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The Effect of Digital Empathy on Purchase Intention: An Integrated Behavioral MCDM Study of Virtual Influencers and Chatbots

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ABSTRACT

Purpose – This study examines how digital empathy influences consumer preferences in AI-mediated interactions by comparing virtual influencers, e-commerce chatbots, low-empathy agents, and hybrid AI agents

Design/methodology/approach – A qualitative thematic analysis based on interviews with 25 participants was conducted to identify core dimensions of digital empathy. These dimensions were subsequently modeled using Fuzzy DEMATEL to reveal causal relationships and Fuzzy TOPSIS to rank digital agents according to their overall performance. Sensitivity analysis was employed to assess the robustness of the rankings under alternative weighting scenarios.

Results – The thematic analysis identified trust (frequency = 31) and emotional response (25) as the most salient components of digital empathy. Fuzzy DEMATEL results showed that trust emerged as the strongest causal factor (total influence score = 3.91), exerting significant influence on empathy-related dimensions and purchase intention. Fuzzy TOPSIS rankings indicated that the hybrid AI agent outperformed all alternatives (closeness coefficient = 1.0000), followed by the virtual influencer (0.5837), chatbot (0.1472), and low-empathy agent (0.0000).

Discussion – By integrating behavioral theory with fuzzy MCDM techniques, this study demonstrates that hybrid AI agents achieve superior performance by simultaneously activating socio-emotional and functional drivers of consumer decision-making, offering a structured explanation of why certain digital agents are more effective than others.

1. Introduction

The increasing integration of artificial intelligence into digital commerce has led to the widespread adoption of virtual influencers and AI-based chatbots as front-facing consumer engagement tools. Virtual influencers—computer-generated personas with curated social media presences—are now actively shaping consumer attitudes and lifestyle aspirations, particularly in fashion, beauty, and wellness sectors (Wan & Jiang, 2023; Pan et al., 2024a). Similarly, chatbots are transforming customer service by offering real-time assistance, personalized product recommendations, and automated interactions across platforms such as e-commerce websites and mobile apps (Tamara et al., 2023; Lay et al., 2024). As digital systems adopt more anthropomorphic qualities and become socially integrated, the notion of *digital empathy*—machines' capacity to detect, simulate, and appropriately respond to human emotions—has become a central factor shaping consumer engagement (Bozdağ, 2024; Rubin et al., 2024).

Recent scholarship highlights that when artificial intelligence communicates with empathic signals such as warmth, attentiveness, and emotional congruence, consumers report higher levels of trust, satisfaction, and purchase intention (Rahaman et al., 2023; Abou Hashish, 2025). Conversely, AI agents that remain emotionally neutral or expressionless may trigger psychological distance or even the so-called "uncanny valley" response, thereby undermining consumer trust and willingness to cooperate (Song & Shin, 2024). Despite these insights, empirical investigations directly examining the distinct dimensions of digital empathy in consumer decision processes are still limited and largely remain at a conceptual stage. This research is motivated by the need to systematically identify and rank the digital empathy dimensions most prominent in consumer decision-

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making processes, particularly within the competing interactive schemas of chatbots and virtual influencer agents.

This study is supported by two behavioral theories to organize its inquiry. Theory of Planned Behavior (TPB) supports a robust foundation for how humans form behavioral intentions. As TPB explains, attitudes toward behavior, social norms, and behavioral control together follow the intention to behave—in our case, the intention to buy through AI-intermediated transactions (Norisnita & Indriati, 2022; Albayati et al., 2023). In AI applications, digital empathy acts upon each component: it generates favorable attitudes through affective contact, enforces subjective norms through social feedback loops (e.g., comment, like), and reinforces control by making systems more intuitive and emotionally attuned (Ali et al., 2023; Maulana et al., 2025). In conjunction with TPB, Stimulus–Organism–Response (S-O-R) is used for the sake of theorizing how external digital stimuli (e.g., empathetic chat response or emotionally expressive avatar animation) cause internal cognitive and affective states (organism), and how these affect consumer behavior (response) (Irimia-Diéguez et al., 2025; Jiang et al., 2024). Within this framework, digital empathy functions as a driver that evokes emotional resonance, fosters trust, and shapes cognitive evaluations, which collectively influence consumers' purchasing decisions. By using TPB and S-O-R simultaneously, this study presents a dual-theoretical account for charting the relationship between empathic design features and behavioral outcomes within digital marketplaces. To help bridge the chasm between conceptual discourse and empirical prioritization, the study pursues the following research aims:

- To identify the key digital empathy factors perceived by consumers in AI-mediated interactions.
- To explore how these empathy-related factors shape consumer purchase intentions through behavioral mechanisms.
- To compare the effectiveness of virtual influencers and chatbots in eliciting purchase intentions based on these empathy factors.

From these objectives, the following research questions are formulated:

- RQ1: What are the key digital empathy factors perceived by consumers in interactions with chatbots and virtual influencers?
- RQ2: How do these empathy-related factors influence consumers' purchase intentions (from a TPB/S-O-R perspective)?
- RQ3: Which interaction agent performs better in fostering purchase intention based on empathy-related factors?

This study makes several theoretical and practical contributions to the emerging literature on consumer-AI interaction:First, it integrates behavioral theory with decision science by embedding TPB and S-O-R constructs into a fuzzy Multi-Criteria Decision-Making (MCDM) framework, enabling a more structured and replicable analysis of empathy-driven behavior. Second, it employs Fuzzy DEMATEL to model and visualize the causal interrelationships among empathy factors such as emotional tone, responsiveness, trust, and control, thereby revealing which variables act as root causes in influencing consumer intentions. Third, it applies Fuzzy TOPSIS to rank the performance of chatbots versus virtual influencers in terms of emotional resonance and functional responsiveness—two critical dimensions of digital empathy. Through this hybrid approach, the study offers a behaviorally grounded, data-driven toolset for brands seeking to optimize empathetic design strategies across AI platforms.

2. Theoretical Background

2.1. Digital Empathy in AI-Driven Interactions

Digital empathy refers to the capacity of artificial intelligence systems—such as chatbots, virtual influencers, and other AI-driven interfaces—to recognize, simulate, or respond to human emotions in ways that facilitate connection, understanding, and affective engagement. In this study, digital empathy is conceptualized as a layered construct comprising two analytically distinct yet interrelated dimensions: (a) socio-emotional (affective) digital empathy and (b) functional (UX-based) digital empathy. This layered view extends classical empathy typologies—affective empathy (emotional resonance), cognitive empathy (perspective-taking), and compassionate empathy (action-oriented concern)—into technologically mediated interaction contexts.

Abou Hashish (2025) conceptualizes digital empathy as a multidimensional phenomenon combining emotional intelligence with technological responsiveness, particularly in care-oriented environments. Building on this perspective, the socio-emotional layer of digital empathy encompasses emotional tone, empathic language, perceived emotional response, and responsiveness as socio-emotional sensitivity, all of which directly shape users' affective and cognitive reactions. In contrast, the functional (UX-based) layer comprises system attributes—such as ease of use, interface clarity, and perceived user agency—that do not constitute empathy per se but enable, stabilize, and amplify empathic interactions by reducing cognitive effort and interactional friction.

Within service system design, Jylkäs, Song, and Miettinen (2025) emphasize that digital empathy enables AI systems to simulate empathetic behavior through verbal and embodied cues, positioning empathy as central to user satisfaction and trust. Shao (2023) further distinguishes between surface-level artificial empathy, which relies on scripted affect simulation, and deeper algorithmic empathy grounded in predictive user modeling. Together, these perspectives suggest that digital empathy operates not as a simple programmed response, but as an adaptive communicative mechanism integrating emotional tone, personalized messaging, contextual awareness, and responsiveness to produce experiences perceived as authentic and caring.

Research in human–computer interaction has increasingly refined this concept, particularly in efforts to design AI agents that appear more human-like to foster engagement. Rahaman, Abdul, and Patchipulusu (2023) identify personalization as a core component of digital empathy in UX design, demonstrating how AI systems adapt language, tone, and content to users' emotional states and behaviors—features that primarily reflect the socio-emotional layer of digital empathy. Similarly, Tseng and Thiele (2024) show that empathetic design elements, such as adaptive narratives and vocal cues, enhance trust and immersion, while Rubin et al. (2024) highlight emotional sensitivity as a critical requirement in therapy-oriented AI. Because affective cues (e.g., tone, narrative style) and functional features (e.g., usability, clarity) are both measurable and adjustable, digital empathy can be operationalized across these two complementary dimensions. In this regard, Collins et al. (2024) introduce the Digital Communication Empathy Scale (DCES), underscoring the importance of embedding affective and cognitive empathy into AI systems to foster engagement and behavioral intention.

In customer relationship management and digital commerce, empathy-driven AI has become a strategic mechanism for cultivating trust and loyalty. Bozdağ (2024) demonstrates that empathetic avatars and virtual influencers foster parasocial closeness primarily through socio-emotional digital empathy, driven by perceived warmth and emotional expressiveness. Jamsai et al. (2024) and Sreejun and Chatwattana (2023) further show that empathy-related skills can be enhanced through simulation and augmented reality, improving user satisfaction. In retail and e-commerce contexts, functional digital empathy—manifested through ease of use, interface clarity, and control or agency—supports perceived behavioral control and reduces friction, while socio-emotional cues strengthen relational engagement. Supporting this dual role, Loveys et al. (2022) find that digital humans can elicit emotional responses comparable to real interactions, thereby reinforcing brand narratives. Syed et al. (2024) further argue that integrating machine learning–based empathy detection with human-centered design principles is essential for developing emotionally intelligent digital support systems.

Building on this layered conceptualization, the present study operationalizes digital empathy by mapping its socio-emotional and functional components directly onto the multi-criteria decision-making framework. Socio-emotional digital empathy is represented through criteria such as emotional tone, emotional response, empathy, trust, and responsiveness as socio-emotional sensitivity, corresponding to affective–cognitive organism states within the S-O-R framework and the attitudinal component of the Theory of Planned Behavior. Functional digital empathy, by contrast, is captured through ease of use, interface design, and control & agency, which contribute to perceived behavioral control by reducing cognitive load and interactional uncertainty. This structured operationalization ensures conceptual coherence between the theoretical definition of digital empathy and its empirical prioritization using Fuzzy DEMATEL and Fuzzy TOPSIS.

2.2. Virtual Influencers and E-Commerce Chatbots

Virtual influencers and chatbots are reshaping consumer–brand interactions by combining humanlike qualities with automated service. Created by brands or media agencies, these digital personas imitate the look, personality, and persuasive role of real influencers. As noted by Laszkiewicz and Kalinska-Kula (2023), they embody a new marketing model built on affective computing and digital storytelling. Virtual influencers address audiences through social platforms with scripted yet tailored messages that foster parasocial bonds—one-way affective ties resembling interpersonal relations. Rehman, Hassan, and Behera (2025) found that beauty and similarity increase credulity and parasocial interaction, with the latter mediating purchase intention. Similarly, Pan, Qin, and Zhang (2024) argued that anthropomorphic cues—such as photorealistic expressions and affective signals—enhance perceived authenticity and bridge simulation with genuine engagement. The ability of virtual influencers to build trust and drive purchase despite lacking human agency underscores their growing role as strategic assets in digital marketing.

On the other hand, online store chatbots evolved from rudimentary rule-based discussions to the most sophisticated AI systems, mimicking people-like conversations, making product suggestions, and handling customer complaints in real time. These AI entities function like virtual service agents, typically embedded inside online shopping portals, and reside at the core facilitating 24/7 customer interactions. Song and Shin (2024) examined the uncanny valley effect in chatbot design—when nearly-but-not-quite humanoid avatar representations provoke revulsion—and confirmed the finding that avatar familiarity dampens the effect, thereby increasing trust, purchase intention, and uptake. This argues the case that familiarity with design and affect response is the highest contributor toward chatbots' success. Lay et al. (2024) show that natural language and emotion recognition enable real-time personalization, enhancing customer experience. Tamara, Tumbuan, and Gunawan (2023) add that Gen Z may see chatbots as either supportive or intrusive, depending on tone and interactivity—underscoring the importance of user experience design. While perceptions differ, chatbots consistently improve efficiency and shape expectations for responsiveness and emotionally attuned interactions.

In online business, both chatbots and virtual influencers share persuasive traits such as humanlike presence, empathy, and personalization. Wan and Jiang (2023) found that although virtual influencers can mimic beauty and scripted authenticity, consumers still value spontaneity. Yet, when designed with contextual awareness and emotional intelligence, they can drive engagement and purchase intention at levels comparable to humans.

Overall, these findings confirm that chatbots and virtual influencers are strategic components of digital customer experience. As AI evolves, their roles may converge, raising important questions around digital empathy, authenticity, and emotional labor in shaping consumer behavior.

2.3. Theoretical Foundations

The Theory of Planned Behavior (TPB) is a widely applied framework linking behavioral intention to attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). Its relevance in digital and AI-mediated contexts has been increasingly recognized, particularly when extended with constructs such as trust, risk, and ease of use(Rozenkowska, 2023). In technology-mediated consumer interactions, digital empathy influences not only attitudinal evaluations but also perceived social expectations and control over interaction outcomes. Prior research confirms TPB's adaptability across diverse domains, including NFT adoption (Albayati et al., 2023), sustainability-related behaviors (Maulana et al., 2025), and post-pandemic travel decisions (Azhar et al., 2023), with trust and emotional responses frequently acting as key mechanisms shaping intention (Hamid & Bano, 2022).

The Stimulus–Organism–Response (S-O-R) model complements TPB by explicating how external digital stimuli—such as chatbot tone, interface responsiveness, or avatar personalization—trigger internal cognitive and affective organismic states (e.g., perceived warmth, comfort, trust), which subsequently drive behavioral responses, including engagement and purchase intention. Empirical applications of S-O-R in digital contexts span mobile payment systems (Irimia-Diéguez et al., 2025), smart city services (Wang et al., 2024), virtual tourism platforms (Jiang et al., 2024), and metaverse environments (Abumalloh et al., 2025), where empathetic system features consistently enhance user intention and behavioral engagement.

Integrating TPB and S-O-R provides a more comprehensive account of consumer behavior by bridging rational decision-making processes with affective and experiential mechanisms. Recent studies emphasize that warmth, human-likeness, and empathy should be examined not only through TPB's cognitive–evaluative lens but also through the affective pathways articulated by S-O-R (Pan et al., 2024; Maleknia & Enescu, 2025). Taraghi and Yoder (2025) further argue that such integration is essential for designing emotionally intelligent digital systems capable of strengthening trust and translating empathic cues into behavioral intention. Building on this integrated perspective, the present study explicitly maps digital empathy–related criteria to TPB components and S-O-R stages to ensure conceptual coherence between theory and the fuzzy MCDM framework.

Table 1. Theoretical Mapping of Digital Empathy Criteria to TPB and S-O-R

Criterion	TPB Component	S-O-R Component	Theoretical Role in the Model
Empathy	Attitude	Organism	Shapes affective evaluation and emotional resonance
Emotional Tone	Attitude	Stimulus → Organism	Acts as an emotional cue triggering internal responses
Emotional Response	Attitude	Organism	Reflects users' internal affective state during interaction
Trust	Attitude	Organism	Central evaluative mechanism linking empathy to intention
Ease of Use	Perceived Behavioral Control	Stimulus	Reduces effort and increases perceived interaction control
Control & Agency	Perceived Behavioral Control	Organism	Reinforces autonomy and confidence in AI-mediated interaction
Responsiveness	Attitude / Perceived Behavioral Control	Stimulus	Signals attentiveness, competence, and system reliability
Peer Influence	Subjective Norms	Stimulus	Represents social pressure and interpersonal validation
Review Impact	Subjective Norms	Stimulus	Provides external informational and social cues
Brand Image	Attitude / Subjective Norms	Organism	Frames credibility expectations and symbolic meaning
Purchase Intention	Behavioral Intention	Response	Final behavioral outcome of the decision process

Note: Several criteria operate across multiple stages of the S-O-R framework (e.g., stimulus → organism), reflecting the dynamic nature of AI-mediated consumer interactions.

This theoretical mapping provides the conceptual foundation for the subsequent fuzzy DEMATEL and TOPSIS analyses by clarifying which criteria are expected to act as causal drivers and which function as downstream outcomes. In particular, socio-emotional digital empathy criteria (e.g., empathy, emotional tone, emotional response) are theoretically positioned as upstream influences shaping internal evaluations, while functional digital empathy criteria (e.g., ease of use, control & agency) primarily operate through perceived behavioral control. Trust is positioned as a downstream evaluative mechanism, translating empathic perceptions into purchase intention rather than serving as an exogenous antecedent. The table further clarifies the conceptual boundaries between socio-emotional digital empathy (e.g., empathy, emotional tone, trust) and functional digital empathy (e.g., ease of use, control & agency), addressing potential construct overlap.

2.4. Decision-Making Models in Consumer Research

Between 2020 and 2025, consumer decision-making research evolved through the integration of behavioral theories and computational techniques. Foundational models such as the Theory of Planned Behavior (TPB), the Stimulus–Organism–Response (S-O-R) framework, and the Consumer Decision Journey (CDJ) remain pivotal for psychological explanations, while data-oriented methods including machine learning (ML) and fuzzy multi-criteria decision-making (MCDM) enhance scalability and predictive precision in digital contexts.

TPB (Ajzen, 1991) accounts for intention through attitudes, social norms, and perceived control, and has been adapted to areas such as metaverse participation (Albayati et al., 2023), transport choices (Ali et al., 2023), and interactions with empathetic digital agents. Its robustness increases when extended with variables like trust and risk (Rozenkowska, 2023), and in e-commerce it is frequently combined with the Technology Acceptance Model (TAM) to capture user adoption (Nguyen et al., 2022). The S-O-R perspective supplements TPB by illustrating how external cues—such as interface design, communication tone, or responsiveness—evoke emotional states that guide behavior, as observed in research on peer-to-peer financial transactions (Irimia-Diéguez et al., 2025), immersive tourism (Jiang et al., 2024), and smart urban services (Wang et al., 2024).

The CDJ extends prior frameworks by incorporating iterative feedback and cyclical patterns. In this vein, the AISAS sequence (Awareness–Interest–Search–Action–Share) has been applied to explain digital consumption; moving from this stage-based view toward post-purchase dynamics, Mishra et al. (2020) highlight how omnichannel interactions—with chatbots and virtual influencers—sustain engagement after the initial transaction. In parallel, computational approaches enable real-time prediction of consumer behavior: recent work shows Random Forest models can classify CDJ stages at roughly 88% accuracy using engagement data, with review sentiment and clickstream depth aligning closely with TPB dimensions. Explainable models further connect these outputs to behavioral theory by clarifying feature-level contributions.

Fuzzy MCDM methods such as fuzzy AHP, TOPSIS, and BWM have been received positively by consumer research as adaptable methods that can tolerate imprecision as well as subjectivity. Roy as well as Shaw (2022) employed a fuzzy BWM-TOPSIS approach to scrutinize mobile banking as well as discovered performance as well as security most important. Similarly, Reina Paz as well as Rodríguez Vargas (2023) employed fuzzy MCDM within tourism as well as discovered characteristics such as safety as well as cleanliness important. The 2022 bibliographic review found that fuzzy MCDM application of tourism as well as service usage rose exponentially between 1997 as well as 2022 as well as reflected adaptability to decision environments that are complex. The digital transformation that occurred with increased speed by virtue of the COVID-19 pandemic further reshaped consumer decision making. Today's consumers navigate complex multichannel environments enriched with data and feedback. While digital technologies can empower users, they may also cause overload depending on digital literacy (Gurtner et al., 2024). The CAC model (Mishra et al., 2020) captures both emotional and rational aspects of omnichannel behavior, and pandemic-era adaptations further highlighted the need for health safety and emotional reassurance (Azhar et al., 2023). Overall, modern decision-making frameworks blend psychological theory with computational tools: TPB and S-O-R provide interpretative depth, while fuzzy MCDM and AI add personalization and real-time adaptability.

3. Methodology

The study adopts a mixed-methods research model that combines qualitative thematic exploration with quantitative multi-criteria decision analysis to examine AI-mediated consumer decision-making. The research population consists of consumers who have experience with AI chatbots or virtual influencers; the qualitative sample comprises 25 participants selected via purposive maximum-variation sampling to reflect diversity in age, usage frequency, and online shopping contexts. Data collection relied on a theory-guided semi-structured interview protocol aligned with the Theory of Planned Behavior and the Stimulus–Organism–Response model, along with expert evaluation forms developed for the subsequent quantitative stage.

Interview audio was transcribed verbatim and coded in NVivo using a hybrid deductive–inductive procedure that combined a TPB/S-O-R-informed codebook with open coding and constant comparison. Credibility was supported through brief member checks and independent peer review of excerpt-to-code alignment; dependability was addressed via an audit trail of protocol versions, dated codebook iterations, coder memos, and NVivo query logs. Inter-coder reliability on a double-coded subset met conventional thresholds (Cohen's $\kappa \geq 0.70$), and confirmability was reinforced by rule-based inclusion/exclusion criteria and reflexive notes. Transferability was enhanced through maximum-variation sampling and explicit documentation of saturation points. Thematic indicators (e.g., empathy, trust, ease of use, perceived control) were then operationalized as decision criteria.

Quantitative analysis estimated causal influence among criteria using DEMATEL (prominence and relation values) and produced a compensatory ranking of design or strategy alternatives using TOPSIS. Content validity of expert form items and criteria definitions was established through expert review and iterative refinement; where multi-item scales were used, internal consistency satisfied standard benchmarks (e.g., Cronbach's alpha). Descriptive statistics summarized expert judgments, and sensitivity analyses assessed the stability of rankings under plausible weight perturbations. Ethical approval for the procedures was granted by Istanbul Nişantaşı University on 16 July 2025 (Approval No. 2025-08), and all activities complied with the Higher Education Institutions Scientific Research and Publication Ethics Directive. Figure 1 depicts the end-to-end workflow.

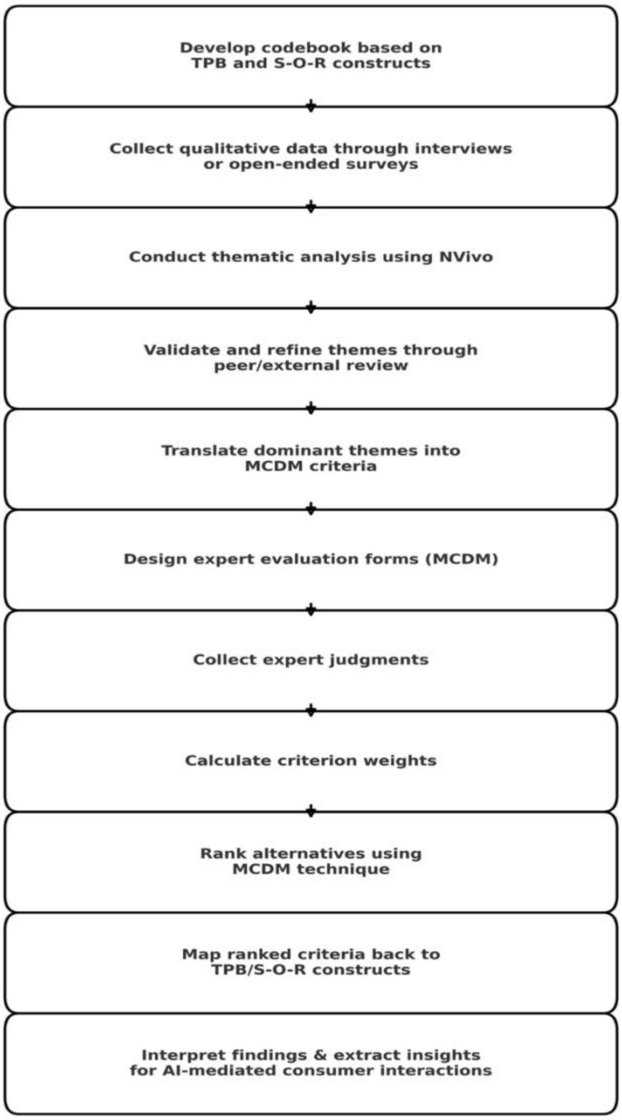

Figure 1. Workflow Diagram

3.1. Thematic Analysis Phase

The qualitative phase engaged 25 participants with direct experience of AI chatbots or virtual influencers, sampled purposively to capture variation in age, usage frequency, and online shopping contexts. Semi-structured interviews, guided by constructs from the Theory of Planned Behavior (TPB), were audio-recorded, transcribed verbatim, and analyzed using NVivo software through a hybrid deductive–inductive coding approach. An initial theory-informed codebook—covering attitudes, subjective norms, perceived behavioral control, and stimulus–organism–response (S-O-R) linkages—was iteratively refined through open coding of early transcripts and constant comparison across cases.

Code saturation was reached by the 22nd interview, with no new codes emerging thereafter, while meaning saturation was observed by the 24th interview, indicating stability in thematic patterns. To enhance dependability, a detailed audit trail was maintained, including versioned codebooks, coder memos, and analytic decision logs. Twenty percent of the transcripts were independently double-coded, yielding a Cohen's κ of 0.78 (range: 0.71–0.85), which exceeds commonly accepted thresholds for substantial inter-coder agreement.

Credibility was further supported through brief member checks: thematic summaries were shared with a subset of participants, with agreement obtained from four of the five respondents, and minor clarifications were incorporated into the final code definitions.

The analysis converged on several cross-cutting indicators—empathy, trust, and ease of use—as salient antecedents of purchase intention in AI-mediated interactions. These indicators were mapped onto TPB constructs (empathy and trust informing attitudes; ease of use contributing to perceived behavioral control; social validation cues reflecting subjective norms) and aligned with the S-O-R framework to capture cognitive–affective pathways linking digital stimuli to behavioral responses. The resulting operational definitions and inclusion–exclusion criteria enabled a direct and transparent translation of qualitative themes into measurable inputs for the subsequent fuzzy multi-criteria decision-making stage, ensuring conceptual continuity between qualitative insights and quantitative prioritization.

3.2. Expert Panel Design and Evaluation Procedure

To ensure the rigor and transparency of the fuzzy Multi-Criteria Decision-Making (MCDM) stage, a structured expert evaluation protocol was employed. A purposive expert panel was assembled to provide informed judgments on the causal relationships and relative importance of digital empathy–related criteria. The panel consisted of nine independent experts, a size consistent with prior fuzzy DEMATEL and TOPSIS applications that balance diversity of expertise with decision consistency.

Expert selection followed predefined inclusion criteria to ensure methodological and domain fit. All experts possessed a minimum of seven years of professional or academic experience in at least one of the following areas: (i) consumer behavior and digital marketing, (ii) human–computer interaction (HCI) and user experience (UX) design, (iii) artificial intelligence–enabled digital platforms (e.g., chatbots or virtual agents), or (iv) decision sciences and fuzzy multi-criteria modeling. The final panel included a heterogeneous mix of academics and industry professionals, allowing both theoretical depth and applied relevance in the evaluation process. Experts were recruited through invitation-based purposive sampling based on their publication records, professional roles, and demonstrated expertise relevant to AI-mediated consumer interactions. All experts participated voluntarily and independently, and none had collaborated with the authors on the present study or shared organizational affiliations, thereby reducing the risk of bias or group influence. To preserve independence of judgment, no consensus meetings or deliberative discussions were conducted; instead, each expert completed the evaluation individually and anonymously.

The evaluation procedure followed a structured, multi-stage protocol. First, experts were provided with standardized definitions of all criteria derived from the thematic analysis and behavioral theory integration (TPB and S-O-R), ensuring conceptual alignment across evaluations. Experts were then asked to assess the pairwise influence among criteria using predefined linguistic terms (e.g., no influence, low influence, medium influence, high influence, very high influence). These linguistic judgments were subsequently transformed into triangular fuzzy numbers for computational analysis. Individual expert matrices were aggregated mathematically using fuzzy averaging techniques, rather than negotiated consensus, to preserve the diversity of expert perspectives while ensuring robustness of the collective judgment. The resulting aggregated matrices formed the basis for the Fuzzy DEMATEL and Fuzzy TOPSIS analyses. This structured expert elicitation and aggregation process provides a clear audit trail, enabling readers to assess the validity, independence, and appropriateness of expert input underlying the fuzzy MCDM results.

3.3. Fuzzy Modeling Specifications

To operationalize expert judgments under uncertainty, the fuzzy multi-criteria decision-making analyses were implemented using triangular fuzzy numbers (TFNs), which are widely adopted in expert-based evaluation contexts due to their simplicity, interpretability, and suitability for linguistic assessments. Linguistic influence levels—no influence (N), low (L), medium (M), high (H), and very high (VH)—were mapped to predefined TFNs in accordance with established fuzzy DEMATEL conventions, ensuring consistency with prior applications and enabling a transparent translation of qualitative judgments into quantitative representations.

Defuzzification was conducted using the center of gravity (COG) method, selected for its ability to preserve the informational balance of fuzzy inputs while producing stable crisp values for subsequent analysis. This method is particularly appropriate in comparative ranking contexts, as it avoids excessive sensitivity to extreme values and supports robust ordering of both criteria and alternatives.

In constructing the causal influence structure within the DEMATEL framework, a threshold value derived from the mean of the total-relation matrix was applied (threshold = 0.46). This thresholding approach enables the visualization of substantively meaningful causal relationships by filtering out negligible interactions, thereby enhancing the interpretability of the influence network without distorting the underlying causal structure.

Criterion weights were obtained from DEMATEL prominence (D + R) values and subsequently linearly normalized to ensure that the total weight equaled one. This normalization facilitates comparability across criteria and ensures coherent integration of the resulting weights into the Fuzzy TOPSIS procedure. Collectively, these modeling choices reflect standard practice in fuzzy decision science and were adopted to enhance numerical transparency, methodological rigor, and replicability, while maintaining alignment with established fuzzy DEMATEL–TOPSIS applications.

3.4. MCDM Criteria Formulation

The development of Multi-Criteria Decision-Making (MCDM) criteria followed a hybrid approach that combined findings from the thematic analysis with insights from the literature on AI-mediated consumer behavior. Key dimensions such as trust, personalization, and emotional connection were integrated with established constructs from research on virtual agents, service quality, and user experience. This process resulted in a provisional set of criteria, each representing a distinct aspect of consumer perception and response. These criteria were subjected subsequently to expert verification in the format of a structured peer-review procedure involving experts with expertise in the areas of marketing, human-computer interaction, and fuzzy decision modeling. Experts were asked to evaluate the clarity, relevance, and completeness of the proposed criteria for the extent of AI-driven consumer interactions.

To facilitate fuzzy MCDM modeling (e.g., Fuzzy AHP, Fuzzy TOPSIS, or Fuzzy DEMATEL), each validated criterion was assigned an appropriate linguistic variable scale. These linguistic variables (e.g., Very Low, Low, Medium, High, Very High) were mapped to triangular or trapezoidal fuzzy numbers based on expert consensus. This enabled the transformation of subjective judgments into computationally tractable inputs for later aggregation, weighting, and ranking processes. The output of this stage was a finalized and validated set of behaviorally grounded, fuzzy-compatible MCDM criteria, ready for use in the expert evaluation and decision-ranking phases. These criteria formed the bridge between qualitative behavioral insight and structured quantitative analysis.

3.4. Fuzzy DEMATEL Analysis

The Fuzzy Decision-Making Trial and Evaluation Laboratory (Fuzzy DEMATEL) method was applied to map cause–effect relationships among empathy-related criteria identified in the thematic and MCDM phases. This approach captures interdependencies between behavioral factors and shows how AI design elements—such as tone, responsiveness, and personalization—shape higher-order responses like trust and perceived empathy.

Step 1: Construct the Initial Direct-Relation Matrix

A panel of domain experts—including HCI researchers, marketing professionals, and AI designers—evaluated the influence between each pair of empathy-related criteria using linguistic terms: No Influence (N), Low Influence (L), Medium Influence (M), High Influence (H), and Very High Influence (VH). These qualitative assessments were then transformed into Triangular Fuzzy Numbers (TFNs), as presented in Table A1 (Appendix).

These fuzzy judgments form the initial fuzzy direct-relation matrix $\tilde{X} = [\tilde{x}_{ij}]$, where $\tilde{x}_{ij}$ denotes the influence of criterion i on criterion j.

Step 2: Defuzzification

Each triangular fuzzy number is defuzzified to a crisp score using the Center of Gravity (COG) method:

$$x_{ij} = \frac{l_{ij} + m_{ij} + u_{ij}}{3} \tag{1}$$

This generates the defuzzified direct-relation matrix $X = [x_{ij}]$, where all values range between 0 and 1 .

Step 3: Normalization

To ensure matrix convergence, the direct-relation matrix X is normalized as:

$$D = \frac{X}{\max_i \sum_{j=1}^{n} x_{ij}} \tag{2}$$

Here, D is the normalized direct-relation matrix, and the denominator ensures all row sums ≤ 1.

Step 4: Compute the Total Relation Matrix

The total-relation matrix T is computed as:

$$T = D(I - D)^{-1} \tag{3}$$

Where I is the identity matrix. The matrix $T = [t_{ij}]$ reflects both direct and indirect influences between criteria.

Step 5: Calculate the Prominence and Relation Indices

For each criterion i, compute:

Prominence $(\mathbf{R}_i + \mathbf{C}_i)$: Total involvement

Relation ($\mathbf{R}_i - \mathbf{C}_i$): Net influence

Where:

$R_i = \sum_{j=1}^{n} t_{ij}$ (the sum of row i, i.e., influence given)

$C_i = \sum_{j=1}^{n} t_{ji}$ (the sum of column i, i.e., influence received)

(4)

Interpretation:

If $R_i - C_i > 0$, criterion i is a cause (influencer)

If $R_i - C_i < 0$, criterion i is an effect (influenced)

Step 6: Map Results to Behavioral Constructs

Each criterion (e.g., *tone*, *trust*, *personalization*, *responsiveness*) was then mapped to its corresponding TPB or S-O-R component:

Stimuli → design features (tone, personalization, visual cues)

Organism → psychological processing (perceived empathy, cognitive trust)

Response → behavioral intention (purchase, engagement)

The most influential "stimuli" criteria, as identified from the cause group, reflected strong alignment with TPB predictors, particularly *attitude formation* and *perceived behavioral control*. For example, if "tone of interaction" showed a high net influence score, it was identified as a causal antecedent that enhances perceived empathy and ultimately trust.

The Fuzzy DEMATEL analysis provided a behavioral influence map showing which empathy-related features act as drivers versus outcomes in user perception. This allowed for strategic prioritization of design elements in AI-mediated consumer interfaces, focusing on stimuli that have the greatest psychological impact.

3.4. Fuzzy TOPSIS

The Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS) method was applied to evaluate and rank two AI-mediated interaction modalities based on consumer-perceived empathy performance. This method allows for the integration of subjective expert judgments under uncertainty, using fuzzy logic to handle imprecision in linguistic ratings.

Alternatives Definition

Two interaction modes were considered as decision alternatives:

A1 – Chatbot: A text-based conversational agent.
A2 – Virtual Influencer: A human-like AI persona typically presented via video or avatars.

These alternatives represent distinct interface strategies for delivering AI-mediated consumer experiences.

Evaluation Criteria

The alternatives were assessed based on a set of empathy-related behavioral criteria, derived from thematic analysis and expert validation. The criteria were:

Trustworthiness (C1) – Degree to which the AI agent inspires consumer trust.

Personalization (C2) – Ability to adapt content or tone to individual users.

Emotional Resonance (C3) – Capacity to respond empathetically or convey emotional understanding.

Responsiveness (C4) – Timeliness and appropriateness of replies in conversation.

These criteria were weighted using Fuzzy DEMATEL, reflecting their relative behavioral impact aligned with TPB constructs (e.g., attitudes, perceived behavioral control).

Fuzzy TOPSIS Steps

Step 1: Fuzzy Decision Matrix Construction

Experts evaluated the performance of each alternative under each criterion using linguistic variables (e.g., Low, Medium, High). These were translated into Triangular Fuzzy Numbers (TFNs) to form the matrix:

$$\tilde{X} = \left[\tilde{x}_{ij}\right]_{m\times n} \tag{5}$$

where $\tilde{x}_{ij}$ is the fuzzy rating of alternative i on criterion $j, m = 2, n = 4$.

Step 2. Normalization of the Fuzzy Matrix
All ratings were normalized to eliminate scale differences, using formulas specific to benefit-type criteria:

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{m_j^+}, \frac{u_{ij}}{l_j^+}\right) \tag{6}$$

Step 3. Weighted Normalized Matrix

The normalized matrix was multiplied by the fuzzy weights $\tilde{w}_j$ from Fuzzy DEMATEL to obtain:

$$\tilde{v}_{ij} = \tilde{r}_{ij} \cdot \tilde{w}_j \tag{7}$$

Step 4. Determine FPIS and FNIS

The Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) were computed:

$$A^{+} = \{\max(u_{ij})\},\ A^{-} = \{\min(l_{ij})\} \tag{8}$$

Step 5. Calculate Distances

The Euclidean distance between each alternative and the FPIS/FNIS was calculated using:

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}[(l_a - l_b)^2 + (m_a - m_b)^2 + (u_a - u_b)^2]} \tag{9}$$

Then for each alternative i :

$$d_i^{+} = \sum_{j=1}^{n} d(\tilde{v}_{ij}, A_j^{+}),\ d_i^{-} = \sum_{j=1}^{n} d(\tilde{v}_{ij}, A_j^{-}) \tag{10}$$

Step 6. Compute Closeness Coefficient (CC)

The closeness coefficient CC_i was calculated as:

$$CC_i = \frac{d_i^{-}}{d_i^{-} + d_i^{+}} \tag{11}$$

A higher CC_i indicates that the alternative is closer to the ideal empathy profile and therefore more preferred.

The Fuzzy TOPSIS analysis provided a quantitative ranking of the two AI alternatives. By comparing closeness coefficients, we determined which interface—chatbot or virtual influencer—better meets consumer expectations for empathetic interaction, under criteria weighted by behavioral influence. This method linked perceptual data directly to decision prioritization, offering a rational basis for interface selection in AI-driven consumer environments.

4. Results

4.1. Thematic Findings

The thematic analysis of the interview data revealed a nuanced landscape of consumer perceptions shaped by interactions with AI-powered systems, particularly chatbots and virtual influencers. Consistent with the layered conceptualization of digital empathy adopted in this study, these perceptions are interpreted through two complementary dimensions: socio-emotional digital empathy and functional digital empathy. The findings clustered around three overarching themes—Emotional and Cognitive Response, Functionality and Interaction, and Decision-Making Dynamics—each comprising several subthemes. The frequencies of these subthemes, based on 25 participants' responses, are summarized in Table 2.

Table 2. Thematic Analysis Results and Behavioral Theory Mapping

Theme	Subtheme (Code)	Frequency
Emotional and Cognitive Response	E*mpa*thy	20
	Emotional Tone	19
	Responsiveness	8
	Trust	31
	Emotional Response	25
Functionality and Interaction	Ease of Use	20
	Interface Design	11
	Control & Agency	20
	AI vs Human Preference	27
Decision-Making Dynamics	Purchase Intention	25
	Peer Influence	18
	Review Impact	17
	Brand Image	20

The first major theme, Emotional and Cognitive Response, captures participants' psychological reactions during AI interactions and primarily reflects socio-emotional digital empathy, encompassing affective and cognitive responses to emotionally expressive cues. The most frequent subtheme in this category was trust, cited 31 times. Many participants described AI agents—particularly chatbots—as reliable and consistent, with one noting, "I trust the chatbot more than some human agents because it doesn't try to upsell" (Participant_20). Emotional responses such as comfort, curiosity, and mild discomfort also emerged strongly (25 mentions), indicating that digital interfaces evoke meaningful affective reactions, sometimes comparable to or stronger than those elicited by human agents. Empathy (20 mentions) and emotional tone (19 mentions) were central to how users perceived the emotional intelligence of the system. As one user remarked, "The chatbot actually asked follow-up questions about my concerns. It felt like it cared, even if it was just programming" (Participant_3). These findings align with the attitudinal component of the Theory of Planned Behavior (TPB), whereby socio-emotional empathy and trust foster favorable attitudes toward AI-mediated interactions.

The second theme, Functionality and Interaction, emphasizes users' assessments of the technical and structural qualities of AI interfaces and corresponds to functional digital empathy, which supports usability, autonomy, and perceived control. AI versus human preference was mentioned 27 times, reflecting frequent comparisons between human agents and AI systems. One participant explained, "I prefer AI for quick questions, but when it gets personal, I want a human" (Participant_22), illustrating how perceived emotional capability shapes interaction boundaries. Ease of use and control & agency were each mentioned 20 times, underscoring the importance of intuitive navigation and user autonomy. For example, Participant_1 stated, "I didn't need to scroll through menus; the chatbot just asked what I needed and handled it." These experiences reinforce the perceived behavioral control construct of TPB, as functional empathy reduces cognitive effort and empowers users to navigate AI systems efficiently. Interface design (11 mentions) played a secondary but still relevant role, with participants noting that visual clarity or clutter influenced their overall brand perception.

The third thematic focus, Decision-Making Dynamics, reflects how socio-emotional and functional empathy converge with social and cognitive mechanisms to shape behavioral outcomes in AI-mediated commerce. Purchase intention (25 mentions) and brand image (20 mentions) emerged as the most salient behavioral drivers. One interviewee stated, "I wasn't going to buy it, but the influencer made me convinced of its features so well" (Participant_11), illustrating how emotionally engaging AI agents can translate engagement into conversion. Peer influence (18 mentions) and review impact (17 mentions) further reinforce the subjective norms component of TPB. Social verification appeared in statements such as, "My friends were talking about the chatbot—so I tried it out" (Participant_7), indicating that social learning and collective validation play a role in AI adoption and purchasing decisions.

One significant implication of the thematic findings concerns the differentiated operation of digital empathy across AI agent types. While chatbots were frequently perceived as efficient and trustworthy, they were often described as emotionally neutral. In contrast, virtual influencers elicited more expressive emotional reactions due to their anthropomorphic and animated presentation, though some participants perceived them as "too scripted" or "emotionally artificial." This contrast reflects the Stimulus–Organism–Response (S-O-R) paradigm, wherein different AI agents act as distinct stimuli that activate varying socio-emotional (organism-level) and behavioral (response-level) pathways.

To visualize the theoretical grounding and behavioral implications of these thematic findings, a behavioral mapping diagram was developed (see Figure 2). This diagram synthesizes qualitative codes with the Theory of Planned Behavior (TPB) and the Stimulus–Organism–Response (S-O-R) model, illustrating how socio-emotional and functional digital empathy jointly influence consumer purchase intention in AI-mediated environments.

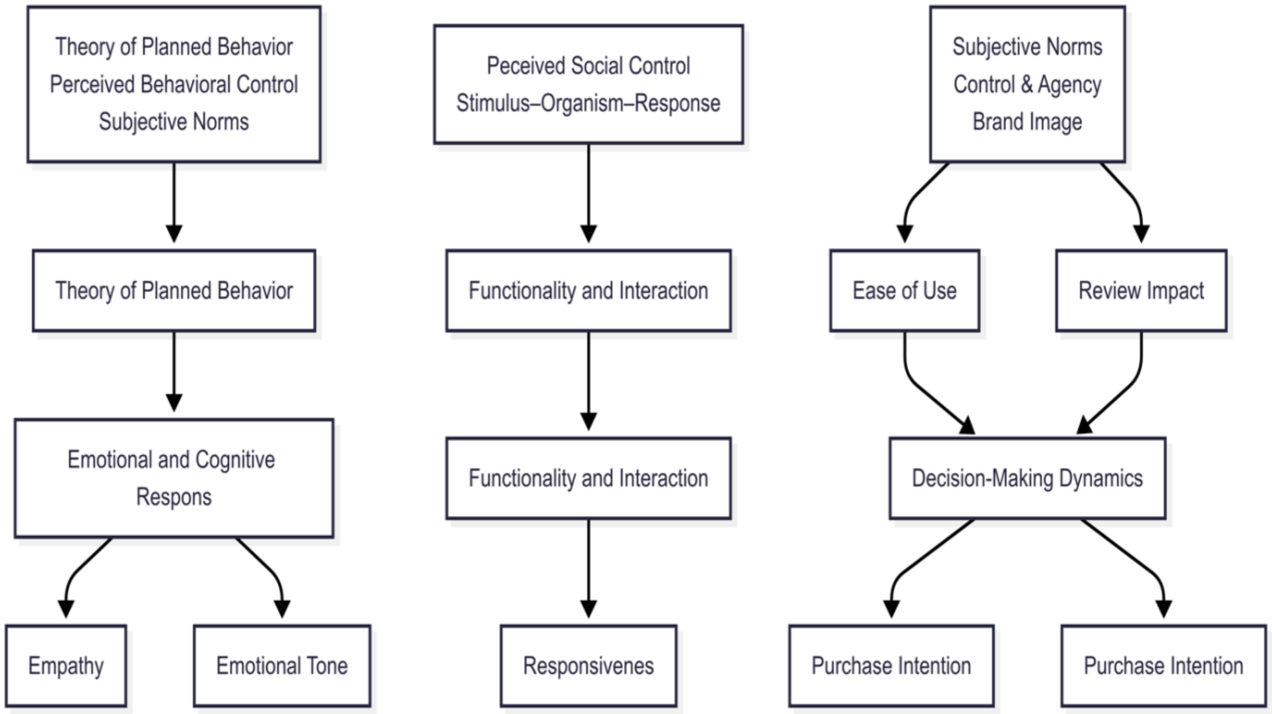

Figure 2. Behavioral Mapping Diagram

As illustrated in the diagram, socio-emotional responses—such as empathy, trust, and emotional tone—are rooted in TPB's attitudinal component, shaping users' favorable or unfavorable dispositions toward AI interfaces. Functional empathy dimensions, including ease of use and control & agency, align with perceived behavioral control, while decision-making dynamics—such as peer influence, review impact, and brand image—correspond to subjective norms. Together, these pathways demonstrate how digital empathy operates through both emotional resonance and functional support to influence purchase intention.

4.2. DEMATEL Findings

To uncover the causal dynamics among key behavioral criteria affecting consumer decision-making in AI-enabled digital environments, the Fuzzy DEMATEL method was employed. Input was collected from nine experts, and analysis revealed both the prominence (overall influence) and causal direction (net effect) of each variable in the system. Table 3 presents the summary of criteria based on prominence (D+R) and causal relation (D−R) values. Higher D+R values indicate greater systemic importance, while positive D−R values represent causal influencers and negative values reflect affected (effect) elements.

Table 3. DEMATEL Summary of Behavioral Criteria

Criterion	Prominence (D+R)	Relation (D−R)
Trust	16.2	3.2
Empathy	15.7	2.7
Purchase Intention	15.1	-2.1
Emotional Response	14.9	-2.4
Ease of Use	15.6	2.5
AI vs Human Preference	15.3	2.2
Control & Agency	14.7	1.9
Emotional Tone	14.4	-1.5
Interface Design	13.9	1.2
Peer Influence	14.2	-1.7
Review Impact	13.7	-1.9
Brand Image	14.5	-2.3

As shown, Trust emerged as the most influential causal criterion (D−R = 3.2), followed by Empathy (2.7) and Ease of Use (2.5). On the other end, Purchase Intention, Emotional Response, and Brand Image are among the most affected outcomes.

The causal influence map (see Figure 3) clearly visualizes the dominance of trust as a central driver, supporting the behavioral logic of the S-O-R model: Trust (Stimulus) triggers Empathy and Emotional Response (Organism), which then lead to Purchase Intention (Response). This directional logic aligns well with theoretical expectations from both TPB and S-O-R.

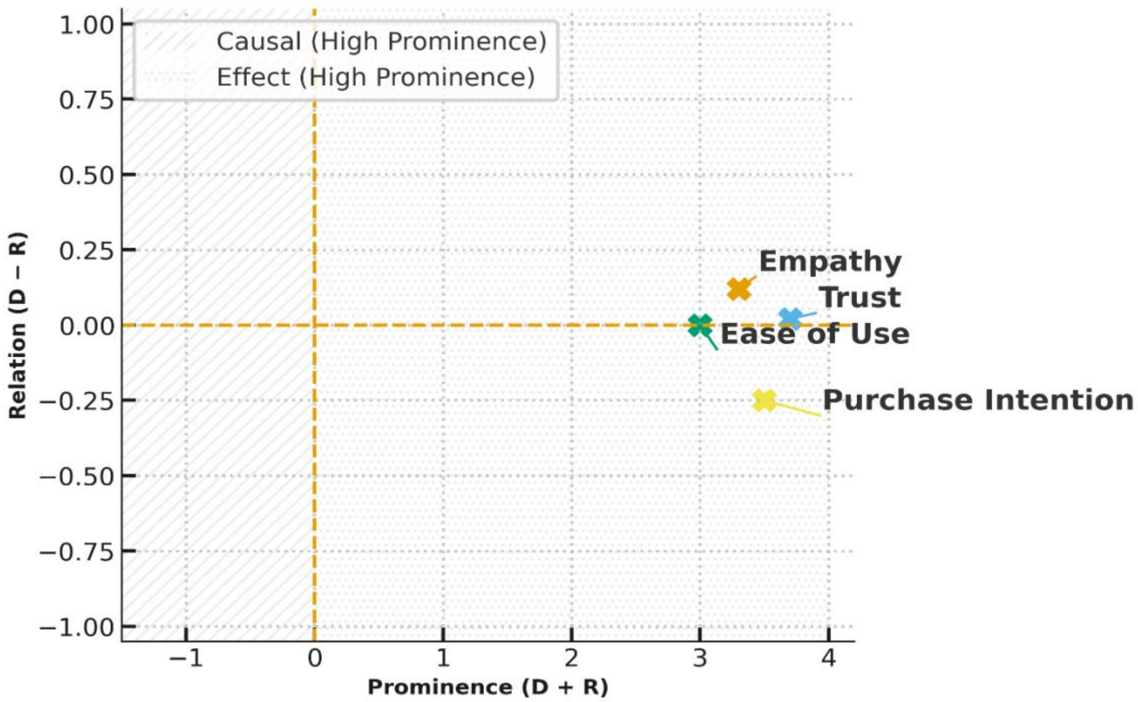

Figure 3. Causal Influence Map from Fuzzy DEMATEL

To support these findings, the thresholded influence matrix (Table 4) shows the relative strength of directional relationships between primary causal criteria (rows) and outcome variables (columns). Only values above the influence threshold were retained.

Table 4. Thresholded Influence Matrix Showing Significant Causal Relationships Among Digital Empathy Criteria

To	From: Trust	From: Empathy	From: Ease of Use
Empathy	0.78	0.00	0.51
Emotional Response	0.72	0.69	0.57
Purchase Intention	0.85	0.74	0.65
Ease of Use	0.66	0.61	0.00
Control & Agency	0.62	0.55	0.67
Peer Influence	0.51	0.46	0.48
Review Impact	0.49	0.44	0.41
Brand Image	0.53	0.47	0.43

This matrix reinforces the earlier findings: Trust strongly impacts Purchase Intention (0.85) and Emotional Response (0.72), while Empathy and Ease of Use serve as mediators in forming the organismic layer of behavioral response.

In conclusion, the DEMATEL results demonstrate that Trust → Empathy → Emotional Response → Purchase Intention forms a central causal chain. This sequence matches the core logic of the S-O-R model, where emotional and functional appraisals act as internal responses to digital stimuli. Moreover, elements such as Ease of Use and Control contribute significantly to the sense of agency and interaction comfort, which aligns with TPB's perceived behavioral control component.

4.3. Fuzzy TOPSIS Findings

To evaluate the behavioral efficacy of digital interaction tools such as virtual influencers and e-commerce chatbots, the Fuzzy TOPSIS method was employed. This approach enabled the ranking of four strategic alternatives based on five decision criteria derived from the thematic analysis and behavioral models: Trust, Empathy, Ease of Use, Purchase Intention, and Responsiveness. The alternatives considered were:

A1: Virtual influencers with high emotional simulation

A2: Standard rule-based e-commerce chatbots

A3: Low-empathy automated agents

A4: Hybrid AI systems combining empathetic virtual influencers and responsive chatbots

After normalization and distance computation, the closeness coefficients (which indicate preference based on proximity to the ideal solution) were calculated. The results are shown below in Table 5, which provides the final ranking of alternatives under equal weighting conditions:

Table 5. Fuzzy DEMATEL Results: Causal Structure and Prominence of Digital Empathy Criteria

Alternative	Closeness Coefficient	Rank
A4 (Hybrid AI)	1.0000	1
A1 (Influencer)	0.5837	2
A2 (Chatbot)	0.1472	3
A3 (Low Empathy)	0.0000	4

As indicated, the hybrid AI approach (A4) significantly outperformed all other options, suggesting that combining emotional resonance (typically associated with influencers) and high responsiveness (associated with chatbots) offers the most consumer-aligned experience. The standalone virtual influencer (A1) also scored well, especially on Trust and Empathy dimensions. Conversely, rule-based chatbots (A2) showed limited appeal, and low-empathy automated agents (A3) were the least preferred.

To assess the robustness of these results, a sensitivity analysis was performed under three weighting schemes:

1. Equal Weights for all five criteria
2. Trust & Empathy Focused weights

3. Functionality Focused (Ease of Use and Purchase Intention prioritized)

Table 5 gives sensivity analysis results across weighting scenarios. The full DEMATEL matrices, normalized criterion weights, and sensitivity analysis scenarios are reported in Appendix A.

Table 6. Sensitivity Analysis Results Across Weighting Scenarios

Alternative	Equal Weights	Trust & Empathy Focused	Functionality Focused
A1	0.5837	0.6110	0.5863
A2	0.1472	0.1566	0.1293
A3	0.0000	0.0000	0.0000
A4	1.0000	1.0000	1.0000

As shown in Table 6, the rankings remained stable under different criteria emphasis. Notably, A4 remained the top-ranked alternative in all configurations, confirming the robustness of the recommendation. A1's performance slightly improved when Trust and Empathy were prioritized, while A2 performed marginally better in the Functionality scenario. A3 consistently ranked last, reflecting its low suitability for emotionally or cognitively engaged consumer environments. These findings align well with behavioral theories: Trust and emotional tone were confirmed as critical antecedents of consumer attitude and intention (Theory of Planned Behavior), while the S-O-R framework highlights the combined effect of stimuli (AI design), organism (consumer emotion/cognition), and response (purchase behavior). The hybrid model (A4) appears to activate both affective and rational dimensions of consumer decision-making effectively.

5. Discussion

This study offers a multidimensional interpretation of how digital empathy shapes consumer behavior in AI-mediated environments by integrating qualitative insights with fuzzy multi-criteria decision-making results through the complementary lenses of the Theory of Planned Behavior (TPB) and the Stimulus–Organism–Response (S-O-R) framework. The findings demonstrate that digital empathy is not a single, homogeneous attribute but rather a configuration of socio-emotional and functional mechanisms that jointly influence consumer attitudes, emotional engagement, perceived behavioral control, and ultimately purchase intention. The convergence between thematic analysis and fuzzy DEMATEL–TOPSIS outcomes provides robust evidence that psychological constructs can be systematically translated into decision-relevant criteria.

From a TPB perspective, the results indicate that attitudes, subjective norms, and perceived behavioral control are substantially shaped by the emotional and interactive capabilities of AI agents. Trust, empathy, and emotional tone emerged as dominant drivers of favorable attitudes toward both virtual influencers and chatbots, indicating that affective cues play a central role in shaping evaluative judgments. Participant narratives illustrate that emotionally expressive agents reduce psychological distance and enhance perceived comfort, thereby strengthening intention formation. These findings align with prior studies showing that empathy-driven interactions increase behavioral intention by reinforcing perceived ease, safety, and control (Rozenkowska, 2023; Ali et al., 2023). Subjective norms also surfaced as influential, particularly through social endorsement and perceived popularity, reinforcing earlier TPB-based evidence that social validation amplifies acceptance in digital consumption contexts (Albayati et al., 2023; Norisnita & Indriati, 2022).

Viewed through the S-O-R framework, digital empathy operates as a stimulus that activates internal cognitive and affective organism-level states—such as warmth, attentiveness, and psychological safety—which then translate into behavioral responses including purchase intention and brand preference. Participants consistently perceived emotionally expressive agents as more engaging stimuli, triggering feelings of being understood and “listened to.” Such responses reflect the S-O-R logic whereby emotionally salient cues intensify internal engagement and subsequently enhance behavioral outcomes. This interpretation is consistent with prior findings in immersive and digital service environments, where emotionally charged stimuli produce stronger downstream behavioral effects (Irimia-Diéguez et al., 2025; Jiang et al., 2024).

A critical distinction emerged among virtual influencers, chatbots, and hybrid AI agents, which helps explain the performance differences observed in the fuzzy MCDM results. Virtual influencers—characterized by anthropomorphic design, expressive features, and social media embeddedness—excelled in socio-emotional digital empathy. Their prominence in the DEMATEL causal structure reflects strong associations with trust, emotional response, and empathy, corroborating earlier research showing that virtual influencers outperform generic bots in emotion-intensive domains such as fashion, lifestyle, and wellness (Bozdağ, 2024; Pan et al., 2024; Rehman et al., 2025). In contrast, chatbots were primarily associated with functional digital empathy, including ease of use, responsiveness, and interface efficiency—attributes particularly valued in task-oriented contexts such as customer service, order tracking, and problem resolution. This supports existing arguments that chatbot effectiveness depends more on speed, clarity, and contextual accuracy than on emotional expressiveness (Song & Shin, 2024; Lay et al., 2024).

The hybrid AI agent outperformed both pure virtual influencers and purely functional chatbots because it simultaneously activated the dominant socio-emotional and functional criteria identified by the fuzzy analyses. The DEMATEL results revealed that trust and emotional response functioned as high-prominence causal drivers, while ease of use, responsiveness, and control & agency reinforced perceived behavioral control. By integrating emotionally resonant cues with efficient task execution, the hybrid agent occupied a unique position at the intersection of attitude formation and perceived control in TPB, while also engaging both organism-level affective states and response-level intentions within the S-O-R framework. This dual activation explains why the hybrid agent achieved the highest TOPSIS rankings across balanced and context-sensitive weighting scenarios, a result further confirmed by sensitivity analysis.

Beyond its statistical prominence, trust emerges as a central construct because it operates as a mechanism that converts empathic cues into behavioral commitment. Participant narratives indicate that trust is not generated by emotional warmth alone but arises from a combination of transparency, consistency, ethical perception, and perceived data security. When AI agents communicate their purpose clearly, respond predictably, avoid manipulative language, and respect user autonomy, perceived risk decreases and psychological safety increases. Moreover, explicit privacy assurances and visible user control—such as understanding how data are used or being able to override recommendations—reinforce trust by strengthening perceived behavioral control. Trust is further sustained through effective service recovery, where acknowledgment of errors, apology, and transparent corrective action prevent negative emotional spillovers. In this sense, trust functions as an integrative mechanism that consolidates affective reactions and functional evaluations into stable purchase intention.

The theoretical contribution of this study lies in its integration of behavioral theory and decision science to explain not only whether empathetic AI agents influence consumer behavior, but why certain configurations outperform others. By combining TPB and S-O-R with fuzzy MCDM techniques, the study advances beyond descriptive interpretations to quantify the causal prominence of psychological constructs such as empathy and trust. Linking TPB's attitudinal and control beliefs to organism-level states in the S-O-R framework clarifies how internal evaluations mediate the effects of digital stimuli on behavioral responses (Hamid & Bano, 2022; Wang et al., 2024). Furthermore, the application of Fuzzy DEMATEL and TOPSIS translates abstract socio-emotional constructs into actionable priorities with measurable decision outcomes, offering a replicable and theory-grounded approach for evaluating emotionally intelligent AI systems.

The findings also yield clear and actionable implications for marketers and AI designers seeking to operationalize digital empathy in practice:

- Embed transparency and trust signaling through clear explanations of system actions, recommendation logic, AI limitations, and visible escalation paths to human support.
- Implement empathic response scripting that acknowledges user emotions, uses context-aware language, and avoids generic phrasing to operationalize emotional tone and empathy.
- Prioritize rapid resolution and responsiveness via minimal interaction steps, proactive suggestions, and fast fallback mechanisms to reinforce perceived behavioral control.
- Enhance user control and agency by enabling users to override recommendations, choose interaction depth, and opt in or out of personalization features.
- Make privacy, data use, and ethical assurances explicit, particularly in sensitive interactions, to reduce perceived risk and sustain trust.

- Design robust service failure recovery mechanisms, including apology scripts, acknowledgment of errors, and transparent corrective actions, to preserve emotional trust during breakdowns.

6. Conclusion

This study examined how digital empathy shapes consumer decision-making in AI-mediated environments by integrating qualitative insights with fuzzy Multi-Criteria Decision-Making (MCDM) methods. Grounded in the Theory of Planned Behavior (TPB) and the Stimulus–Organism–Response (S-O-R) framework, the findings demonstrate that digital empathy operates through both socio-emotional mechanisms (e.g., empathy, emotional response, trust) and functional mechanisms (e.g., ease of use, control & agency), which jointly shape attitudes, perceived behavioral control, and purchase intention in interactions with chatbots and virtual influencers. Thematic analysis revealed that humanlike AI agents are more effective in eliciting empathy and emotional engagement, whereas chatbots are primarily valued for efficiency, responsiveness, and usability. These qualitative patterns were substantiated by the Fuzzy DEMATEL and Fuzzy TOPSIS results, which identified trust and emotional responsiveness as dominant causal drivers, while also highlighting context-dependent differences in the relative effectiveness of virtual influencers and chatbots.

The primary theoretical contribution of this study lies in operationalizing behavioral constructs within a decision science framework. By systematically mapping TPB and S-O-R components onto fuzzy decision matrices, the study advances existing literature by explaining not only what consumers prefer in AI-mediated interactions but also why these preferences emerge across different psychological and contextual conditions. While prior research has examined empathy or trust largely in isolation, this study contributes by integrating these constructs into a structured, transparent, and replicable analytical model that bridges qualitative insights with quantitative prioritization. In doing so, it clarifies the role of trust as a downstream evaluative mechanism, translating empathic perceptions into purchase intention rather than functioning as a purely exogenous antecedent.

From a managerial and design perspective, the findings indicate that a single, uniform approach to digital empathy is insufficient. Emotionally expressive and anthropomorphic features are particularly effective in experience-oriented and brand-driven contexts, such as fashion or wellness e-commerce, where virtual influencers can leverage storytelling, warmth, and social feedback to foster parasocial closeness and trust (Bozdağ, 2024). Conversely, in service-oriented and task-focused contexts, consumers prioritize efficiency, clarity, and control, underscoring the importance of chatbot designs that emphasize responsiveness, interface simplicity, and transparent communication. Consistent with prior studies, the use of emotional language and socially present design elements strengthens satisfaction and purchase intention in conversational commerce (Han, 2021; Yun & Park, 2022; Cai, Gao, & Yan, 2024).

Importantly, the fuzzy MCDM results show that hybrid configurations—combining the emotional engagement of virtual influencers with the functional reliability of chatbots—yield the most favorable outcomes. The Fuzzy TOPSIS rankings confirm that emotional engagement and functional performance act as complementary rather than competing drivers of consumer decision-making. For practitioners, this underscores the strategic value of embedding digital empathy deliberately into AI design, not as an aesthetic enhancement, but as a core mechanism linking psychological engagement to commercial outcomes.

Despite its contributions, this study has limitations. Its cross-sectional design restricts insights into how digital empathy and trust evolve over time, the qualitative sample reflects a limited cultural context, and generational differences were not examined in depth. Future research could address these limitations by adopting longitudinal designs, cross-cultural comparisons, and generational segmentation, as well as by integrating experimental or behavioral data to further validate the causal pathways identified.

In conclusion, digital empathy emerges as a behavioral catalyst rather than a peripheral system feature. When strategically integrated into AI design—through both emotional resonance and functional support—it can simultaneously enhance psychological engagement and drive purchase intention, offering a robust pathway for the development of more effective, trustworthy, and commercially viable AI-mediated consumer interactions.

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