



## Consumer Behavior Theory in the Era of Generative AI

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**ABSTRACT:** With the rapid development of generative AI, traditional consumer behavior theories centered on "information search-rational decision-making" are undergoing structural changes. Consumers no longer rely solely on static information platforms but engage in interactive dialogue with generative AI, completing needs identification, solution generation, and decision optimization with the support of dynamically generated content. This paper proposes a "Generative AI-Driven Interactive Consumer Behavior Model" (GAIBB) based on the integration of classic consumer behavior theories (such as the Theory of Rational Behavior, the Theory of Planned Behavior, and the Theory of Experiential Consumption). This model emphasizes three mechanisms: "co-creation decision-making," "generative recommendation," and "instant feedback loop," explaining how AI reshapes consumers' cognitive paths and purchasing behavior. The research further indicates that generative AI is driving a shift in consumer behavior from "information acquisition" to "co-creation of cognition," and reconstructing the power structure between platforms, brands, and users.

**KEYWORDS:** Generative Artificial Intelligence (Generative AI), Consumer Behavior Theory, Human-AI Interaction, Consumer Decision-Making, Interactive Consumer Behavior Model (GAICB).

### I. INTRODUCTION

Consumer behavior has always been an important topic in marketing, consumer psychology, and management research [1]. For a long time, mainstream consumer behavior theories have mostly been based on the assumptions of information asymmetry and bounded rationality, believing that when facing purchasing decisions, consumers need to actively obtain product information, compare different options, and weigh costs, utility, and risks to make relatively rational choices [2]. In the traditional business environment, consumers mainly rely on advertising, product descriptions, media reports, and personal experience to complete

information collection [3]. In the Internet era, search engines, e-commerce platforms, and social media have further expanded consumers' information sources, significantly improving information acquisition efficiency [4]. However, whether in the era of traditional media or the era of Internet platforms, consumers still need to integrate a large amount of scattered information themselves and complete analysis and decision-making through their own cognitive abilities. Therefore, the essence of consumer behavior is still a process centered on information search and information processing [5].

In recent years, with the rapid development of generative artificial intelligence [6], especially the widespread application of large language models, multimodal models, and intelligent agent technologies, the way consumers acquire and process information is undergoing profound changes [7]. Unlike traditional information systems, generative AI can not only quickly retrieve information based on user needs, but also understand user intent, analyze user preferences, and proactively generate complete solutions [8]. In this process, a continuous interactive relationship is formed between consumers and AI. Consumer decision-making is no longer a one-sided information processing process for consumers, but has gradually evolved into a collaborative decision-making process involving both consumers and artificial intelligence [9].

For example, in tourism consumption scenarios, consumers no longer need to search for airfares, hotels, attractions, and transportation information separately, but can directly request AI to generate a complete travel plan based on budget, time constraints, and personal interests; in the e-commerce field, consumers no longer need to browse numerous product pages, but can obtain product combination solutions, performance comparison reports, and purchase suggestions tailored to their needs through dialogue with AI; similar human-machine collaborative decision-making phenomena are also rapidly spreading in education, finance, healthcare, and entertainment consumption. Generative AI has gradually transformed from a simple information tool into an



important participant in consumer cognitive activities, and has begun to influence multiple aspects such as demand identification, solution design, value judgment, and final purchase decision-making. This change means that consumer behavior is shifting from "information retrieval driven" to "content generation driven," and from "independent consumer decision-making" to "human-machine collaborative decision-making." Many basic assumptions in traditional consumer behavior theory are being challenged. For example, are consumer preferences still predetermined? Does the decision-making process still follow linear information search logic? Is the recommendation system still just an information distribution tool? These questions need to be re-examined in the new technological environment. Therefore, it is necessary to construct a new theoretical framework that can reflect the characteristics of the generative AI era to explain the structural changes in consumer behavior and provide a theoretical basis for future consumer research, digital marketing practices, and intelligent business system design.

## II. LITERATURE REVIEW

### 2.1 Traditional Consumer Behavior Theories

Consumer behavior research has formed a relatively mature theoretical system [10]. Among them, the Theory of Reasoned Action (TRA) believes that individual behavior is mainly influenced by behavioral attitudes and subjective norms. When consumers have a positive attitude towards a certain behavior and feel social support, their behavioral intentions will be significantly enhanced [11]. The Theory of Planned Behavior (TPB), which was developed later, further introduced perceived behavior control variables, arguing that consumers are not only influenced by attitudes and norms, but also constrained by their own resources and cognitive abilities, thus improving the model's explanatory power for actual behavior [12].

Meanwhile, the Consumer Decision Model (CDM) describes consumer behavior as a continuous process, including stages such as problem identification, information search, alternative evaluation, purchase decision, and post-purchase evaluation [13]. This model has long been widely used in the fields of marketing and consumer research. Furthermore, the Experiential Consumption Theory emphasizes the important role of emotional experience, symbolic meaning, and psychological satisfaction, pointing out that consumers purchase not only the product's function

itself, but also the emotional and social value it brings.

Although the above theories differ, they share the common feature of viewing information as a relatively stable and exogenous resource. Consumers actively search for information and then use their cognitive abilities to complete analysis and decision-making. In these theoretical frameworks, consumers are always regarded as the core subject of decision-making activities, while the technological system mainly undertakes the functions of information transmission and auxiliary support. However, in the era of generative AI, information itself can be dynamically generated and reorganized, and AI has begun to participate in the consumer cognitive process, which poses new challenges to the applicability of traditional theories.

### 2.2 Research on Digital Platforms and Recommendation Systems

With the development of the internet platform economy, a large number of studies have begun to focus on the impact of recommendation systems on consumer behavior [14]. E-commerce platforms utilize users' historical behavior, purchase records, and interests to push personalized product information to consumers through collaborative filtering, content recommendation, and deep learning algorithms [15]. Compared with traditional search models, this algorithmic recommendation model reduces consumers' information search costs, improves consumption efficiency, and significantly changes consumers' purchasing paths [16].

However, traditional recommendation systems are essentially still information filtering mechanisms, and their core task is to filter out the content most likely to meet user needs from a massive amount of goods [17]. The system output is usually manifested as a sorted list, a recommendation page, or an advertisement push, and consumers still need to further analyze and compare this information [18]. Therefore, although recommendation systems have changed the way information is obtained, they have not changed the basic logic of consumer decision-making, that is, consumers are still the final information integrators and decision-makers [19]. In addition, the interaction depth between traditional recommendation systems and users is relatively limited. Users can only indirectly provide feedback on preferences through clicks, browsing, or purchasing behavior, and cannot express complex needs in real time and obtain immediate responses. This one-way output mode limits the recommendation system's ability to understand complex consumer needs, and also creates



development space for the emergence of generative AI.

### 2.3 Generative AI Related

Research In recent years, generative AI has gradually become an important research direction in the field of artificial intelligence [20]. Related research mainly focuses on education, medical care, content creation, knowledge management, and office automation, exploring its potential value in improving productivity, promoting knowledge acquisition, and enhancing creativity. In the field of education, researchers have found that generative AI can provide personalized learning support; in the field of enterprise management, AI can assist in decision analysis and knowledge integration; in the content industry, AI has been able to participate in the generation process of text, images, videos, and audio content. Compared with the above fields, research on consumer behavior is still in its infancy. Existing research mainly focuses on the application effects of generative AI in customer service systems, intelligent shopping guides, personalized marketing, and consumer experience, and generally believes that generative AI can improve service quality and user satisfaction. However, most research remains at the level of technological application, lacking theoretical explanations for the underlying mechanisms of changes in consumer behavior. In particular, a systematic theoretical framework has not yet been formed regarding consumer cognitive structures, human-machine collaborative decision-making processes, and preference generation mechanisms. Therefore, constructing a new theory of consumer behavior applicable to the era of generative AI has significant academic value and practical implications.

## III. THEORETICAL FRAMEWORK: GAICB MODEL

To explain the new characteristics of consumer behavior in the context of generative AI, this paper proposes a Generative AI-Driven Interactive Consumer Behavior Model (GAICB). This model posits that generative AI has transformed from a traditional information tool into a crucial participant in consumer cognitive activities, influencing the formation of consumer needs, solution generation, and decision optimization processes through continuous interaction.

### 3.1 Core Assumptions

The GAICB model is built upon three core assumptions. First, generative AI is not only a

source of information but also a cognitive collaborator for consumers. AI can understand user intent, offer suggestions, and participate in problem-solving; therefore, its role transcends that of traditional search engines and recommendation systems. Secondly, consumer decisions no longer follow a traditional linear process but exhibit cyclical generation characteristics. Consumers and AI continuously exchange information and adjust based on feedback, making the decision-making process dynamic and iterative rather than a fixed phase. Finally, consumer preferences are not entirely pre-existing but gradually form and evolve through continuous interaction with AI. Consumers may discover new needs, new evaluation criteria, and new consumption goals during the interaction process, thereby changing their original decision-making direction.

### 3.2 Three Major Mechanisms

#### (1) Co-Creation Decision Mechanism

The GAICB model posits a co-creation decision-making relationship between consumers and generative AI. In this process, consumers provide initial needs and constraints, while AI utilizes its knowledge base and reasoning abilities to generate possible solutions. When consumers further suggest modifications, AI can continuously optimize based on feedback. For example, if a consumer initially expresses only a vague need like "I want to travel," AI will further inquire about budget, time, interests, and other information, gradually generating multiple feasible solutions. Through continuous interaction, the needs themselves become clearer and more specific. Therefore, consumer decision-making is no longer a solitary information processing activity for consumers, but a process in which consumers and AI jointly construct a decision-making space and refine decision-making solutions.

#### (2) Generative Recommendation Mechanism

Traditional recommendation systems primarily display product lists to users, while generative AI can directly generate complete consumption plans. For example, when buying a computer, AI can not only recommend multiple brands and models, but also generate detailed configuration plans based on the user's budget, intended use, and performance requirements; in home decoration scenarios, AI can even simultaneously generate furniture matching, budget planning, and space design suggestions. Therefore, the core characteristic of the generative recommendation mechanism lies in shifting from



"recommending products" to "generating solutions," and from "information sorting" to "content creation." Consumers no longer receive fragmented information, but rather structured decision support after integration and reasoning.

### (3) Real-Time Feedback Loop

The real-time feedback loop mechanism is an important component of the GAICB model. Consumers can provide feedback on the content generated by AI at any time, such as requesting a reduction in budget, a change of brand, an adjustment of style, or the addition of functional requirements. AI then instantly regenerates results based on new inputs, creating a continuous optimization loop in the decision-making process. Compared to traditional consumption models, this mechanism significantly improves decision-making efficiency and personalization, allowing consumers to explore more possible solutions in a shorter time. As the number of interactions increases, the decision-making results jointly constructed by consumers and AI continuously approach the optimal state, thus forming a dynamic human-machine collaborative consumption model.

## IV. EVOLUTIONARY MODEL OF CONSUMER BEHAVIOR

Under the GAICB (Generative AI-Driven Interactive Consumer Behavior) framework, the consumer decision-making process no longer follows the linear pattern described by traditional consumer theory. Past consumer behavior typically followed a unidirectional process of "demand generation—information search—solution comparison—purchase decision," while the intervention of generative AI has made this process dynamic, cyclical, and continuously optimized. Consumers and AI constantly exchange information, modify needs, and iterate solutions, gradually transforming consumer behavior into a human-machine collaborative cognitive activity. Therefore, this paper divides consumer behavior in the era of generative AI into five core stages: the demand ambiguity stage, the AI interaction clarification stage, the generative solution stage, the collaborative optimization stage, and the action execution stage.

### 4.1 Demand Ambiguity Stage

The starting point of consumer behavior is usually not a clear purchase goal, but a vague consumption intention [21]. In traditional consumption models, consumers often have a relatively clear understanding of their needs, such as determining what products they need to buy and

what core attributes they need to focus on [22]. However, in the generative AI environment, consumers are increasingly inclined to enter the decision-making process with incomplete or even uncertain needs. For example, a consumer might only realize they "want to get a new phone," "want to plan a trip," or "want to improve their home office environment," but they are unclear about what specific products to buy, which brand to choose, or what solution to adopt.

A significant characteristic of this stage is the uncertainty and openness of the demand. Consumers have not yet formed stable preferences and lack a clear understanding of product categories, functional requirements, and budget ranges. Traditional theories typically view demand as a fixed starting point for consumer behavior, while the GAICB model argues that demand itself may be dynamically generated. The emergence of generative AI allows consumers to enter the decision-making process even before their needs are fully defined, and to gradually discover and shape their own needs through subsequent interactions.

### 4.2 AI Interaction Clarification Stage

When consumers begin to interact with generative AI, the consumer behavior enters the demand clarification stage. Unlike traditional search engines where results are obtained by entering keywords, generative AI can understand the user's true intentions through continuous dialogue and proactively guide consumers to further describe their needs. In this process, AI not only answers questions but also helps consumers re-understand their own needs through questioning and feedback.

For example, when a consumer says "I want to buy a computer," the AI may further inquire about their budget range, main purpose, brand preference, usage scenarios, and performance requirements. As the interaction deepens, the consumer's originally vague needs gradually transform into a demand structure with clear constraints and evaluation criteria. In fact, many consumers discover important factors they previously overlooked during this process, thus readjusting their decision-making direction.

Therefore, this stage is not only an information gathering process but also a demand construction process. Consumers gradually form an understanding of their own needs through continuous dialogue with the AI, while the AI plays the role of cognitive guide and demand interpreter. This phenomenon indicates that consumer behavior has shifted from the traditional "information



acquisition activity" to a "cognitive negotiation activity."

#### 4.3 Generative Solution Stage

Once the consumer's needs are fully clarified, the generative AI begins to generate specific solutions based on user characteristics and constraints. In the traditional consumer environment, consumers usually need to browse a large number of product pages, read evaluation information, and complete comparative analysis themselves [23]. In the generative AI environment, the system can directly generate multiple structured decision solutions for consumers to choose from. For example, when purchasing a smartphone, AI can not only recommend several models but also generate budget plans, performance comparison reports, and analyses of advantages and disadvantages in different usage scenarios. In travel consumption, AI can even simultaneously generate complete content such as itinerary arrangements, accommodation suggestions, budget planning, and risk warnings. Consumers no longer receive fragmented information but rather a holistic solution that has been integrated and reasoned.

This stage embodies the core characteristic that distinguishes generative AI from traditional recommendation systems. Traditional recommendation systems primarily filter information, while generative AI can create new decision-making content. Consumers are no longer faced with a list of products but multiple consumption options with different value orientations and optimization goals. Therefore, consumption decisions begin to shift from "choosing a product" to "choosing a solution."

#### 4.4 Collaborative Optimization Stage

The generated solution is not the final result but rather the starting point for consumers and AI to jointly optimize decisions. In the collaborative optimization stage, consumers adjust and provide feedback on the AI-generated content based on their personal preferences, while AI regenerates a solution that better meets their needs based on the new input. This continuous iteration constitutes one of the most representative characteristics of generative AI consumption behavior.

For example, consumers may request a lower budget, added features, a change in style, or an adjustment in brand selection. AI then recalculates and generates solutions based on the new requirements. As the number of interactions increases, the decision-making outcome jointly constructed by consumers and AI gradually

becomes more refined. In this process, consumers not only obtain solutions that better meet their needs but also continuously deepen their understanding of their own preferences.

Compared to traditional consumer behavior, the collaborative optimization stage exhibits significant dynamic characteristics. Decision-making is no longer a one-off event but a continuous iteration; preferences are no longer fixed but constantly evolving; information processing is no longer entirely the responsibility of the consumer but is jointly completed by the consumer and AI. Therefore, consumer behavior gradually demonstrates a new characteristic of human-machine collaboration in creating value.

#### 4.5 Action Execution Stage

After multiple rounds of interaction and optimization, consumers finally enter the action execution stage, including purchasing products, accepting services, or adopting solutions provided by AI. In this stage, consumers complete the final decision and translate the solution into actual consumption behavior. However, unlike traditional consumption models, action execution does not signify the end of the decision-making process.

New feedback generated by consumers after using products or experiencing services can be input into the AI system again, thereby influencing future decisions. For example, user satisfaction ratings, usage experiences, and subsequent changes in needs after purchasing goods can all be recorded and learned by the system, forming a feedback loop for continuous improvement. Therefore, consumer behavior in the GAICB model exhibits a closed-loop structure; the consumption outcome is not only the output of the decision-making process but also a crucial input for the next round of consumption decisions.

## V. THEORETICAL PROPOSITIONS

Based on the GAICB model, this paper proposes five theoretical propositions to explain the core patterns of consumer behavior in the era of generative AI and to provide a theoretical foundation for subsequent empirical research.

Proposition 1 argues that the higher the frequency of generative AI use, the shorter the consumer's decision-making path, but the higher the degree of dependence on AI. Because AI can quickly integrate information and generate solutions, consumers spend significantly less time on information search and comparative analysis. However, as decision-making efficiency improves, consumers may gradually rely on the judgments and



suggestions provided by AI, thereby reducing the proportion of independent analysis.

Proposition 2 argues that generative AI improves consumers' perception of "solution quality," not just their perception of "information quality." Traditional information systems primarily improve information acquisition efficiency, while generative AI can directly generate complete decision-making solutions. Therefore, consumer evaluation will shift its focus from information accuracy to the rationality and feasibility of the solutions.

Proposition 3 argues that the impact of generative AI will be more significant in high-uncertainty consumption scenarios. For example, complex consumption areas such as travel planning, electronics purchases, financial investments, and education and training involve large amounts of information and high decision-making risks; therefore, consumers are more inclined to rely on AI for decision support.

Proposition 4 argues that generative AI will weaken the information intermediary power of traditional platforms and enhance the dialogical power of algorithms. In the past, platforms mainly influenced consumer choices by controlling information flow; in the future, consumers may directly obtain decision-making advice through AI, thereby reducing their reliance on traditional platform interfaces.

Proposition 5 argues that consumer preferences are generative rather than stable. Traditional consumption theories generally assume that preferences exist before the decision-making process begins, while the GAICB model argues that preferences are continuously formed, adjusted, and evolved through ongoing interaction between consumers and AI. Therefore, preferences are no longer a prerequisite for decision-making but may become one of the outcomes of the decision-making process.

## **VI. DISCUSSION**

### **6.1 Impact on Consumer Theory**

The GAICB model presents new challenges to traditional consumer behavior theories. For a long time, most consumer theories have been based on the premise that consumers have stable preferences, understanding consumer behavior as a preference-driven information processing process. However, consumer behavior in the era of generative AI shows that consumer preferences are not entirely a priori, but gradually formed through interaction with AI. Need identification, value judgment, and solution

selection can all be influenced by AI feedback. Therefore, future consumer research needs to shift from static preference models to dynamic preference generation models to explain new consumer behaviors in a human-machine collaborative environment.

### **6.2 Impact on Business Models**

The development of generative AI is changing the competitive logic of enterprises. In the past, companies mainly gained consumer attention through advertising, brand building, and channel layout. In the future, companies will also need to consider whether their products can be accurately understood, organized, and recommended by AI. In other words, companies not only need to optimize the product itself, but also need to improve the product's "AI-readability." Whoever can more effectively enter the AI recommendation and generation system is more likely to gain consumer attention. Therefore, AI-oriented product descriptions, knowledge structures, and data organization capabilities will become new competitive advantages.

### **6.3 Impact on the Platform Economy**

The development of the platform economy has long relied on traffic allocation mechanisms and information aggregation capabilities. However, generative AI may change this competitive landscape. Consumers will no longer need to browse numerous pages and product listings, but will directly seek decision-making advice from AI. Therefore, future platform competition may shift from traffic competition to competition for generative capabilities, and from interface design competition to competition for cognitive services. The core value of a platform will no longer be merely connecting supply and demand, but providing more powerful intelligent decision support capabilities.

### **6.4 Potential Risks**

While generative AI can improve consumption efficiency and enhance the decision-making experience, its widespread application also carries certain risks. First, consumers may become overly reliant on AI, thereby weakening their independent thinking and autonomous judgment. Second, AI-generated content may be influenced by training data and algorithmic objectives, subtly guiding consumer preferences and subjecting consumption choices to hidden mechanisms. Furthermore, as AI gradually assumes more and more cognitive tasks, consumers' autonomy and agency may be weakened. Therefore, while



promoting the application of generative AI, it is also necessary to pay attention to issues such as algorithmic transparency, fairness, and consumer rights protection.

## VII. CONCLUSION

This paper, focusing on the new changes in consumer behavior under the background of generative AI, proposes a Generative AI-Driven Interactive Consumer Behavior Model (GAICB) and systematically explains the theoretical logic of the evolution of consumer behavior from traditional models to human-machine collaborative models. Research shows that generative AI not only changes the way consumers obtain information but also profoundly affects key aspects such as demand formation, solution design, preference construction, and decision execution. Consumer behavior is shifting from an information-driven model to a generative-driven model, and from an independent consumer decision-making model to a human-machine collaborative model where consumers and AI co-create value.

The GAICB model proposed in this paper enriches the development path of consumer behavior theory in the era of artificial intelligence and provides a new theoretical perspective for future research on digital marketing, intelligent recommendation systems, and platform economies. Future research can further verify relevant theoretical propositions through questionnaires, experimental studies, and large-scale behavioral data analysis, and explore the differences in the evolutionary mechanisms of consumer behavior under different cultural backgrounds, different consumption fields, and different AI application scenarios, thereby continuously improving the theoretical system of consumer behavior in the era of generative AI.

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