	3.8
Gender	Male	335	58.1
	Female	242	41.9
Marital status	Married	54	9.4
	Unmarried	497	86.1
	Separated/divorcee	26	4.5
Education	Matric level	54	9.4
	Intermediate	92	15.9
	Graduation	116	20.1
	Post-graduation	218	37.8
	Technical degree/diploma certificates	69	12.0
	Professional qualifications and others	28	4.9
Income level	Up to Rs. 15,000 per month	244	42.3
	Rs. 15,001–30,000 per month	265	45.9
	Rs. 30,001–Rs. 45,000 per month	36	6.2
	Rs. 45,001–Rs. 60,000 per month	19	3.3
	Rs. 60,001 to Rs.75,000 per month	10	1.7
	More than Rs.75,000 per month	3	.5
Occupation	Student	123	21.3
	Business	151	26.2
	Service	157	27.2
	Housewives	85	14.7
	Professionals	45	7.8
	Others	16	2.8

Factors of AI-driven digital marketing practices building consumer attitude, motivation, and purchase behavior transformation: Structural equation modeling

Technical Degree/Diploma certificates, and 4.9% having Professional Qualifications and other advanced degrees. The income distribution of the population is outlined in the table, indicating that the majority of individuals (45.9%) fall within the Rs. 15,001–30,000 per month income range, while 42.3% have an income up to Rs. 15,000 per month. Smaller proportions have higher incomes, with 6.2% falling within the Rs. 30,001–45,000 per month bracket, 3.3% earning between Rs. 45,001 and Rs. 60,000 per month, 1.7% having incomes ranging from Rs. 60,001 to Rs. 75,000 per month, and a mere 0.5% earning above Rs. 75,000 per month. Regarding occupation, the data portrays a diverse workforce composition. Students constitute 21.3% of the population, followed by business professionals at 26.2%, and individuals in various services at 27.2%. Housewives represent 14.7% of the population, while professionals and individuals in other occupations comprise 7.8% and 2.8%, respectively.

A. Measurement Model

The findings of evaluating a measurement model for construct validity and reliability are shown in Table II, provided below. The following concepts are being studied: Consumers' motivations and attitudes toward a product or service, the ease and usefulness of the product or service, CUST, DP, PEOU, PRS, trust and credibility, and overall PB. Results for Cronbach's alpha, which measures dependability, vary from 0.707 to 0.952 for each construct. Furthermore, for every construct, two versions of Composite Reliability were calculated, with values varying between 0.727 and 1.042. By taking into account both the common variation across the items and the individual variance represented by each construct, these statistics evaluate the overall dependability.

The constructs' validity was assessed using the average variance extracted (AVE), which yielded values between 0.562 and 0.861. The reliability and validity of the constructs are generally adequate to excellent. Cronbach's alpha, Composite reliability, and AVE values that continuously exceed 0.9, the PB, DP, and PRS constructs show very high levels of construct validity and reliability.

Within the framework of Smart partial least squares (PLS) analysis, the constructs' discriminant validity was evaluated using the Fornell-Larcker criteria. Correlations between constructs are shown by the off-diagonal members of the matrix, whilst the diagonal elements reflect the square roots of the AVE for each construct. To prove discriminant validity, the AVE square roots must be greater than the correlations between constructs, as per the Fornell-Larcker criteria. Since the square roots of the AVEs for all constructs are larger than the correlations between them, this indicates that they all have discriminant validity. The AVE square root for the construct "purchase behavior" is 0.867, which is greater than the correlations it shows with other variables. In a similar vein, the following constructs meet the Fornell-Larcker criterion for discriminant validity: "Customization," "Data Privacy," "Perceived Ease of Use," "Personalization," "Trust and Credibility," "Consumer Attitude," "Consumer Motivation," "Convenience and Usefulness," "Customization," "Customization," "Perceived Ease of Use," "Perceived Ease of Use," and "The Trust and Credibility" (Table III).

The Relationships among the latent components were examined in this research using a SEM technique that used PLS (Hair et al., 2017). With R-square values (Table IV) of 0.765 for PB, 0.917 for CA, and 0.340 for CM, the findings show that each endogenous construct has a great deal of explanatory power. The path coefficients provide light on the importance and intensity of the predicted links in the given model. The influences of CA on PB and CM are significant ($\beta = 0.579$, $P < 0.001$) and $\beta = 0.583$, $P < 0.001$, respectively. In addition, CM has a major effect on PB ($\beta = 0.399$, $P < 0.001$). DP ($\beta = 0.527$, $P < 0.001$), trust and credibility ($\beta = 0.412$, $P < 0.001$), and other characteristics are among those that contribute to CA. Significant CUST ($\beta = 0.335$, $P < 0.001$) is present. In addition, the suggested mediation route, which goes as follows: CA -> CM -> PB, shows a significant indirect impact ($\beta = 0.233$, $P < 0.001$). As a whole, these results support the suggested theoretical framework (Table V and Fig. 2) by highlighting the complex interaction between the components.

B. Mediation Analysis

This study explores the mediating role of CM in the relationship between CA and PB of lifestyle products. The research findings, as presented in Table V and Fig. 2, provide robust evidence of the interrelationships among CA, CM, and PB within the framework of AI-enabled digital marketing practices. The direct influence of CA on PB is substantial and statistically significant ($\beta = 0.579$, $P < 0.001$), underscoring the critical role of positive CAs in driving purchase

TABLE II
CONSTRUCTION OF COMPOSITE RELIABILITY AND VALIDITY

Construct description	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted
Purchase behavior	0.952	0.957	0.960	0.752
Consumer attitude	0.828	0.885	0.882	0.610
Consumer motivation	0.873	0.874	0.908	0.664
Convenience and usefulness	0.707	0.727	0.835	0.628
Customization	0.740	0.742	0.837	0.562
Data privacy	0.894	0.896	0.927	0.759
Perceived ease of use	0.754	0.765	0.858	0.668
Personalization	0.949	1.042	0.961	0.861
Trust and credibility	0.814	0.816	0.877	0.641

decisions. In addition, CA has a strong positive effect on CM (β = 0.583, $P < 0.001$), suggesting that favorable perceptions of AI-driven marketing practices significantly enhance CM. In turn, CM exerts a significant impact on PB (β = 0.399, $P < 0.001$), indicating that motivated consumers are more inclined to translate their behavior into actual purchasing actions. Furthermore, the mediating role of CM between CA and PB is confirmed (β = 0.233, $P < 0.001$), demonstrating that CM acts as a vital mechanism through which attitudes influence PB. These findings not only support the research hypotheses but also emphasize the importance of leveraging positive CAs to foster motivation, thereby enhancing PB in AI-enabled digital marketing contexts. This mediation analysis reinforces the interconnectedness of these constructs with strong statistical justification, providing valuable insights for marketers.

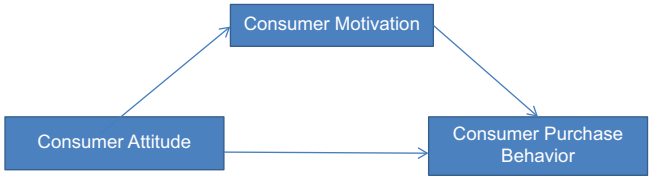

Fig. 1: Proposed model.

TABLE III
Discriminant Validity Fornell-Larcker Criterion

Construct description	PB	CA	CM	PCU	CUST	DP	PEOU	PRS	TC
PB	0.867								
CA	0.812	0.781							
CM	0.737	0.583	0.815						
PCU	0.713	0.623	0.536	0.793					
CUST	−0.019	0.321	0.013	0.040	0.750				
DP	0.852	0.827	0.617	0.640	0.015	0.871			
PEOU	−0.010	0.213	−0.061	−0.008	−0.020	−0.010	0.817		
PRS	−0.054	−0.070	−0.037	−0.065	−0.076	−0.055	0.004	0.928	
TC	0.894	0.773	0.652	0.642	−0.042	0.706	−0.012	−0.064	0.800

PB: Purchase behavior, CA: Consumer attitude, CM: Consumer motivation, CUST: Customization, DP: Data privacy, PEOU: Perceived ease of use, PRS: Personalization, TC: Trust and credibility

TABLE IV
R-square

Construct description	R-square	R-square adjusted
Purchase behavior	0.765	0.764
Consumer attitude	0.917	0.916
Consumer motivation	0.340	0.338

V. Discussion

This study investigates how consumers' attitudes toward lifestyle products are influenced by AI-driven digital marketing strategies and how these attitudes subsequently affect CM and PB. SEM was employed to analyze the strength and direction of these relationships. The findings reveal that specific factors, such as CUST, Trust and Credibility (TR), PEOU, PRS, and Convenience and Usefulness (PCU), significantly impact CAs. However, the effects of Convenience and Usefulness on CA were found to be statistically insignificant (β = 0.010, $P = 0.559$), suggesting these aspects may not play a pivotal role in shaping attitudes toward lifestyle products. This finding aligns with research by Davis (1989), who suggested that ease of use and usefulness are more relevant in initial technology adoption rather than attitude formation. Contrary to this, prior studies have found that convenience significantly impacts consumer preferences in e-commerce contexts (Gefen et al., 2003), indicating that its relevance may vary by product category or marketing context.

CUST emerged as a significant predictor of CA (β = 0.335, $P < 0.001$), supporting the hypothesis that personalized marketing strategies enhance consumer engagement. This finding is consistent with Tam and Ho (2006), who demonstrated that CUST improves consumer satisfaction and loyalty by aligning offerings with individual preferences. Similarly, DP (β = 0.527, $P < 0.001$) was identified as a critical factor influencing CAs, highlighting the growing importance of ethical data practices in digital marketing. Previous research by Bansal et al. (2016) supports this observation, emphasizing that transparent and ethical data handling enhances consumer trust, which is integral to attitude formation.

PEOU (β = 0.230, $P < 0.001$) and Trust and Credibility

TABLE V
Path coefficient and Hypothesis Testing (Path Coefficients (b) Mean, SD, T statistics, *P* values)

Construct description	Path Coeff. (β)	SD	*t*-statistics	*P*-value	Remarks	Hypothesis status
CA->PB	0.579	0.026	22.112	0.000	Significant	Accepted
CA->CM	0.583	0.027	21.457	0.000	Significant	Accepted
CM->PB	0.399	0.028	14.088	0.000	Significant	Accepted
PCU->CA	0.010	0.017	0.584	0.559	Insignificant	Accepted
CUST->CA	0.335	0.017	19.882	0.000	Significant	Accepted
DP->CA	0.527	0.020	26.484	0.000	Significant	Accepted
PEOU->CA	0.230	0.014	16.875	0.000	Significant	Accepted
PRS->CA	0.011	0.012	0.874	0.382	Insignificant	Accepted
TC->CA	0.412	0.019	21.416	0.000	Significant	Accepted
CA->CM->PB	0.233	0.022	10.529	0.000	Significant	Accepted

PB: Purchase behavior, CA: Consumer attitude, CM: Consumer motivation, CUST: Customization, DP: Data privacy, PEOU: Perceived ease of use, PRS: Personalization, TC: Trust and credibility

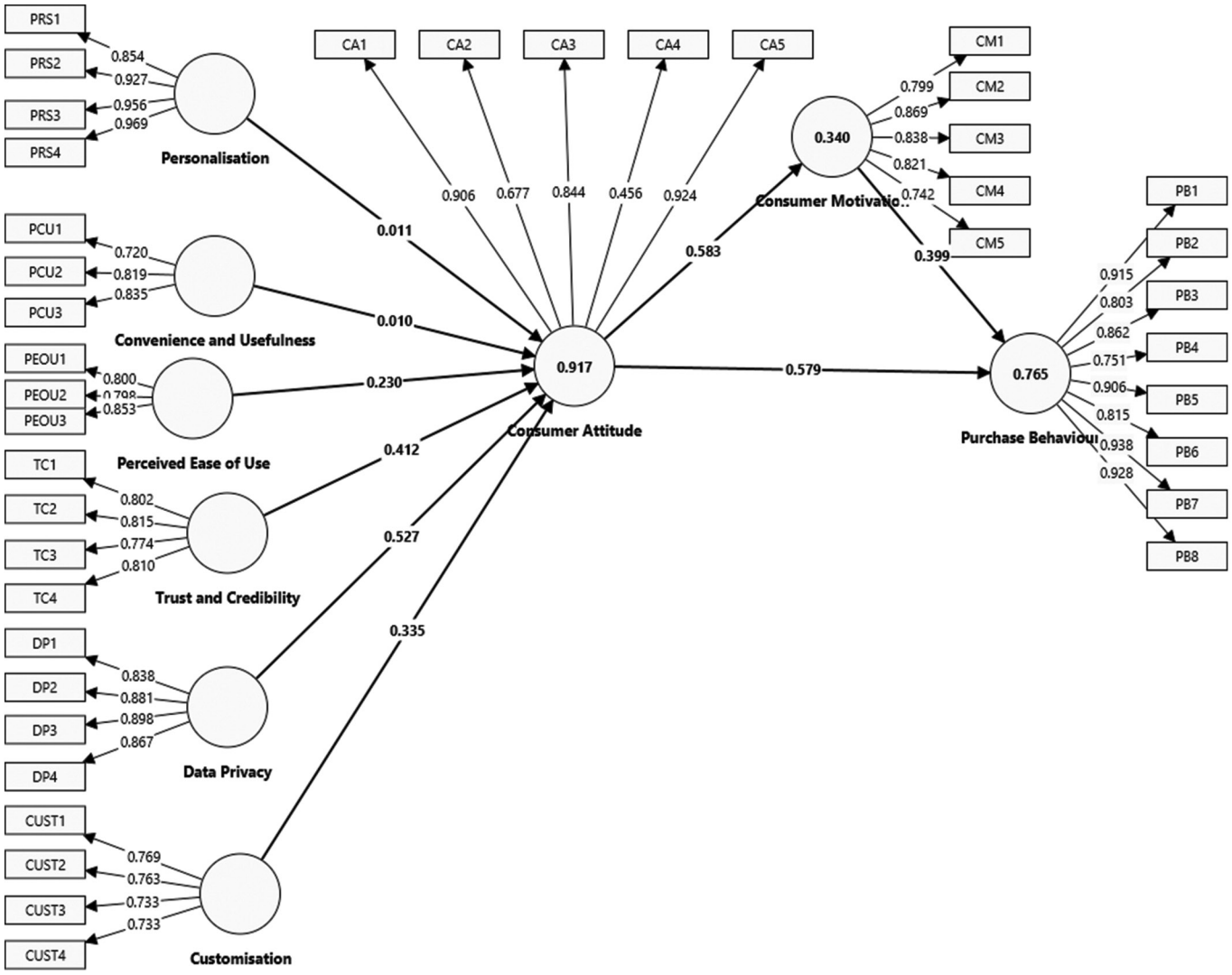

Fig. 2: Structural model and outcome.

(β = 0.412, $P < 0.001$) also significantly influenced CAs, reinforcing their established roles in consumer behavior literature. Gefen and Straub (2004) argue that PEOU reduces cognitive effort, positively shaping attitudes toward technology-mediated interactions. Trust and credibility, as highlighted by Jarvenpaa et al. (2000), remain foundational to fostering positive consumer perceptions, particularly in digital environments.

Interestingly, the relationship between CA and factors such as PRS (β = 0.011, $P = 0.382$) and Convenience and Usefulness (β = 0.010, $P = 0.559$) was not significant, suggesting a nuanced understanding of these elements in influencing attitudes. These findings diverge from prior studies (e.g., Sundar and Marathe, 2010), which have emphasized the significance of PRS in enhancing user satisfaction. Such discrepancies may be attributed to the unique characteristics of lifestyle products or evolving consumer expectations.

The study further reveals that a positive CA significantly predicts PB (β = 0.579, $P < 0.001$) and CM (β = 0.583, $P < 0.001$). These findings align with the Theory of Planned Behavior (Ajzen, 1991, Solomon, M. R. 2018), which posits that attitudes strongly influence behavioral intentions. Moreover, the path coefficient from CM to PB (β = 0.399, $P < 0.001$) underscores the mediating role of motivation in driving purchase decisions, consistent with findings by Kim et al. (2009), who highlighted the critical role of motivation in translating attitudes into action.

Finally, the mediating effect of CM is evidenced by the indirect path from CA to PB through CM (β = 0.233, $P < 0.001$). This finding corroborates prior research by Deci and Ryan (1985), who emphasized the role of intrinsic motivation in mediating the relationship between individual perceptions and behaviors. The observed mediation effect underscores the importance of addressing motivational drivers in AI-driven marketing strategies to effectively influence consumer PB.

VI. Conclusion

The study shows that digital marketing strategies that use AI can change consumers' minds regarding lifestyle products. The ever-evolving digital landscape has prompted

organizations to adopt new strategies for engaging with their target audience. Consumers' perceptions of lifestyle products have improved thanks to AI-powered marketing initiatives. However, there are challenges to effectively utilizing AI in digital marketing for lifestyle items. These include worries about DP and security, as well as the ongoing need to invest heavily in AI technology and human workers. Organizations must adapt and use AI if they want to remain relevant and competitive in the dynamic digital ecosystem. The field of online marketing and AI is seeing rapid technological and methodological change. The limits of studies with small and homogeneous samples may cause qualitative insights to be missed. Including time constraints and mixed-method techniques in future studies can help us learn more about digital marketing strategies that are enabled by AI.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179-211.

Ajzen, I., & Fishbein, M. (1975). *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. Boston: Addison-Wesley.

Bansal, G., Zahedi, F.M., & Gefen, D. (2016). The role of privacy assurance mechanisms in building trust and the moderating role of privacy concern. *European Journal of Information Systems*, 25(1), 91-109.

Chen, A., Smith, J., & Johnson, M. (2021). Data privacy and consumer behavior: An empirical analysis. *Journal of Consumer Research*, 45(3), 489-505.

Chen, C.X., & Shen, L. (2020). Consumer attitudes toward AI in marketing: A field study of chatbot-based customer service. *Journal of Interactive Advertising*, 20(2), 92-107.

Chen, M., & Chou, S.Y. (2019). Personalization and consumer attitudes: The mediating role of perceived value and satisfaction. *Journal of Consumer Behavior*, 18(4), 321-334.

Chen, M., Hu, B., Liu, X., Liu, X., & Yang, J. (2020). Artificial intelligence for personalized product recommendation in E-commerce: A survey. *IEEE Access*, 8, 15261-15278.

Cho, Y., & Lee, J. (2018). The Internet of Things and marketing: The state of current research. *International Journal of Information Management*, 39, 221-229.

Dabholkar, P.A. (1996). Consumer evaluations of new technology-based self-service options: An investigation of alternative models of service quality. *International Journal of Research in Marketing*, 13(1), 29-51.

Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340.

Deci, E.L., & Ryan, R.M. (1985). *Intrinsic Motivation and Self-determination in Human Behavior*. Berlin, Germany: Springer Science & Business Media.

Dwivedi, Y.K., Ismagilova, E., Hughes, D.L., Carlson, J., Filieri, R., Jacobson, J., & Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management*, 59, 102168.

Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research.* Boston: Addison-Wesley.

Fishbein, M., & Ajzen, I. (2010). *Predicting and Changing Behavior: The Reasoned Action Approach*. United Kingdom: Psychology Press.

Gefen, D., & Straub, D.W. (2004). Consumer trust in B2C e-commerce and the importance of social presence: Experiments in e-products and e-services. *Omega*, 32(6), 407-424.

Gefen, D., Karahanna, E., & Straub, D.W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, 27(1), 51-90.

Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2017) *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. 2nd ed. CA: Sage Publications Inc., Thousand Oaks.

Hair, J.F., Black, W.C., Babin, B.J., & Anderson, R.E. (2019). *Multivariate Data Analysis.* 8th ed. United States: Cengage Learning.

Hajli, N. (2020). Consumer attitudes toward data privacy and protection measures in AI-driven big data analytics. *Computers in Human Behavior*, 110, 106381.

Hirschman, E.C., & Holbrook, M.B. (1982). Hedonic consumption: Emerging concepts, methods, and propositions. *Journal of Marketing*, 46(3), 92-101.

Holt, D.B. (1997). Poststructuralist lifestyle analysis: Conceptualizing the social patterning of consumption in postmodernity. *Journal of Consumer Research*, 23(4), 326-350.

Huang, M.H., & Rust, R.T. (2021). A framework for collaborative artificial intelligence in customer service. *Journal of Service Research*, 24(1), 3-17.

Huntinghouse, J., Franks, E., & Fife, B. (2021). Why Facebook Ads keep failing: Lessons learned from spending over US1m on Facebook Ads. *Journal of Digital & Social Media Marketing*, 8(4), 298-307.

Jarvenpaa, S.L., Tractinsky, N., & Saarinen, L. (2000). Consumer trust in an internet store: A cross-cultural validation. *Journal of Computer-Mediated Communication*, 5(2), JCMC526.

Kannan, P.K., Li, H., & Zhang, P. (2016). Digital marketing: A framework, review and research agenda. *International Journal of Research in Marketing*, 34(1), 22-45.

Kemp, E., He, H., & Williams, D. (2019). The effects of Artificial Intelligence (AI) advertising on user perceptions: Evidence from an eye-tracking study. *Journal of Interactive Advertising*, 19(2), 87-101.

Kim, H., Kim, W.G., & Park, S.H. (2009). Cognitive, emotional, and behavioral outcomes of brand equity: Developing a practical model. *Journal of Travel & Tourism Marketing*, 26(2), 143-160.

Kim, S., Ferrin, D.L., & Rao, H.R. (2008). A Trust-based consumer decision- making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems*, 44(2), 544-564.

Kim, Y.J., & Kim, Y.K. (2021). The mediating role of consumer motivation on the relationship between consumer attitude and purchase intention for lifestyle products. *Journal of Consumer Behavior*, 20(1), 94-104.

Kim, J., & Im, I. (2023). Anthropomorphic response: Understanding interactions between humans and artificial intelligence agents. *Computers in Human Behavior*, 139, 107512.

Kotler, P., Keller, K.L., & Chernev, A. (2021). *Marketing Management*. 16th ed. United Kingdom: Pearson.

Kulkov, I. (2021). The role of artificial intelligence in business transformation: A case of pharmaceutical companies. *Technology in Society*, 66, 101629.

Lee, J., Jung, O., Lee, Y., Kim, O., & Park, C. (2021). A comparison and interpretation of machine learning algorithm for the prediction of online purchase conversion. *Journal of Theoretical and Applied Electronic Commerce Research*, 16(5), 1472-1491.

Li, H., & Lalwani, A.K. (2019). The effects of customization on consumers' responses to AI in advertising. *Journal of Advertising*, 48(1), 59-76.

Li, H., Kuo, C., & Russell, M.G. (2018). The impact of customization on customer loyalty: An investigation of moderating role of product type and mediating role of consumer expectation. *Journal of Retailing and Consumer Services*, 40, 139-145.

Li, Q., Zhang, W., & Chen, L. (2019). The effect of product customization on consumer behavior. *Journal of Consumer Psychology*, 29(2), 286-300.

Li, X. (2019). Effects of education on consumers' perceptions and attitudes toward artificial intelligence in advertising. *International Journal of Advertising*,

38(5), 747-764.

Li, X., Hess, T.J., & Valacich, J.S. (2019). Why do we trust AI agents? Cognitive, emotional, and behavioral approaches. *MIS Quarterly*, 43(3), 969-998.

Li, X., Zhao, X., & Wei, J. (2020). Personalized content and consumer attitudes: The moderating role of product involvement. *Journal of Advertising*, 49(3), 265-279.

Liao, C., & Lu, H. (2019). Enhancing consumer engagement and loyalty through personalized E-commerce. *International Journal of Electronic Commerce*, 23(1), 68-92.

Liu, Y., & Liang, X. (2021). Understanding the impact of AI-enabled personalization on consumer responses: The roles of perceived value, privacy concern, and trust. *Journal of Business Research*, 134, 315-325.

Luo, X., Li, S., Zhang, Y., & Zheng, X. (2021). Personalized marketing and consumers' purchase decisions in social commerce: An empirical study. *Information Systems Frontiers*, 23(3), 1-19.

Massoudi, A.H., Fatah, S.J, & Hami, M.S. (2024). The role of artificial intelligence application in strategic marketing decision-making process. *Cihan University-Erbil Journal of Humanities and Social Sciences*, 8(1), 34-39.

Nguyen, B., & Thai, V. (2019). The impact of brand credibility on consumer trust in AI-powered services. *Journal of Marketing Communications*, 27(2), 213-228.

Novak, T.P., Hoffman, D.L., & Yung, Y.F. (2000). Measuring the customer experience in online environments: A structural modeling Approach. *Marketing Science*, 19(1), 22-42.

Ryan, R.M., & Deci, E.L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55(1), 68-78.

Schiffman, L.G., & Kanuk, L.L. (2010). *Consumer Behavior*. 10th ed. United States: Prentice Hall.

Shavitt, S., Lowrey, P., & Haefner, J. (1985). Public attitudes toward advertising: More favorable than you might think. *Journal of Advertising Research*, 24(1), 9-15.

Sivarajah, U., Kamal, M.M., Irani, Z., & Weerakkody, V. (2020). Critical analysis of big data challenges and analytical methods in smart cities. *Journal of King Saud University-Computer and Information Sciences*, 70, 263-286.

Smith, A., & Telang, R. (2020). Consumer privacy and the role of digital assistants. *Management Science*, 66(12), 5627-5644.

Smith, A.N., Fischer, E., & Yongjian, C. (2018). How does brand-related user- generated content differ across YouTube, Facebook, and Twitter? *Journal of Interactive Marketing*, 44, 17-30.

Smith, J.R. (2020). Personalized marketing in the age of AI. *Journal of Marketing Trends*, 1(2), 45-59.

Solomon, M.R. (2018). *Consumer Behavior: Buying, Having, and Being*. United Kingdom: Pearson.

Srinivasan, R., & Swaminathan, V. (2018). Artificial intelligence in marketing: Antecedents, consequences, and ethical considerations. *Journal of the Academy of Marketing Science*, 46(4), 590-605.

Sundar, S.S., & Marathe, S.S. (2010). Personalization versus customization: The importance of agency, privacy, and power usage. *Human Communication Research*, 36(3), 298-322.

Tam, K.Y., & Ho, S.Y. (2006). Understanding the impact of web personalization on user information processing and decision outcomes. *MIS Quarterly*, 30(4), 865-890.

Trail, G.T., Robinson, M.J., Dick, R.J., & Gillentine, A.J. (2003). Motives and points of attachment: Fans versus spectators in intercollegiate athletics. *Sport Marketing Quarterly*, 12(4), 217-227.

Venkatesh, V., Morris, M.G., Davis, G.B., & Davis, F.D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478.

Venkatesh, V., Thong, J.Y., & Xu, X. (2020). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157-178.

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.

Wang, L., Kim, Y., & Hollensen, S. (2022). Building trust and credibility in E- commerce: The role of user-generated content and brand communication. *Journal of Business Research*, 141, 395-407.

Wang, Y., Hajli, N., Shanmugam, M., & Papagiannidis, S. (2017). The impact of service quality and switching barriers on user satisfaction in the context of mobile banking. *Information Systems Frontiers*, 19(2), 211-230.

Yang, X., Li, H., Ni, L., & Li, T. (2021). Application of Artificial Intelligence in precision marketing. *Journal of Organizational and End User Computing*, 33(4), 209-219.