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AI sensation and engagement: Unpacking the sensory experience in human-AI interaction

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ABSTRACT

Given the limited studies on AI sensation and its impact on consumer emotional response and engagement, we investigate its impact to drive engagement. Employing a mixed-methods approach, we began with a qualitative phase consisting of 68 interviews (18 healthcare employees, 37 users of Wearable Health Devices, 7 AI developers, and 6 academics). Grounded in the theories of constructed emotion and the uncanny valley, as well as insights from the qualitative phase, we developed a robust model investigating the role of AI sensation on costumer emotional responses and engagement. This was followed by a survey of 557 healthcare employees. Data analysis was conducted using SPSS for descriptive statistics and reliability assessments, and AMOS for confirmatory factor analysis to validate the robustness of our measurement models. our findings show that AI sensation can drive customer subjective feeling state and AI affects. We also found empirical evidence that both can mediate the relationship between AI sensation, customer subjective feeling state, AI affects and activation engagement. Our findings can offer valuable understanding for managers and AI developers, underscoring the important role of AI sensation for driving engagement.

1. Introduction

The interaction between consumers and emergent technologies has undergone substantial development in recent years (Noble & Mende, 2023; Marvi et al., 2025). Artificial intelligence (AI) stands at the core of this evolution, primed to reshape our understanding of how consumers experience AI through sensory stimuli (Clegg et al., 2024; Puntoni et al., 2021). For example, robots are now commonplace in homes, healthcare settings, hotels, and restaurants, automating numerous aspects of daily life. Virtual bots have transformed customer service into self-service experiences (Roberts & Maier, 2024), while AI applications utilizing big data are replacing traditional portfolio managers (Javelosa, 2017). Additionally, social robots like Pepper are replacing human greeters in customer-facing roles (Choudhury, 2016).

Most AI applications in sensory and consumer science utilize machine learning (ML), primarily for modelling sensory data from panels or consumers (Bertolini et al., 2021). Examples include predicting the sensory attributes of fruits based on physicochemical measurements (Ribeiro et al., 2021), analysing acceptance and sensory characteristics of alcoholic beverages (Fuentes et al., 2020), or meat products (Hernández-Ramos et al., 2020) using spectroscopic data, and assessing the acceptability and sensory profiles of offering based on electronic sensor signals. Furthermore, AI applications in enhancing sensory experience encompass the use of robotics and computer vision to capture preferences and sensory or emotional responses to AI offering (Xi & Hamari, 2021), as well as to determine appearance-related parameters through digital image analysis (Vaid et al., 2023; Marvi et al., 2025).

Against this backdrop, marketers have come to recognise the pivotal role of sensory experience in engaging customers and influencing their decision making. As evidenced by Kantar's (2023) BrandZ Most Valuable Global Brands Report, Apple, renowned for its ability to deliver a superior sensory experience, achieved a market value of USD 6.9 trillion in 2023. Similarly, Visa, emphasising a sensory strategy, ranked as the sixth most valuable global brand with a market value of USD 169,092 million in 2023. It is beyond dispute that a positive sensory experience has now emerged as a critical differentiator when firms consider integrating AI into their business activities.

Despite the importance of sensory experience also gaining significant attention in the existing literature in branding, business and management and consumer research (Guerreiro & Loureiro, 2023; Joy et al., 2023; Roy & Singh, 2023; Zha et al., 2024; 2023), but very little progress has been made in the examination of the psychological architecture of

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the sensory experience process in an AI setting. Building on and integrating ecological and embodiment perspectives, scholars (Schwarz et al., 2021; Zha, Foroudi, Melewar, 2022; Marvi et al., 2024) have proposed sensory experience involves the intrinsic process of sensory data, where sensory information is actualised as sensations, affects, and subjective feeling states. However, this conceptualisation has yet to be operationalised in an AI setting.

Our study addresses this gap by testing how AI-induced sensations influence affects and subjective feeling states. In this AI context, we define sensory experience as comprising three components: *AI sensations,* the initial neurophysiological responses triggered at the interaction between AI stimuli and the consumer's sensory receptors; *AI affects,* the immediate emotional reactions elicited by AI cues; and *subjective feeling states,* the deeper emotional states that arise from integrating and consolidating these affects. This framework provides a structured approach to understanding the complex sensory and emotional responses that AI interactions can evoke in consumers.

In greater depth, extant research studied the impact of sensory experience on different consumer outcomes such as attachment, satisfaction and loyalty (Elder & Krishna, 2022; Shahid et al., 2022). However, a gap remains in understanding whether sensory experience might influence activation engagement. This concept is critical, as activation engagement reflects the extent of users' investment commitment in terms of energy, effort, and time when interacting with AI, including their readiness to invest substantial energy of time (Blut et al., 2023). Sensory triggers may increase action-oriented engagement, encouraging behaviours such as spending more time, leaving comments, sharing content, and expressing positive sentiments about a product/service (Lim et al., 2024). Furthermore, while prior research has explored the managerial and societal impacts of AI (Iveson et al., 2022) and focused on enhancing its functional capabilities to promote adoption (Wang & Uysal, 2024), there remains a gap in understanding how employees perceive and accept AI agents within this framework. In this line and grounded on the above discussions, the current study explores the effect of AI sensations on activation engagement and the moderating role of AI affects and AI subjective feeling states on this relationship.

From a service perspective, empathy is a key factor in fostering engagement during human-AI interactions within a sensory-rich environment. The extent to which AI demonstrates empathetic responses and accurately recognizes user emotions can significantly impact engagement levels, enhancing the quality and depth of user interactions (Huang & Rust, 2024). Moreover, AI literacy—the user's understanding of AI capabilities, limitations, and responsiveness—further influences this dynamic. Users with higher AI literacy may better appreciate and respond to the empathetic cues provided by AI, resulting in more active and meaningful engagement (Polanco-Levicán & Salvo-Garrido, 2022). while those with lower AI literacy may miss or misunderstand these cues, affecting the overall interaction experience. In doing so, it is essential to explore the mediating role of empathy and AI literacy in the relationship between subjective feeling states, AI sensation, AI affects and activation engagement.

Grounded on the theories of constructed emotion and the uncanny valley, alongside literature on sensory experience and artificial intelligence, we developed and operationalized a robust model of sensory experience within an AI context. Our study makes sevral contributes. First, using a mixed-methods approach, we expand current understanding of sensory experience in AI settings by examining its psychological structure—from AI sensations through AI affects to AI subjective feeling states—alongside the moderators, mediators, and behavioural outcomes that shape this process (Zha, Foroudi, Melewar, & Jin, 2022; Zha et al., 2024). Second, our study provides unique insights into how these sensory processes influence activation engagement, particularly in health settings from an employee perspective, offering practical implications for enhancing engagement within human-AI collaboration environments (Huang & Rust, 2024). Finally, by uncovering the mechanisms through which AI sensations drive active engagement—via subjective feeling states and AI affects—this research extends the understanding of sensory experience in AI settings and equips practitioners with strategies to foster meaningful engagement in AI-integrated workplaces.

In the following sections, we begin with the review of AI sensation. Then we provide our results of preliminary qualitative study in order to develop our conceptual framework and theorise the relationship between AI sensation and its outcomes. We then proceed with the hypotheses that were tested in our quantitative study. This research then concludes with the discussion of findings along with theoretical and managerial contributions.

2. Literature review

2.1. The theory of constructed emotion and AI sensory experience (AI sensation, AI affects, and AI subjective feeling states)

The theory of constructed emotion was introduced by Barrett in 2017, representing a ground-breaking paradigm shift in our understanding of emotions. It is based on an emerging computational and evolutionary perspective of the nervous system (Barrett, 2017). This theory, firmly rooted in constructivism, emphasises the role of sensory experiences as a pivotal biopsychological process. It revolves around the consumer's internal processing of neurophysiological information derived from external stimuli, which is then relayed through neural circuits to command centres within the brain. Importantly, the primary focus of this theory is on people themselves rather than AI systems (Barrett & Russell, 2014; Williams & Poehlman, 2017).

Recently, research has underscored the potential applicability of this theory in examining the intricate interplay between cognition and emotion. Two pivotal concepts have emerged: 'core affect,' representing an individual's prevailing affective state, where pleasure and arousal are intrinsic components of any conscious experience, and 'emotions', construed as conscious thoughts (Dreisbach, 2023).

The introduction of this novel perspective has sparked significant advancements in sensory experience, leading to novel conceptual contributions (see, for a review, Foroudi and Foroudi, 2021; Zha, Foroudi, Melewar, & Jin et al., 2022). It is increasingly evident that SBE is a multi-pragmatic concept, comprising a structured process encompassing sensations, affects, and subjective feeling states. In the AI setting, sensation is defined as the raw neurophysiological information of the AI instantiated and generated at the first point of interaction between the AI stimuli and a consumer's sensory receptor. including both exteroceptive and interoceptive data (Zha, Foroudi, Melewar, & Jin et al., 2022). Exteroceptive data are the information of an event through the sense organs; for example, what is the raw information about this event (e.g., the sight of AI outputs, the sound of a song played by AI). Interoceptive data are the condition of an event generated via interoceptive activities at both somatosensory and visceral levels. Therefore, neurophysiology theorists and consumer behaviour researchers (Barrett, 2017; Zha, Foroudi, Jin, & Melewar et al., 2022) argue that multiple sensory modalities such as visual, auditory, tactile, olfactory, and taste provide valuable neurophysiological data about an AI.

While AI affects capture the immediate emotional responses evoked within a AI setting, encompassing valence and arousal, with valence encompassing both positive and negative feelings and arousal manifesting as both activated and inactivated emotions. Subjective feeling states refer to the subjective perception of conscious thought processes (Krishna and Schwarz, 2014; Scherer, 2005).

This perspective carries profound implications for has important implications for machine learning and AI's predictive capabilities, which reshape relationships between actants in AI settings and influence how sensory experiences are represented in consumers' minds (Kautish & Khare, 2022; Petit et al., 2022; Puntoni et al., 2021). As AI continues to evolve within brand settings, there is a pressing need to operationalise the sensory experience model (Zha, Foroud, Jin, & Melewar et al., 2022) specifically in AI contexts. Such an approach would enable companies to leverage neuropsychological data to develop effective marketing strategies, thereby creating memorable multisensory experiences and driving desired behavioural outcomes when consumers use and interact with AI-driven systems.

3. Hypothesis development

3.1. Impact of AI sensation on subjective feeling state

AI systems have the capability to increasingly evoke subjective feeling state (Garvey et al., 2023). Subjective feeling states is defined as the A pre-cognitive sense of an entity results from the merging and integration of related emotions associated with it (Zha, Foroudi, Melewar, & Jin et al., 2022) which can evoke emotion. In this context, when an entity—such as an AI system—displays specific qualities (e.g., visual sensations created by AI) that resonate with users, their brains incorporate these impressions to form an emotional response before they consciously think about it (Hagtvedt, 2022). One participant provided further explanation in this regarding by stating that “When our virtual assistant uses a calming blue colour or gentle screen transitions, it can foster a sense of relaxation and trust over time, making patients feel reassured whenever they interact with it”. AI systems with advanced sensory capabilities can create a responsive and immersive interactive atmosphere for users (Buhalis et al., 2023), generating virtual environments that stimulate sensory experiences and evoke a range of strong emotional responses, from relaxation to excitement. Additionally, AI-driven music recommendations can suggest songs that match users’ moods (Fan et al., 2023), potentially enhancing their subjective feeling state.

Activation engagement is the extent of users’ investment in terms of energy, effort, and time when interacting with AI systems (Blut et al., 2023; Marvi et al., 2023). AI sensory features can create a more appealing, emotion-based environment (Hartmann et al., 2023). A sensory-rich environment can more effectively replicate the feelings associated with real-life, in-person interactions (Oh et al., 2018) and reflect users “real-life” experiences (Humphreys, 2018) encourages them to spend more time interacting. In this line, one participant pointed out that “When AI can mirror real-life experiences with sensory visuals, sounds, or other sensory effects, it creates a familiar, comfortable vibe. It feels more like the real world, which makes people want to hang around and interact more". Thereby, it can be expected that in AI-driven sensory digital environments, users are more likely to engage in real-time experiences (Han et al., 2022; Hartmann et al., 2023), with little, if any, concern about whether the settings accurately reflect reality.

AI affects capture the immediate emotional responses evoked within a brand setting, encompassing valence and arousal, with valence encompassing both positive and negative feelings, and arousal manifesting as both activated and inactivated emotions. Russell (2003) argued that all affects can be boiled down to two dimensions: valence and arousal. Valence—which at its most basic level is the approach and withdrawal reaction—in an advanced stage is represented by the pleasure variable. Arousal, arising from the body’s wanting mechanism, is the body’s estimate of the required physiological and mental mobilization prompted by the brand event. Any specific feeling state is made up of different combinations of valence and arousal (Yik and Russell, 2003). This transition from AI sensations to brand affects provides the study with an AI-denominated nomenclature to describe how sensory inputs from AI settings are translated into the vernacular of the brain (Panksepp, 2011). AI systems are often equipped with number of multiple sensory inputs (e.g., visual and auditory) which can gather more comprehensive data and respond more accurately to user’s emotional state (Du & Xie, 2021) which can then evoke consumers sense of arousal and pleasure. Taken together based on above discussions we propose the following hypotheses:

H (1). : AI sensation can impact on subjective feeling state (H1a), activation engagement (H1b), and AI affects (H1c).

3.2. Mediating role of subjective feeling state and brand affect

Studies which are focused on AI sensation studies’ the view that sensations affect and feeling states are tools that the consumers use for adopting and using AI; that is, the assessment and categorisation of AI events to improve future usage (Biswas, 2019). Firmly rooted in the theory of constructed emotion, AI sensation views feeling states as emotion as constructive events, as the brain’s attempt at making sense of the perturbations emerging from the sub-cortical regions represented by sensations and affects which are raw bodily assessments of consumption events (e.g., volume, duration, or safety). In this instance, sensation helps the consumers to detect a niche potential positive emotion of applying and using virtual environment created by metaverse or AI (Foroudi et al., 2025). As such, positive emotion can result in enhancing how consumers view AI sensation and subsequently drive higher level of engagement. Such alignment between AI sensation and users subjective state can result in a feedback loop that actively and effectively personalise and adopt to users subjective feeling which can foster sense of trust (Ågerfalk, 2020; Vassilakopoulou et al., 2023; Venkatachalam & Ray, 2022) in accommodating users needs. Such positive loop can subsequently drive users to be actively engaged with the metaverse offering.

Whilst AI sensation is the first point of contact between the AI and the organism’s internal environment, AI affect is the pivotal body–mind interface where a value is ascribed to the sensations mined at the interaction event (Barrett 2007). In doing so, the AI the consumption events with an affective tinge or an affective category and, in some instances, an affective signature to single out their uniqueness and to differentiate one event from another. Barrett (2009) noted that “Human brains categorise continuously, effortlessly, relentlessly”. From an evolutionary perspective, she noted, this ability is “biologically preserved” because categorising “confers adaptive advantage” (p.1291). AI systems have the capacity to create a sense of emotional resonance (Loebbecke et al., 2024; Lomas et al., 2022; Wong et al., 2022) which can suit consumers induvial preferences and affect patterns. Such level of personalization to consumers AI affect can then result in consumers to be actively engaged with AI. Taken together based on above discussions we propose the following hypotheses:

H (2). : subjective feeling state (H2a), and brand affect (H2b) can mediate the relationship between AI sensation and activation engagement.

3.3. Moderating role of AI empathy

Empathy refers to the emotional reaction to another individual’s emotional state (Eisenberg & Strayer, 1987). In AI setting, artificial empathy involves expressing human-like cognitive and emotional empathy through computational models in AI system development and deployment (Zhu & Luo, 2024). This concept encompasses integrating empathy into AI agents using AI systems (Asada, 2015). Empathy is acknowledged as crucial for establishing and maintaining interpersonal relationships (Wieseke et al., 2012) between consumers and AI setting. Recent research highlights that employees’ perceptions of AI empathy significantly affect their interactions with AI systems and higher level of empathic responses from AI can make result in how consumer emotionally respond to AI. Similar to how empathetic human employees improve satisfaction and relationship quality (Joireman et al., 2006) and can drive pleasant subjective feeling state and affect, higher empathy in AI interactions can enhance acceptance and trust, thereby increasing user engagement. Further, empathic response is focused on validating consumers feeling experiences and affect (Koopman et al., 2021), therefore, higher level of empathy can make consumer to be feel more supported and understood and thereby increase their sense of pleasure and improve their emotional state (Lin et al., 2022; Yam et al., 2021) and their level of engagement (Hollebeek et al., 2024). Taken together based on above discussions we propose the following hypotheses:

H (3). *: Artificial empathy can moderate the relationship between AI sensation and subjective feeling state (H3a), activation engagement (H3b), and AI Affects (H3c).*

3.4. Moderating role of AI literacy

In recent years, the concept of "literacy" has expanded to encompass a broad array of competencies across various domains, including finance, health, and science. Modern literacies now prioritize skills related to information technology, such as digital literacy, media literacy, information literacy, technology literacy, IT literacy, social media literacy (Polanco-Levicán & Salvo-Garrido, 2022), and digital interaction literacy (Carolus et al., 2023). In AI setting, AI literacy refers to possessing the essential skills needed to navigate, learn, and work in our digital world using AI-driven technologies (Cuomo et al., 2021; Foroudi et al., 2025; Ng et al., 2021; Paul et al., 2024). Higher level of AI litracy can enable consumers to comprehend and understand the capabilities and functionalise of AI more effectively and efficiently (Laupichler et al., 2023).

Such understanding can result in finding a clearer understanding how AI driven systems can respond to consumer emotional state and thereby increase the level of active engagement. Further, users with higher level of AI literacy are more likely to make informed decisions about how using AI technologies (Long, and Magerko, 2020) in which is aligned with their emotional state. Such capability can make these consumers to be more likely actively become engaged. Further, consumers who are more literate in using AI are more likely customize and configure their preferences (Pinski & Benlian, 2024; Laupichler et al., 2023) based on AI affect which subsequently can drive their active engagement. Increased AI literacy can make consumers to interpret and comprehend AI sensory outputs generated by AI driven systems (Ng et al., 2024). Such understanding can allow discern the relevance of AI generated sensation more accurately which can impact on their engagement level (Fig. 1). Taken together based on above discussions we propose the following hypotheses:

H (4. *: AI literacy can moderate the relationship between subjective feeling state (H4a), AI sensation (H4b), AI affects (H4c), and activation engagement*

4. Study methodology and data analysis

In the initial stage of our study, we utilized a qualitative approach to explore the perceptions of AI use among employees in the health sector. We conducted 18 in-depth interviews with healthcare employees, 37 interviews with users of Wearable Health Devices, 7 interviews with AI developers, and 6 interviews with academics. The aim of this qualitative data collection was to uncover gaps and insights related to the integration and application of AI technologies in healthcare settings from the user's perspective. To analyse the interview data, we employed a two-step triangulation method based on Creswell and Miller's (2000) and Foroudi et al. (2023; 2025) recommendations. In the first step, we performed manual coding, developing codes aligned with the research problem, questions, and key constructs. In the second step, experts reviewed the codes, plan, and instructions to ensure the reliability of the results. This systematic coding process, along with the trustworthiness assessment, provided confidence that our findings accurately capture the essence of AI sensation, along with its primary outcomes, moderators, and mediators. Additionally, we used NVivo, a qualitative data analysis software, to systematically manage and analyze the interview transcripts (Foroudi et al., 2014; 2019; 2020). This approach allowed us to comprehensively identify key areas of importance and concern among healthcare users regarding Wearable Health Devices and AI adoption. Based on the qualitative findings, we recognized the importance of investigating the perceived effectiveness and practical challenges of AI tools used by healthcare users. This informed the subsequent quantitative phase of our study.

We conducted a questionnaire survey with 557 global healthcare employees who had experience using AI applications particularly Wearable Health Devices and gathered extensive data on the impact of AI Sensation on AI Activation Engagement. A research company implemented a two-fold sampling approach to gather data efficiently and ensure relevance. First, a convenience sampling strategy was used to access readily available participants without a structured selection

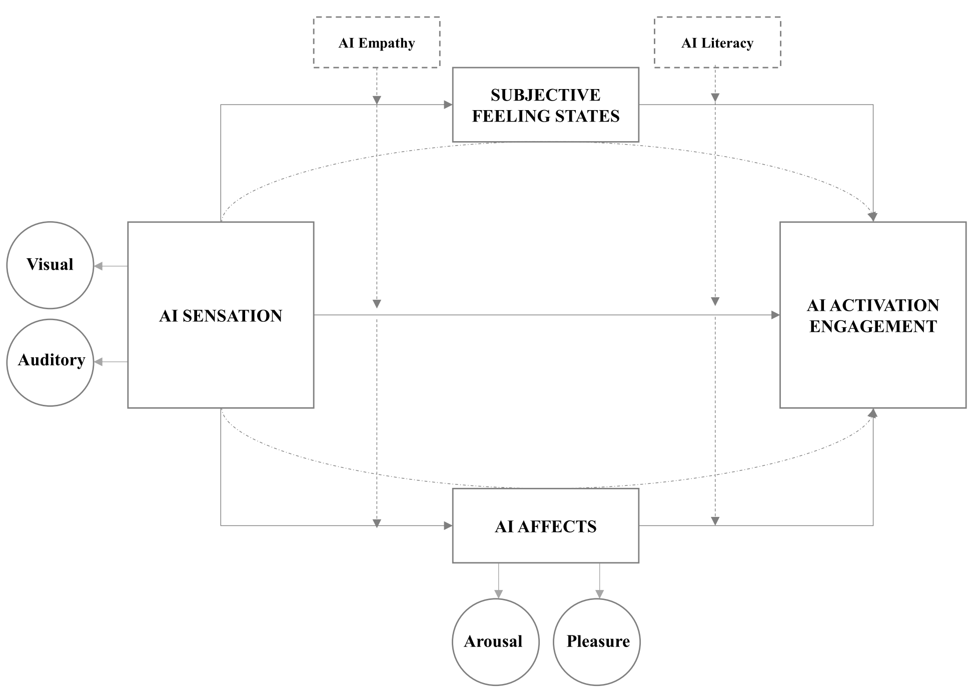

Fig. 1. Conceptual model.

method, allowing for a broad range of perspectives. Second, a purposive sampling method was employed to specifically target subgroups crucial to the research goals, including healthcare employees, AI developers, and academics. This combined approach ensured a comprehensive representation of the healthcare sector, with a focus on those who have direct experience with AI applications, such as Wearable Health Devices. To further validate our findings, we rigorously screened the initial responses, assessing their relevance and accuracy. This process led to the exclusion of 29 data points based on an informant competency check, resulting in a final, high-quality sample of 557 participants.

We employed SPSS for descriptive statistics and reliability assessments, and AMOS for confirmatory factor analysis to ensure the robustness of our measurement models. Our multi-method approach provided a comprehensive understanding of employees' perspectives on AI, facilitating a nuanced analysis of the factors influencing AI Sensation, Subjective Feeling States, and AI Affects on AI Activation Engagement in the health sector. The survey was divided into two sections: (1) demographic information and (2) a 7-point Likert-type scale (1 = strongly disagree, 7 = strongly agree) derived from academic literature and tailored to our specific context. The detailed list of items and their original sources are presented in Table 1. This version omits the exact number of initially collected data points and emphasizes the careful selection process to ensure relevance and quality.

The majority of participants are female (51.5 %), possess postgraduate education (53.5 %), and are aged between 35 and 44 years (39 %) and 45–54 years (34.3 %) (Table 2). To assess potential nonresponse bias, we performed t-tests comparing the initial 50 respondents to the final 50 respondents across all study constructs. The results indicated no statistically significant differences ($p < .05$) between the two groups for any construct. This lack of significant variation implies that nonresponse bias does not pose a significant threat to the integrity of our study's findings.

5. Data examination

We used SPSS (Statistical Package for the Social Sciences) to perform descriptive statistical analysis on the entire sample. The reliability of the constructs was evaluated using Cronbach's alpha, which yielded high scores, aligning with the validity standards established by researchers like Aaker (1997), Churchill (1979), Foroudi (2020); and Foroudi and Dennis (2023). To address potential common method variance, we applied Harman's single-factor test, guided by the recommendations of Lindell and Whitney (2001), Malhotra et al. (2006), and Podsakoff et al. (2003). This process included performing a chi-square difference test between the original model and a fully constrained model across all four datasets, which demonstrated distinct variances among the models, thus mitigating concerns about common method variance. Additionally, we followed Podsakoff et al. (2003) by considering four distinct sources of common method variance. To investigate potential non-response bias, we conducted a Mann-Whitney *U* test comparing the responses of the first 50 respondents with those of the last 50, finding no significant differences. Therefore, non-response bias was not considered an issue, allowing us to measure the model without accounting for method bias. Consequently, confirmatory factor analysis (CFA) was recommended (Foroudi, 2019; 2020; 2023).

For validating the measurement model, we used AMOS (Analysis of Moment Structures) to assess discriminant validity and the overall model quality. We examined composite reliability (CR) and average variance extracted (AVE) to evaluate reliability and convergent validity, respectively (Table 3). The AVE values ranged from 0.703 to 0.888, indicating satisfactory convergent validity. The composite reliability for all constructs exceeded 0.899, confirming that respondents could clearly differentiate the constructs being investigated. After removing overlapping constructs, the CFA results showed a good model fit with Chi-square = 1526.266, Degrees of freedom = 309, RMSEA = .084, CFI = .939, TLI = .931, NFI = .925, IFI = .939, and RFI = .914, which meet

Table 1
Item measurement and reliability.

Construct, Sub-construct, Item measurements, and references			Factor Loading	Mean	Std. Deviation
BRAND SENSATION					
Visual					
Cronbach's alpha = .978					
BSV1	I find the colors used in the design of this AI device very appealing.	Faircloth et al. (2001)	.943	5.2136	2.00699
BSV2	This AI device's design style is appealing to me.	Chebat and Morrin (2007); Chen and Lin (2018)	.927	5.0395	1.99871
BSV3	The brightness and color of this AI device's display are appealing.	The qualitative study	.955	5.1544	2.03332
BSV4	This AI device's lighting and color give off a sleek but appealing vibe.	Foroudi et al. (2020); Chen and Lin (2018)	.943	5.1311	2.05650
BSV5	I find the lighting design of this AI device's display to be very appealing.	The qualitative study	.937	5.0521	2.01946
BSV6	This AI device has an appealing architectural style.	Adapted from Faircloth et al. (2001)			
BSV7	I consistently find the promotional materials for this AI device attractive.	Chebat and Morrin (2007); Chen and Lin (2018)	.918	5.0987	2.03723
BSV8	This AI device's promotional designs always attract my attention.	The qualitative study			
BSV9	The use of imagery in this AI device's interface feels engaging and evokes positive emotions in me.	Adapted from Foroudi et al. (2020); Chen and Lin (2018)			
BSV10	The overall presentation of this AI device consistently maintains a neat appearance.	qualitative study			
Auditory					
Cronbach's alpha = .967					
BSA1	I find the background music of this AI device pleasing.	Chen and Lin (2018)	.911	5.2908	1.49633
BSA2	I find the style of music played with this AI device enjoyable.		.889	5.3070	1.54111
BSA3	The tone of voice in the customer reviews or video demonstrations for this AI device is always pleasant.	The qualitative study	.900	5.2783	1.56276
BSA4	The background noise in the AI device's doesn't bother me.	Booms and Bitner (1982); Bitner (1992)	.909	5.3232	1.50767
BSA5	The sound effects in the AI device's promotional				

(*continued on next page*)

Table 1 (*continued*)

Construct, Sub-construct, Item measurements, and references			Factor Loading	Mean	Std. Deviation
	videos enhance the overall experience.				
BSA6	The narration or voice-over in the AI device's promotional content is clear and engaging.				
BSA7	The audio quality in the AI device's promotional materials meets my expectations.				
SUBJECTIVE FEELING STATES					
Cronbach's alpha = .923					
SFS1	This AI device impresses me.	Brakus et al. (2009); Barnes et al. (2014)	.882	5.3878	1.77525
SFS2	This AI device appears innovative.	The qualitative study	.894	5.3016	1.72546
SFS3	I feel comfortable when looking at this AI device's image.		.895	5.2729	1.81843
SFS4	This AI device seems more convenient compared to my current one.				
SFS5	This AI device is fun to use.				
SFS6	This AI device elicits an extraordinary feeling state.				
SFS7	This AI device is interesting to me.		.785	5.2496	1.96933
SFS8	This AI device elicits an empathetic feeling state.		.770	5.3142	2.00809
BRAND AFFECTS					
Arousal					
Cronbach's alpha = .946					
BAA1	This AI device stimulates my senses.	Chaudhuri and Holbrook, 2001	.892	5.4901	1.71703
BAA2	Interacting with this AI device excites me.		.918	5.5583	1.72025
BAA3	I find this AI device to be energizing.		.905	5.4093	1.76429
BAA4	This AI device captures my attention.				
BAA5	This AI device makes me feel alert.				
Pleasure					
Cronbach's alpha = .966					
BAP1	I enjoy engaging with this AI device.	Chaudhuri and Holbrook, 2001	.886	5.2011	1.74317
BAP2	This AI device makes me feel happy.		.894	5.2549	1.77705
BAP3	Interacting with this AI device brings me joy.		.900	5.1400	1.78174
BAP4	I find this AI device to be satisfying.		.876	5.1885	1.83354
BAP5	I experience pleasure when using this AI device.		.854	5.2262	1.78195
ACTIVATION ENGAGEMENT					
Cronbach's alpha = .960					
ENG1	I intend to spend more time interacting with this AI device.	Coker; 2021; Hollebeek et al., 2014; Mirbagheri and Najmi, 2019	.881	5.3070	1.62849
ENG2	I intend to view comments about this AI device.		.870	5.3950	1.50724
ENG3	I intend to read the information related to this AI device.		.855	5.3357	1.58467
ENG4	I intend to share this AI device with others.		.892	5.2424	1.66550
ENG5	I intend to speak positively about this AI device.				
AI Empathy					
Cronbach's alpha = .942					
AE1	Gen AI in the hotel would understand my specific needs.	Klein et al., 2024: Spieth et al., 2021			
AE2	Gen AI in the hotel would usefully give me individual attention.		.844	4.8241	1.64730
AE3	Gen AI in the hotel would be available whenever it is convenient for me.		.887	4.9408	1.68096
AE4	If I required help, Gen AI in the hotel would do its best to assist me.		.870	4.8959	1.70587
AI Literacy					
Cronbach's alpha = .950					
By using AI,		Adopted from Qualitative Study			
ALY1	I usually support new ideas.		.956	5.5404	1.76004
ALY2	I find most changes pleasing.		.938	5.3860	1.78624
ALY3	I usually benefit from change.		.950	5.3034	1.79514
ALY4	I intend to do whatever possible to support change.				
ALY5	Change usually benefits the organization.				
ALY6	Change usually helps improve unsatisfactory situations at work.				
ALY7	Most of my coworkers benefit from change.				
ALY8	I am inclined to try new ideas.				
ALY9	I look forward to changes at work.				
ALY10	I often suggest new approaches to things.				

Table 2
Sample descriptive characteristics (n = 557).

	Frequency	Percent		Frequency	Percent
Gender			**Age**		
Male	270	48.5	under 25	1	.2
Female	287	51.5	25–34	51	9.2
Education			35–44	217	39.0
PhD	43	7.7	45–54	191	34.3
Postgraduate	298	53.5	55–64	89	16.0
Undergraduate	215	38.6	65 and over	8	1.4
Pre-university	1	.2			

the good fit criteria proposed by Hair et al. (2006).

5.1. Evaluation of hypotheses

To examine the hypotheses, we utilized the PROCESS bootstrapping method developed by Preacher and Hayes (2008), employing 5000 bootstrapped samples with bias-corrected percentile confidence intervals. This technique was complemented by regression analysis in SPSS to evaluate the main effects model. One of the significant advantages of using bootstrapping techniques is that they do not rely on traditional distributional assumptions needed for inferential analyses, as highlighted by Preacher, Rucker and Preacher (2019). Detailed results from our model evaluation can be found in Table 4. The analysis of the direct effects of AI sensation on various outcomes was conducted using Hayes' PROCESS macro.

The analysis supports the hypothesis that AI Sensation positively affects Subjective Feeling States (β=0.05, t = 3.82, p = 0.00), indicating that increased AI Sensation significantly enhances Subjective Feeling States. This result suggests that when users perceive AI in a positive and engaging manner, it enhances their subjective feelings and emotions. Similarly, AI Sensation is found to have a positive effect on AI Affects (β=0.03, t = 5.26, p = 0.00), demonstrating a significant influence of AI Sensation on AI Affects. This implies that users' emotional responses and attitudes towards AI are positively shaped by their sensations and interactions with AI. Additionally, AI Sensation significantly contributes to AI Activation Engagement (β=0.15, t = 3.42, p = 0.00) indicating that positive AI Sensation can drive users to engage more actively with AI technologies. This finding is crucial for designing AI systems that encourage user interaction and engagement.

The hypothesis that Subjective Feeling States positively affect AI Activation Engagement is marginally supported (β=0.06, t = 1.92, p = 0.05). This suggests that while subjective feelings do contribute to AI Activation Engagement, the impact is not as strong. This marginal support could be due to the complex nature of emotions and engagement, where other factors may also play significant roles. Furthermore, AI Affects have a strong positive effect on AI Activation Engagement (β=0.25, t = 5.18, p = 0.00). This strong support indicates that users' emotional responses to AI significantly drive their engagement levels, emphasizing the importance of designing emotionally resonant AI interactions.

Indirect effects analysis reveals that AI Sensation has a positive indirect effect on AI Activation Engagement through Subjective Feeling States (Effect = 0.0923, p = 0.01 [0.0198, 0.1647]), supporting the mediation role of Subjective Feeling States. This means that part of the reason AI Sensation enhances AI Activation Engagement is through improving users' subjective feelings. Similarly, AI Sensation has a positive indirect effect on AI Activation Engagement through AI Affects (Effect = 0.2889, p = 0.00 [0.1936, 0.3842]), confirming the mediation role of AI Affects. This indicates that the positive sensations users experience with AI lead to better engagement primarily through enhancing their emotional responses. Empathy significantly moderates the relationship between AI Sensation and Subjective Feeling States, with a stronger effect at lower levels of Empathy (β=0.4951, t = 5.96,

Table 4
Model estimations.

Variables	Model	
Direct Effects		
AI Sensation -> Subjective feeling states	.05 (3.82), *p* = .00	
AI Sensation -> AI Affect	.03 (5.26), *p* = .00	
AI Sensation -> AI Activation Engagement	.15 (3.42), *p* = .00	
Subjective feeling states -> AI Activation Engagement	.06 (1.92), *p* = .05	
AI Affects -> AI Activation Engagement	.25 (5.18), *p* = .00	
Indirect Effects		
AI Sensation -> Subjective feeling states -> AI Activation Engagement	.0923, p = .01 [.0198,.1647]	
AI Sensation -> AI Affects -> AI Activation Engagement	.2889, p = .00 [1936,.3842]	
Interaction	Low	High
AI Sensation × AI empathy -> Subjective feeling states	.4951 (5.96), *p* = 0.00	.21 (3.45), *p* = .00
AI Sensation × AI empathy -> AI Affects	.70 (11.18), *p* = 0.00	.62 (4.79), *p* = 0.00
AI Sensation × AI empathy -> AI Activation Engagement	.38 (3.13), *p* = 0.00	.09 (2.50), *p* = 0.01
AI Sensation × AI Literacy -> AI Activation Engagement **.004 (.03), *p* = .97**	.39 (3.12), *p* = 0.00	0.14 (2.53), *p* = 0.01
Subjective feeling states × AI Literacy -> AI Affects .12 (1.07), *p* = .28	0.70 (11.1), *p* = 0.00	0.15 (3.37), *p* = 0.00
AI Affects × AI Literacy -> AI Activation Engagement .16 (1.11), *p* = .26	0.10 (.9), *p* = 0.34	.21 (5.95), *p* = 0.00
Gender	.13, *p* = .97	
Age	.07, *p* = .14	
Education	.11, *p* = .48	
F-statistic	20.85, *p* = .00	
R^2	.18	

Notes: Main effects multiple regression analysis SPSS; parallel mediation Hayes Process Model 4;full PROCESS Model 29.
Sample size is 557; t-values are denoted in parentheses; Where Hayes PROCESS does not report the p-values, confidence intervals at 95 % are indicated in square brackets; 5000 samples were used for bootstrapping; We conducted two-sided tests for significance.~
* For simplicity of presentation, indirect effects in the full model are reported as the moderated indirect effects, i.e. at the 84th percentile values of the moderators.

Table 3
Validity, reliability, and correlation matrix.

	CR	AVE	MSV	Pleasure AI Affects	Visual AI Sensation	Auditory AI Sensation	Subjective	Arousal AI Affects	AI Activation Engagement
Pleasure AI Affects	0.966	0.852	0.222	**0.923**					
Visual AI Sensation	0.979	0.884	0.102	0.086	**0.940**				
Auditory AI Sensation	0.966	0.878	0.178	0.402	0.181	**0.937**			
Subjective	0.924	0.714	0.104	0.314	0.187	0.322	**0.845**		
Arousal AI Affects	0.945	0.852	0.102	0.269	0.320	0.311	0.227	**0.923**	
AI Activation Engagement	0.960	0.858	0.222	0.471	0.207	0.422	0.279	0.287	**0.926**

$p = 0.00$) and a weaker yet significant effect at higher levels of Empathy (β=0.21, $t = 3.45$, $p = 0.00$). This suggests that users with lower empathy levels are more influenced by AI Sensation in terms of their subjective feelings compared to those with higher empathy levels.

Similarly, Empathy moderates the relationship between AI Sensation and AI Affects, with a stronger effect at lower levels of Empathy (β=0.70, $t = 11.18$, $p = 0.00$) and a weaker effect at higher levels of Empathy (β=0.62, $t = 4.79$, $p = 0.00$). This indicates that users with lower empathy are more significantly affected by AI Sensation in their emotional responses than those with higher empathy. Furthermore, Empathy moderates the relationship between AI Sensation and AI Activation Engagement, showing a stronger effect at lower levels of Empathy (β=0.38, $t = 3.13$, $p = 0.00$) and a weaker effect at higher levels of Empathy (β=0.09, $t = 2.50$, $p = 0.01$). This suggests that AI Sensation is more impactful in driving engagement among users with lower empathy. The analysis indicates that AI Literacy does not significantly moderate the relationship between AI Sensation and AI Activation Engagement (β=0.004, $t = 0.03$, $p = 0.97$). This non-significant result suggests that regardless of their level of AI literacy, users respond similarly to AI Sensation in terms of engagement. However, AI Sensation has a significant impact on AI Activation Engagement at both low (β=0.39, $t = 3.12$, $p = 0.00$) and high levels of AI Literacy (β=0.14, $t = 2.53$, $p = 0.01$) indicating that the positive impact of AI Sensation on engagement holds across different literacy levels. For example, with Wearable Health Devices like the Apple Watch, whether a user has high or low literacy in AI does not significantly change how the AI's visual and auditory features (such as interactive health summaries and spoken alerts) affect their engagement with the device. Both high-literacy and low-literacy users may show similar levels of engagement with the AI-enhanced feedback mechanisms of the Apple Watch, indicating that the visual and auditory elements are universally engaging, regardless of the users' familiarity with AI.

Although AI Literacy does not significantly moderate the relationship between Subjective Feeling States and AI Affects (β=0.12, $t = 1.07$ $p = 0.28$), Subjective Feeling States significantly impact AI Affects at both low (β=0.70, $t = 11.1$, $p = 0.00$) and high levels of AI Literacy (β=0.15, $t = 3.37$, $p = 0.00$). This suggests that subjective feelings consistently enhance emotional responses to AI across different literacy levels. For example, with Wearable Health Devices, users' emotional responses (AI Affects) to positive interactions (Subjective Feeling States) are similar regardless of their AI literacy. Whether a user is highly knowledgeable about AI or not, their positive emotional response to the device's feedback (like achieving a fitness goal displayed visually and acknowledged by an auditory notification) remains consistent, indicating that the beneficial emotional impact of the AI does not depend on the user's understanding of AI. Lastly, AI Literacy does not significantly moderate the relationship between AI Affects and AI Activation Engagement (β=0.16, $t = 1.11$, $p = 0.26$). This non-significant result implies that the level of AI literacy does not alter how AI affects influence engagement. However, AI Affects have a significant impact on AI Activation Engagement at high levels of AI Literacy (β=0.21, $t = 5.95$, $p = 0.00$), but not at low levels (β=0.10, $t = 0.9$, $p = 0.34$). This indicates that emotional responses to AI are more critical in driving engagement among users with higher AI literacy. For example, with Wearable Health Devices like the Apple Watch, the emotional impact (AI Affects) of encouraging messages and progress tracking provided by the AI leads to increased engagement (AI Activation Engagement) in users. This engagement boost occurs irrespective of whether users are familiar with AI technologies. Both novice and experienced AI users are similarly motivated and engaged by the positive feedback and emotional support provided by the Apple Watch, highlighting that the emotional efficacy of the AI's motivational messages transcends users' AI literacy levels.

6. Discussion

The advancement in technology has shaped fully how consumer perceive and interact with AI technologies. Previous studies (Manis & Madhavaram 2023; Zhan et al., 2024) have examined AI adoption's impact on firm performance primarily from a capability perspective; our research introduces a novel sensory perspective. Specifically, we explore the psychological architecture of sensory experience in an AI context, including its moderators, mediators, and outcomes. This approach provides unique insights into how sensory interactions with AI shape user engagement, distinguishing our study from existing capability-focused research and broadening the understanding of AI's impact on employees' AI sensory experiences including AI sensations, AI affects and AI subjective feeling states. To this end, by combining qualitative and quantitative approach, we tried to understand how AI sensation can have different outcomes. As such, this study addresses previous calls on developing novel theoretical mechanism to evaluate and address consumers emotions when interacting with AI sensation (Deryl et al., 2023; Huang & Rust, 2024; Zhang et al., 2024). Doing so can have number of theoretical and managerial implications being discussed in below.

6.1. Theoretical contributions and implications

The sensory experience model developed and operationalized in this study offers an integrated perspective on AI sensory interactions, encompassing key processes, outcomes, moderators, and mediators. This model provides a novel understanding of AI sensory experience as a series of interconnected processes, capturing the progression from AI sensations to emotional and engagement outcomes. To our knowledge, this is the first research to operationalize sensory experience in an AI context using the theories of constructed emotion and the uncanny valley, while also validating the recent conceptualization by Zha, Foroudi, Jin, and Melewar (2022). Our model serves as a foundational framework for future studies on AI sensory experience, enabling further development and exploration of sensory dynamics in AI interactions.

Additionally, our work expands current literature on human-AI interactions by emphasizing the moderating roles of AI empathy and AI literacy on the relationship between sensory experience and engagement (Huang & Rust, 2024). While AI capabilities are fundamental, our findings reveal that psychological processes within sensory experience play a pivotal role in fostering user engagement. Interestingly, our results suggest that higher levels of AI empathy can sometimes evoke discomfort rather than positive engagement. This aligns with the uncanny valley theory (Mende et al., 2019; Crolic et al., 2022), which posits that AI perceived as overly human-like, particularly in demonstrating empathy, may provoke unease in users (Marvi et al., 2024; 2025). However, it is also important to recognize that AI lacks true emotional understanding and subjective consciousness. Its expressions of empathy are based on algorithms that simulate affective responses using predefined rules or trained patterns. This computational mimicry means that AI can misinterpret emotional cues, particularly in nuanced or culturally specific contexts, leading to erroneous or inappropriate responses. As such, AI empathy should be designed with functional limitations in mind, clearly signalling to users that the AI is supportive but not sentient. Addressing this constraint in AI design ensures transparency, user trust, and ethical alignment, especially in emotionally sensitive applications like healthcare or customer support.

In this context, a nuanced approach to AI empathy entails designing AI systems that express context-appropriate emotional responses rather than mimicking full-spectrum human emotions. This includes calibrating empathic expressions to match users' needs and the interaction setting, such as using subtle verbal affirmations, adaptive tone modulation, or limited emotional cues, to demonstrate attentiveness without triggering discomfort. For example, rather than replicating human-like emotional depth (e.g., sadness, sympathy), AI should instead convey empathy through functional emotional resonance, acknowledging user concerns and offering relevant support—thereby maintaining user trust without entering the 'uncanny valley' zone. This approach avoids over-humanization while preserving affective utility.

Our study also contributes to the information management literature by identifying AI sensations as the crucial initial point of interaction in AI sensory environments, demonstrating that these sensations drive immediate emotional responses that can heighten user engagement. By investigating each component of the sensory experience process in a healthcare setting, we provide practical insights into how sensory experiences shape user interactions in AI-integrated environments. Our findings build on previous research showing sensory experience as a component of brand experience affecting various outcomes (Clegg et al., 2024; Noble & Mende, 2023). However, unlike prior studies focused solely on end outcomes, this study examines the fundamental role of AI sensations in influencing subjective feelings, AI affects, and activation engagement, revealing the moderating impact of AI empathy and literacy. In doing so, we contribute significantly to an emerging area of research, providing a nuanced understanding of how sensory experiences within AI interactions can drive meaningful user engagement in various applications, particularly in human-AI collaboration.

6.1.1. Managerial implications

This study provides impactful managerial contributions for both marketers and AI key decision-makers, providing guidance on crafting effective multi-sensory strategies to enhance AI activation engagement. By emphasizing the role of sensory management, this research equips marketers and AI developers with a deeper understanding of how sensory experiences impact engagement, benefiting both firms and consumers. Additionally, this study serves as a resource for marketers seeking to educate managers on the skills and knowledge necessary to leverage a multisensory approach in integrating AI into consumer-facing systems. Thus, new AI systems should develop and be more focused on developing sensational experiences with consumers, particularly in settings where interaction with human personnel are limited. Practitioners can use our findings as guidance when developing AI sensational based experience to drive AI activation engagement. Specifically, AI developers and service designers should prioritize multi-sensory design strategies that incorporate visually engaging interfaces (e.g., dynamic color palettes, responsive lighting cues) and emotionally resonant auditory feedback (e.g., soothing voice tones, personalized sound alerts). For instance, in healthcare settings, wearable devices or virtual assistants can be designed to adapt sensory outputs based on the user's emotional state, enhancing comfort, trust, and continued interaction. Moreover, personalizing sensory elements to user preferences, especially in terms of visual stimuli and auditory cues, can help reduce perceived detachment often associated with AI and foster stronger affective connections. Firms should also invest in user training and onboarding programs to improve AI literacy, ensuring that users understand how these sensory features function and how they can be customized to enhance their individual experience. Additionally, managers are advised to implement continuous feedback loops, allowing users to report their sensory experiences and emotional reactions, thereby enabling ongoing AI refinement and more emotionally intelligent interaction.

7. Limitations and future studies

Despite all the contributions, this study is subject to number of limitations. Firstly, this study did not address the intensity of consumer emotional response when faced with AI. Therefore, future research could explore: *How the intensity of AI-induced sensations influences the frequency and persistence of consumer emotion over time.*? For example, adopting a longitudinal approach examining the impact of AI sensation on the chronometry of emotional response would provide new insights. Further, in this study, we were only focused on consumer positive emotional responses. Future studies are encouraged to examine a broader range of emotional responses, especially negative emotions. Key questions for future exploration include: *What types of negative emotions (e.g., disappointment, guilt, envy) might consumers experience in response to AI sensations?* and *how do these emotions affect consumer perceptions and engagement with AI?* Investigating these aspects could help expand the spectrum of emotions AI interactions can evoke, offering a more comprehensive understanding of the consumer-AI emotional landscape.

CRediT authorship contribution statement

Marvi Reza: Writing – original draft, Conceptualization. **Forouudi Pantea:** Writing – original draft, Visualization, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Zha Dongmei:** Writing – original draft, Conceptualization.

Declaration of Competing Interest

The authors declare no conflict of interest. The research was conducted independently without any influence or support from any commercial entity that could benefit from the results of this study. All procedures performed in this study involving human participants were in accordance with ethical standards and approved by the appropriate ethics committee.

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References

Ågerfalk, P. J. (2020). Artificial intelligence as digital agency. *European Journal of Information Systems, 29*(1), 1–8.
Barnes, S. J., Mattsson, J., & Sørensen, F. (2014). Destination brand experience and visitor behavior: Testing a scale in the tourism context. *Annals of tourism research, 48*(2), 121–139.
Barrett, L. F. (2009). The future of psychology: Connecting mind to brain. *Perspectives on psychological science, 4*(4), 326–339.
Barrett, L. F. (2017). The theory of constructed emotion: an active inference account of interoception and categorization. *Social cognitive and affective neuroscience, 12*(1), 1–23.
Bertolini, M., Mezzogori, D., Neroni, M., & Zammori, F. (2021). Machine Learning for industrial applications: A comprehensive literature review. *Expert Systems with Applications, 175*, Article 114820.
Biswas, D. (2019). Sensory aspects of retailing: Theoretical and practical implications. *Journal of Retailing, 95*(4), 111–115.
Blut, M., Kulikovskaja, V., Hubert, M., Brock, C., & Grewal, D. (2023). Effectiveness of engagement initiatives across engagement platforms: A meta-analysis. *Journal of the Academy of Marketing Science, 51*(5), 941–965.
Buhalis, D., Leung, D., & Lin, M. (2023). Metaverse as a disruptive technology revolutionising tourism management and marketing. *Tourism Management, 97*, Article 104724.
Carolus, A., Augustin, Y., Markus, A., & Wienrich, C. (2023). Digital interaction literacy model–Conceptualizing competencies for literate interactions with voice-based AI systems. *Computers and Education: Artificial Intelligence, 4*, Article 100114.
Chen, H. T., & Lin, Y. T. (2018). A study of the relationships among sensory experience, emotion, and buying behavior in coffeehouse chains. *Service Business, 12*, 551–573.
Clegg, M., Hofstetter, R., de Bellis, E., & Schmitt, B. H. (2024). Unveiling the mind of the machine. *Journal of Consumer Research, 51*(2), 342–361.
Creswell, J. W., & Miller, D. L. (2000). Determining validity in qualitative inquiry. *Theory Into Practice, 39*(3), 124–130.
Cuomo, M. T., Tortora, D., Foroudi, P., Giordano, A., Festa, G., & Metallo, G. (2021). Digital transformation and tourist experience co-design: Big social data for planning cultural tourism. *Technological Forecasting and Social Change, 162*, Article 120345.
Deryl, M. D., Verma, S., & Srivastava, V. (2023). How does AI drive branding? Towards an integrated theoretical framework for AI-driven branding. *International Journal of Information Management Data Insights, 3*(2), Article 100205.
Du, S., & Xie, C. (2021). Paradoxes of artificial intelligence in consumer markets: Ethical challenges and opportunities. *Journal of Business Research, 129*, 961–974.
Elder, R. S., & Krishna, A. (2022). A review of sensory imagery for consumer psychology. *Journal of Consumer Psychology, 32*(2), 293–315.
Faircloth, J. B., Capella, L. M., & Alford, B. L. (2001). The effect of brand attitude and brand image on brand equity. *Journal of marketing theory and practice, 9*(3), 61–75.
Fan, Y., Wong, I. A., & Lin, Z. C. (2023). How folk music induces destination image: A synthesis between sensory marketing and cognitive balance theory. *Tourism Management Perspectives, 47*, Article 101123.
Foroudi, P. (2019). Influence of brand signature, brand awareness, brand attitude, brand reputation on hotel industry's brand performance. *International journal of hospitality management, 76*, 271–285.

Foroudi, P. (2020). Corporate brand strategy: drivers and outcomes of hotel industry's brand orientation. *International Journal of Hospitality Management, 88*, Article 102519.

Foroudi, P. (2023). Conceptualizing, measuring, and managing marketing assets: developing the marketing assets, communication focus, and capability nexus. *Corporate Reputation Review, 26*(3), 203–222.

Foroudi, M. M., Balmer, J. M., Chen, W., & Foroudi, P. (2019). Relationship between corporate identity, place architecture and identification: An exploratory case study. *Qualitative Market Research: An International Journal, 22*(5), 638–668.

Foroudi, M. M., Balmer, J. M., Chen, W., Foroudi, P., & Patsala, P. (2020). Explicating place identity attitudes, place architecture attitudes, and identification triad theory. *Journal of Business Research, 109*, 321–336.

Foroudi, P., Marvi, R., Cuomo, M. T., Bagozzi, R., Dennis, C., & Jannelli, R. (2023). Consumer perceptions of sustainable development goals: conceptualization, measurement and contingent effects. *British Journal of Management, 34*(3), 1157–1183.

Foroudi, P., Marvi, R., Cuomo, M. T., & D'Amato, A. (2025). Sustainable Development Goals in a regional context: conceptualising, measuring and managing residents' perceptions. *Regional Studies, 59*(1), Article 2373871.

Foroudi, P., Marvi, R., Zha, D., Kooli, K., & Bagozzi, R. (2025). Metaverse in hospitality and tourism in the International Journal of Contemporary Hospitality Management: Guest Editorial. *International Journal of Contemporary Hospitality Management, 37*(4), 1037–1044.

Foroudi, P., Melewar, T. C., & Gupta, S. (2014). Linking corporate logo, corporate image, and reputation: An examination of consumer perceptions in the financial setting. *Journal of Business Research, 67*(11), 2269–2281.

Foroudi, M. M., & Foroudi, P. (2021). Corporate Brand Design. London: Routledge. https://doi. org/10.4324/9781003054153.

Foroudi, P., & Dennis, C. (Eds.). (2023). Researching and analysing business: Research methods in practice. Taylor & Francis.

Fuentes, S., Torrico, D. D., Tongson, E., & Gonzalez Viejo, C. (2020). Machine learning modeling of wine sensory profiles and color of vertical vintages of pinot noir based on chemical fingerprinting, weather and management data. *Sensors, 20*(13), 3618.

Garvey, A. M., Kim, T., & Duhachek, A. (2023). Bad news? Send an AI. Good news? Send a human. *Journal of Marketing, 87*(1), 10–25.

Guerreiro, J., & Loureiro, S. M. C. (2023). I am attracted to my cool smart assistant! Analyzing attachment-aversion in AI-human relationships. *Journal of Business Research, 161*, Article 113863.

Han, P., Su, T., & Hummel, T. (2022). Human odor exploration behavior is influenced by olfactory function and interest in the sense of smell. *Physiology & Behavior, 249*, Article 113762.

Hartmann, J., Bergner, A., & Hildebrand, C. (2023). MindMiner: Uncovering linguistic markers of mind perception as a new lens to understand consumer–smart object relationships. *Journal of Consumer Psychology, 33*(4), 645–667.

Hernández-Ramos, P., Vivar-Quintana, A. M., Revilla, I., González-Martín, M. I., Hernández-Jiménez, M., & Martínez-Martín, I. (2020). Prediction of sensory parameters of cured ham: A study of the viability of the use of nir spectroscopy and artificial neural networks. *Sensors, 20*(19), 5624.

Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014). Consumer brand engagement in social media: Conceptualization, scale development and validation. *Journal of interactive marketing, 28*(2), 149–165.

Hollebeek, L. D., Menidjel, C., Sarstedt, M., Jansson, J., & Urbonavicius, S. (2024). Engaging consumers through artificially intelligent technologies: Systematic review, conceptual model, and further research. *Psychology Marketing, 41*(4), 880–898.

Huang, M. H., & Rust, R. T. (2024). The caring machine: Feeling AI for customer care. *Journal of Marketing*.

Humphreys, L. (2018). *The qualified self: Social media and the accounting of everyday life*. MIT Press.

Iveson, A., Hultman, M., & Davvetas, V. (2022). The product life cycle revisited: an integrative review and research agenda. *European Journal of Marketing, 56*(2), 467–499.

Joireman, J., Kamdar, D., Daniels, D., & Duell, B. (2006). Good citizens to the end? It depends: Empathy and concern with future consequences moderate the impact of a short-term time horizon on organizational citizenship behaviors. *Journal of Applied Psychology, 91*(6), 1307.

Joy, A., Wang, J. J., Orazi, D. C., Yoon, S., LaTour, K., & Peña, C. (2023). Co-creating affective atmospheres in retail experience. *Journal of Retailing, 99*(2), 297–317.

Kantar, (2023) BrandZ Global Report, access at: ⟨https://www.kantar.com/campaigns/brandz/global⟩.

Kautish, P., & Khare, A. (2022). Investigating the moderating role of AI-enabled services on flow and awe experience. *International Journal of Information Management, 66*, Article 102519.

Klein, U., Depping, J., Wohlfahrt, L., & Fassbender, P. (2024). Application of artificial intelligence: risk perception and trust in the work context with different impact levels and task types. *AI & SOCIETY, 39*(5), 2445–2456.

Koopman, J., Conway, J. M., Dimotakis, N., Tepper, B. J., Lee, Y. E., Rogelberg, S. G., & Lount, R. B., Jr (2021). Does CWB repair negative affective states, or generate them? Examining the moderating role of trait empathy. *Journal of Applied Psychology, 106*(10), 1493.

Laupichler, M. C., Aster, A., Haverkamp, N., & Raupach, T. (2023). Development of the "Scale for the assessment of non-experts' AI literacy"–An exploratory factor analysis. *Computers in Human Behavior Reports, 12*, Article 100338.

Lim, L. X., Medina-Plaza, C., Arías-Perez, I., Wen, Y., Neupane, B., Lerno, L., & Oberholster, A. (2024). Using sensory and instrumental analysis to assess the impact of grape smoke exposure on different red wine varietals in California. *Scientific Reports, 14*(1), 27033.

Lin, S. H. J., Poulton, E. C., Tu, M. H., & Xu, M. (2022). The consequences of empathic concern for the actors themselves: Understanding empathic concern through conservation of resources and work-home resources perspectives. *Journal of Applied Psychology, 107*(10), 1843.

Loebbecke, C., Obeng-Antwi, A., Boboschko, I., & Cremer, S. (2024). Towards AI-based thumbnail design for fostering consumption on digital media platforms. *International Journal of Information Management, 78*, Article 102801.

Lomas, J. D., Lin, A., Dikker, S., Forster, D., Lupetti, M. L., Huisman, G., & Cross, E. S. (2022). Resonance as a design strategy for AI and social robots. *Frontiers in Neurorobotics, 16*, Article 850489.

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. April *In Proceedings of the 2020 CHI conference on human factors in computing systems*, 1–16.

Marvi, R., Foroudi, P., & AmirDadbar, N. (2025). Dynamics of user engagement: AI mastery goal and the paradox mindset in AI–employee collaboration. *International Journal of Information Management, 83*, Article 102908.

Marvi, R., Foroudi, P., & Cuomo, M. T. (2024). Past, present and future of AI in marketing and knowledge management. *Journal of Knowledge Management, 29*(11), 1–31.

Mende, M., Scott, M. L., Van Doorn, J., Grewal, D., & Shanks, I. (2019). Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *Journal of Marketing Research, 56*(4), 535–556.

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence, 2*, Article 100041.

Ng, D. T. K., Wu, W., Leung, J. K. L., Chiu, T. K. F., & Chu, S. K. W. (2024). Design and validation of the AI literacy questionnaire: The affective, behavioural, cognitive and ethical approach. *British Journal of Educational Technology, 55*(3), 1082–1104.

Noble, S. M., & Mende, M. (2023). The future of artificial intelligence and robotics in the retail and service sector: Sketching the field of consumer-robot-experiences. *Journal of the Academy of Marketing Science, 51*(4), 747–756.

Oh, C. S., Bailenson, J. N., & Welch, G. F. (2018). A systematic review of social presence: Definition, antecedents, and implications. *Frontiers in Robotics and AI, 5*, Article 409295.

Paul, J., Ueno, A., Dennis, C., Alamanos, E., Curtis, L., Foroudi, P., & Wirtz, J. (2024). Digital transformation: A multidisciplinary perspective and future research agenda. *International Journal of Consumer Studies, 48*(2), Article e13015.

Petit, O., Velasco, C., Wang, Q. J., & Spence, C. (2022). Consumer consciousness in multisensory extended reality. *Frontiers in Psychology, 13*, Article 851753.

Pinski, M., & Benlian, A. (2024). AI literacy for users–A comprehensive review and future research directions of learning methods, components, and effects. *Computers in Human Behavior: Artificial Humans*, Article 100062.

Polanco-Levicán, K., & Salvo-Garrido, S. (2022). Understanding social media literacy: A systematic review of the concept and its competences. *International journal of environmental research and public health, 19*(14), 8807.

Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and artificial intelligence: An experiential perspective. *Journal of Marketing, 85*(1), 131–151.

Ribeiro, M. N., Carvalho, I. A., Fonseca, G. A., Lago, R. C., Rocha, L. C., Ferreira, D. D., … Pinheiro, A. C. (2021). Quality control of fresh strawberries by a random forest model. *Journal of the Science of Food and Agriculture, 101*(11), 4514–4522.

Roberts, C., & Maier, T. (2024). The evolution of service toward automated customer assistance: There is a difference. *International Journal of Contemporary Hospitality Management, 36*(6), 1914–1925.

Roy, S., & Singh, P. (2023). The olfactory experience (in retail) scale: Construction, validation and generalization. *Journal of Service Management, 34*(3), 403–432.

Rucker, D. D., & Preacher, K. J. (2019). Models, Methods, and Considerations. *Handbook of Research Methods in Consumer Psychology*, 373.

Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychological review, 110*(1), 145.

Scherer, K. R. (2005). What are emotions? And how can they be measured? *Social science information, 44*(4), 695–729.

Schwarz, N., Jalbert, M., Noah, T., & Zhang, L. (2021). *Metacognitive experiences as information: Processing fluency in consumer judging- men*.

Shahid, S., Paul, J., Gilal, F. G., & Ansari, S. (2022). The role of sensory marketing and brand experience in building emotional attachment and brand loyalty in luxury retail stores. *Psychology Marketing, 39*(7), 1398–1412.

Spieth, P., Röth, T., Clauss, T., & Klos, C. (2021). Technological frames in the digital age: Theory, measurement instrument, and future research areas. *Journal of Management Studies, 58*(7), 1962–1993.

Vaid, S., Puntoni, S., & Khodr, A. (2023). Artificial intelligence and empirical consumer research: A topic modeling analysis. *Journal of Business Research, 166*, Article 114110.

Vassilakopoulou, P., Haug, A., Salvesen, L. M., & Pappas, I. O. (2023). Developing human/AI interactions for chat-based customer services: Lessons learned from the Norwegian government. *European Journal of Information Systems, 32*(1), 10–22.

Venkatachalam, P., & Ray, S. (2022). How do context-aware artificial intelligence algorithms used in fitness recommender systems? A literature review and research agenda. *International Journal of Information Management Data Insights, 2*(2), Article 100139.

Wang, Y. C., & Uysal, M. (2024). Artificial intelligence-assisted mindfulness in tourism, hospitality, and events. *International Journal of Contemporary Hospitality Management, 36*(4), 1262–1278.

Wieseke, J., Geigenmüller, A., & Kraus, F. (2012). On the role of empathy in customer-employee interactions. *Journal of service research, 15*(3), 316–331.

Wong, L. W., Lee, V. H., Tan, G. W. H., Ooi, K. B., & Sohal, A. (2022). The role of cybersecurity and policy awareness in shifting employee compliance attitudes:

Building supply chain capabilities. *International Journal of Information Management, 66*, Article 102520.

Xi, N., & Hamari, J. (2021). Shopping in virtual reality: A literature review and future agenda. *Journal of Business Research, 134*, 37–58.

Yam, K. C., Bigman, Y. E., Tang, P. M., Ilies, R., De Cremer, D., Soh, H., & Gray, K. (2021). Robots at work: People prefer—and forgive—service robots with perceived feelings. *Journal of Applied Psychology, 106*(10), 1557.

Zha, D., Foroudi, P., Jin, Z., & Melewar, T. C. (2022b). Making sense of sensory brand experience: Constructing an integrative framework for future research. *International Journal of Management Reviews, 24*(1), 130–167.

Zha, D., Foroudi, P., Melewar, T. C., & Jin, Z. (2022). Experiencing the sense of the brand: The mining, processing and application of brand data through sensory brand experiences. *Qualitative Market Research An International Journal, 25*(2), 205–232.

Zha, D., Foroudi, P., Melewar, T. C., & Jin, Z. (2024). Examining the impact of sensory brand experience on brand loyalty. *Corporate Reputation Review*, 1–29.

Zha, D., Marvi, R., & Foroudi, P. (2023). Synthesizing the customer experience concept: A multimodularity approach. *Journal of Business Research, 167*, Article 114185.

Zha, D., Marvi, R., & Foroudi, P. (2024). Embracing the paradox of customer experiences in the hospitality and tourism industry. *International Journal of Management Reviews, 26*(2), 163–186.

Zhan, Y., Xiong, Y., Han, R., Lam, H. K., & Blome, C. (2024). The impact of artificial intelligence adoption for business-to-business marketing on shareholder reaction: A social actor perspective. *International journal of information management, 76*, Article 102768.

Zhang, J., Chen, Q., Lu, J., Wang, X., Liu, L., & Feng, Y. (2024). Emotional expression by artificial intelligence chatbots to improve customer satisfaction: Underlying mechanism and boundary conditions. *Tourism Management, 100*, Article 104835.

Zhu, Q., & Luo, J. (2024). Toward artificial empathy for human-centered design. *Journal of Mechanical Design, 146*, 6.