Dynamic Processing and Neural Mechanisms of Conversational Intelligence Features in Marketing Digital Humans

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Abstract

As a new interactive entry point for digital marketing, marketing digital human intelligent dialogue systems are becoming an important engine for driving consumption expansion and upgrading and cultivating new scenarios and new business forms in the digital economy. However, due to the complexity of multi-dimensional dialogue intelligence features, the dynamic nature of multi-turn interaction patterns, and the difficulty of disentangling dual trust effects, the mechanism through which marketing digital human dialogue intelligence features influence consumer behavior remains to be clarified, hindering the healthy development of the marketing digital human industry. Based on cognitive-affective trust theory, this research focuses on: (1) consumer behavior phenomena under the interactive influence of multi-dimensional dialogue intelligence features and diverse external factors; (2) the dynamic encoding psychological process of dual trust after being influenced by dialogue intelligence features; (3) the cognitive neural mechanisms of dual trust in marketing digital humans; (4) optimization and application validation of marketing digital human dialogue intelligence features. Based on the above research findings, this study explores effective pathways for empowering applications of digital human intelligent dialogue systems, thereby promoting optimization of consumer experience and enterprise cost reduction and efficiency improvement.

Full Text

Preamble

Dynamic Processing of Conversational Intelligence Features in Marketing Digital Humans and Its Neural Mechanisms

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Abstract

As a new-generation human-computer interaction interface, marketing digital human conversational intelligence systems have emerged as a crucial engine for driving consumption upgrades and cultivating new scenarios and business forms in the digital economy. However, the mechanisms through which the conversational intelligence features of marketing digital humans influence consumer behavior remain unclear due to the complexity of multidimensional conversational intelligence characteristics, the dynamics of multi-turn interaction patterns, and the challenges in decoupling dual-trust effects. This lack of clarity hinders the healthy development of the marketing digital human industry. Guided by cognitive-affective trust theory, this study primarily investigates: (1) consumer behavior phenomena under the interactive influence of multidimensional conversational intelligence features and various external factors; (2) the dynamic psychological encoding processes of dual trust when influenced by conversational intelligence features; (3) the cognitive neuroscience mechanisms underlying dual trust in marketing digital humans; and (4) the optimization of conversational intelligence features in marketing digital humans and practical application validation. Based on these findings, we aim to explore effective pathways for leveraging digital human conversational intelligence systems to enhance consumer experiences while optimizing business costs and improving efficiency.

Keywords: marketing digital humans, cognitive-affective trust theory, intelligent dialogue systems, multidimensional intelligent features, consumer behavior

Classification Code: B842

1. Problem Statement

The digital economy has become a new engine for high-quality development, and marketing digital human conversational intelligence systems have played a pivotal role as novel human-computer interaction interfaces in cultivating new marketing scenarios, business forms, and models. In response to the "AI Plus" initiative, national consumption expansion and upgrading needs, and the development trends of new quality productive forces, marketing digital human conversational intelligence systems have emerged as a critical lever for activating the online new economy and promoting the "virtual-real integration and virtual strengthening real" paradigm in e-commerce. In recent years, with the continuous empowerment of generative pre-trained large models, the market size of marketing digital humans has expanded rapidly, gradually becoming a powerful tool in e-commerce live streaming for reducing labor costs, providing 24/7 online services, attracting traffic, and shaping brand images (Ham et al., 2023; Xiang et al., 2025).

Marketing digital human conversational intelligence systems are characterized by high initial R&D investment and low marginal costs in later stages. However, the lack of scientific design and blind investment in early stages is hindering the healthy development of the industry. Marketing digital humans possess both external virtual personas and internal natural human-computer interaction capabilities, supported by technologies such as computer graphics and large language models, which require substantial initial R&D investment. In later stages, because they can be reused at low cost across different products and scenarios, marginal or incremental costs are reduced (Sands et al., 2022). Consequently, the "modeling" process becomes critically important. Currently, most technology companies specializing in digital human production can only provide customized technical solutions for e-commerce businesses, yet they know little about how to scientifically design intelligent dialogue systems to enhance marketing effectiveness. This uncertainty leads enterprises to reduce investment, creating a vicious cycle: low investment degrades dialogue system quality, reducing consumers' perceived trust and purchase intention, resulting in blocked online traffic, low sales conversion rates, and declining ROI, ultimately impeding the healthy development of the marketing digital human industry.

To address these practical challenges, we must begin by exploring the mechanisms through which marketing digital human conversational intelligence features influence consumer behavior, uncovering the internal logic of consumer trust building and purchase conversion. This will enable us to truly leverage the advantages of marketing digital humans, achieving cost reduction and efficiency improvement while optimizing consumer experiences.

Marketing digital human conversational intelligence systems influence consumers' dual trust (cognitive trust and affective trust) and ultimately affect consumer behavior through multidimensional features of conversational persona intelligence, logical intelligence, and emotional intelligence in anthropomorphic natural interactive marketing (Agnihotri et al., 2025; Chaihanchanchai et al., 2024). Researchers have conducted substantial work to bridge the gap between intelligent dialogue system design and expected outcomes through phenomenon characterization and internal mechanism analysis. However, several issues remain: (1) Research on how multidimensional conversational intelligence features interact with external factors to affect consumer behavior is still in its infancy, lacking systematic and holistic phenomenon characterization and key factor identification; (2) Current research on digital human trust predominantly adopts a static perspective, failing to consider the dynamic trust evolution process in real-world multi-turn interaction scenarios; (3) Due to the subjective and implicit nature of trust perception, it is difficult to distinguish cognitive trust from affective trust through consumer self-reporting, and effective methods to separate the different roles of dual trust are currently lacking.

To address these research bottlenecks involving complex multidimensional factors, difficulties in dynamic quantitative modeling, and challenges in separating dual trust effects, this study proposes to employ cognitive-affective trust theory and integrate multiple methods including big data empirical analysis, Bayesian decision modeling, and neuroscience experiments. We aim to characterize consumer behavior phenomena under the interactive influence of multidimensional conversational intelligence features and various external factors, reveal the dynamic psychological encoding processes of dual trust when influenced by conversational intelligence features, differentiate the distinct internal mechanisms through which cognitive and affective trust operate in human-digital human dialogue contexts, and explore effective pathways for leveraging digital human conversational intelligence systems based on these findings to optimize consumer experiences and improve business cost-effectiveness.

2.1 Phenomenon Research on Marketing Digital Human Conversational Intelligence Systems'Influence on Consumer Behavior

Marketing digital human conversational intelligence systems refer to intelligent systems driven by generative AI and computer graphics that exist in digital form in online marketing scenarios, capable of anthropomorphic interactive communication and emotional relationship building. They are also known as marketing virtual persona dialogue systems, marketing virtual human intelligent dialogue systems, or marketing virtual anchors (Silva & Bonetti, 2021; Zhang et al., 2025). One of the most typical characteristics of marketing digital humans is their anthropomorphic appearance. Persona intelligence is primarily based on computer graphics modeling, physical simulation, and rendering technologies, capable of presenting dynamic digital effects including facial driving, body driving, and multi-style outfit changes. Due to the external intuitiveness of persona intelligence, it is considered a direct indicator of digital human intelligence level (Kim et al., 2025). Research shows that persona intelligence features help highlight corporate innovation (Lim & Lee, 2023), enhance authority perception (Gao et al., 2025), boost initial trust and intrinsic motivation for interaction (Chattaraman et al., 2014; Silva & Bonetti, 2021), increase consumer attraction and the persuasiveness of interactive content, and make people more inclined to adopt recommended products (Khan & Sutcliffe, 2014; Yang et al., 2023). Persona intelligence design has long been a focus of e-commerce platforms, employing fashion elements and high-definition visual presentation to make digital humans lifelike, thereby guiding customer traffic, attracting younger consumer groups, and enhancing product marketing effectiveness.

Digital humans' conversational ability represents a learning and projection of human conversational capabilities, representing the most natural interaction method aligned with human language characteristics and social-like interaction (Willems et al., 2017). Conversational logical intelligence primarily employs natural language understanding and generation technologies, enabling digital humans to comprehend consumer intentions and possess controllable dialogue text generation and matching voice-lip synchronization capabilities. Logical intelligence allows digital humans to respond quickly and targeted after consumers ask questions or express opinions, increasing user novelty and experience. It is considered an important tool for influencing consumers in online marketing and is reshaping information acquisition and human-computer interaction patterns in online marketing (Shen & Wang, 2023). Through applications of large language models and multimodal analysis technologies, digital humans' conversational logical intelligence has achieved relatively high accuracy and stability. This convergence of human-computer and human-human interaction patterns supports the "Computers Are Social Actors" (CASA) theoretical framework (Campbell & Farrell, 2020; M. Miao et al., 2022; Shen & Wang, 2023). Digital humans that can accurately interact with individuals and align values can not only effectively enhance marketing experiences but also help reduce labor operating costs in e-commerce live streaming (Grewal et al., 2020; Shen & Wang, 2023; Silva & Bonetti, 2021). However, the robustness of marketing digital human logical intelligence has not received sufficient attention. In fields such as assisted driving, elderly care, and medical planning, digital human robustness directly relates to life safety and thus has strict intelligence standards. In contrast, marketing digital humans have higher fault tolerance, which may significantly negatively impact consumers' perceived trust levels, thereby altering brand loyalty and product purchase behavior (Gillath et al., 2021). Therefore, scientific design of logical intelligence features should be strengthened.

Conversational emotional intelligence primarily employs affective computing technologies, endowing digital humans with the ability to perceive, recognize, and understand individual emotions, and provide empathetic feedback through emotional text generation, emotional speech synthesis, and expression generation (Llanes-Jurado et al., 2024). The biggest difference between digital human anchors and natural person anchors lies in emotional capabilities. Digital humans are generally considered to lack empathy, stemming from the stereotype that machines are "cold and emotionless" (Luo et al., 2019). Emotional intelligence features represent a key advancement in making digital humans closer to human intelligence (Huang & Rust, 2018). Scientific application of emotional intelligence features helps improve digital humans' sensitivity to consumer emotions, enhance personalized services, reduce customer complaints (Puntoni et al., 2021), significantly boost customer loyalty (Prentice & Nguyen, 2020), and increase trust, response probability, and information disclosure (Xu et al., 2024). Although academia and industry have shown great interest in the technical prospects and marketing applications of emotional intelligence, systematic research on conversational emotional intelligence features is still lacking. Studying linguistic behavior as an important carrier of emotional information is significant for filling this research gap.

The multidimensional conversational intelligence features of marketing digital humans and various external factors together constitute an interconnected influence network. Current research has begun to examine how interactions between different features and between features and external factors affect consumer behavior. Studies find that human-like cues from persona-logical intelligence raise users' social expectations, significantly increasing requirements for task-oriented dialogue logic (Li & Lan, 2022; Prakash & Rogers, 2015). Additionally, the matching degree between persona-emotional intelligence directly affects interaction naturalness; mismatches are considered violations of social interaction norms and easily lead to alienation (Crolic et al., 2022; Vuong et al., 2024). Some research from the cue consistency theory perspective suggests considering the fit between product types and intelligence features (Guo et al., 2024; Li et al., 2023; F. Miao et al., 2022). For example, when promoting hedonic products, overly complex logical dialogue guiding comments and sharing is ineffective or even harmful; in such cases, strengthening emotional dialogue such as likes and follows is a wiser choice (Guo et al., 2024). Other studies find that compared to experience products, digital human persona intelligence features are more effective for enhancing the attractiveness and sales performance of search products and low-involvement products (Park et al., 2024; Song et al., 2024). Notably, Generation Z is gradually entering the workforce with increasing purchasing power, and their lives, social interactions, and consumption show clear "digital" and "virtual" trends. Pure product functional value can no longer meet consumers' diverse needs; instead, the emotional value experience attached to products and trust in brands have become important factors influencing Generation Z customers' purchase decisions (Angmo & Mahajan, 2024; Duffett, 2020). Therefore, consumer profiling analysis is crucial, as different customer groups have varying internal needs, product preferences, and value orientations, leading to different response mechanisms to conversational intelligence features.

In summary, marketing digital human conversational intelligence systems are becoming important tools for e-commerce 3.0 to build brand reputation and enhance sales effectiveness, with enormous market potential and commercial value. However, existing literature is insufficient to explain which conversational intelligence features of marketing digital humans and digital environmental factors affect consumer behavior. Moreover, research has paid insufficient attention to digital humans' internal capability features such as logical and emotional intelligence, and lacks studies on how multiple elements including "intelligence features-product features-scenario features-consumer features" jointly affect consumer behavior. A comprehensive and systematic perspective is needed to characterize the phenomenon of marketing digital humans influencing consumer behavior, to align with the trend of increasingly refined, anthropomorphic, and complex conversational scenarios (Zhang et al., 2025). Based on this, this study proposes to mine and analyze historical data from marketing digital human live streaming platforms, using the multivariate analysis capabilities of panel vector autoregression models to systematically analyze how multidimensional intelligence features and various external factors influence consumer trust and consumer behavior, characterize consumer phenomena under the interactive influence of multidimensional heterogeneous elements, and focus on the differential impacts of multidimensional conversational intelligence features.

2.2 Research on Dual Trust Processing in Marketing Digital Human Conversations

Consumer trust is considered a key prerequisite for the development and popularization of digital humans (Afroogh et al., 2024; Glikson & Woolley, 2020). Trust is a fundamental concept in management research, initially studied as an important construct in organizational management and interpersonal relationships, and now extended to artificial intelligence and human-computer interaction. This study adopts the classic definition proposed by Rousseau et al. (1998): trust is a psychological state in which one party is willing to accept vulnerability based on positive expectations about the intentions or behaviors of the other party in a relationship. The more willing individuals are to accept potential harm from digital humans, the greater the trust they display. Cognitive-affective trust theory posits that trust stems from both a cautious, rational thinking pattern (cognition-based) and from examining feelings, instincts, and intuitions about digital humans (affect-based), with cognitive trust and affective trust together constituting overall trust (Lewis & Weigert, 1985). In a human-machine symbiotic society, digital human conversational intelligence system design needs to consider establishing dual trust relationships with humans to enhance the adoption and acceptance of intelligent services.

The cognitive pathway of trust relies on rational thinking and knowledge systems, primarily used for evaluating digital human conversational logical intelligence (usefulness, reliability, stability, risk predictability, etc.). This represents a rational evaluation process of digital human performance and task completion capabilities (Glikson & Woolley, 2020; Hopko & Mehta, 2024). Due to continuous performance leaps in pre-trained models represented by Transformer neural network architectures in recent years, people have shown higher expectations and dependence on AI conversational logical intelligence (Afroogh et al., 2024; Klingbeil et al., 2024). Particularly for tasks involving complex calculations, people are more inclined to trust digital humans. For example, in chess tasks, humans trust suggestions from machine teammates more (Zhang et al., 2023). This aligns with the MABA-HABA ("Machines Are Better At vs. Humans Are Better At") framework, which indicates that AI has advantages over humans in intelligent computing and other fields, making it easier to gain human trust (Castelo et al., 2023; De Ruyter et al., 2022).

The affective pathway of trust originates from emotional reactions accompanying individuals' processing of external information, primarily used for evaluating digital human conversational emotional intelligence, and closely associated with preferences, belonging, loyalty, and other emotional experiences or consumer behaviors (Glikson & Woolley, 2020). Interpersonal emotional dynamics research shows that emotions of interacting parties influence each other in cyclical and reciprocal ways, with key mechanisms for creating such emotional cycles being shared emotional understanding, emotional contagion, and security in emotional connection (Hopko & Mehta, 2024; Hortensius & Wiese, 2023). These human social habits have been confirmed to map onto natural person-digital human interaction mechanisms. Compared to communicating with humans, people are more willing to disclose personal sensitive information to machines, and machine empathy can increase acceptance and trust of AI advice (Pelau et al., 2021). It also helps repair trust issues arising from logical intelligence and persona intelligence features, making emotional intelligence features considered an important trust recovery strategy (Kox et al., 2021; Lin et al., 2021). The application of emotional intelligence increases people' s tolerance for machine errors; even robots that make mistakes are more popular than perfect ones because people generally consider such robots more "likable" (Mirnig et al., 2017). Therefore, the application of digital human conversational emotional intelligence features helps create harmonious human-computer interaction environments, enhances trust, affinity, and agreeableness, increases consumer stickiness and loyalty, and subsequently boosts product liking and influences consumer behavior (Zhang et al., 2025). However, some research suggests that human emotional instincts may be suppressed by rational cognition (Porra et al., 2020), making this relationship worthy of further exploration.

In summary, the key to successful marketing digital human implementation lies in consumer trust, and human distrust of digital humans is a critical factor hindering marketing effectiveness improvement. Current research on digital human conversational intelligence features predominantly adopts a structural analysis paradigm, with relatively limited research employing process-tracing paradigms. Since real interactions between humans and digital humans are multi-turn and bidirectional, while most existing studies examine single-turn interactions or adopt static perspectives, there is a lack of exploration into the dynamic psychological encoding processes of trust during multi-turn dialogues. To address these issues, this study proposes to adopt a process-tracing paradigm, using Bayesian decision models to dynamically simulate trust levels, establish a process model of consumer dual trust encoding, explore the differential psychological process impacts of different conversational intelligence features, provide richer evidence for model comparison and validation, and enhance theoretical depth.

2.3 Neural Mechanism Research on Dual Trust in Human-Digital Human Conversations

The cognitive neuroscience approach holds an important position in research on the internal mechanisms of trust, helping to simultaneously track individual responses and effectively differentiate the distinct roles of cognitive trust and affective trust. With the development of brain imaging technology, the brain distribution of trust processing has become increasingly clear. Specifically, brain regions related to cognitive trust include the ventromedial prefrontal cortex, anterior medial prefrontal cortex, anterior cingulate cortex, and striatum (Bellucci et al., 2017; Casado-Aranda et al., 2019; Haas et al., 2015; Wu et al., 2021). These brain regions are widely involved in social evaluation, interactive reasoning, and cognitive regulation, thereby mediating the entrustment and reciprocity processes of cognitive trust. Brain regions related to affective trust mainly include the amygdala, insula, and caudate nucleus (Koscik & Tranel, 2011; Sato et al., 2019). These brain regions are extensively involved in emotional experience, reward processing, and risk perception, thereby mediating the dependence and benevolence processes of affective trust.

As an advanced psychological process, the neural mechanisms of trust involve not only independent brain region activation but also rely on dynamic brain network interactions. The brain network systems perspective suggests that trust primarily originates from the functioning of cognitive and affective systems (Bressler & Menon, 2010; Chen et al., 2020). The trust cognitive system refers to individuals adopting reliable strategies to evaluate digital human credibility driven by uncertainty during human-machine trust establishment, thereby ensuring normal human-computer interaction. Its brain mapping takes the form of the central-executive network (CEN) and default-mode network (DMN). The CEN, as the cognitive control system for trust, is responsible for determining strategy selection during trust processes. This process requires individuals to judge digital human conversational intelligence features, conduct rigorous logical analysis and precise computational reasoning based on available cues during dialogue, and ultimately make trust decisions. Therefore, this process is a purely rational thinking process based on computation (Sherman et al., 2014; Chen et al., 2020). The DMN is primarily used for evaluating trusted objects, mainly from the perspective of digital human anthropomorphism and sociality, and is activated during human-like interactions (Bressler & Menon, 2010). The trust affective system refers to personality units involving feelings, emotions, and emotional reactions in human-computer interaction. When individuals process trust information, they are accompanied by emotional perception and generate corresponding emotional experiences. The brain mapping of the trust affective system is the salience network (SAN), which may originate from evaluations of conversational emotional intelligence features and potential risks. Positive interaction experiences generate positive emotions and make individuals more inclined to trust digital humans; negative interaction experiences induce negative emotions and cause individuals to exhibit distrust in subsequent dialogues (Menon, 2023; Chen et al., 2020).

In summary, existing research has confirmed the advantages of cognitive neuroscience methods in observing implicit variables such as trust, but has overlooked the potential value of brain networks in separating the roles of cognitive trust and affective trust. Regarding the brain spatial mapping triggered by persona intelligence, logical intelligence, and emotional intelligence features of digital humans and the resulting consumer behavior outcomes, brain network approaches can provide global descriptions and systematic analyses of mechanisms, which are more scientifically effective than independent brain region activation studies, and can form theoretical models at the neural level that include different roles of cognitive trust and affective trust. Therefore, based on the research foundation of cognitive trust and affective trust, combined with differences in brain spatial mapping of trust triggered by different intelligence features, this study aims to separate the different roles of intelligence features on cognitive trust and affective trust, as well as their differential impacts on consumer behavior.

3. Research Framework

This study addresses the practical needs for the healthy development of the marketing digital human industry and the application challenges of marketing digital human conversational intelligence systems. Based on cognitive-affective trust theory, we design research content following the approach of "big data empirical analysis of behavioral phenomena - computational modeling of psychological processes - neural indicators reflecting internal mechanisms - field experiments validating research conclusions."

The research framework is shown in Figure 1 [Figure 1: see original paper]. Specifically, we first employ big data empirical analysis methods to study the phenomena of how multidimensional intelligence features and various external factors influence consumer trust and consumer behavior, focusing on the differential roles of different intelligence features (Study 1). Second, through multi-turn dialogue behavioral experiments and Bayesian decision models, we dynamically simulate trust levels to establish a process model of consumer dual trust encoding (Study 2). Subsequently, from a neuroscience perspective, we separate the different internal mechanisms through which dual trust operates in human-digital human dialogue contexts to construct a dual-trust brain network model (Study 3). Finally, through field experiments, we explore effective pathways for optimizing dialogue system design and improving marketing effectiveness (Study 4). The four research components are elaborated below.

3.1 Phenomenon Research on Marketing Digital Human Conversational Intelligence Systems'Influence on Individual Trust and Consumer Behavior

Study 1 examines behavioral phenomena from a global perspective of "intelligence features-product features-scenario features-consumer features,"conducting mining and analysis of historical live streaming platform data. It aims to explore how multidimensional intelligence features and various external factors during marketing digital human-consumer dialogues influence consumer trust and consumer behavior. The study plans to obtain de-identified digital human live streaming platform data through partnerships with technology companies, including digital human live videos, dialogue content, intimacy task completion status, UV value[2], conversion rates, changes in viewership numbers, etc., while incorporating consumer demographic variables and consumption preference tags (such as product type preferences and purchase frequency) to systematically and comprehensively reflect the relationships between digital humans' multidimensional intelligence features, various external factors, and consumer heterogeneity, providing data support for accurately characterizing consumer behavior phenomena.

The analytical approach includes: (1) Feature extraction: comprehensively employing speech recognition, text mining, contrastive learning, and econometric tools to conduct multimodal data conversion and feature extraction of digital human appearance, dialogue text, and emotional expressions. (2) Panel vector autoregression model: analyzing the complex interactive mechanisms among digital human conversational intelligence features, product attribute features, scenario attribute features, consumer attribute features, consumer trust, and consumer behavior during live streaming processes, and deeply exploring the differential impacts of different conversational intelligence features.

The expected findings of this study are:

[2] UV value = Sales revenue / Number of visitors, referring to the value generated by each unique visitor on the live streaming platform.

Proposition 1: Enhanced conversational persona intelligence level (digital human appearance refinement, motion driving smoothness) will increase consumers' initial trust level.

Proposition 2: Enhanced conversational logical intelligence feature level (dialogue text generation accuracy) will increase consumer trust and purchase intention for functional products.

Proposition 3: Enhanced conversational emotional intelligence feature level (emotional text quality, emotional voice matching degree, emotional expression granularity) will increase consumer trust and purchase intention for hedonic products, accelerating consumers' purchase decisions.

Proposition 4: The matching degree between conversational persona-logical intelligence features and persona-emotional intelligence features will significantly affect the degree of trust level change.

Proposition 5: Various external factors such as product features, scenario features, and consumer features will significantly moderate the influence of conversational intelligence features on consumer purchase intention.

3.2 Research on Dynamic Processing of Dual Trust and Consumer Behavior in Marketing Digital Human Multi-turn Dialogues

Study 2 reveals the dynamic processes through which marketing digital humans' multidimensional conversational intelligence features influence consumer behavior at the psychological process level. During human-computer interaction, consumers' dual trust levels in digital humans show dynamic changes. As dialogue turns with digital humans increase, consumers continuously adjust and calibrate their trust evaluations of digital humans, ultimately affecting individual product preference, value assessment, and purchase intention. This study plans to simulate marketing digital human-consumer dialogue processes through behavioral experiments, randomly assigning participants to two different digital human live streaming room scenarios (ordinary dialogue scenario and emotional dialogue scenario). Each scenario employs a 3 (logical intelligence: high/medium/low) × 2 (persona intelligence: high vs. low) experimental design. In each live streaming room scenario, digital humans introduce multiple products, with each product introduction containing multiple interactions. After each interaction, participants report their trust level evaluation of the digital human. Participants evaluate subjective preference, subjective value, and purchase intention during the pre-experiment phase and after each product introduction is completed.

The analytical approach includes: (1) Dummy variable regression model: using dummy variable regression of multidimensional intelligence feature differences, trust level changes, consumer behavior changes, etc., to explore the role of multidimensional intelligence features in trust level dynamic changes and their impact on final consumer behavior. (2) Bayesian decision model: constructing consumer trust encoding process models in multi-turn dialogue scenarios based on digital human multidimensional intelligence features under different feature influence conditions. Using Beta distribution to model the process of individual perceived trust level changes over time, with model parameters calculated through maximum a posteriori estimation and maximum likelihood estimation methods. (3) Generalized additive model: exploring intelligent level as a discretized representation of ordered continuous variables, revealing through its smoothing function whether complex relationships such as saturation effects or inverted U-shaped curves exist between intelligence level and trust degree.

The expected findings of this study are:

Proposition 1: During multi-turn dialogues, consumers' dual trust levels in marketing digital humans show dynamic changes and gradually stabilize as dialogue turns increase.

Proposition 2: Negative performance of digital human conversational intelligence features has a greater impact on consumer trust than positive performance, and this difference is more significant in the early stages of dialogue.

Proposition 3: Different conversational intelligence features have different dynamic change paths for consumer dual trust. Conversational persona intelligence features mainly affect the initial anchor point of trust, logical intelligence features mainly affect the fluctuation amplitude of trust, and emotional intelligence features mainly affect the dynamic adjustment frequency of trust.

Proposition 4: Dynamic changes in consumer trust levels can significantly predict consumer behavior outcomes.

3.3 Neural Mechanism and Consumer Behavior Prediction Research on Dual Trust in Marketing Digital Humans

Study 3 leverages the advantages of neuroscience methods in implicit variable measurement and dual trust separation, using functional magnetic resonance imaging (fMRI) technology to observe brain region activation and brain functional network conditions related to individuals' trust cognitive system and trust affective system under different levels of digital human persona intelligence, logical intelligence, and emotional intelligence features, to construct a cognitive-affective trust brain network model. Through dual trust role separation, activation intensity difference assessment, and effective functional pathway distinction, we aim to clarify the internal mechanisms through which multidimensional intelligence features influence dual trust. This study plans to conduct neuroscience experiments where participants with purchasing experience on marketing digital human live streaming platforms watch videos of marketing digital human-consumer dialogue processes from a third-party perspective, employing a 3 (intelligence type: persona intelligence, logical intelligence, emotional intelligence) $\times$ 2 (intelligence level: high vs. low) experimental design. In each experimental trial, participants first rate their purchase intention for the presented product (all products are frequently purchased by college students). Subsequently, a 30-second video of the marketing digital human live streaming room is presented. Persona intelligence levels are set through digital human appearance refinement and motion smoothness; logical intelligence levels are set through digital human response accuracy; emotional intelligence levels are set through emotional text quality, emotional voice matching degree, and emotional expression granularity. After watching the product recommendation video, participants rate trust level and purchase intention.

The analytical approach includes: (1) GLM analysis: based on General Linear Model analysis to observe brain region activities related to trust encoding and conduct between-group comparisons. Using the neuroimaging analysis software SPM (Statistical Parametric Mapping) based on the Matlab platform to linearly model collected blood oxygen level-dependent magnetic resonance data and events, with results presented through the xjView plugin. (2) MVPA method: based on Multi-Voxel Pattern Analysis (MVPA) methods and extended unified Structural Equation Modeling (euSEM) to study brain activation patterns and brain network mechanisms of conversational intelligence feature processing, constructing effective connectivity brain networks corresponding to each stimulus condition to analyze interactions among widely interconnected brain region sets and key functions in dual trust perception. (3) CNN-LSTM consumer behavior prediction model: first using Convolutional Neural Networks (CNN) to automatically extract high-impact features from individual historical consumption data, behavioral data, and brain network data, then using Long Short-Term Memory neural networks (LSTM) to establish time series prediction models, and finally outputting model predictions through fully connected layers.

The expected findings of this study are:

Proposition 1: Digital human logical intelligence features primarily activate brain regions related to cognitive trust (such as ventromedial prefrontal cortex, dorsolateral prefrontal cortex, etc.), while emotional intelligence features primarily activate brain regions related to affective trust (such as amygdala, insula, etc.).

Proposition 2: The trust cognitive system (CEN, DMN) is extensively involved in processing digital human logical intelligence features, while the trust affective system (SAN) is extensively involved in processing digital human emotional intelligence features.

Proposition 3: A CNN-LSTM consumer behavior prediction model integrating neural data (such as brain region activation intensity, dual trust separation, effective functional connectivity between brain regions), behavioral data (such as trust level ratings, purchase intention ratings), and historical consumption data has higher accuracy than single-modality models.

3.4 Research on Optimization of Marketing Digital Human Conversational Intelligence Features and Marketing Strategies

Study 4 applies the main conclusions from the aforementioned "behavioral phenomena-psychological processes-internal mechanisms" research in practical scenarios through field experiments to evaluate actual effects, continuously optimize dialogue system design, and achieve improvements in business ROI and consumer shopping experience. This study addresses full-process management, including early-stage first impression construction, mid-stage trust dynamic maintenance, and late-stage trust-purchase conversion, with consumer grouping (e.g., Generation Z vs. non-Generation Z, high-involvement vs. low-involvement consumers) to examine how customer group differences affect marketing strategy responses. Three sub-experiments are planned: (1) Focusing on key variables (early stage): based on the differential roles of multidimensional heterogeneous features, observing sales effects and conducting statistical analysis through variations in different levels of key variables, aiming to guide enterprises to "focus on the critical few" and achieve cost reduction and efficiency improvement through focused investment in and efficient reuse of key variables. (2) Focusing on intervention timing of relevant variables (mid-stage): based on dynamic change patterns of trust levels, observing sales effects and conducting statistical analysis through variations in the timing of conversational emotional intelligence feature interventions, aiming to guide enterprises in service recovery and trust repair to enhance consumer shopping experiences. (3) Focusing on feature combinations (late stage): based on combination optimization conclusions from consumer behavior prediction models, observing sales effects and conducting statistical analysis through different ways of feature combination, aiming to promote consumer conversion from trust to purchase and achieve cost reduction, efficiency improvement, and performance enhancement based on optimized consumer experiences and efficient reuse of elements.

This study primarily employs field experiments, using A/B testing and multivariate testing to focus on different levels of key variables, intervention timing of relevant variables, and feature combination methods, observing sales effects (such as UV value, conversion rate, transaction volume, etc.) and conducting differential statistical analyses to validate the effectiveness of theoretical findings.

The expected findings of this study are:

Proposition 1: In actual marketing scenarios, optimization design based on key variables can significantly improve business ROI.

Proposition 2: Adjusting the intervention timing of conversational emotional intelligence features according to dynamic change patterns of trust levels can effectively enhance consumer trust levels and shopping experiences.

Proposition 3: Feature combination optimization based on model conclusions can significantly improve consumer purchase intention and actual purchase behavior, achieving trust-to-purchase conversion.

4.1 Theoretical Contributions

This study is cutting-edge in its topic selection and makes certain contributions to existing literature. First, regarding behavioral phenomena, this study expands the current literature' s holistic understanding of how marketing digital human conversational intelligence features influence consumer behavior. Large language model technology development has created opportunities for digital humans to reshape human-computer interaction patterns in sales scenarios. Research shows that online consumer behavior is influenced by digital humans' conversational persona intelligence features, logical intelligence features, emotional intelligence features, fit with products, live streaming atmosphere, and other factors, with interactive effects among these factors—mismatches between features may reduce consumer purchase behavior (Crolic et al., 2022; Guo et al., 2024; Li & Lan, 2022; Park et al., 2024; Prakash & Rogers, 2015; Vuong et al., 2024). However, research on how multidimensional conversational intelligence features interact with external factors to affect consumer behavior is still in its infancy, lacking systematic and holistic phenomenon characterization and key factor identification (Zhang et al., 2025). In marketing digital human live streaming platforms, conversational scenarios where "intelligence features-product features-scenario features-consumer features" jointly affect consumer behavior are very common, requiring a comprehensive and systematic perspective to characterize the phenomenon of marketing digital humans influencing consumer behavior, to align with the trend of increasingly refined, anthropomorphic, and complex conversational scenarios. This study plans to use panel vector autoregression models and other methods to characterize the interactive influence of multidimensional heterogeneous elements and the differential impacts of different conversational intelligence features on consumer behavior, helping to form holistic understanding and identify important influencing factors. Persona intelligence features play a decisive role in first impressions and determine initial trust levels; for utilitarian products, logical intelligence features play a key role in purchase decisions; for hedonic products, emotional intelligence features play a key role in purchase decisions; consistency between conversational intelligence features has a critical impact on trust changes.

Second, regarding psychological processes, this study innovatively proposes a dynamic processing framework for trust in marketing digital human multi-turn dialogues. Perceived trust is an important factor affecting the consumer-digital human interaction ecosystem and marketing effectiveness (Akhtar et al., 2024; Kim & Park, 2024; Strohmann et al., 2023). Current research on perceived trust in digital human conversational contexts mostly examines single-turn interactions or adopts static perspectives, while real interactions between natural persons and digital humans are multi-turn and bidirectional. Human-machine trust establishment is a continuously dynamic adjustment and calibration process, with trust levels changing over time and eventually stabilizing (Guo & Yang, 2021; Mehrotra et al., 2024). Due to the lack of process-tracing research on trust encoding, current research on how digital human conversational intelligence features affect consumer behavior lacks process-level understanding. Compared to previous structural analysis paradigms, this study plans to adopt a process-tracing paradigm, using Bayesian decision modeling methods and Beta distribution to integrate three hypotheses of human-computer interaction trust dynamics: current trust is influenced by previous trust (continuity), negative performance has greater impact than positive performance (negativity bias), and trust levels stabilize in repeated interactions (stability) (Guo & Yang, 2021; Yang et al., 2023; Yang et al., 2022). By constructing a psychological process encoding model of trust levels, this study helps explain the psychological processes behind human-computer interaction behavior, enhances theoretical depth, and provides richer evidence for comparing and validating divergent conclusions in the human-machine trust field.

Third, regarding internal mechanisms, this study systematically reveals the neural mechanisms of dual trust in marketing digital humans. According to cognitive-affective trust theory, consumer trust includes cognitive trust and affective trust, with different conversational intelligence features having differential roles on dual trust and consequently different impacts on consumer behavior. However, due to the subjective and implicit nature of trust perception, it is difficult to distinguish cognitive trust from affective trust through consumer self-reporting. Neuromarketing methods have significant advantages in observing implicit variables (Solnais et al., 2013). This study plans to use fMRI as a tool for representing dual trust neural mechanisms and studying consumer behavior. Based on the research foundation of trust cognitive system and trust affective system, through dual trust role separation, activation intensity difference assessment, and effective functional pathway distinction, we construct a dual-trust brain network model. On this basis, this study plans to use neural data (such as brain region activation intensity, dual trust separation, effective functional connectivity between brain regions) and behavioral data, historical consumption data as input variables, with trust level and purchase intention as output variables. Using deep learning methods combining Convolutional Neural Networks (CNN) and Long Short-Term Memory neural networks (LSTM), we construct a consumer behavior prediction model in marketing digital human conversational contexts, and use k-fold cross-validation for model training and validation to improve prediction accuracy while avoiding overfitting.

4.2 Practical Implications

Through in-depth research on the relationship between digital human conversational intelligence features and consumer behavior, this study helps provide references for scientific dialogue system design, achieving cost reduction and efficiency improvement while optimizing consumer experiences and promoting the healthy development of the digital human industry. First, this study' s examination of the psychological processes and internal mechanisms behind how digital human conversational intelligence features affect consumer behavior helps guide enterprises to focus on consumers' real feelings, better understand the basic logic of digital human conversational intelligence system design and the internal reasons for consumer behavior generation, shift from "technology-oriented" to "value-oriented," deepen understanding and thinking from "what can be done" to "what should be done," build harmonious human-computer interaction environments, and ultimately achieve consumer experience optimization. Second, the application of digital human conversational intelligence is an unstoppable trend. Given the significant characteristics of high initial R&D investment and low marginal costs in later stages for marketing digital human conversational intelligence systems, this study helps guide enterprises to achieve scientific design and demonstration in early stages, enhance the certainty of effect expectations, and reduce the risk of 兑现 large-scale investments. Simultaneously, it helps guide full-process management optimization of dialogue systems, fully leveraging the advantages of efficient reuse of digital elements and labor cost savings, ultimately promoting enterprise cost reduction and efficiency improvement.

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