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Human-Centered Marketing 5.0 Practices and Consumer Trust among University Students in Klang Valley

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Abstract

The study examined the relationship between human-centered Marketing 5.0 practices and consumer trust among university students in Klang Valley, Malaysia. It was grounded in Marketing 5.0 as the primary framework and guided by the Technology Acceptance Model and Commitment-Trust Theory, with a particular emphasis on predictive, contextual and augmented marketing as consumer-oriented applications of AI. The data were collected through a quantitative, cross-sectional survey using convenience and purposive sampling to get 200 usable responses from the university students aged 18-29 who have experience in digital-platform or online-transaction. The data were gathered by a self-administered online questionnaire with 20 measurement items on a five-point Likert scale and analyzed using IBM SPSS Statistics. Consumer trust was significantly positively related to all three practices. The standardized contribution (β) was highest for augmented marketing (β = .371, $p < .001$), followed by contextual marketing (β = .352, $p < .001$) and predictive marketing (β = .141, p = .022). The three predictors accounted for 60.9% of the variance in consumer trust ($R^2 = .609$). The results of predictive and contextual marketing should be interpreted with caution as these measures had lower internal consistency and factor suitability. The results offer actionable insights for companies aiming to create clear, meaningful, and responsive AI-driven marketing strategies that support consumer trust.

Keywords: Marketing 5.0, Predictive Marketing, Contextual Marketing, Augmented Marketing, Consumer Trust, Artificial Intelligence

Introduction

Marketing has evolved from product- and customer-centered orientations toward a technology-enabled, human-centered approach. Marketing 5.0 describes the use of next-generation technologies to create, communicate, deliver and enhance value while retaining technology-for-humanity as its organizing principle (Kotler et al., 2021). Artificial intelligence

(AI), automation, analytics and connected interfaces enable companies to predict customer needs, tailor content to the moment and support customer-facing tasks. These capabilities can enhance relevance and convenience, but their value can only be judged in terms of technical efficiency. The experience should also be understandable and reliable in consumer markets.

The Malaysian context makes this issue particularly relevant. In 2025, 97.1% of households had access to the internet, and 98.3% of individuals used the internet (Department of Statistics Malaysia [DOSM], 2026). GlobalData estimated the e-commerce market in Malaysia at RM147.9 billion in 2025, growing at 13.4% annually (2026). The growing digital economy generates numerous platform-based interactions that can influence consumers' perceptions of businesses, including through recommendations, targeted messages, and automated support. The university students in Klang Valley are particularly relevant as they are active users of digital platforms, regularly engage in online transactions, and are familiar with technology-based decision environments (Chan & Lee, 2023; Djafarova & Bowes, 2021).

Consumer trust is central to these interactions. In AI-driven marketing, consumers may be using systems that they don't fully understand how they collect data and make decisions. Trust involves beliefs that the firm or system is competent, reliable, honest and attentive to consumer interests, and a willingness to be vulnerable in an exchange (Gefen et al., 2003; Morgan & Hunt, 1994). Personalization can be a sign of relevance and service quality but can also raise concerns if it involves too much behavioral monitoring or if it is used in ways that consumers were not expecting. This paradox is known as the personalization–privacy paradox, where consumers are willing to receive personalized value but not without transparency or control (Awad & Krishnan, 2006; McKee et al., 2024).

Existing studies on Marketing 5.0 and AI in marketing have often focused on organizational performance, technological capability, adoption, and overall customer experience (Alanazi, 2022; Huang & Rust, 2021). The relationship between specific consumer-oriented Marketing 5.0 practices and trust is still limited in Malaysia and Southeast Asia, especially among digitally active university students. Treating all technology-enabled marketing as one practice may also hide important differences. Predictive systems operate mainly through analysis and recommendation, while contextual systems adapt content to timing, location or activity, and augmented systems make AI visible through chatbots, virtual assistants and automated support. Consumers can then assess each practice in various combinations of usefulness, intrusiveness, transparency and interaction quality.

This study aims to fill this gap by studying the relationship between predictive marketing, contextual marketing, augmented marketing and consumer trust among the university students in Klang Valley. It contributes theoretically by placing trust as a result of consumer-oriented Marketing 5.0 practices and by combining three complementary views. Marketing 5.0 outlines the practices, the Technology Acceptance Model helps to understand consumer evaluation of technology, and Commitment-Trust Theory helps to understand the importance of reliable exchanges in sustaining relationships. The study also offers practical understanding of the relationship between consumer trust and various AI-powered marketing practices.

Literature Review

Theoretical Underpinnings

Marketing 5.0 is the main framework for this study. Kotler et al. (2021) describe it as the application of technologies that mimic human beings to develop and enhance value throughout the customer journey. It consists of data-driven, predictive, contextual, augmented and agile marketing. Predictive, contextual and augmented marketing were chosen as they are more directly experienced by consumers. Data-driven marketing is primarily about the information foundation, and agile marketing is about the responsiveness and execution of the organization. Predictions and recommendations, situation-specific content and AI-assisted interfaces, on the other hand, are experienced at the point where trust judgments are formed.

Davis (1989) suggests that the perceived usefulness and perceived ease of use influence users' evaluation and acceptance of technology, which is known as the Technology Acceptance Model (TAM). TAM is not a separate empirical model but rather an interpretive lens to understand consumers' assessment of the usefulness and accessibility of AI-powered marketing technologies. Search effort can be reduced, digital interactions can be more relevant with contextual messages, and assistance can be more easily accessed with augmented interfaces. These benefits can contribute to positive assessments, but usefulness does not necessarily eliminate concerns about data use or transparency (Sohn & Kwon, 2020). Commitment-Trust Theory suggests that trust is an important component of effective relationship marketing because trust is essential for reliable and valuable exchanges, which in turn facilitate cooperation (Morgan & Hunt, 1994). The theory serves as the relational foundation for consumer trust as the main outcome in this study; relationship commitment itself falls outside the empirical model. It clarifies the importance of consistent, honest and beneficial exchanges with AI beyond the single transaction. The three perspectives play different roles: Marketing 5.0 is about the practices, TAM is about how consumers might assess the technology, and Commitment-Trust Theory is about the importance of trust in the exchange for sustaining relationships.

Human-centered application is crucial because AI marketing has functional and social impacts. While technology can handle more information than a consumer or frontline employee, consumers still assess if recommendations are suitable, timely and respectful, and whether personal information is being handled responsibly. Marketing 5.0 is not about eliminating the relationship aspect from marketing. Instead, it places many of these considerations within technology-based touchpoints. The framework is most useful when technological capability and consumer well-being are considered together rather than when automation is treated as an end (Kotler et al., 2021).

The three practices also differ conceptually in the extent to which consumers experience the underlying technology directly. Predictive marketing is less visible because modeling takes place before an output is produced. Contextual marketing is partially evident in the match between communication and the consumer's context. Augmented marketing is more interactive as the consumer interacts with an AI-powered interface by sending messages or requests. This difference offers a theoretical basis for examining the constructs individually and indicates that the constructs of visibility and ease of evaluation and perceived control may vary across the practices.

TAM and Commitment-Trust Theory also support a consumer-focused interpretation of these differences. TAM focuses on the value and effort experienced by the consumer, while Commitment-Trust Theory focuses on the trust in the exchange partner. A system can be helpful in accomplishing a task, but it does not necessarily provide complete reassurance to the consumer about the organization's intentions. Likewise, a reliable organization can have a frustrating or ineffective interface. A human-centered perspective thus considers the immediate technology assessment as well as the broader significance of the exchange.

Consumer Trust

Consumer trust refers to a willingness to rely on another party under conditions of uncertainty and vulnerability. In digital commerce, it is commonly associated with competence, integrity and benevolence. The provider must be able to deliver its promise, act consistently and honestly, and avoid taking advantage of the consumer's dependence (Gefen et al., 2003; Hallikainen & Laukkanen, 2021). Reliability and transparency are especially important when AI selects, prioritizes or presents marketing content because consumers may see the output without seeing the processes that produced them.

Trust in AI-enabled marketing is both evaluative and relational. Consumers judge whether an automated system performs accurately, whether its recommendations or communication are dependable, and whether the organization remains accountable. Younger consumers may be comfortable with digital channels while still maintaining boundaries around privacy and personalized persuasion (McKee et al., 2024). Familiarity with technology should therefore not be treated as unconditional trust. For digitally active university students, confidence may depend on whether technology produces helpful experiences while maintaining transparency, fairness and control (Afroogh et al., 2024; Choung et al., 2023).

In this study, consumer trust is conceptually separated from satisfaction, intention to use and technology acceptance. Satisfaction can be related to an assessment of a specific outcome, and acceptance can be related to the adoption of technology. Trust is the willingness to trust an AI-powered marketing system or the organization that provides it, even when there is not enough information. Confidence does not come with repeated exposure. Consumers may continue using a convenient platform while remaining uncertain about its data practices, and they may value personalization while wanting clearer limits on how it is produced (Hallikainen & Laukkanen, 2021; Choung et al., 2023).

Predictive Marketing

Predictive marketing applies historical and current behavioral data, statistical modeling and AI analytics to anticipate likely preferences, needs or actions. Recommendation systems can identify patterns in searches, purchases and interactions, allowing marketers to present products or information that may be useful before consumers directly request them (Alshaketheep et al., 2024; Kasemrat et al., 2025). Accurate anticipation can reduce search effort, improve discovery and make the customer journey more responsive.

The same predictive capacity can create concerns about behavioral monitoring and unclear algorithmic processes. A recommendation may be helpful while leaving the consumer unsure about what information was collected or why a particular option appeared. Trust may

therefore depend not only on predictive accuracy but also on the perceived fairness, transparency and privacy of the process (Puntoni et al., 2021; Xu & Chen, 2025).

Predictive value depends on a sequence of activities: collecting relevant data, identifying patterns, estimating likely behavior and turning the estimate into a customer-facing action. Errors at any stage may produce irrelevant or repetitive suggestions. Even accurate outputs may be viewed differently depending on how closely they appear to reveal private activity. Trust therefore depends on whether the recommendation is useful, whether the basis of personalization appears acceptable and whether the consumer retains meaningful choice (McKee et al., 2024; Xu & Chen, 2025).

Contextual Marketing

Contextual marketing adapts communication to a consumer's immediate situation, including current interests, timing, browsing activity, location or other contextual information. Its main benefit is immediate relevance: content can be delivered when it is most useful rather than according to a fixed segment alone (Irgui & Qmichchou, 2023). Appropriate timing and fit may signal attention to the consumer and reduce irrelevant promotional content.

Context can also be sensitive. Location, GPS, real-time browsing and inferred circumstances may feel intrusive when data use is unexpected or consumer control is limited. The boundary between relevant service and perceived surveillance is therefore important. Contextual relevance may support trust when the use of information fits consumer expectations, but it may create concern when the same information is viewed as intrusive (Boerman & Smit, 2023; Zhu & Kanjanamekanant, 2021).

Context is dynamic rather than fixed. A message that is useful at one time can be distracting at another, while location-aware content can be valuable during an active search but uncomfortable when it appears without an obvious reason. Previous research therefore connects consumer responses to contextual marketing with timing, relevance, privacy expectations and perceived control (Boerman & Smit, 2023).

Augmented Marketing

Augmented marketing uses technology to improve customer-facing interaction rather than only replacing human activity. Chatbots, virtual assistants, automated customer support and other AI-enabled interfaces can provide continuous access, fast responses and guided problem resolution (Chen et al., 2022; Li et al., 2025). These encounters make technological performance directly observable because consumers can assess whether the interface understands a request, communicates clearly and provides a useful answer.

Because augmented interfaces are part of a direct customer touchpoint, service quality and social presence become important. Responsiveness without meaningful resolution may reduce confidence, while useful and reliable assistance can demonstrate competence. Anthropomorphic features may support interaction, but they should not hide the automated nature of the service or create misleading expectations (Janson, 2023; Chi & Hoang Vu, 2023). Augmentation can take several forms, from answering routine questions to helping consumers compare options, solve service problems or obtain information outside normal operating hours. Its relationship value depends on the quality and consistency of the

interaction. A chatbot that responds immediately but cannot solve common problems may signal weak service, whereas useful responses and suitable transfers to human support may improve confidence (Janson, 2023).

Relationship Between Predictive Marketing and Consumer Trust

Predictive marketing may support consumer trust when recommendations appear accurate, useful and consistent with consumers' needs. Anticipation may reduce effort and signal that the business understands the customer. In contrast, unexplained tracking or unexpected inferences may reduce confidence. Perceived usefulness and personalization are explanatory concepts rather than tested mediators in this study. Overall, previous literature supports an expected positive association when predictive value is delivered responsibly (Alshaketheep et al., 2024; Xu & Chen, 2025).

H1: There is a significant relationship between Predictive Marketing and Consumer Trust among university students in Klang Valley.

Relationship Between Contextual Marketing and Consumer Trust

Contextual marketing may support trust when immediate relevance, suitable timing and responsiveness show that digital communication fits the consumer's present needs. However, the use of location or real-time activity may create uncertainty if it crosses expected privacy boundaries. The expected relationship therefore reflects the value of context when balanced with transparency and control (Irgui & Qmichchou, 2023; White et al., 2008).

H2: There is a significant relationship between Contextual Marketing and Consumer Trust among university students in Klang Valley.

Relationship Between Augmented Marketing and Consumer Trust

Augmented marketing provides a setting in which consumers can directly observe AI assistance, response quality and reliability. Successful problem resolution and accessible support may demonstrate competence and support a willingness to rely on the provider. Because interaction quality is visible, augmented interfaces may be especially important for relationship evaluations (Chen et al., 2022; Cheng & Jiang, 2022).

H3: There is a significant relationship between Augmented Marketing and Consumer Trust among university students in Klang Valley.

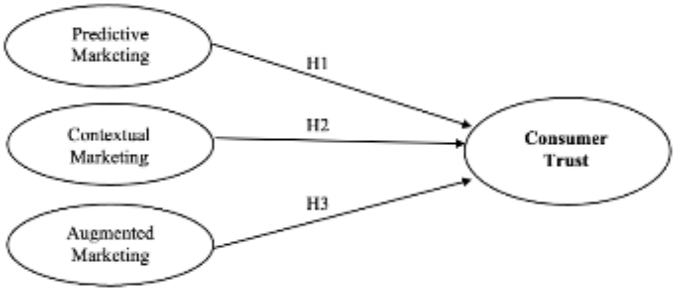


Figure 1 Research Framework

Methodology

Overall Design, Target Population, Sampling, and Sample Size

The study adopted a positivist philosophy, deductive approach, quantitative mono-method, survey strategy and cross-sectional time horizon. This design supported hypothesis testing through numerical evidence collected at one point in time. The target population comprised university students in Klang Valley, with an operational age range of 18–29. Eligibility also required relevant experience with digital platforms or online transactions so that respondents could evaluate the AI-enabled marketing practices described in the questionnaire.

Non-probability convenience and purposive sampling were used to reach eligible respondents through accessible digital channels. These methods supported recruitment within the study's practical limits but do not establish population representativeness. G*Power analysis was conducted using an assumed medium effect size ($f^2 = .15$), $\alpha = .05$, statistical power = .95 and three predictors, producing a minimum sample of 119. The final dataset contained 200 usable responses, exceeding the minimum.

The unit of analysis was the individual student respondent. The study examined reported perceptions of marketing practices and trust rather than firm-level adoption or platform performance. A cross-sectional survey was suitable for estimating relationships across respondents, but it could not show how evaluations changed after repeated encounters. The deductive approach linked the three relationship hypotheses to the conceptual framework and assessed whether the sample evidence supported those expectations.

Instrumentation

The online questionnaire contained two sections. Section A captured demographic characteristics. Section B comprised 20 measurement items: five for consumer trust, five for predictive marketing, five for contextual marketing and five for augmented marketing. Responses used a five-point Likert scale from 1 = Strongly Disagree to 5 = Strongly Agree. Consumer trust items were adapted from Koneti (2025), Sarwar and Malik (2025), and Gefen et al. (2003); predictive marketing from Alshaketheep et al. (2024); contextual marketing from Irgui and Qmichchou (2023); and augmented marketing from Chen et al. (2022) and Li et al. (2025).

The adapted items captured confidence and reliance for consumer trust, recommendation and anticipation for predictive marketing, situational relevance and timing for contextual marketing, and AI-assisted service interaction for augmented marketing.

Data Collection and Data Analysis

Data was collected through a self-administered Microsoft Forms questionnaire distributed through relevant online and social channels. Participation was voluntary and based on informed consent, and responses were treated anonymously and confidentially for research purposes. After data editing and coding, IBM SPSS Statistics was used for demographic and descriptive analysis, Cronbach's Alpha, KMO and Bartlett's Test of Sphericity, distributional normality checks, Pearson correlation, multiple linear regression and hypothesis testing. KMO was treated as an indicator of factor-analysis suitability rather than reliability statistics.

Descriptive statistics summarized the respondents and constructed scores. Cronbach's Alpha assessed the internal consistency of the multi-item measures, while KMO and Bartlett's Test assessed whether the item correlation structure was suitable for factor analysis. Distributional checks combined formal significance tests with skewness and kurtosis criteria. Pearson coefficients described bivariate relationships, and multiple linear regression estimated the unique standardized contribution of each predictor while the other predictors were included in the model. Decisions were based on the significance values reported in the SPSS output.

Results

Demographic Information of Respondents

The 200 respondents represented a digitally active student sample. Men comprised 56.5%, 56.0% were aged 21–23, 96.5% were studying at bachelor's level, 63.0% were in Year 3 and 57.0% studied Business or Management. Online transaction frequency was high: 43.0% transacted daily and 40.5% weekly, meaning 83.5% transacted online either daily or weekly.

The demographic profile should be considered when interpreting the findings. The high proportions of bachelor's and Year 3 students, together with the dominance of Business/Management, mean that the results reflect a specific educational group rather than the full diversity of university students. However, the high frequency of daily or weekly online transactions shows that respondents had regular opportunities to experience recommendation systems, targeted communication and automated support.

Table 1
Demographic Profile of Respondents

Characteristic	Largest / focal category	n	%
Gender	Male	113	56.5
Age	21–23 years	112	56.0
Education level	Bachelor's degree	193	96.5
Year of study	Year 3	126	63.0
Field of study	Business/Management	114	57.0
Online transactions	Daily	86	43.0
Online transactions	Weekly	81	40.5
Online transactions	Daily or weekly	167	83.5

Note: N = 200. The table reports the most relevant profile categories rather than every response category.

Descriptive Statistics

All construct means exceeded 4.0, indicating generally positive perceptions across the sample. Augmented marketing had the highest mean (4.219), followed closely by predictive marketing (4.201), contextual marketing (4.131) and consumer trust (4.094). The differences were small and should not be overstated. Table 2 presents the means, standard deviations and reliability values.

Table 2
Descriptive Statistics and Reliability

Construct	Mean	SD	Cronbach's α
Consumer Trust	4.094	.45009	.631
Predictive Marketing	4.201	.35102	.360
Contextual Marketing	4.131	.42703	.505
Augmented Marketing	4.219	.46054	.670

Reliability and Measurement Quality
Table 2 also presents the reliability results. Cronbach's Alpha was .631 for consumer trust and .670 for augmented marketing, indicating marginal internal consistency. Contextual marketing produced α = .505, indicating weak internal consistency. Predictive marketing produced α = .360, indicating poor internal consistency and falling substantially below the conventional .70 threshold (Cortina, 1993; Tavakol & Dennick, 2011). While predictive marketing and contextual marketing exhibited lower internal consistency than typically recommended thresholds, these constructs were retained for further analysis because they are conceptually important dimensions of Marketing 5.0 and demonstrated statistically significant relationships with consumer trust. Nevertheless, the low reliability values suggest that the corresponding items may not have fully captured a single underlying construct, thereby increasing the possibility of measurement error. Consequently, findings involving these constructs should be interpreted with caution and regarded as preliminary evidence pending further scale refinement and validation in future studies.

Factor Analysis Suitability
KMO values were .526 for consumer trust, .473 for predictive marketing, .459 for contextual marketing and .655 for augmented marketing. Augmented marketing showed adequate factor suitability, consumer trust was marginal, and predictive and contextual marketing showed weak suitability. Bartlett's Test was significant at $p < .001$ for every construct, showing that relationships existed among the items, but the significant results do not remove the concerns created by the low KMO values (Shrestha, 2021; Williams et al., 2010). The relatively weak KMO values reported for predictive marketing and contextual marketing indicate that the inter-item correlations may not be sufficiently strong to reflect a well-defined underlying factor structure. This may suggest that respondents interpreted certain items differently or that the constructs contain multiple dimensions not fully captured by the current measurement scales. Accordingly, subsequent regression analyses involving these constructs should be interpreted with additional caution, particularly when comparing the relative strength of predictor effects.

Table 3
Factor Analysis Suitability

Construct	KMO	Bartlett's Test	Assessment
Consumer Trust	.526	p < .001	Marginal
Predictive Marketing	.473	p < .001	Weak
Contextual Marketing	.459	p < .001	Weak
Augmented Marketing	.655	p < .001	Adequate

Distributional Normality
Skewness ranged from −0.267 to −0.995 and kurtosis ranged from 0.111 to 1.970. Kolmogorov–Smirnov and Shapiro–Wilk tests were significant at $p < .001$. However, the skewness and kurtosis values remained within the thresholds proposed by Kim (2013), where absolute skewness values below 2 and absolute kurtosis values below 7 were treated as acceptable. The distributions were therefore considered approximately acceptable for the subsequent analyses (Ghasemi & Zahediasl, 2012; Kim, 2013).

Pearson Correlation
Each predictor was positively and significantly correlated with consumer trust. The correlation was $r = .604$ for predictive marketing, $r = .722$ for contextual marketing and $r = .727$ for augmented marketing (all $p < .001$). These values represent associations rather than causal relationships. Augmented and contextual marketing showed similarly strong bivariate relationships with trust, while predictive marketing showed a smaller but still substantial relationship (Schober et al., 2018).

Table 4
Pearson Correlations with Consumer Trust

Predictor	r	p-value	Direction
Predictive Marketing	.604	< .001	Positive
Contextual Marketing	.722	< .001	Positive
Augmented Marketing	.727	< .001	Positive

Note: N = 200. All reported relationships are bivariate associations.

Multiple Linear Regression
The multiple regression model produced $R = .781$, $R^2 = .609$ and adjusted $R^2 = .603$, with a standard error of estimate of .28347. The overall model was significant, $F(3, 196) = 101.894$, $p < .001$. Together, predictive, contextual and augmented marketing explained 60.9% of the variance in consumer trust.

All three coefficients were statistically significant. Augmented marketing had the strongest standardized contribution ($B = .363$, $\beta = .371$, $t = 5.169$, $p < .001$), followed closely by contextual marketing ($B = .371$, $\beta = .352$, $t = 4.923$, $p < .001$). Predictive marketing had the smallest unique contribution but remained significant ($B = .181$, $\beta = .141$, $t = 2.315$, $p = .022$). The constant was not significant ($B = .270$, $t = 1.093$, $p = .276$).

Table 5

Multiple Regression Model Summary and ANOVA

R	R^2	Adjusted R^2	SEE	F(df)	p-value
.781	.609	.603	.28347	101.894 (3,196)	< .001

Note: Dependent variable = Consumer Trust; predictors = Predictive, Contextual, and Augmented Marketing; N = 200.

Hypothesis Testing

Table 6

Regression Coefficients and Hypothesis Decisions

Hypothesis / Predictor	B	β	t	p-value	Decision
H1: Predictive Marketing	.181	.141	2.315	.022	Supported
H2: Contextual Marketing	.371	.352	4.923	< .001	Supported
H3: Augmented Marketing	.363	.371	5.169	< .001	Supported

Discussion, Implications, Limitations, and Recommendations

Discussion

H1 was supported: predictive marketing was positively associated with consumer trust, although its standardized contribution was the smallest of the three predictors. Predictive systems commonly operate behind the scenes. Consumers may appreciate recommendations that reduce search effort or anticipate relevant needs while being less able to observe behavioral learning and algorithmic decision processes. From a TAM perspective, usefulness can support favorable evaluation, but unclear processes may limit the confidence gained from that usefulness. The result reflects the personalization–privacy tension rather than showing that more prediction always produces more trust (Awad & Krishnan, 2006; Puntoni et al., 2021). Because predictive marketing showed poor internal consistency and weak KMO suitability, the size of its coefficient should be interpreted cautiously.

H2 was supported: contextual marketing showed a strong positive relationship with consumer trust and the second strongest unique contribution. Immediate relevance, suitable timing and responsiveness may help consumers recognize the value of context-aware marketing. These features fit TAM's focus on useful technology experiences, but contextual practice also depends on whether consumers view the use of information as acceptable. Location, GPS and real-time behavioral information can shift an experience from helpful relevance to perceived surveillance when purpose and control are unclear. The finding therefore highlights the balance between relevance and control (Irgui & Qmichchou, 2023; Zhu & Kanjanamekanant, 2021). Because contextual marketing also showed weak internal consistency and KMO suitability, the size of its coefficient should be interpreted cautiously.

H3 was supported, and augmented marketing recorded the strongest standardized contribution. Chatbots, virtual assistants and automated support make responsiveness and service reliability visible during the interaction. Consumers can directly evaluate whether assistance is accessible, whether the response addresses the problem and whether the interface communicates clearly. This direct interaction may make augmented marketing

easier to evaluate than processes that remain behind the interface. From a Commitment-Trust perspective, useful and dependable exchanges may contribute to relationship confidence, while TAM helps explain why accessible assistance may be evaluated positively (Chen et al., 2022; Cheng & Jiang, 2022). The result identifies augmented marketing as the strongest contribution in the observed model.

An additional consideration is the influence of measurement quality on regression estimation. Constructs with weaker internal consistency typically contain greater random measurement error, which can attenuate observed relationships and reduce coefficient stability. Therefore, while predictive marketing and contextual marketing emerged as statistically significant predictors, their regression coefficients may not represent the full strength or precise magnitude of their true relationships with consumer trust. The significance of these relationships provides preliminary support for the proposed hypotheses, but future studies employing more robust and validated measures are required before stronger conclusions regarding their relative importance can be drawn.

One possible explanation for the weaker measurement quality is that the predictive marketing items covered several AI functions, including recommendation accuracy, behavioral learning, usefulness, reduced search effort and future prediction. Respondents may value personalization but respond differently to tracking and prediction. The contextual marketing items also combined relevance and timing with privacy-sensitive features such as location, GPS and real-time information. Consumers may value contextual relevance while responding differently to more intrusive forms of data use. These interpretations were not directly tested and should be examined in future research.

Taken together, the results indicate that consumer-facing Marketing 5.0 practices are not interchangeable. All three were positively associated with trust, but their contributions differed. Practices that allow consumers to directly evaluate service competence may be especially important, while predictive and contextual value may depend more heavily on how consumers understand less visible data processes. This pattern supports a human-centered view in which technological capability becomes valuable through clear and confidence-building experiences.

The smaller standardized coefficient for predictive marketing, despite its positive bivariate correlation with consumer trust, indicates that part of its relationship with trust overlaps with the other Marketing 5.0 practices in the regression model. This overlap does not mean that predictive marketing is unimportant, but it shows that its unique contribution was smaller when contextual and augmented marketing were included in the same model.

Implications

Theoretical Implications

For Marketing 5.0, the study positions consumer trust as an important outcome alongside customer experience and technological performance. The three practices collectively explained 60.9% of the variance in consumer trust among university students in Klang Valley, while their different coefficients show the value of examining the practices separately. The findings extend human-centered Marketing 5.0 research to a digitally active Malaysian

student context rather than viewing the framework only as an organizational capability (Kotler et al., 2021).

From a TAM-informed perspective, the findings suggest that technological value may need to be supported by transparency and ease of evaluation when trust is the outcome. From a Commitment-Trust perspective, AI-enabled touchpoints may contribute to relationship building when they provide consistent, reliable and valuable exchanges. Together, these perspectives help explain why the usefulness of technology and the quality of the wider relationship both matter in AI-enabled marketing.

Because consumers mainly experience AI through its outputs and interfaces rather than its underlying technical processes, they may judge capability and integrity through recommendations, explanations, error handling and service responses (Puntoni et al., 2021). Augmented marketing provides more opportunities for these judgments because interaction occurs in real time. Predictive and contextual systems may therefore need clear explanations and settings that help consumers understand how the technology works.

The findings should also be considered alongside the positive mean scores. Respondents generally agreed with favorable statements about all constructs, suggesting that they were not broadly rejecting AI-enabled marketing. The regression results therefore show differences within a generally receptive group. They should not be viewed as a comparison between technology users and non-users or as evidence that one practice should replace another. Businesses often use the practices together, and trust may reflect the consistency of the overall customer journey.

The order of the standardized coefficients: augmented, contextual and predictive marketing provides a useful pattern, but the weaker measurement quality of two predictors limits detailed comparison. Further studies with improved measures are needed before this order can be treated as stable across student groups, markets or digital platforms.

The clearest conclusion is that all three relationships were positive and statistically significant within this sample. However, because predictive marketing and contextual marketing demonstrated weaker measurement quality, the relative ordering and magnitude of their regression effects should be interpreted as exploratory rather than definitive. Additional validation using stronger measurement instruments is required before these comparisons can be generalized to broader consumer populations.

Practical Implications

Augmented marketing should be designed as relationship-building AI. Businesses should evaluate chatbots and assistants based on responsiveness, useful problem resolution, communication quality, suitable empathy or social presence, and the confidence created by the interaction, not only automation speed or cost reduction. Clear routes to human support can also protect trust when automated assistance is not enough.

Contextual marketing requires relevance and control. Businesses should explain why contextual content appears, provide accessible personalization controls, communicate the use of location or real-time information and avoid practices that make relevance feel like

surveillance. Permission and preference controls should be easy to understand when consumers need them.

Predictive marketing requires clearer recommendations. Businesses should make recommendation reasons easier to understand, explain relevant data use and provide clear privacy communication and manageable preferences. Across the model, advanced personalization should be supported by transparency, control and trust.

This study found that predictive marketing, contextual marketing, and augmented marketing were positively associated with consumer trust among university students in Klang Valley. Augmented marketing demonstrated the strongest and most robust relationship within the model. However, because predictive marketing and contextual marketing exhibited weaker measurement properties, their estimated contributions should be interpreted cautiously and viewed as preliminary evidence requiring further validation. The findings nevertheless suggest that AI-enabled marketing practices can support consumer trust when implemented within a transparent, human-centred, and consumer-responsive framework.

For managers and researchers, this conclusion shifts attention from whether AI improves targeting or efficiency alone to how each AI-enabled interaction communicates competence and respect. Trust develops through consumers' combined experience of recommendations, contextual messages and service interactions. Businesses should therefore align data use, interface design, explanations and support across these touchpoints rather than treating them as separate technical projects.

This alignment is important for responsible, human-centered adoption in a growing digital market.

Limitations and Future Research Directions

First, the cross-sectional design captured perceptions at one point in time. It cannot establish temporal order or causal effects. Longitudinal research could examine whether trust changes with repeated exposure, while carefully designed experiments could strengthen cause-and-effect understanding.

Second, this study relied on a student-based sample recruited through convenience and purposive sampling. Although university students represent an appropriate group for examining digitally intensive consumer behaviour due to their frequent use of online platforms and AI-supported services, they may differ from the broader consumer population in terms of technological familiarity, digital literacy, privacy expectations, and trust perceptions. Consequently, the findings should not be generalized to all Malaysian consumers, older age groups, or less digitally engaged populations. The results are therefore most appropriately interpreted as evidence from a specific digitally active student segment rather than as representative of the national consumer population. Future research should employ more diverse and probability-based samples to strengthen external validity.

Third, the self-reported questionnaire may be affected by response tendencies and social-desirability bias. Future studies could combine surveys with behavioral data, interviews, observation or other evidence, subject to suitable privacy and ethical safeguards.

Fourth, predictive and contextual marketing showed low internal consistency and weak factor-analysis suitability. Their scales should be pilot-tested, refined and validated before stronger conclusions are made. Item analysis and qualitative testing may identify unclear or multidimensional content. Later studies may use exploratory factor analysis and confirmatory factor analysis before structural testing (Hair et al., 2022; Williams et al., 2010).

Finally, only three Marketing 5.0 practices were examined. Future research may consider other practices and trust-related variables, including privacy, transparency, perceived usefulness, AI experience and relevant consumer characteristics. These factors may be examined in broader models, but the present study does not establish that any specific untested factor accounts for the remaining 39.1% of variance.

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