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Marketing Psychology in the Era of AI "Agentification": An Integrative Review of Agentic vs. Traditional AI Tools

Renjie Quan

Columbia Univeristy, New York, USA
rq2203@columbia.edu

Abstract. This paper constructs a strategic framework based on the AISAS consumer decision-making model to compare the application of traditional tool-based AI and Agentic AI marketing. The framework identifies the critical psychological drivers in five stages of consumer decision-making process, respectively. attention (visual saliency and personalization), interest (emotional resonance and curiosity stimulation), search (information sufficiency and credibility), action (decision confidence and risk reduction), and share (social bonding and self-expression). Within this framework, traditional AI primarily fulfills mechanical tasks, such as data processing and standardized content creation, but struggles to respond adaptively to situational shifts and consumer emotions. In contrast, Agentic AI, characterized by autonomous goal-setting, adaptive learning, and empathic responsiveness, effectively addresses complex psychological consumer needs across the AISAS journey. The authors further propose the concept of "Psychological–Technological Fit," recommending that marketers prioritize the implementation of Agentic AI at Interest, Search, and Action stages, where psychological needs are highest. Additionally, companies should enhance AI marketing effectiveness by emphasizing transparency, emotional interaction design, and cross-functional collaboration.

Keywords: Technological Fit, Strategic Marketing Framework, Literature Review

1. Introduction

Artificial intelligence (AI) is now widely utilized in various industries worldwide, particularly in marketing and customer service. Currently, more than 70% of companies use AI in daily operations [1]. Nearly half of marketing executives believe AI has significantly altered the way companies interact with customers. More than half of e-commerce companies utilize AI to enhance user experience, and 64% of B2B marketers consider AI to be very valuable for marketing [2]. However, according to reports, 74% of businesses have failed to achieve significant returns from their AI projects. Nearly half admit their AI efforts are either unprofitable or result in negative returns [3].

Since most companies deploy AI (such as service robots or chatbots) primarily to cut operational costs and maximize profits, it often overlooks the customer journey. Consumers interpret this as the company prioritizing profits over their needs, causing them to rate AI services lower than human services, even if the actual quality is identical [4]. Thus, although companies use AI to save costs

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and improve efficiency, ignoring customer experiences can negatively impact consumer responses, thereby failing to promote purchase decisions and customer loyalty effectively.

In academic research, research on AI applications in marketing primary focus on consumer sentiment analysis, AI applications in industry, customer relationship management, market performance improvement, brand management, and emerging AI-enabled services [5], and ost of these studies remain at the tactical level. While some scholars have proposed strategic marketing frameworks for AI applications [6], there remains insufficient discussion on the clear definition of agentic AI and its strategic value.Furthermore, existing literature has distinguished between large language models (LLMs), AI agents, and agentic AI [7], but these discussions have not specifically targeted marketing applications.Thus, while existing research has laid a solid foundation for AI applications in marketing, and gaps remain.

This study aims to fill these gaps by systematically exploring how companies can strategically integrate Agentic AI within marketing frameworks to drive consumer conversions effectively. Furthermore, this research will draw on practical experiences and algorithmic insights from existing studies to provide broader implications for both academia and industry. In the flowing article we will compare each stage of the AISAS model, the consumer's psychology and needs, and how different AI tools (LLM, traditional AI agents, Agentic AI) match consumer psychological needs at each stage, and identify the advantages of the three models in different aspects.

2. Agentic AI V.S. traditional AI tool

2.1. Agentic AI

Agentic AI posits that individuals can actively set clear goals, adjust their behaviors through forward-looking planning, reflection, and self-regulation, thereby achieving their expected goals and outcomes [8]. Unlike traditional AI, which only passively executes predefined tasks, Agentic AI has human-like autonomous goal-setting ability, actively senses changes in the external environment, reflects on its own experiences and memories, and independently adjusts strategies and goals [9]. Importantly, Agentic AI has "agency for learning," meaning the AI system can actively plan and manage its learning process, including clear goal intention, forward-looking planning ability, self-regulation, and self-efficacy, allowing it to proactively achieve learning goals and more effectively adapt to complex real-world environments [10].

2.2. AI Agents

AI Agents are a type of traditional artificial intelligence tool widely used in business practices, typically for carrying out specific, predefined tasks. These tools include customer service chatbots, intelligent recommendation systems, and marketing automation systems. For example, customer service chatbots are used to automatically answer customer questions, providing basic customer service and technical support. Recommendation systems analyze users' historical data and preferences to suggest suitable products or content proactively. Marketing automation tools automate marketing campaigns and customer management tasks based on predefined rules and conditions. Generally, these AI Agents operate based on preset rules or models, helping businesses improve efficiency, reduce operating costs, and achieve automated workflows in specific areas [11].

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2.3. Large language models

LLMs are AI tools specifically focused on text understanding and generation, including GPT series (such as GPT-3 and GPT-4), DeepSeek, and O3. These tools learn from massive amounts of text data, mastering the patterns of language expression. They efficiently perform tasks such as content generation, text translation, automated question-answering, copywriting, and code generation [12]. The strength of LLMs is their ability to process and quickly understand large amounts of professional text content across various fields, requiring only a few examples to learn new language tasks rapidly. Additionally, through special prompting methods (such as the "Chain-of-Thought" method), LLMs perform exceptionally well in handling complex logical reasoning or computational tasks [13].

3. Customer journey (AISAS model)

This study adopts the AISAS model as the core theoretical framework for analyzing user behavior paths in an agentic AI environment. Adapted from the classic AIDA marketing model, AISAS better reflects contemporary consumer behavior by emphasizing online interactions and social media sharing, making it particularly suitable for exploring consumer journeys in the digital era. AISAS stands for the five stages of attention, interest, search, action, and share. AISAS considers both the psychological changes within consumers and their observable behavioral patterns (Figure 1). For example, the initial stages of attention and interest represent psychological changes (capturing attention and generating interest). At the same time, search and action are clear external behaviors (seeking information and making a purchase). The final stage of share encompasses both psychological drivers (satisfaction or emotional willingness to share) and behavioral expressions (actually posting content). This intertwined chain of psychological and behavioral elements makes AISAS a comprehensive framework for observing consumer decision-making. For example, scholars have applied AISAS to analyze the online behavior of tourism consumers, finding that the elements of “Attention-Interest-Search-Action-Share” significantly influence tourism product purchase decisions in real-world scenarios, including sightseeing browsing, interest stimulation, information retrieval, ticket purchase decisions, and post-trip sharing [14,15].

Although the AISAS model is constructed around consumer autonomous behavior, in the Agentic AI consumption scenario, each stage is influenced by AI. The key psychological needs and behavioral factors that consumers experience at each AISAS stage are shown in Table 1.

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Table 1. Key psychological and behavioral factors influencing consumer decision-making across AISAS stages

Consumer Stage	Key Psychological / Behavio ral Factors	Detailed Explanation	Citations
Attention	Visual Saliency	Advertisements with bright colors, large headlines, or unusual placements quickly capture consumers’ attention and increase impressions.	[16]
	Personalization & Relevance	Advertisements matching consumers’ interests increase perceived relevance and attract attention.	[17]
	Stimulus Novelty	Creative or unexpected elements in ads break usual browsing habits, stimulate curiosity, and enhance memorability.	[18]
Interest	Curiosity Stimulation	Ads or brand messages intentionally leave suspense or incomplete details, prompting consumers' curiosity to learn more.	[19]
	Emotional Resonance	Content that evokes clear emotions (e.g., happiness, empathy) encourages consumers to engage longer and build emotional connections.	[20]
	Information Gap	Consumers feel tension or curiosity upon realizing they lack essential information. Brands often deliberately create gaps or suspense to motivate consumers to seek further details actively.	[21]
Search	Information Sufficiency	Consumers require detailed and clear product information to reduce purchase anxiety and uncertainty.	[22]
	Information Credibility	Consumers prefer trustworthy information from experts or genuine user experiences to build confidence.	-
	Comparative Evaluation	Consumers typically compare multiple brands in detail (prices, features, reviews) to find the best product for their needs, enhancing their decision confidence.	[23]
	Risk Avoidance	Consumers carefully consider negative reviews, warranties, or return policies to reduce perceived risk before buying.	[23]
Action	Decision Confidence	Clear, reliable product information strengthens consumer confidence, prompting purchase decisions.	[24]
	Value Confirmation	Before purchasing, consumers reassess if the product's value truly exceeds its cost. Only if this evaluation confirms positive value will they proceed confidently.	[25]
	Risk Reduction & Commitment	Clear return policies, reputable brands, or promotional guarantees reduce consumer fears, prompting final purchases.	[24]
Share	Social Connection Motivation	Consumers share their purchase experiences to strengthen relationships and gain approval from others, especially when brands provide personalized attention or discounts.	[26]
	Emotion-driven Sharing	Consumers experiencing strong emotions (such as excitement, surprise, or disappointment) feel a strong urge to express or vent these feelings, leading to active sharing.	[27]
	Self-expression Motivation	Consumers share product experiences to express their tastes, knowledge, or unique personality.	[28]
	Content Resonance & Shareability	Consumers prefer to share interesting content, storytelling-rich, or related to trending topics, as this type of content resonates easily and spreads widely within social circles.	[29]

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4. Comparison between traditional AI tools and agentic AI at different stages

Businesses can increase consumers' likelihood of purchase by effectively addressing these needs at each stage. This highlights the importance of companies leveraging AI strategically.

4.1. Attention

4.1.1. Current applications & shortcomings of traditional AI tools

Traditional AI tools primarily assist brands in attracting consumers through three key applications. First, AI is used to design eye-catching advertisements by enhancing visual saliency. For example, Memorable AI identifies and analyzes the most visually appealing areas in ads, enabling brands to strategically place logos and images [30]. Second, AI tools recommend products based on user interests, preferences, and past behaviors. Starbucks, for instance, suggests drinks tailored to consumers' purchase history, location, and local weather, making consumers feel understood [31]. Third, AI supports brands in creating engaging, novel content to boost visibility. Coca-Cola's collaboration with OpenAI enabled consumers to generate unique artistic posters, which were shared widely on social media, significantly increasing brand exposure [32].

However, Traditional AI tools still face several noticeable shortcomings in effectively capturing consumers' attention. First, in terms of visual presentation, AI-generated images appear unrealistic or contain detail errors, reducing their appeal to consumers and making it difficult to sustain attention [33]. Second, recommendations provided by traditional AI based on extensive user data suffer generic and repetitive, the phenomenon known as 'uniqueness neglect' [34]. This refers to the fact that recommendations often lack personalization, failing to reflect each consumer's specific needs or preferences. Consequently, users perceive these recommendations as standardized rather than customised, thereby reducing engagement.Third, traditional AI struggles with content creativity. As these tools primarily rely on historical data, their generated content can appear monotonous or excessively similar, lacking innovation. Attempts to create novel content often result in inaccuracies or unrealistic elements (AI "hallucinations"), further eroding consumers' trust and interest [35]. Ultimately, traditional AI struggles to excel in emotional interactions. Many chatbots and recommendation systems still rely on aggregated data rather than dynamically sensing consumers' real-time emotions. Surveys indicate that 71% of consumers expect personalized emotional interactions from brands, and the lack of genuine emotional engagement can cause AI interactions to feel mechanical and impersonal, weakening consumers' attention and trust [36].

4.1.2. Change comes from agentic AI

Compared to traditional AI tools, Agentic AI has several clear advantages in the Attention stage of the AISAS model, effectively attracting and holding consumers' attention. First, it deeply understands each consumer's characteristics and preferences, continuously learns through interactions, and adjusts strategies immediately, providing highly personalized content an interactive experiences. For example, when users browse products, Agentic AI can instantly capture what interests them and proactively offer relevant information or promotions. Research has shown this "extreme personalization" effectively reduces consumers' resistance to AI recommendations [34].

Additionally, Agentic AI possesses autonomous situation-adaptation abilities, enabling it to quickly recognize changes in consumer behavior and their environment, and rapidly make the best decisions and adjustments to capture fleeting consumer attention. For example, when Agentic AI

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detects a sudden change in consumer interest, it immediately emphasizes relevant information. If user attention wanes, Agentic AI quickly adjusts its strategy to re-engage the user. This real-time and dynamic enables more efficient user engagement [6].

In addition, Agentic AI also shows notable improvements in emotional interactions. Using advanced emotion recognition technology and natural language generation abilities, Agentic AI can accurately capture user's emotional cues (such as facial expressions or tone of voice) and provides empathetic responses, thereby establishing genuine emotional connections with users. For instance, when consumers express doubts during the purchasing process, Agentic AI can proactively offer professional advice tailored to consumer needs. This emotionally resonant interaction effectively overcomes the mechanical and impersonal issues in traditional AI emotional recognition, further enhancing consumers trust and interest in the brand [37].

Meanwhile, Agentic AI can continuously creates novel and diverse content experiences for consumers, thereby avoiding the issue of consumer boredom caused by traditional AI generating repetitive content. Through collaboration among multiple specialized AI agents, it produces content with richer styles and forms. Agentic AI also actively learns from user feedback, recommending content users like while occasionally offering new and surprising content, continuously stimulating consumers' curiosity and desire to explore.

Ultimately, Agentic AI autonomously creates and constantly improves visual effects based on real-time consumer reactions. For example, it simultaneously tests multiple ad versions, proactively selects the most attention-grabbing version, and quickly enhances less effective content. This ensures each target audience group sees the most visually attractive advertisements [38].

4.2. Interest

4.2.1. Current applications & shortcomings of traditional AI tools

Traditional AI tools primarily employ three strategies, emotional resonance, curiosity stimulation, and information gaps, to effectively capture consumer attention and engagement. AI tools can infer users' emotional states and recommend relevant content based on users' past behaviors (such as browsing history or buying habits). For example, Amazon analyzes products that a user has recently browsed, which create nostalgia, and then actively recommends similar items to resonate with consumers emotionally. TikTok accurately recognizes users' real-time emotions, recommending videos matching their current mood, consistently enhancing user interaction experiences [39]. AI is also good at creating freshness and surprises to stimulate users' curiosity. For instance, chatbots like ChatGPT share interesting facts or ask intriguing questions to encourage users to interact more deeply. Netflix and TikTok recommend new and unusual content that users don't usually encounter, making users continually curious and actively explore more [40]. Traditional AI tools widely use the "Information Gap" strategy. This means intentionally withholding key details or creating suspense, making users eager to explore further. For example, standard ads like "You won't believe what happens next!" motivate users to click, watch, or engage due to curiosity actively [41].

However, In the Interest stage of the AISAS model, traditional AI tools still have several clear problems that negatively impact actual marketing effectiveness, Inability to accurately recognize emotions is one of shortcoming. Traditional AI usually makes simple guesses based on users' past data and lacks a deep understanding and timely response to users' real-time emotional changes. For example, if a user accidentally watches videos of a certain emotional type, the AI might continuously recommend similar content. It cannot effectively detect the user's current emotional needs, which might even cause the user to become stuck in an "emotional echo chamber" [42].

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Another shortcoming is exaggerated or misleading information, which means quickly stimulate user curiosity, many AI tools often use exaggerated, inaccurate, or deliberately hidden key information to attract users' clicks and interactions. Although this method is effective in the short term, over the long term, it easily makes users feel misled, tricked, or even annoyed, ultimately reducing their trust and loyalty toward the brand [41].

4.2.2. Change comes from agentic AI

Agentic AI can significantly enhance the limitations of traditional AI in the Interest stage by sensing user states in real-time, actively guiding user exploration, and precisely managing user emotions. First, Agentic AI can sense the user's level of curiosity in real-time. For example, it can accurately judge whether a user's interest is effectively stimulated through facial expressions, eye movements, tone of voice, and clicking behavior. Suppose it detects users losing attention or feeling confused. In that case, the AI actively changes topics or provides additional background information, preventing users from stopping the interaction due to a loss of interest. Agentic AI can also actively design the user's exploration path. Unlike traditional AI, which passively responds to questions, Agentic AI acts like an experienced guide, planning interaction content and guiding users step-by-step into more profound exploration of a topic. This effectively stimulates user curiosity and encourages them to take action. In addition, Agentic AI can precisely manage users' emotions. By using advanced emotion recognition technology, it accurately detects emotional changes and proactively adjusts the interaction pace and style. For example, it speeds up interactions to boost interest when users feel excited, and slows down to guide them when they feel tired or confused patiently. Agentic AI can also adjust information density and suspense timing in real-time. Depending on the user's cognitive state, it flexibly controls when and how much information to provide, ensuring users remain curious without losing patience from waiting too long [43].

4.3. Search

4.3.1. Current applications & shortcomings of traditional AI tools

Traditional AI tools primarily assist users in reducing information overload and enhancing search efficiency within the AISAS model. Taking shopping as an example, when consumers struggle to make decisions among many products, traditional AI tools (such as generative chatbots like ChatGPT) summarize information from multiple sources, clearly providing product comparisons, including advantages, disadvantages, and specifications, to help users quickly make choices [44]. Research also indicates that users who search with AI tools tend to find content more quickly, ask more precise questions, and experience higher overall satisfaction with their search results [45].

However, traditional recommendation systems commonly suffer from the "cold start" and "data sparsity" problems. When new users register or when the system lacks sufficient user history data, recommendation accuracy drops significantly, making it challenging to effectively satisfy users' personalized needs [46]. Additionally, large language models (like ChatGPT) often experience "hallucinations," generating information that seems reasonable but is incorrect or lacks evidence. This problem reduces users' trust in AI-generated search results.

Furthermore, the information provided by these generative AI tools often lacks clear sources and references, making it hard for users to verify reliability. This can lead users to easily believe incorrect or biased information [47]. Overall, traditional AI tools have clear limitations in terms of recommendation accuracy, information truthfulness, and transparency.

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4.3.2. Change comes from agentic AI

Agentic AI employs more active interaction and decision-making, effectively addressing problems such as “cold start,” data sparsity, information hallucinations, and a lack of information transparency. Specifically, Agentic AI can utilize active learning methods by directly asking users about their preferences or needs (for example, inquiring whether a user is interested in a specific product) and quickly collecting user information. This approach avoids the issue of inaccurate recommendations resulting from insufficient data from new users [48]. Additionally, when there isn’t enough user data, Agentic AI can introduce extra information from users’ social networks or their friends’ purchase history. It can also divide recommendation tasks into multiple smaller and simpler subtasks, completed separately by numerous intelligent agents, improving data accuracy and processing efficiency [49]. To address the shared “information hallucination” problem of generative AI tools (which produce incorrect or invented information), agentic AI can use collaboration among multiple intelligent agents. For example, the first agent creates an initial answer, and other agents check and correct any mistakes, ensuring the final answer is carefully reviewed multiple times. This dramatically reduces error rates [50]. At the same time, to improve information transparency and trustworthiness, Agentic AI can use Retrieval-Augmented Generation (RAG) technology. This means that when generating an answer, it automatically searches for reliable sources of information and directly includes these sources within the answer, making it easy for users to verify the origin of the information [51]. Agentic AI coordinates multiple agents to separately collect various types of information sources, such as expert reviews, user comments, and third-party evaluations, and then combines them into a final summary. This method ensures that the recommendations are objective, reduces biases by relying on multiple sources of information, and increases users’ trust in the recommendations [46].

4.4. Action

4.4.1. Current applications & shortcomings of traditional AI tools

Traditional AI tools primarily support user decision-making through personalized advice, price-tracking services, and tailored investment recommendations. In healthcare, AI tools such as Eye1 provide users with personalized medical suggestions and relevant knowledge, effectively reducing uncertainty and enhancing their confidence when making medical decisions [52]. In the education field, AI-driven course recommendation systems analyze students’ past grades, interests, and career goals to recommend suitable courses, clearly explaining why each course aligns with their career paths [53]. Additionally, in the investment and financial sectors, AI-powered robo-advisors offer personalized investment suggestions based on users’ financial goals and risk preferences. For instance, Expedia’s AI-driven flight price-tracking tool helps users identify optimal purchasing times by analyzing historical price data, significantly improving their decision confidence [54]. Many financial institutions are also increasingly utilizing explainable AI, which clearly demonstrates the rationale behind algorithm-generated advice, thereby enhancing user trust and confidence in their financial decisions [55]. In summary, current AI applications in the action stage primarily focus on providing accurate and personalized decision support, explicit value confirmation, and timely feedback, thereby significantly enhancing consumer confidence in the decision-making processes while reducing uncertainty.

Although traditional AI tools can assist users in making decisions, they still face several significant limitations. First, the algorithms of traditional AI tools often lack transparency, a

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phenomenon known as the "black-box" issue. Users often struggle to understand exactly the specific recommendation made by AI tools. This unclear reasoning reduces users' trust in the recommendation, making it difficult for user to determine whether the recommendation truly suitable for their needs [56]. Second, traditional AI tools often struggle to provide emotional support or reassurance. For example, during financial market downturns, human advisors naturally comfort their clients by addressing emotional concerns, whereas AI advisors, unable to genuinely understand users' nuanced emotional reactions, typically limit themselves to technical advice, often appearing cold or indifferent. This limitation renders AI less effective in emotionally sensitive decision-making scenarios, such as those involving medical or investment choices [57].

Lastly, traditional AI adopts a mostly passive approach, unable to address user uncertainties during decision-making proactively. Unlike human advisors who actively sense hesitation and provide additional information to clarify doubts, current AI tools rarely take the initiative to ask users about their needs or offer further reassurance. This passive nature means that AI often cannot proactively address users' concerns, ultimately failing to help users achieve psychological certainty or complete confidence in their final decisions.

4.4.2. Change comes from agentic AI

In the Action stage, Agentic AI effectively solves the shortcomings of traditional AI tools by increasing transparency, enhancing emotional interactions, and providing active decision support. Agentic AI utilizes "Chain-of-Thought" technology to provide users with clear explanations of the exact reasons behind its recommendations. For example, it might say, "I recommend option B because it meets your two main requirements, X and Y, and the price difference is less than 5%." It also clearly informs users about the sources of information, increasing their trust in the decision-making process [58].

Agentic AI also has stronger emotional computing and empathy interaction abilities. When it notices users feeling anxious, it naturally expresses understanding and support to immediately alleviate users' emotions [59]. For instance, if a user hesitates, Agentic AI might say, "I understand this decision isn't easy, and I'll carefully help you analyze all the information." Additionally, Agentic AI proactively provides decision encouragement, guiding users to confirm their choices clearly and removing decision hesitation. For example, it explicitly states, "Our analysis shows this option is very suitable for you; you can feel confident choosing it". Moreover, Agentic AI not only gives decision suggestions but can also proactively execute specific actions based on the user's decisions, such as automatically completing reservations or order processes. This prevents users from repeatedly hesitating during complicated procedures. For example, AutoGPT can independently complete a restaurant reservation in under 30 seconds without requiring manual intervention from the user, automatically correcting any issues and following up if necessary [60]. This ability to actively handle actions and track subsequent outcomes makes users feel more confident and assured during the decision execution stage.

4.5. Share

4.5.1. Current application

In the Share stage of the AISAS model, traditional AI tools primarily assist users in efficiently generating shareable content and analyzing user interactions to identify popular trends. Generative AI tools, such as ChatGPT and Midjourney, enable users to quickly create articles and images

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suitable for sharing on social media. For instance, on the Pixiv art platform, around 2.4 million of the 15.2 million artworks uploaded between 2022 and 2024 were AI-generated, increasing the overall content volume by nearly 50% [61]. Additionally, traditional AI analyzes large amounts of user-generated content, such as product reviews or social media comments, enabling brands to grasp trending topics and consumer sentiments quickly. For instance, Amazon introduced AI-generated review summaries, simplifying thousands of user comments into clear highlights [62].

But, current AI tools still have shortcomings in effectively triggering user interactions and emotional resonance. Research has found that although the amount of AI-generated content has increased significantly, user interactions have not increased accordingly. For example, on the Pixiv community, even though AI-generated works have grown in proportion, each AI-generated image receives only about one-fifth of the average number of comments compared to human-created works. This indicates that AI-generated content struggles to create emotional resonance and active interactions among users. The main reason for this problem is that AI-generated content often lacks genuine human warmth, making it hard to stimulate emotional exchanges among users. Additionally, many creators who use AI tools rarely actively participate in social interactions. They tend to view content simply as a tool to attract traffic, resulting in a lack of active community discussions around AI-generated content [61]. Also, AI-generated content often faces problems of being formulaic and repetitive, making it difficult for users to truly express personalized self-expression through AI. For example, one study mentioned a family that used ChatGPT to generate birthday cards, resulting in almost identical card messages. This made the recipients feel a lack of sincerity, reducing the emotional value and trustworthiness of the sharing [63]. Additionally, traditional AI tools are limited in creating valuable resonance and effective content sharing. AI recommendation algorithms typically focus on click rates or viewing duration, often leading to recommended content that is too superficial and lacking in real value, reducing users' willingness to actively share [64]. Moreover, AI tools do not deeply understand the personalized needs, interests, and specific contexts within users' social circles. As a result, recommended shareable content often fails to precisely match the real interests of users and their social groups, making it difficult to achieve effective social sharing and emotional resonance [64].

4.5.2. Change comes from agentic AI

To overcome the limitations of traditional AI tools during the sharing phase, agentic AI can help users create and share high-quality content in a more personalized and emotionally way. Agentic AI can better satisfy users' needs for self-expression by generating personalised content based on user characteristics. Also, it collaborates with users to improve the quality of the content produced. For example, the Agentic AI might proactively suggest adding humour or enhancing the presentation style of social media post. Agentic AI can also suggest adding real experiences or cited sources to make the content more credible. In terms of enhancing emotional resonance, agentic AI can monitor emotional responses from users and their audience in real-time, actively suggesting content adjustments to better reach readers emotionally. For instance, before users share content, Agentic AI might point out certain expressions that could cause misunderstandings. Additionally, Agentic AI incorporates the latest trends, providing suggestions that align with current popular culture or social topics, making content easier to resonate with audiences. It can also automatically recommend suitable emojis, images, or video clips to make users' emotional expressions more vivid and rich.

Moreover, Agentic AI intelligently helps users create valuable and easily shareable content. It automatically analyzes content for its usefulness, entertainment value, or social meaning, providing timely suggestions for improvement before posting, ensuring the content is worth sharing. It can even predict how well content will spread by running small-scale A/B tests in advance, quickly helping users identify which content style is more popular. Additionally, Agentic AI automatically searches for reliable information and authoritative sources, guiding users to incorporate these authentic materials into their sharing content to improve credibility and persuasiveness. Unlike traditional AI tools that mainly focus on short-term effects, Agentic AI pays more attention to long-term social value, continuously learning the preferences and interests of the user’s social circle, helping users create shares that generate lasting and deep interactions and spreading.

5. Conclusion

This study analyses and explains why have companies invested heavily in AI tools in marketing, yet have not seen clear improvements in actual marketing results. Through analyzing the AISAS consumer decision-making model, the key reason identified for this phenomenon is that traditional AI tools have apparent shortcomings in meeting consumers’ psychological needs, which have failed to effectively convert companies’ marketing investments into tangible outcomes. Further analysis reveals that agentic AI can effectively overcome these weaknesses, particularly excelling in the interest, search, and action stages, due to its capacity for real-time emotional sensing, provision of more trustworthy information, and transparent decision-making support, thus strengthening consumer trust and decision confidence. However, in the attention and share stages, there is still require further enhancement regarding content novelty and authentic emotional interaction. Therefore, this study recommends that companies prioritize deploying agentic AI in stages with higher emotional and trust-related requirements (interest, aearch, and action) to maximize marketing effectiveness. Ultimately, when selecting and implementing AI tools, companies must emphasize aligning AI capabilities closely with consumers' psychological needs rather than solely pursuing technological advancement.

Academically, this paper clearly identifies the psychological limitations of traditional AI tools in marketing and introduces the concept of “Agentic AI” within the AISAS consumer decision-making model. Unlike prior research focused mostly on technical performance, this study emphasizes aligning AI with consumers’ emotional and psychological needs, proposing the novel “Psychological-Technological Fit” framework to guide future studies. For businesses, it provides a clear and structured approach to strategically deploying Agentic AI across different stages of consumer decision-making, helping managers effectively plan and optimize their AI investments to improve marketing outcomes.

However, this study primarily develops a theoretical analysis framework and has not yet been validated with data from real business situations. Therefore, future research should adopt empirical methods using real-world scenarios (such as field experiments in companies or consumer surveys) to verify further the causal relationship between Agentic AI’s satisfaction of consumers' psychological needs and actual purchasing behaviors. In addition, considering that different industries (such as healthcare, finance, or high-risk consumption scenarios) and diverse cultural backgrounds may have varying effects on the effectiveness of Agentic AI, future research should also investigate how these contextual factors impact the actual performance of Agentic AI.

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