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The Impact of Digital Marketing Mix on Purchase Intention: A Survey in the Used Car Market in Hanoi City

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ABSTRACT

In the digital age, the traditional 4Ps of marketing product, price, place, and promotion are undergoing a significant transformation to adapt to the complex dynamics of online consumer behavior, particularly in sectors like the used car market. This study investigates the predictive relationship between the digital marketing mix and purchase intention, with a focus on the Hanoi used car market. It explores how the digital adaptation of the 4Ps influences consumers' buying decisions and examines the mediating role of customer engagement often referred to as the customer mix in this context. A quantitative research approach was employed using a predictive causal model based on Partial Least Squares Structural Equation Modeling (PLS-SEM4). The study surveyed 89 targeted respondents through purposive sampling. The results reveal that the evolution of the digital marketing mix has both direct and indirect significant impacts on purchase intention. Customer engagement was found to play a significant mediating role, enhancing the explanatory and predictive power of the model. These findings contribute to bridging a knowledge gap by demonstrating that the modernization of the marketing mix, aligned with digital platforms and centered around customer experience, is highly relevant and effective in influencing purchase intentions especially in a competitive and information-intensive market like that of used cars in Hanoi.

Keywords: Evolving Marketing Mix; Customer Mix; Purchase Intention; PLS-SEM

INTRODUCTION

The rapid advancement of technology under the Industrial Revolution 4.0 has fundamentally reshaped global business models, including how products and services are marketed and consumed especially in consumer-sensitive industries like the used car market. Disruptive technologies have heightened the need for organizational agility, enabling firms to respond quickly to shifting consumer demands through innovative digital marketing strategies and platforms (Firmansyah, Wahdiniwaty, et al., 2023). The traditional 4Ps framework product, price, place, and promotion long regarded as the backbone of marketing strategy and decision-making (Kotler & Armstrong, 2017), is now under transformation in response to the digital revolution (Bezhovski, 2025). In today's volatile digital economy, companies must adapt their marketing mix to meet evolving consumer behavior across online and hybrid platforms to maintain competitiveness.

This evolution has triggered the expansion of the marketing mix from its classical 4Ps to more customer-centric and digitally integrated models. For example, McCarthy's 4Ps model (1979) has been reimagined into Lauterborn's 4Cs focusing on customer needs, cost, convenience, and communication (Lauterborn, 1990). Subsequent models such as the 7Cs, the 7Ps (Booms, 1981; Constantinides, 2002, 2004), and the 8Ps (Goldsmith, 1999; Bitner et al., 1990; Morgan, 1994; Lovelock & Gummesson, 2004; Lindgreen & Wynstra, 2005; Sulaj & Pfoertsch, 2024) have attempted to contextualize marketing in more service-oriented and experience-driven environments. In addition, newer frameworks like the SIVA model (Dev & Schultz, 2005), the SAVE model (Ettenson et al., 2013), and even conceptual approaches like the 5E (Constantinides, 2014) and Batat's 7E experiential mix (Batat, 2024) further signal an industry shift toward digitally interactive, value-centered consumer experiences.

Promotional strategies, once limited to traditional media, have also undergone significant transformation through the rise of Integrated Marketing Communication (IMC), encompassing broader communication tools such as

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personal selling, public relations, direct marketing, and increasingly, digital content creation and social media (Jackson & Ahuja, 2016). This new environment often referred to as IMC 2.0 integrates viral marketing and real-time digital engagement, expanding the influence of the promotional mix in a way that directly affects consumer purchase intentions, particularly in digitally-informed sectors like the used car market. Despite the diversification of Ps and the emergence of new models, the core concept remains: the marketing mix, however adapted, serves as a controllable strategic toolset to drive market growth and secure consumer interest.

The ongoing transformation of the traditional 4Ps marketing model is particularly evident in the digital marketplace, where the concept of place has evolved into platform representing online environments such as e-marketplaces, websites, and social media channels that form the operational infrastructure for contemporary business activities (Bezhovski, 2025). This shift is especially pronounced in the used car market in Hanoi, where consumers increasingly engage with digital touchpoints throughout their purchase journey. Despite this evolution, the overarching objective of the marketing mix remains: to structure internal managerial strategies aimed at driving sales, attracting customers, and enhancing competitive advantage across strategic business units.

In the context of the used car market, digital platforms now serve as key mediators between marketing efforts and customer decision-making processes. As digital channels disrupt traditional sales models, marketers aim to influence purchase intention through a mix of product availability, dynamic pricing, and targeted promotion strategies implemented through platforms rather than physical locations. Purchase intention itself encompasses various psychological dimensions, including transactional interest, exploratory interest, referential intention, and preference formation (Charlesworth, 2018; Wahdiniwaty et al., 2023, pp. 52-54; Kotler & Keller, 2016; Assael, 2002; Indriani & Firmansyah, 2020).

At the same time, the integration of customer-specific traits captured in the emerging customer mix model adds a critical dimension to understanding how marketing efforts translate into consumer behavior. The customer mix, comprising key elements such as people, personality, perception, and participation (Jackson & Ahuja, 2016), provides a more holistic view of what drives demand in the digital era. In the Hanoi used car market, these elements help explain how consumers interact with marketing messages, form trust through reviews and social proof, and develop intention to purchase.

This study addresses the gap in current literature by empirically testing a predictive model that links the evolution of the digital marketing mix to purchase intention, with customer mix acting as a mediating variable. Unlike earlier studies that focused solely on internal managerial implications, this research bridges the company's internal marketing objectives with external consumer dynamics, offering a more integrative approach to marketing strategy in the context of technological disruption. In this digitally transformed business environment, platforms not only replace traditional places, but also become central communication and conversion spaces that foster real-time engagement, personalized interaction, and ultimately, customer purchase decisions.

By situating the digital marketing mix especially the evolved 4Ps model of product, price, promotion, and platform within the framework of customer characteristics and behaviors, this study proposes a responsive and adaptive marketing model. This model captures both managerial priorities and customer-centric considerations, offering new insights into how businesses in Hanoi's used car market can leverage digital tools to effectively influence purchase intention in an increasingly competitive and interactive digital economy.

METHOD

This study adopts a quantitative research approach, grounded in theoretical foundations to develop a predictive causal model that examines the relationships among key constructs relevant to digital marketing in the used car market. Specifically, the research explores the interaction between the digital evolution of the 4P marketing mix, the customer mix, and consumer purchase intention in the context of a digitally-driven, consumer-centric environment. The analytical framework is based on Partial Least Squares-Structural Equation Modelling version 4 (PLS-SEM4), as recommended by Hair et al. (2011b), utilizing a reflective measurement model. Hypothesis testing is rooted in predictive power analysis (Firmansyah & Wahdiniwaty, 2023). The study employs an explanatory survey design (Strydom, 2013; Ginsberg, 2001; Firmansyah et al., 2024), with data collected from 89 purposively selected respondents through a non-probability sampling technique (Firmansyah, 2022).

The research was conducted in the used car market of Hanoi, Vietnam, focusing on consumers actively engaging with digital platforms particularly social media and e-marketplaces in their car purchasing journey. Respondent selection was based on interaction with digital ads and showroom platforms, primarily through platforms such as Facebook, Zalo, and WhatsApp. The respondent profile was predominantly male (74.16%), with the largest age group between 41-50 years (57.30%). Most participants were permanently employed or operated private businesses and fell within the upper-middle-income bracket.

The core constructs measured include the digital 4P marketing mix (product, price, platform, promotion), the customer mix (people, personality, perception, participation), and purchase intention (transactional, referential, preferential, exploratory). These were operationalized using 10 indicators for the marketing mix (MM1-MM10), 10 for the customer mix (CM1-CM10), and 12 for purchase intention (PI1-PI12). Data was collected via structured questionnaires using a 7-point Likert scale, administered online through Google Forms and distributed primarily via social media and messaging platforms.

Data analysis was conducted in SmartPLS through two main stages: the measurement model and the structural model. The measurement model was evaluated for convergent and discriminant validity. Convergent validity was assessed via factor loadings (>0.7), Cronbach's alpha, composite reliability (CR ≥ 0.7), and average variance extracted (AVE ≥ 0.5) (Hair, Anderson, et al., 2010; Ghozali, 2014; Firmansyah & Wahdiniwaty, 2023; Dijkstra & Henseler, 2015; Mâță et al., 2020). Discriminant validity was established through cross-loadings, the Fornell-Larcker criterion (Fornell & Larcker, 1981), and Heterotrait-Monotrait Ratio (HTMT < 0.90) (Hair et al., 2021; Franke & Sarstedt, 2019; Henseler et al., 2016; Budiarti & Firmansyah, 2024).

Multicollinearity was evaluated using the full collinearity test (VIF < 3.3) (Kock & Lynn, 2012), and latent variable correlations were assessed (r < 0.85). The model's overall fit was validated using the coefficient of determination (R^2), effect size (f^2) (Cohen, 1988; Hair et al., 2019), and global fit indices including Standardized Root Mean Square Residual (SRMR < 0.90) and Normed Fit Index (NFI ≥ 0.90) (Henseler et al., 2016; Hair et al., 2017; Firmansyah et al., 2024).

The structural model and hypothesis testing phase used the bootstrapping procedure. Both direct and indirect (mediating) effects were tested by evaluating t-statistics at a 5% significance level (p = 0.05), with hypotheses accepted when t-values exceeded 1.96 (Firmansyah, 2024). This comprehensive statistical approach ensured robustness in understanding how the evolution of the digital marketing mix, when mediated by the customer mix, shapes purchase intention in Hanoi's used car market.

RESULTS AND DISCUSSION

Measurement Model

Measurement model estimation ensures that respecification and improvement of the constructed model needs to be carried out, referring to the results of the initial estimate which shows that some of the criteria of the measurement model are not met in several indicators between each construction. The findings from the results of the estimation of the measurement model after respecification and model improvement (see figure 1), show that the marketing mix (MM) is formed by ten indicators (MM1-MM10), where there are nine indicators that meet the *standardized loading factors* (μ) greater than 0,7 (μ>0,7), but one indicator, namely MM2, is forced to be removed because it has μ<0,7, so that the MM construction leaves nine indicators that are maintained. The customer mix (CM) is formed by ten indicators (CM1-CM10), but there are nine indicators having μ>0,7, and one indicator (MM8) should be eliminated from the model because it is not within the recommended μ criteria, ensuring the remaining nine indicators are maintained for the CM construction. Purchase intention (PI) is measured by twelve constituent indicators (PI1-PI12), where ten indicators meet the standardized loading factors (μ) greater than 0,7 (μ>0,7), but there are two indicators (PI4 and PI10) that are forced to be eliminated and discarded because they have ☐<0,7, finally the latent PI variable leaves ten indicators that are maintained.

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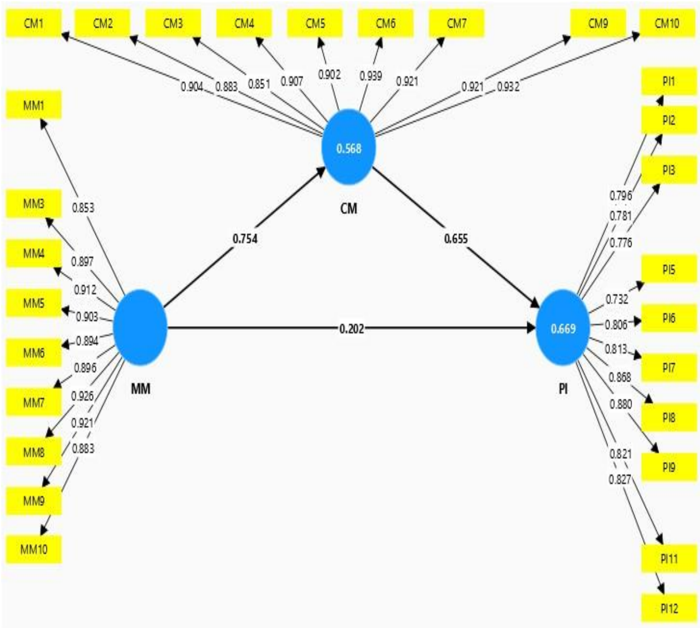

Figure 1: Estimation Results of Post-Respecification and Repair Measurement Models

The evaluation of the test results was also carried out by assessing Cronbach's Alpha (Cα), Composite Reliability (C.R), AVE, Cross Loadings values, Fornell-Larcker criteria, HTMT, and multicollinearity indications, all of which were re- evaluated to ensure that convergent validity and discriminant validity could be met so that the overall model fit criteria were achieved and predictive causality at the hypothesis testing stage could be carried out. The results of the convergence validity evaluation can be seen in table 1. The construction parameters MM, CI, and PI have α value; Cα; and C.R>0,70, with an AVE>0,5 value, the recommended Cα, C.R, and AVE criteria can be met. The constituent indicators of each construction also have a value of VIF<3,3, so that the full collinearity criterion can be achieved. Therefore, the convergent validity for each construct in the model can be met according to the recommended criteria (see table 1).

Table 1: Convergent Validity of MM, CM, and PI Constructs

Variables	Indicators	μ	Cα	C.R	AVE	VIF
	MM1	0,853				2,045
	MM3	0,897				2,409
	MM4	0,912				2,957
Marketing Mix (MM)	MM5	0,903	0,973	0,977	0,822	2,217
	MM6	0,894				2,412
	MM7	0,896				2,149
	MM8	0,926				2,488
	MM9	0,921				2,193
	CM1	0,904				3,046
Customer Mix (CM)	CM2	0,883	0,970	0,974	0,807	2,763
	CM3	0,851				2,440
	CM4	0,907				2,668
	CM5	0,902				2,581
	CM6	0,939				3,115
	CM7	0,921				3,096
	CM9	0,925				3,122
	PI1	0,796				2,556
	PI2	0,781				2,589

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	PI3	0,776				2,481
	PI5	0,732				2,204
Purchase Intention (PI)	PI6	0,806	0,943	0,950	0,658	2,851
	PI7	0,813				2,856
	PI8	0,868				2,987
	PI9	0,880				2,945
	PI11	0,821				2,835
	PI12	0,827				2,997

Note: μ = SLF; Cα = Cronbach's Alpha; CR, Composite Reliability; AVE, average variance extracted.

The results of the evaluation of the validity of the discriminant based on the cross loading criteria show the correlation of each parameter of one construction with another construction to ensure that the required criteria are met in the model. Meanwhile, the results of the Heterotrait-Monotrait Ratio (HTMT) assessment and the Fornell-Larcker criterion, are presented in table 2.

Table 2: HTMT and Fornell-Larcker Criterion

Heterotrait-Monotrait Ratio (HTMT)				**Fornell-Larcker Criterion**			
Variables	**CM**	**MM**	**PI**	**Variables**	**CM**	**MM**	**PI**
CM	-			**CM**	0,907	-	
MM	0,775	-		**MM**	0,754	0,899	-
PI	0,881	0,716	-	**PI**	0,807	0,695	0,811

Note: HTMT criterion<0.90; Fornell-Larcker criterion, comparing the AVE root of each construct with other constructs diagonally.

The HTMT between MM construction and PI construction = 0,716 is smaller by 0,90 (0,716<0,90), as well as for the correlation between constructs in the structural model, each has HTMT<0,90 (see table 2, sub HTMT). The Fornell-Larcker criterion can be met (see table 2, sub Fornell-Larcker criterion), each construction (CM, MM, and PI) diagonally has a larger AVE root compared to the correlation with other constructions (Hair et al., 2021; Franke & Sarstedt, 2019; Henseler et al., 2016); in Budiarti & Firmansyah (2024). These findings ensure that the criteria for discriminant validity can be met. Predictively, the magnitude of correlation (r) at the construction level in the structural relationship of the model between each construct was also evaluated on the criterion of r<0,85, see table 3.

Table 3: Predictive Correlation of Causality between MM, CM, and PI

Variables	**CM**	**MM**	**PI**
CM	-	0,754	0,807
MM	0,754	-	0,695
PI	0,807	0,695	-

Note: maximum correlation height at r criterion ≤0.85.

Predictively, the structural relationship between each construction model has a value of r<0,85. These findings conclude that the predictive correlation of causality of each construct in the constructed model has a good and positive validity level at the level of r<0,85. Each relationship between constructions is sure to occur in the same direction. This finding completes the fulfillment of the criteria of convergent validity and discriminant validity.

Evaluasi Goodness of Fit

The overall model fit (GoF) was assessed from the criteria of parameters f^2 and R^2, SRMR and NFI in the fit sub-model.

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Table 4: Evaluation of Criteria f^2 and R^2

Structural Model	f^2	R^2
CM => **PI**	0,559	0,669
MM => **PI**	0,053	
MM => **CM**	0,615	0,568

Note: f^2, magnitude of effect size; and R^2, predictive power.

The predictive relationship between MM and PI had an f^2 of 0,053 greater than the criterion of f^2 = 0,02, in the low effect size category. CM with PI has an f^2 of 0,559 greater than the criterion of f^2 = 0,15, the category of moderate effect size towards a strong size effect on the criterion of f^2 = 0,75. Likewise, MM with CM has an f^2 of 0,615 greater than the criterion of f^2 = 0,15, a moderate effect size points strongly to the criterion of f^2 = 0,75.

The findings show that the prediction of causality among each construction in the structural model of this study has a moderate effect size. At the same time, the customer mix (CM) has an R^2 value of 0,568, so the construction of the structural model in the construction relationship that predicts CM has a prediction model match that is leading to the strong category, at R^2 = 0,568>0,50; R^2<0,75. The same finding occurred in the construction of the structural model in the construction relationship that predicts the purchare intention (PI) has a prediction model match that is approaching the strong category, with a value of R^2 = 0,669.

Table 5: Fit Model on SRMR and NFI Criteria

GoF Criteria	Estimates Model Fit	Cut-Off	Evaluation Results
SRMR	0,081	<0,90; <1,00	Fit
NFI	0,928	>0,90	Fit

Note: Model fit at SRMR<0.90; and NFI>0.90.

The fit model (table 5), ensures that the SRMR has a value of 0,081 less than 0,90; 1,00 (SRMR = 0,081<0,90; <1,00) so that the fit model is achieved, and the NFI is 0.928 greater than 0,90 (fit). The criteria for good model compatibility (GoF) with the fit model at SRMR<0,81 and NFI>0.90, then it can be concluded that the GoF criteria can be met in the construction of the structural model of this study.

Hypothesis Testing

The construction of the PLS-SEM structural model is based on the theory that will be tested and developed in this study, by proposing four hypotheses that need to be proven. Where, there are three hypotheses of direct effect (H1, H2, and H3), and one hypothesis for indirect effect (H4), with predictions relying on the strength of mediation effects. The results of the direct effect test were analyzed based on the data in table 6.

Table 6: Direct Effect Test Results

Hypothesis	Structural Model	Coeff.	t-Statistics	p-value	Results
H1	MM => PI	0,202	2,061*	0,039	Accepted
H2	CM => PI	0,655	7,262***	0,000	Accepted
H3	MM => CM	0,754	10,850***	0,000	Accepted

Note: *.Significant level at p<0,05; ***.Significant level at p<0,001.

The findings show that the coefficient value in the structural model between the evolution of the 4P marketing mix (MM) with a purchase intention (PI) of 0,202 with p-value = 0,039<□ = 0,05 and t-statistic of 2.061 is greater than t-critical 1.96 (t- stat = 2,061>t-critical = 1,96; *p*<0,05). The findings confirm that *H*1 is accepted, that the evolution of the 4P marketing mix has a significant direct effect on purchase intention. Customer mix (CM) with purchase intention (PI) of 0,655 with p-value = 0,000<□ = 0,05 and t-statistic of 7,262 greater than t-critical 1,96 (t-stat = 7,262>t- critical = 1,96; *p*<0,05). So *H*2 is accepted, that the customer mix has a positive and significant

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effect on purchase intention. The results also found that *H*3 was accepted, with a coefficient value between the evolution of the 4P marketing mix (MM) and the customer mix (CM) of 0,754 with p-value = 0,000<□ = 0,05 and t-statistics of 10,850 greater than t-critical of 1,96 (t-stat = 10,850>t-critical = 1,96; p<0,05), so that the marketing mix had a positive and significant effect on the customer mix. The results of the indirect effect test by considering the mediation effect of the customer mix (CM), are presented in table 7.

Table 7: Indirect Effect Test Results

Hypothesis	Structural Model	Coeff.	t-Statistics	p-value	Results
H4	MM => CM => PI	0,494	6,576***	0,000	Accepted

Note: ***.Significant level at p<0,001.

The evaluation of the mediation model on the indirect effect model (table 7), shows that the value of the structural coefficient between the evolution of the 4P marketing mix (MM) and the purchase intention (PI) through the customer mix (CM) is 0,494 with p-value = 0,000<□ = 0,05 and the t-statistic of 6,576 is greater than the t-critical 1,96 (t-stat = 6,576>t-critical = 1,96; p<0,05). The results of the study found that *H*4 was accepted, that the customer mix had a positive mediating effect on the relationship between the marketing mix and purchase intention, and was significant at □ = 0,05. The findings of this study can also fill the existing gap and expand the recognition that the evolution of the 4P marketing mix that is in line with technological developments has relevance to the modern business landscape based on digital platforms.

DISCUSSION

In the context of Vietnam's growing used car market, the classical 4Ps product, price, place, and promotion continue to form the strategic backbone of marketing. However, in the era of digitalization, the element of place has increasingly been replaced by platform, representing the shift toward e-marketplaces, websites, and social media as the primary means of customer interaction. This transition has enhanced not only marketing efficiency but also the scale and depth of customer engagement. Platforms enable real-time communication, foster participatory interest, and expand market reach in ways that traditional channels cannot, creating a competitive advantage through greater speed and personalization. These digital tools streamline the delivery of used car offerings, facilitating faster transactions and accelerating cash flow key differentiators in a market characterized by intense competition and customer skepticism.

Empirical findings from this study confirm that the digital evolution of the 4P marketing mix, particularly with the integration of platforms, positively influences purchase intention. This validates Hypothesis H1. Even though the used car market may seem localized in terms of demographics and geography, digital platforms allow businesses in Hanoi to map and engage a wider audience with unprecedented speed and accuracy. This supports Bezhovski's (2025) assertion that platforms extend the traditional 4Ps into a digitally connected ecosystem, enabling centralized yet dynamic customer interaction without face-to-face communication. Similarly, Chaffey & Ellis-Chadwick (2019) emphasize that digital platforms foster real-time engagement, deliver personalized content, and enhance targeting precision far beyond what traditional media allows. These findings align with Batat (2024), who highlights the rise of the "phygital" ecosystem a fusion of physical and digital experiences which optimizes marketing operations and elevates customer satisfaction through seamless integration.

Equally crucial to purchase behavior in the digital environment is the role of the customer mix comprising people, personality, perception, and participation as a pivotal mediator in the marketing process. Understanding how these individual characteristics influence consumer responses is essential for marketers aiming to convert digital engagement into real purchase behavior. The findings of this research provide solid support for Hypothesis H2, showing a significant and positive impact of the customer mix on purchase intention. In the case of used car showrooms operating online in Hanoi, active social media followers often represent high-potential buyers. These followers, once engaged through well-executed digital strategies, frequently evolve into loyal customers.

Supporting this, Jackson & Ahuja (2016) observed that customer personalities, perceptions, and emotional connections to brands are critical drivers of their purchasing decisions. In today's digital-first landscape, these factors are magnified customers are more digitally literate, more autonomous in their decision-making, and more

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influenced by personalized marketing content delivered through connected platforms. Their online behavior, including how they consume product information, evaluate offers, and engage with content, strongly reflects their individual traits and ultimately shapes their purchase intention. This underscores the importance of aligning digital marketing strategies not only with the company's internal objectives but also with the nuanced behavioral patterns of modern consumers in a dynamic and highly competitive digital marketplace.

In the digital era, rising levels of consumer digital literacy, access to real-time information, and active engagement on social media platforms have significantly reshaped the landscape of marketing especially in competitive sectors such as the used car market. Smart marketers today develop highly targeted programs based on insights into specific consumer profiles, enabled by data from digital interactions (Jackson & Ahuja, 2016; Jain et al., 2012). Consumers' ability to navigate online environments and their evolving behavioral patterns present both a challenge and an opportunity. For marketers in the used car market in Hanoi, harnessing this data allows them to strategically increase customer participation and engagement key precursors to purchase intention.

Social media platforms are now at the core of marketing communications, functioning not only as promotional tools but as dynamic ecosystems for audience interaction. Customer interest, satisfaction, and brand advocacy expressed through word-of-mouth and online reviews are the result of marketer agility in crafting effective and personalized marketing campaigns. As Bezhovski (2025) suggests, platforms today transcend the physical limitations of traditional "place," enabling hybrid communications and real-time services that foster deeper customer relationships.

The findings of this study validate that the evolution of the 4P marketing mix particularly the transformation of "place" into "platform" has a positive influence on the customer mix, supporting Hypothesis H3. This aligns with Sulaj & Pfoertsch (2024), who highlight that a platform-based approach enhances customer connectivity and participation, aligning marketing more closely with real customer behavior. Chaffey & Ellis-Chadwick (2019) also emphasize that digital platforms enable real-time customer experiences that go beyond traditional distribution channels, while Powers & Loyka (2010) argue that digital platforms allow businesses to capture and act on customer feedback instantaneously. These findings underscore the importance of integrating customer mix variables personality, perception, and participation into platform-based strategies to optimize marketing effectiveness.

Furthermore, the results reveal that the customer mix plays a mediating role in the relationship between the evolved digital marketing mix and purchase intention, validating Hypothesis H4. This mediation reflects a shift toward customer-centric marketing models, in which the customer mix becomes a strategic bridge that aligns internal marketing objectives with external consumer behavior. The study confirms that a well-understood customer mix strengthens the effect of the marketing mix on purchase intention, especially in sectors where high-involvement products like cars require targeted and trust-building communication. Jackson & Ahuja (2016) point out that customer personalities and online engagement are powerful predictors of purchasing decisions, especially in the digital age where consumers are both highly informed and digitally empowered.

Marketing strategies for used cars on social media platforms benefit greatly from an accurate understanding of customer profiles. Posts, interactions, and shares allow marketers to identify and engage potential buyers, even though not all followers convert to purchases due to varying consumption capacity across social classes. This highlights the need to classify and prioritize customer segments based on digital behavior and socioeconomic profiles. Doing so allows the digital marketing mix product, price, promotion, and platform to be implemented more strategically, focusing on high-potential market segments while maintaining broad visibility.

The study also highlights that various dimensions of purchase intention transactional, referential, preferential, and exploratory are deeply influenced by customer personality, perceptions, and participation (Wahdiniwaty et al., 2023; Indriani & Firmansyah, 2020; Jackson & Ahuja, 2016). Consumers' digital interactions on platforms reflect their preferences and facilitate deeper engagement. Thus, the transformation of the 4P marketing mix particularly the evolution of "platform" as a central node enables more targeted promotions, real-time customer feedback, and adaptive pricing, all of which are critical in shaping modern purchase decisions.

Strategically, this evolution of the marketing mix integrating platform and customer mix constitutes a fundamental

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element of differentiation and value creation in the used car market. As Bezhovski (2025), Sulaj & Pfoertsch (2024), and Wichmann et al. (2022) suggest, this integration enables companies to deliver compelling experiences and build long-term satisfaction. A well-articulated customer mix allows marketers to fine-tune digital campaigns, drive interaction, and amplify purchase intent ultimately reducing operational inefficiencies and maximizing ROI in a highly digitized marketplace.

Practically, success in this environment demands not only strategic alignment but also technological competency. Marketers must be proficient in digital analytics, data mining, and automation tools, as well as understand AI-driven personalization. The increasing penetration of smartphones, social platforms, and tech-savvy consumers requires businesses to map product offers, pricing strategies, promotions, and platform choices to customer behavior and social class levels. Only by aligning these factors cohesively can marketers fully leverage the power of the digital marketing mix to stimulate purchase intention in Vietnam's evolving used car industry.

CONCLUSION

The 21st-century wave of technological disruption has profoundly challenged the static nature of the traditional 4P marketing mix, pushing it to evolve in order to accommodate hybrid communication models and service delivery within a digital ecosystem. This study empirically validates that the evolution of the 4P marketing mix redefined to include digital platforms as a replacement for the traditional notion of "place" has a direct, positive, and statistically significant impact on consumers' purchase intention in the used car market in Hanoi. In parallel, the customer mix encompassing key variables such as personality, perception, and participation also demonstrates a strong and positive influence on purchase intention. Moreover, the study reveals that the evolution of the marketing mix exerts an indirect positive effect on purchase intention through the mediating role of the customer mix, with the mediation pathway exhibiting moderate predictive strength.

These findings contribute significantly to the growing body of literature on digital marketing strategy and customer behavior in technology-driven markets. They address a critical research gap by highlighting the practical relevance of aligning the marketing mix with technological advancements, particularly in the context of customer-centric business models based on digital platforms. The integration of the customer mix as a mediating construct in this digital landscape reinforces the role of consumer interactivity and personalization in shaping effective marketing strategies. As a result, the reimagined 4P model, now platform-driven, not only supports product communication and promotional precision but also facilitates real-time responsiveness and engagement core ingredients in stimulating customer purchase intention in the digital era.

The research model proposed here serves as an adaptive framework that bridges internal managerial goals and external market demands in a seamless, real-time digital ecosystem. Practically, this study offers fresh empirical evidence on the continued relevance and adaptability of the marketing mix in a customer-centered digital economy. It affirms the strategic necessity of transforming conventional marketing elements into dynamic, digital-first tools capable of driving viral engagement and sustained purchase interest through platforms such as Facebook, Zalo, and e-marketplaces.

However, this study is not without limitations. First, the predictive causality model was tested using data from a single sample consumers interacting with a specific used car showroom operating on digital platforms in Hanoi limiting the generalizability of the findings. Second, the research did not disaggregate car types by brand, production year, or luxury category, which may influence purchase intention. Future research should consider expanding the sample size across multiple showrooms and locations, employing comparative models, and introducing new variables such as digital trust, perceived value, or e-WOM. In addition, segmenting consumers by socioeconomic status and integrating AI-based behavioral data could further enhance predictive accuracy and practical applicability in marketing decision-making.

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