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Prioritizing Key Factors Influencing University Students' On-Campus Digital Consumption under AI-Powered Precision Marketing in the Greater Bay Area: An AHP-Based Approach

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ABSTRACT

Against the backdrop of digital economy expansion, AI-powered precision marketing heavily shapes university students' campus digital consumption. The Guangdong-Hong Kong-Macao Greater Bay Area (GBA), a strategic hub with concentrated youth consumption power, presents a distinct campus context characterized by enclosed physical spaces and synchronized schedules. This study utilizes the Analytic Hierarchy Process (AHP) to systematically identify, quantify, and prioritize key factors influencing GBA university students' digital consumption decisions under AI-powered precision marketing. We construct a three-layer evaluation index system comprising 5 criterion layers (recommendation fit, marketing appeal, interactive experience, contextual fit, and data trust) and 25 measurable sub-indicators. Based on 114 valid questionnaires, weight calculations and consistency checks were performed. Results indicate that within the criterion layer, data trust exhibits the highest weight (0.2249), followed by interactive experience (0.2124), recommendation fit (0.1964), marketing appeal (0.1898), and contextual fit (0.1765). Globally, secure payment environment (0.0582), recommendation novelty (0.0510), and sufficient privacy protection (0.0507) emerge as the top three factors. Further analysis reveals that recommendation novelty outweighs preference matching; presentation of consumer feedback outperforms discount incentives; ease of use and cross-platform convenience take precedence over extreme response speed; and critical timing responsiveness prevails over real-time location adaptation. These findings demonstrate that GBA university students' decisions are characterized by "trust dominance, exploratory preference, social reliance, timing sensitivity, and convenience priority." This study provides a quantitative basis for relevant stakeholders to optimize the allocation of AI marketing resources. Meanwhile, it enriches the application of the AHP method in AI marketing and offers precise support for enterprises targeting the campus market.

Keywords: AI-Powered Precision Marketing, Guangdong-Hong Kong-Macao Greater Bay Area, On-campus Digital Consumption, Analytic Hierarchy Process (AHP), Decision-making Characteristics.

INTRODUCTION

In the digital economy era, digital consumption has become a core engine driving domestic demand growth. Artificial intelligence has deeply penetrated the marketing domain, shifting precision marketing from experience driven to algorithm driven approaches and significantly improving the efficiency of information matching between firms and consumers. However, different consumption contexts exhibit distinct response mechanisms to AI-powered precision marketing, and generic marketing strategies are difficult to adapt to the demand characteristics of segmented markets. As a national strategic hub for the digital economy, the Guangdong-Hong Kong-Macao Greater Bay Area hosts a high density of universities and a concentrated youth consumption power; university campuses therefore constitute a distinctive digital consumption context characterized by enclosed physical spaces, homogeneous user profiles, synchronized consumption schedules, and clear demand cycles. This concentration attracts substantial investment interest from firms, especially chain operators pursuing cross regional standardized operations. Nevertheless, faced with numerous potential influencing factors, firms lack a systematic basis for understanding the relative importance of these factors. The Analytic Hierarchy Process (AHP), as a mature tool for multi criteria decision making, can convert qualitative judgments into quantitative weights and thus provide methodological support for prioritizing precision marketing resource allocation.

Based on the above background, this study aims to reveal the characteristics of on campus digital consumption among university students in the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) from the perspective of AI-powered precision marketing. The specific objectives are threefold: first, to systematically identify the key factors influencing this group's on campus digital consumption decisions; second, to quantify and rank the relative importance of these factors using AHP; third, to summarize the decision making characteristics of this group based on the weight results, with a view to providing reference for stakeholders' AI marketing resource allocation in the campus market.

LITERATURE REVIEW

Research on university students' on campus digital consumption

Existing studies indicate that digital consumption has become the mainstream consumption form in contemporary society, and that university students—owing to their highly digitalized lifestyles—are frequent participants in digital consumption. Hamzah et al. (2026) show that Malaysian university students exhibit a high dependence on mobile payments and frequent online shopping behavior. In the Greater Bay Area, Wu et al. (2024) note the region's advanced digital economy environment, and Zhao & Wei (2025) further find imbalances in the business environments across cities within the Bay Area, with a consumption capacity gradient between core and peripheral cities. These regional characteristics may amplify differences in digital consumption activity and purchasing power among Greater Bay Area university students.

Regarding the contextual features of student consumption, prior research has highlighted the enclosed and concentrated nature of campus environments. Liu et al. (2025), drawing on consumer behavior and psychology theories and analyzing records such as dining frequency and spending amounts, demonstrate that students' consumption behaviors are continuous and traceable, with demand showing high repetition rates and strong periodicity. Lamichhane (2025) finds that peer influence in digital transactions is an important trigger for excessive consumption among students; Ghorai (2025), in a review, also emphasizes that peer pressure is a key variable affecting young people's risky financial behaviors. These findings indicate rapid social transmission within campuses and a prominent role for word of mouth effects in consumption decisions. Such characteristics lead scholars to regard the campus market as an ideal scenario for firms to implement precision marketing. Freedman & Connors (2010) find that appropriate information presentation and decision support can effectively intervene in students' purchase choices, directly confirming the malleability and commercial value of campus digital consumption. In addition, Liu et al. (2025) note that students' consumption records can effectively reflect their economic status and demand tiers, indicating a high potential for datafication of campus consumption.

Overall, existing research generally concludes that the campus digital consumption ecosystem features concentrated consumption contexts, stable user groups, continuous behavioral data, high demand repetition rates, and rapid social transmission, offering firms a lower cost, higher efficiency market for precision marketing. With the increasing platformization and datafication of campus digital consumption, firms have begun to leverage artificial intelligence to improve marketing precision and conversion efficiency (Zhao et al., 2024). Therefore, understanding the influence mechanisms of AI-powered precision marketing on student consumption decisions and identifying which key factors play more important roles in the Greater Bay Area campus context remain issues that warrant further investigation.

Research on the impact of AI-powered precision marketing on consumer decision-making

Existing studies indicate that AI-powered precision marketing has gradually become an important marketing approach in digital consumption. Zhao et al. (2024) point out that recommendation systems based on large language models can effectively capture users' long-term preferences and short-term behavioral intentions, thereby enabling personalized recommendations. Chen et al. (2023) further find that the ability of recommendation systems to respond quickly and accurately to users' current needs significantly affects perceived usefulness and satisfaction. In terms of price matching, Zheng et al. (2021) incorporate price perception into recommendation models and demonstrate that aligning the price range of recommended products with users' purchasing power can effectively enhance purchase intention. Collectively, these studies show that AI marketing relies on user data to achieve personalized recommendations and content delivery, and has begun to deeply penetrate various consumption contexts, including university campuses.

Regarding how AI marketing influences consumer decision-making, existing research has conducted empirical examinations from multiple perspectives. The experiment by Bian & Che (2025) shows that AI-generated review summaries enhance the "perceived diagnosticity" of information, helping users evaluate product quality more efficiently. Arvaj et al. (2025) find that AI-generated visual content exhibits clear advantages in aesthetic appeal, particularly in promotional scenarios. In interaction processes, Kallweit et al. (2014) regard system responsiveness as a core dimension of service quality and confirm that long loading or feedback delays reduce users' conversion intentions; Song et al. (2023) show that seamless interaction is a prerequisite for transaction completion. In push-notification management, Pretolesi et al. (2025) note that users generally prefer to have customizable control over notification frequency, and excessive frequency leads to annoyance; Shin (2016) demonstrates that cross-platform usability affects the coherence of decision-making.

In addition, users' trust in AI marketing systems has also received extensive attention. Wach et al. (2023) identify data-privacy violations, algorithmic bias, and lack of transparency as core risks of generative AI. Diederich et al. (2022) emphasize that the explainability of recommendation logic and the transparency of data collection are key factors influencing user trust. Jiang et al. (2023) directly address the damage caused by algorithmic discrimination (e.g., price discrimination) to user trust by designing a fairness-verification system. Magesh et al. (2025) find that even with retrieval-augmented generation, AI tools still exhibit hallucination rates as high as 17% to 33%. Although their study focuses on AI tools in the legal domain, the findings also serve as a warning for e-commerce marketing: potential errors in AI-generated content may undermine user trust.

In summary, existing studies have identified multiple factors influencing consumer decision-making in AI-powered precision marketing. However, most current research focuses only on whether these factors exert significant effects, while lacking systematic quantitative comparison of their relative importance—particularly regarding which factors are more critical in the specific context of on-campus digital consumption among university students in the Greater Bay Area. Therefore, this study employs the Analytic Hierarchy Process (AHP) to conduct weight analysis of the above factors, aiming to reveal their relative importance rankings in this context.

RESEARCH METHODOLOGY

Research design

Analytic Hierarchy Process (AHP)

When conducting multi-criteria decision analysis, the AHP has become a widely adopted methodological tool in management, engineering, and consumer-behavior research due to its theoretical advantage of decomposing complex problems into multi-level hierarchical structures and deriving priority weights through pairwise comparisons (Saaty, 1990, 2008). The core of AHP lies in the following: decision-makers first construct a hierarchical model consisting of the goal layer, criterion layer, and alternative layer; then, based on the 1–9 scale, they perform pairwise comparisons among elements within the same layer to obtain a judgment matrix that reflects relative importance. On this basis, priority weights are calculated using the eigenvector method, and the logical consistency of judgments is assessed through the consistency ratio (Saaty, 2008).

Because AHP can effectively handle evaluation contexts involving both qualitative indicators and quantitative data—especially in research problems with complex goal structures, limited objective data, or the need to integrate multiple subjective judgments—it has been widely applied across fields such as manufacturing,

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environmental management, energy, transportation, healthcare, education, e-commerce, and marketing (Sipahi & Timor, 2010; Vaidya & Kumar, 2006). In digital consumption and recommendation-system research, scholars have used AHP to construct network-based mobile-phone recommendation systems and validated their feasibility and user satisfaction through controlled experiments with 244 users (Chen et al., 2010). Other studies have applied fuzzy AHP to analyze shifts in consumer decision-making patterns in digital markets, finding that "innovation and trendiness" and "brand and quality" are the most prioritized factors (Kumar et al., 2018). In addition, AHP has been integrated into occupational safety service-quality evaluation to determine the relative weights of SERVPERF dimensions (Alp et al., 2022).

In summary, AHP not only enables systematic handling of multi-indicator and multi-level evaluation problems but also reduces respondents' cognitive burden through pairwise comparisons and ensures judgment reliability through consistency testing. Therefore, this study adopts AHP as the analytical tool for ranking the weights of key factors, aiming to reveal the relative importance of different influencing factors in the context of AI-powered precision marketing shaping university students' on-campus digital consumption decisions in the Greater Bay Area.

Construction of the AHP evaluation index system

This study adopts the Analytic Hierarchy Process (AHP) to construct an evaluation index system for identifying the key factors through which AI-powered precision marketing influences university students' on-campus digital consumption decisions in the Greater Bay Area. According to the theoretical framework of AHP, the complex decision problem is first decomposed into a hierarchical structural model consisting of the goal layer, criterion layer, and alternative layer (Saaty, 2008).

Goal Layer (G): The goal layer represents the highest level of the hierarchical model and reflects the ultimate purpose of the decision problem. In this study, the goal layer is defined as "Ranking the key factors through which AI-powered precision marketing influences university students' on-campus digital consumption decisions in the Greater Bay Area." This layer focuses on identifying and quantifying the relative importance of the factors affecting students' digital consumption decisions, thereby providing the basis for subsequent weight analysis and strategic recommendations.

Criterion Layer (C): The criterion layer is the direct decomposition of the goal layer and represents the major dimensions influencing the achievement of the goal. The construction of the criterion layer in this study is based on two classical theoretical frameworks in the fields of consumer decision-making and technology acceptance. First, the technology acceptance model points out that users' acceptance of information systems is mainly driven by perceived usefulness and perceived ease of use (Davis, 1989). In the context of AI-powered precision marketing, perceived usefulness is reflected in the degree to which recommended content matches user needs, while perceived ease of use is reflected in the smoothness of the interaction process and the responsiveness of the technology. Second, the elaboration likelihood model reveals that when individuals lack cognitive motivation or ability, their attitudes and decisions are more easily influenced by peripheral cues (Petty & Cacioppo, 1986). In the high-frequency, multi-task scenario of university students' on-campus digital consumption, the attractiveness of marketing content, promotional incentives, and consumption feedback often directly determine the effectiveness of persuasion. In addition, situation awareness theory emphasizes that the system's adaptation to time, location, and user activity status is key to enhancing service relevance; while the integrative model of trust divides users' trust in technology into three dimensions—competence, integrity, and benevolence—providing a theoretical basis for understanding data security, algorithmic fairness, and transparency. Based on the systematic integration of the above theories and related empirical literature, this study identifies five core dimensions influencing university students' on-campus digital consumption decisions in the context of AI-powered precision marketing: recommendation fit, marketing appeal, interactive experience, contextual fit, and data trust. The core connotations of each dimension are shown in Table 1.

Table 1 Overview of Criterion Layer

Dimension Code	Dimension Name	Core Connotation	Literature Support
C1	Recommendation Fit	Degree to which AI recommendations align with users' consumption needs, preferences, and purchasing power.	Zhao et al. (2024)
C2	Marketing Appeal	Persuasive strength of AI marketing in information presentation, discount incentives, and purchase feedback.	Bian & Che (2025)
C3	Interactive Experience	Smoothness of user interaction with the AI marketing system in terms of operation and technical response.	Chen et al. (2021)
C4	Contextual Fit	Extent to which AI marketing content adapts to users' current time, location, and usage context.	Chafiki et al. (2026)
C5	Data Trust	Users' trust in the AI marketing system regarding data use, privacy protection, and transaction security.	Diederich et al. (2022)

Alternative Layer (A): The alternative layer is a further refinement of the criterion layer, with five specific and measurable indicators set under each criterion, resulting in a total of 25 alternative-level indicators. Each indicator is grounded in classical theoretical frameworks and supported by relevant empirical literature. The indicators are explained under each criterion in the following sections.

Table 2 Overview of the C1 Recommendation Fit Dimension

Indicator Code	Indicator Name	Indicator Description	Theoretical Support	Literature Support
C1-1	Immediate Need Matching	Degree to which AI recommendations align with users' current immediate consumption needs.	Expectation Confirmation Theory	Chen et al. (2023)
C1-2	Interest Matching	Degree to which AI recommendations correspond to users' long-term consumption preferences and interests.	Collaborative Filtering Theory	Zhao et al. (2024)
C1-3	Spending Tier Matching	Degree to which the price range of AI-recommended products fits users' routine spending capacity.	Prospect Theory	Zheng et al. (2021)
C1-4	Recommendation Novelty	Degree to which AI recommendations provide exploratory and non-redundant information while maintaining accuracy.	Exploration–Exploitation Theory	Wang et al. (2014)
C1-5	Algorithmic Update Responsiveness	Speed at which AI adjusts recommendations in real time based on users' latest behaviors.	Adaptive Learning Theory	Deldjoo (2025)

Table 3 Overview of the C2 Marketing Appeal Dimension

Indicator Code	Indicator Name	Indicator Description	Theoretical Support	Literature Support
C2-1	Information Accuracy and	Truthfulness and credibility of AI-pushed information regarding product descriptions,	Information	Magesh et

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Indicator Code	Indicator Name	Indicator Description	Theoretical Support	Literature Support
	Reliability	specifications, and reviews.	Quality Theory	al. (2025)
C2-2	Clear Discount Incentives	Attractiveness of economic incentives in AI marketing such as discounts, bundle reductions, and exclusive offers.	Prospect Theory	Nguyen et al. (2019)
C2-3	Clear Decision Support	Effectiveness of AI marketing in helping users quickly compare and filter products.	Cognitive Load Theory	Bian & Che (2025)
C2-4	Engaging Content	Attractiveness of AI-generated or optimized marketing content in visuals, copy, and interactive formats.	Hedonic Motivation Theory	Arvaj et al. (2025)
C2-5	Presentation of Consumer Feedback	Degree to which user ratings, sales figures, and consumption feedback are presented within AI marketing content.	Social Proof Theory	Bian & Che (2025)

Table 4 Overview of the C3 Interactive Experience Dimension

Indicator Code	Indicator Name	Indicator Description	Theoretical Support	Literature Support
C3-1	Ease of Use	Simplicity and usability of the AI recommendation interface during browsing, selection, and checkout.	Technology Acceptance Model (Perceived Ease of Use)	Tan & Lim (2023)
C3-2	System Responsiveness	Response speed of the AI system in page loading, information feedback, and payment processing.	System Response Time Theory	Kallweit et al. (2014)
C3-3	Seamless Interaction	Fluency of AI customer service or shopping assistant in understanding user needs and exchanging feedback.	Social Response Theory	Song et al. (2023)
C3-4	Reasonable Push Frequency	Appropriateness of AI marketing push intervals and the number of pushes.	Interference Theory	Pretolesi et al. (2025)
C3-5	Cross-platform Usability	Degree of information synchronization and continuity of use for AI marketing services across different devices.	Seamless Experience Theory	Shin (2016)

Table 5 Overview of the C4 Contextual Fit Dimension

Indicator Code	Indicator Name	Indicator Description	Theoretical Support	Literature Support
C4-1	Push Timing Match	Degree to which AI marketing push timing aligns with users' peak consumption activity periods.	Moment Marketing Theory	Zhu et al. (2023)
C4-2	Location Matching	Degree to which AI recommendations relate to consumption services near the user's current location.	Location-Based Services Theory	Zhu et al. (2023)

C4-3	Current State Matching	Relevance of AI push content to the user's present activity or situational state.	Activity Theory	Chafiki et al. (2026)
C4-4	Key Moment Matching	AI's ability to identify and respond to critical consumption moments such as promotions or exam weeks.	Event-Driven Marketing Theory	Zhu et al. (2023)
C4-5	Information Presentation Adaptation	Degree to which AI marketing adapts push formats to the user's current usage context.	Adaptive Interface Theory	Wang et al. (2024)

Table 6 Overview of the C5 Data Trust Dimension

Indicator Code	Indicator Name	Indicator Description	Theoretical Support	Literature Support
C5-1	Transparent Data Collection	Degree to which the AI marketing platform discloses the scope of data collection and its intended uses.	Fair Information Practices	Sundjaja et al. (2025)
C5-2	Adequate Privacy Protection	Extent to which the AI system ensures user data security and privacy protection.	Privacy-preserving Computation Theory	Utami & Aimin (2026)
C5-3	Recommendation Logic Explanation	Degree to which the AI system explains the basis and reasons for its recommendations.	Explainable AI Theory	Diederich et al. (2022)
C5-4	Secure Payment Environment	Level of financial and account security guarantees provided during the payment process in the AI marketing system.	E-commerce Trust Model	Jiang et al. (2023)
C5-5	Algorithmic Fairness	Fairness of the AI system in recommendation, pricing, and allocation of discounts.	Algorithmic Fairness Theory	Jiang et al. (2023)

The AHP hierarchical structure model constructed in this study is shown in Figure 1. The goal layer is defined as "Ranking the key factors through which AI-powered precision marketing influences university students' on-campus digital consumption decisions in the Greater Bay Area." The criterion layer consists of five dimensions—recommendation fit, contextual fit, marketing appeal, data trust, and interactive experience. Under each criterion, five alternative-level indicators are established, forming a three-level hierarchical structure.

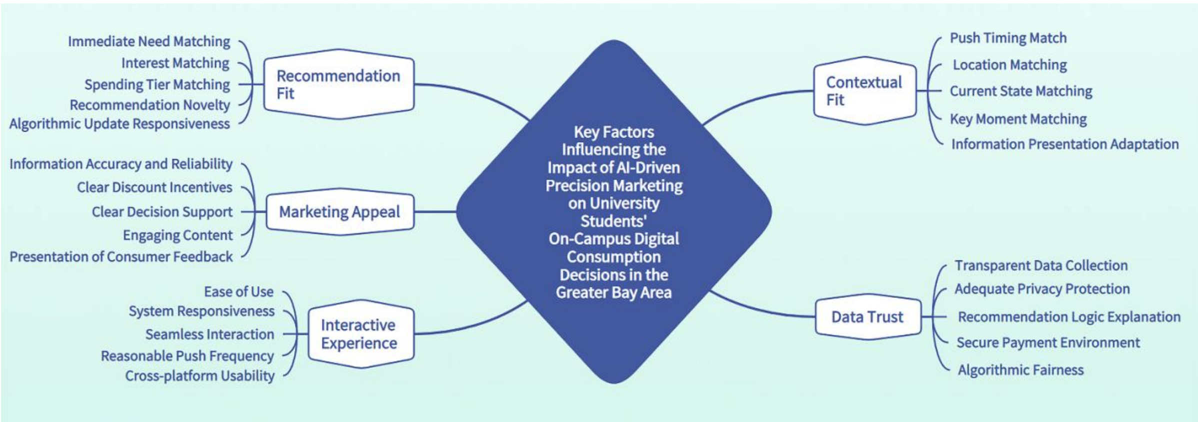

Figure 1. Schematic of the Analytic Hierarchy Process (AHP) hierarchical model

Questionnaire development

This study employed a questionnaire survey to collect data, and the questionnaire design strictly followed the theoretical and application standards of the Analytic Hierarchy Process (AHP) to ensure completeness of the measurement structure and data quality. The questionnaire consisted of two main parts. The first part collected respondents' demographic characteristics and their exposure to and usage of AI-powered precision marketing, including gender, year of study, monthly living expenses, and place of study (cities within the Greater Bay Area). The second part constituted the core of the questionnaire, comprising AHP pairwise-comparison items designed according to the 1–9 scale proposed by Saaty (1990), with a total of 60 pairwise-comparison tasks. Respondents were required to compare the relative importance of the five criterion-level dimensions—recommendation fit, marketing appeal, interactive experience, contextual fit, and data trust—as well as the five alternative-level indicators under each criterion. Through systematic design, this study constructed an evaluation system containing 60 pairwise-comparison tasks, enabling the quantitative acquisition of relative weights across all hierarchical elements.

Data collection

This study targeted university students enrolled in institutions within the Guangdong-Hong Kong-Macao Greater Bay Area, requiring respondents to have actual experience with on-campus digital consumption. Data were collected using a random-sampling approach, combining online questionnaire distribution with offline campus channels to reach student groups across universities in the Greater Bay Area. Data collection took place from March 16 to April 9, 2026, yielding a total of 161 returned questionnaires. After screening and verification—excluding 47 invalid responses (criteria included excessively short completion time and highly patterned answers)—a final sample of 114 valid questionnaires was obtained, resulting in an effective response rate of 70.8%.

Given that on-campus digital consumption is characterized by high frequency, concentration, and strong contextual homogeneity, it effectively activates students' sensitivity in evaluating AI-generated recommendations, interactive experience, and Data Trust. Therefore, although the questionnaire measured respondents' overall perceptions of AI-powered precision marketing, the subsequent analysis focuses specifically on the context of on-campus digital consumption in the Greater Bay Area. This contextual focus enables the identification of the relative importance of influencing factors within this scenario and provides guidance for stakeholders in allocating AI marketing resources in the campus market.

Research Analysis

Sample analysis

This study obtained a total of 114 valid samples. In terms of gender distribution, 62 respondents were male (54.4%) and 52 were female (45.6%), with the proportion of males slightly higher than that of females. Regarding grade level, 23 respondents were first-year students (20.2%), 34 were second-year students (29.8%), 30 were third-year students (26.3%), 26 were fourth-year students (22.8%), and 1 respondent (0.9%) selected "other." The distribution is relatively balanced, with second- and third-year students forming the majority. For monthly living expenses, 12 respondents (10.5%) reported 1,500 RMB or below, 35 (30.7%) reported 1,501–2,000 RMB, 29 (25.4%) reported 2,001–2,500 RMB, 20 (17.5%) reported 3,001–3,500 RMB, 15 (13.2%) reported 3,501–4,000 RMB, and 5 (4.4%) reported 4,001 RMB or above. No respondents fell within the 2,501–3,000 RMB range. The majority were concentrated in the 1,501–2,500 RMB range (56 respondents, 49.1%), which aligns with the typical consumption capacity of university students. Regarding place of study, respondents covered major cities in the Guangdong-Hong Kong-Macao Greater Bay Area: Guangzhou (23, 20.2%), Shenzhen (15, 13.2%), Zhuhai (13, 11.4%), Dongguan (12, 10.5%), Foshan (11, 9.6%), Hong Kong (10, 8.8%), Macao (8, 7.0%), Huizhou (8, 7.0%), Zhongshan (7, 6.1%), Jiangmen (4, 3.5%), and Zhaoqing (4, 3.5%). The sample covers the nine mainland cities and the Hong Kong–Macao regions, demonstrating good geographical diversity.

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Overall, the sample exhibits strong diversity in gender, grade level, consumption level, and geographical distribution, providing a solid data foundation for the subsequent AHP weight analysis.

Weight calculation and consistency testing

This study aims to transform users' subjective judgments regarding the importance of factors influencing university students' on-campus digital consumption decisions under AI-powered precision marketing into systematic and objective weights. Using the mathematical modeling techniques of the Analytic Hierarchy Process (AHP), qualitative user preferences are converted into mathematically grounded and highly reliable weight results through the construction of judgment matrices, the computation of eigenvectors, and rigorous consistency testing. The following section elaborates on the implementation principles and specific operational procedures of this method.

(1) Calculating the weight vector: The geometric mean method is used to calculate the relative weight of each indicator. First, the geometric mean of each row in the judgment matrix is computed as follows:

$$w_i = \left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}} / \sum_{i=1}^{n} a_{ij} \left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}} \quad (1)$$

aij denotes the relative importance scale of indicator i with respect to indicator j, and the judgment matrix A satisfies the positive reciprocal property aij=1/aji.

(2) Compute the maximum eigenvalue λmax: To test the consistency of the judgment matrix, its maximum eigenvalue λmax must be calculated.

$$\lambda_{\max} = \frac{1}{n}\left(\frac{w'_1}{w_1} + \frac{w'_2}{w_2} + \cdots + \frac{w'_n}{w_n}\right) \quad (2)$$

w'i denotes the i component of the vector w'.

$$\begin{bmatrix} 1 & A_{12} & \dots & A_{1n} \\ 1/A_{12} & 1 & \dots & A_{2n} \\ \vdots & \vdots & \dots & \vdots \\ 1/A_{1n} & 1/A_{2n} & \dots & 1 \end{bmatrix} \cdot \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_3 \end{bmatrix} = \begin{bmatrix} w'_1 \\ w'_2 \\ \vdots \\ w'_3 \end{bmatrix} \quad (3)$$

(3) Consistency test: to ensure the logical consistency of the decision maker's judgment, consistency test is needed. First, calculate the Consistency Index (C.I.):

$$C.I = \frac{\lambda_{max} - n}{n-1} \quad (4)$$

Refer to the table7 below for the average Random Index (R.I.) (Saaty, 1990):

Table 7 Standard Random Index (R.I.) Values

Matrix Order (n)	1	2	3	4	5	6	7	8	9
R.I.	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

The consistency ratio (C.R.) is calculated as follows:

$$C.R. = \frac{C.I}{R.I} \tag{5}$$

According to Saaty's consistency-testing criterion, if the Consistency Ratio (C.R.) of a judgment matrix is less than 0.10, the matrix is considered to have high credibility and the weight vector can be extracted; otherwise, the initial judgment matrix must be revised and optimized.

Consistency testing analysis

This study adopts the Consistency Ratio (CR) proposed by Saaty (1990) to examine the logical consistency of the judgment matrices. This indicator measures the degree of consistency in respondents' pairwise comparisons, with CR < 0.1 commonly used as the acceptable threshold. The calculation results indicate that the consistency ratios (CR) of the judgment matrices for both the criterion and alternative layers are less than 0.10 (CR < 0.10), all passing the consistency check and demonstrating good logical consistency and reliability of the data.

Results Analysis

According to the calculation steps of formulas (1) to (5), the judgment matrices from the 114 valid AHP questionnaires were aggregated using the geometric mean to construct the group judgment matrix, after which the weights and consistency ratios of each hierarchical indicator were calculated one by one. Specifically, the weight ranking within the criterion layer is as follows: data trust (0.2249) > interactive experience (0.2124) > recommendation fit (0.1964) > marketing appeal (0.1898) > contextual fit (0.1765).The weight calculation results, consistency-test parameters, global rankings, and criterion-layer codes for both the criterion layer and the alternative layer are presented in Table 8.

Table 8 AHP Evaluation Index System Weights and Consistency Test Results Criterion-level summary

criterion-layer codes	Criterion-level Weight, CI, RI, and CR	Is CR < 0.1	Weight Ranking	Indicator-level Element Name	Weight	Local Rank	Global Weight	Overall Rank
C5	Data Trust Weight：0.2249 CI: 0.0205 RI：1.12, CR: 0.0183	Yes	1	Secure Payment Environment	0.2589	1	0.0582	1
				Adequate Privacy Protection	0.2255	2	0.0507	3
				Algorithmic Fairness	0.1920	3	0.0432	7
				Transparent Data Collection	0.1724	4	0.0388	11
				Recommendation Logic Explanation	0.1540	5	0.0346	22
C3	Interactive Experience Weight：0.2124 CI: 0.0364	Yes	2	Ease of Use	0.2373	1	0.0504	4
				Cross-platform Usability	0.2247	2	0.0477	5
				Reasonable Push Frequency	0.1963	3	0.0417	9

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	RI：1.12, CR: 0.0325			Seamless Interaction	0.1756	4	0.0373	14
				System Responsiveness	0.1661	5	0.0353	20
C1	Recommendation Fit Weight：0.1964 CI: 0.0390 RI：1.12, CR: 0.0348	Yes	3	Recommendation Novelty	0.2595	1	0.0510	2
				Algorithmic Update Responsiveness	0.2032	2	0.0399	10
				Spending Tier Matching	0.1951	3	0.0383	12
				Immediate Need Matching	0.1857	4	0.0365	18
				Interest Matching	0.1565	5	0.0307	24
C2	Marketing Appeal Weight：0.1898 CI: 0.0563 RI：1.12, CR: 0.0503	Yes	4	Presentation of Consumer Feedback	0.2234	1	0.0424	8
				Clear Decision Support	0.1984	2	0.0377	13
				Information Accuracy and Reliability	0.1949	3	0.0370	15
				Engaging Content	0.1941	4	0.0368	16
				Clear Discount Incentives	0.1891	5	0.0359	19
C4	Contextual Fit Weight：0.1765 CI: 0.0239 RI：1.12, CR: 0.0213	Yes	5	Key Moment Matching	0.2539	1	0.0448	6
				Push Timing Match	0.2083	2	0.0368	17
				Location Matching	0.1980	3	0.0349	21
				Information Presentation Adaptation	0.1912	4	0.0337	23
				Current State Matching	0.1487	5	0.0262	25

Based on the weight calculations and ranking results presented in Table 8, the following major findings can be summarized: First, at the criterion-layer level, data trust has the highest weight (0.2249), followed by interactive experience (0.2124), recommendation fit (0.1964), marketing appeal (0.1898), and contextual fit (0.1765). This ranking indicates that, in campus digital consumption decisions, students in the Greater Bay Area place greater emphasis on data security, privacy protection, and algorithmic fairness of AI marketing systems than on the precision of recommended content or the attractiveness of marketing information. In the global ranking, secure payment environment ranks first (0.0582), while recommendation novelty (0.0510) and adequate privacy protection (0.0507) rank second and third. Notably, algorithmic fairness (0.0432) also enters the global top ten, suggesting that students' concern for algorithmic fairness has surpassed the stereotypical perception that they are primarily "price-sensitive and discount-driven." It should be noted that the Greater Bay Area features diverse university types (mainland public universities, private universities, Hong Kong and Macao institutions, and joint programs) and cross-border enrollment. The sample includes mainland students, Hong Kong and Macao students, and cross-border commuters, giving the findings a degree of cross-regional applicability.

Second, within the internal weight distribution of each criterion-layer dimension, three notable differences emerge. Within recommendation fit, recommendation novelty (0.2595) carries a higher weight than interest matching (0.1565), indicating that university students prefer exploratory and non-repetitive AI recommendations rather than those limited to historical consumption records. This suggests that in campus contexts—where users possess high digital literacy and seek novelty—exploration may outweigh exploitation. Within marketing appeal, presentation of consumer feedback (0.2234) outweighs clear discount incentives (0.1891), showing that social-proof information such as user reviews and sales volume exerts greater influence on decision-making than economic incentives such as discounts or price reductions. The tight social networks on campus amplify the reference value of peer evaluations, making social proof a primary mechanism for reducing decision-making costs. Within contextual fit, key-moment matching (0.2539) and push-timing matching (0.2083) carry higher weights than current-state matching (0.1487) and location matching (0.1980), indicating that recognizing macro-level event cycles—such as exam weeks or the start of the semester—is more effective than sensing users' real-time activity states. Collectively, these differences point to a core pattern: in campus digital consumption, exploratory, social, and timing-related factors exert greater influence than traditional factors such as historical preferences, price incentives, and real-time location.

Third, within interactive experience, ease of operation (0.2373) and cross-platform usability (0.2247) carry higher weights than system responsiveness (0.1661), indicating that interface friendliness and multi-device coordination have a greater impact on decision-making than millisecond-level response speed. This suggests that in high-frequency, fragmented campus consumption scenarios, users exhibit relatively high tolerance for loading delays, while streamlined interaction paths and seamless device switching exert stronger influence on decisions.

These three findings collectively reveal the fundamental characteristics of Greater Bay Area university students' on-campus digital consumption decisions under the influence of AI-powered precision marketing: trust takes precedence over precision, exploration and social proof outweigh historical preferences and price incentives, and macro-level timing and interface usability matter more than micro-level contextual cues and extreme system performance. These findings provide a quantitative basis for further summarizing the core characteristics of consumption decision-making in the following section.

CONCLUSION AND RECOMMENDATIONS

Research findings

This study, through AHP-based weight calculations, reveals three core characteristics of Greater Bay Area university students' on-campus digital consumption decisions under the influence of AI-powered precision marketing. First, trust is the highest decision threshold: the weights of secure payment environment and adequate privacy protection rank first and third globally, indicating that data trust surpasses recommendation fit and marketing appeal to become the primary prerequisite for this group's consumption decisions. Second, exploration and social influence outweigh historical dependence and economic incentives: the weight of recommendation novelty is significantly higher than that of interest matching, and presentation of consumer feedback outweighs clear discount incentives, suggesting that in high-frequency campus consumption scenarios, users prefer non-repetitive recommendations and find peer evaluations more persuasive than price discounts. Third, interface ease-of-use and cross-platform experience matter more than extreme system performance: the weights of ease of operation and cross-platform usability are far higher than that of system responsiveness, indicating that enterprises should prioritize optimizing interaction paths and multi-device synchronization rather than pursuing millisecond-level response speed. In summary, the unique context of cross-border enrollment and diverse university types in the Greater Bay Area further highlights the strategic importance of data cross-border security, algorithmic fairness, and cross-terminal collaborative experience.

Recommendations

The above conclusions reveal the main behavioral logic underlying the digital consumption decisions of university students in the Greater Bay Area. Trust is the primary threshold; recommendation novelty exerts greater influence than historical preferences; social-proof information outweighs price discounts; key moments matter more than real-time location; and interface friendliness and cross-platform convenience are more important than extreme response speed. These characteristics not only reflect the common preferences of this group but also provide clear focal points for optimizing AI-powered precision marketing strategies at different levels. Based on this, this section proposes the following targeted recommendations from the perspectives of three relevant stakeholders.

Algorithm optimization recommendations for e-commerce platforms and AI technology providers

Data Trust is the highest-weighted criterion, with secure payment environment (global rank 1) and adequate privacy protection (global rank 3) carrying the greatest weights. Platforms should prioritize strengthening security authentication in payment processes and provide safety-insurance reminders for cross-border transactions, while also establishing clear privacy policies that specify the scope of data collection. Regarding algorithmic fairness (global rank 7), platforms may proactively display price differences and their causes for the same product across Guangzhou, Hong Kong, and Macao to enhance price transparency. Within the recommendation fit dimension, recommendation novelty (global rank 2) carries a higher weight than interest matching (global rank 24), suggesting that platforms may retain personalized recommendations while allocating 15%–20% of recommendation slots to exploratory content such as cross-border new arrivals to avoid “accurate but not novel” recommendation patterns. Although the overall weight of contextual fit is relatively low, key-moment matching ranks sixth globally, indicating that platforms should collect academic-calendar data from universities in the Greater Bay Area and adjust recommendation strategies during key periods such as exam weeks and the beginning of semesters.

Marketing strategy recommendations for chain enterprises and brand merchants

Similarly, based on data trust, secure payment environment (global rank 1) and adequate privacy protection (global rank 3) are foundational elements that enterprises must prioritize. Enterprises are advised to display security-certification labels on payment pages and provide simplified/traditional Chinese bilingual privacy statements for Hong Kong and Macao students. Given the high weight of recommendation novelty (global rank 2), enterprises may include a moderate proportion of cross-border specialty products (such as Hong Kong-version electronics or duty-free cosmetics) in recommendation lists while controlling price ranges (consumption-level matching, global rank 12) to avoid exceeding students’ purchasing capacity. Within marketing appeal, presentation of consumer feedback (global rank 8) carries a higher weight than clear discount incentives (global rank 19), suggesting that enterprises should highlight user reviews, sales volume, and other social-proof information, for example by developing a “Greater Bay Area campus circle” feature that displays purchase activities of students from the same university, while discounts may be paired with “group-purchase exclusive prices.” Given that interactive experience ranks second overall, with ease of operation (global rank 4) and cross-platform usability (global rank 5) far outweighing system responsiveness (global rank 20), enterprises should prioritize simplifying checkout procedures and ensuring synchronized shopping carts across devices.

Collaborative recommendations for universities and regulatory authorities

Secure payment environment (global rank 1) and adequate privacy protection (global rank 3) require external support. It is recommended that education authorities in Guangdong, Hong Kong, and Macao jointly issue guidelines on personal-information protection for campus digital consumption in the Greater Bay Area to standardize data collection and processing practices; regulatory agencies should treat payment-security review as a key criterion for market entry in campus settings and conduct inspections to identify potential price discrimination (algorithmic fairness, global rank 7), while establishing complaint channels for campus users. Given the significant influence of key-moment matching (global rank 6) on consumption decisions, universities may—without involving personal privacy—provide desensitized campus-behavior data (such as cafeteria peak hours or library traffic) to partner enterprises to help identify key periods such as exam weeks and the start of semesters. Since interactive experience ranks second overall, universities may guide students to make reasonable use of cross-platform services to enhance the convenience of digital consumption.

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