How Do Consumers Respond to Ads That Emphasize a Company's Human, Artificial Intelligence, or Hybrid Workforce Composition?

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Abstract

Title: How Do Consumers Respond to Ads That Emphasize a Company's Human, Artificial Intelligence, or Hybrid Workforce Composition? *An Experimental Study Using an Artisan Coffee Brand Context*

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The increasing integration of artificial intelligence into production processes presents a strategic challenge for brands, particularly in product categories associated with craftsmanship and human expertise. While AI signals efficiency and innovation, its communication may undermine perceptions of authenticity and trust. This study examines how advertising narratives emphasizing human-only, AI-only, or human–AI hybrid workforce compositions shape consumer responses in the context of specialty coffee. Using a between-subjects experimental design, participants were randomly exposed to one of three coffee advertisements differing only in production framing. The study assessed perceived authenticity, trust, innovation, efficiency, and purchase intention, while also testing the moderating roles of attitudes toward AI and product involvement. The results reveal a clear functional–emotional trade-off. Human production narratives generated the highest levels of authenticity, trust, and purchase intention, whereas AI production narratives maximized perceptions of innovation and efficiency but incurred significant emotional penalties. Hybrid production narratives produced intermediate evaluations, mitigating but not fully eliminating the drawbacks of full automation. Positive attitudes toward AI increased acceptance of AI and hybrid production, while high product involvement intensified resistance to AI-only narratives. Overall, the findings demonstrate that workforce composition functions as a salient communicative cue rather than a neutral operational detail. For managers, the results highlight the importance of framing AI as a collaborative tool and aligning production narratives with audience characteristics.

Keywords: Artificial Intelligence, Hybrid Workforce, Consumer Perception, Brand Communication, Emotional Resistance, Functional Value

Sumário

Título: Como os Consumidores Respondem a Anúncios Que Enfatizam a Composição da Força de Trabalho de uma Empresa: Humana, Inteligência Artificial ou Híbrida? Um Estudo Experimental Usando o Contexto de uma Marca Artesanal de Café
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A crescente integração da inteligência artificial (IA) nos processos produtivos coloca desafios estratégicos às marcas, especialmente em categorias associadas ao artesanato e à expertise humana. Embora a IA sinalize eficiência e inovação, a sua comunicação pode comprometer percepções de autenticidade e confiança. Este estudo analisa como diferentes narrativas publicitárias sobre a composição da força de trabalho humana, baseada em IA ou híbrida humano–IA influenciam as avaliações dos consumidores no contexto do café de especialidade. Foi conduzido um experimento entre sujeitos, no qual os participantes foram expostos aleatoriamente a um de três anúncios de café que variavam apenas quanto à descrição do processo produtivo. Foram avaliadas percepções de autenticidade, confiança, inovação, eficiência e intenção de compra, bem como os efeitos moderadores das atitudes em relação à IA e do envolvimento com o produto.
Os resultados evidenciam um trade-off funcional–emocional. Narrativas de produção humana geraram maiores níveis de autenticidade, confiança e intenção de compra, enquanto narrativas baseadas em IA maximizaram percepções de inovação e eficiência, mas com penalizações emocionais. A produção híbrida apresentou avaliações intermédias. Atitudes positivas em relação à IA aumentaram a aceitação da tecnologia, enquanto elevado envolvimento com o produto intensificou a rejeição da produção exclusivamente baseada em IA.
Conclui-se que a composição da força de trabalho atua como um sinal comunicacional central, com implicações diretas para a estratégia de comunicação das marcas.

Palavras-chave: Inteligência Artificial, Força de Trabalho Híbrida, Percepção do Consumidor, Comunicação de Marca, Resistência Emocional, Valor Funcional, Envolvimento com o Produto.

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List of Abbreviations

AI – Artificial Intelligence

CBBE – Customer-Based Brand Equity

ELM – Elaboration Likelihood Model

H1 – Hypothesis 1

H2 – Hypothesis 2

H3 – Hypothesis 3

H4 – Hypothesis 4

M – Mean

SD – Standard Deviation

α – Cronbach's Alpha

r – Pearson Correlation Coefficient

p – Probability Value (Significance Level)

N – Sample Size

RQ – Research Question

SPSS – Statistical Package for the Social Sciences

***Acknowledgment**: In the preparation of this thesis, AI was employed to enhance language clarity, readability, and grammatical accuracy for a more refined presentation. However, all ideas, arguments, and perspectives presented remain entirely the original work of the author.*

1. Introduction

Artificial intelligence (AI) is increasingly recognized as a transformative general-purpose technology, reshaping not only operational efficiency but also the ways in which commercial value is created and communicated to consumers (Davenport et al., 2020; Huang & Rust, 2021). Early applications of AI were largely confined to back-end organizational functions, such as logistics optimization, forecasting, and data analytics (Jain & Kumar, 2024). More recent advances in machine learning and generative AI, however, have expanded its role into visible, customer-facing domains, including product design, creative content generation, and personalized marketing communication (Hermann & Puntoni, 2024; Jain & Kumar, 2024). As AI becomes increasingly present in these front-end activities, long-standing consumer beliefs about authorship, craftsmanship, and the role of human involvement in production may be fundamentally challenged, particularly in categories where human effort has traditionally carried symbolic meaning (Fuchs et al., 2015; Morhart et al., 2015).

The growing visibility of AI in value creation introduces a central strategic and theoretical tension for contemporary brands. On the one hand, AI offers well-documented advantages such as scalability, precision, efficiency, and the ability to support innovation at unprecedented speed (Longoni et al., 2019; Huang & Rust, 2021). Communicating AI involvement may therefore signal competence, modernity, and technological leadership. On the other hand, research suggests that explicit disclosures of AI involvement often elicit ambivalent or negative consumer reactions, particularly when products are perceived as lacking human effort or emotional investment (Longoni & Cian, 2022; Newman & Bloom, 2012). These reactions are closely linked to the competence–warmth trade-off identified in social cognition research, whereby AI is generally perceived as highly competent but low in warmth and benevolent intent (Fiske et al., 2007; Aaker et al., 2010).

Within this tension, a critical managerial question emerges: how should brands strategically frame their workforce composition when communicating about production processes?

Brands may emphasize purely human production, purely AI-driven production, or a hybrid configuration in which humans and AI collaborate. Hybrid production models, in which human judgment and creativity are combined with algorithmic execution and optimization, have been proposed as a promising approach to mitigating consumer resistance while retaining technological benefits (Guzman & Lewis, 2020; Huang & Rust, 2021). However, the effectiveness of such hybrid framings depends on whether consumers perceive the collaboration as a credible integration of human warmth and machine competence rather than as a vague or ambiguous compromise. Despite the rapid diffusion of AI across industries, empirical evidence remains limited regarding which workforce communication strategies generate the most favorable and balanced consumer responses.

The artisan coffee industry provides a particularly suitable context for examining these issues. Coffee is a sensory and culturally embedded product category, deeply associated with craftsmanship, ritualized consumption, and personal identity (Beverland, 2005; Motta et al., 2025). The value of specialty coffee is often anchored in narratives of origin, manual selection, and the expertise of skilled roasters and baristas, which serve as strong authenticity cues (Morhart et al., 2015; Napoli et al., 2014). At the same time, the industry increasingly relies on AI-driven technologies, including machine-learning-based roast profiling, automated brewing systems, and computer-vision-assisted bean selection, to enhance consistency and operational efficiency (Park et al., 2023). This coexistence of human-centered tradition and technological optimization makes coffee a theoretically rich domain for studying how consumers interpret and evaluate human versus algorithmic contributions to production.
This shift is particularly salient in high-involvement, artisanal categories, where product value has long been tied to perceived human care, craftsmanship, and maker passion (Morhart et al., 2015). For decades, brands in such categories have relied on narratives emphasizing human effort and emotional dedication mechanisms closely related to the handmade effect identified by Fuchs et al. (2015) to justify premium pricing and cultivate consumer loyalty. As AI increasingly shapes production processes, brands must make deliberate decisions about how these changes are communicated. Disclosing a human-only, AI-only, or human–AI hybrid workforce functions as a strategic signal that can reshape consumers' expectations regarding authenticity, trust, and quality (Guzman & Lewis, 2020; Longoni & Cian, 2022).

1.1 Problem Statement and Research Gaps

The core research problem addressed in this dissertation lies at the intersection of authenticity signaling and technological adoption in marketing communication. Specifically, it concerns how consumers cognitively and affectively respond when products are explicitly framed as being produced by humans, by AI, or through human–AI collaboration. Prior research has established that human labor tends to evoke perceptions of warmth, authenticity, and trust (Beverland, 2005; Fuchs et al., 2015), whereas AI-driven production is commonly associated with competence-related attributes such as innovation, efficiency, and precision (Longoni et al., 2019; Huang & Rust, 2021). However, important gaps remain in the existing literature.

Most empirical studies have focused on comparisons between purely human and fully automated systems, often in the context of algorithmic recommendations or service encounters (Castelo et al., 2019; Dietvorst et al., 2015). Experimental research directly comparing human-only versus AI-only production framings in advertising remains relatively limited, particularly for tangible consumer goods.

The increasingly prevalent human–AI hybrid production model has received little systematic attention. While conceptual work suggests that hybrid arrangements may alleviate consumer concerns by preserving human oversight and moral accountability (Guzman & Lewis, 2020; de Almeida, 2024), it remains unclear whether consumers actually perceive such hybrid framings as reconciling warmth and competence or instead as ambiguous and trust-reducing.

Third, existing research has insufficiently examined the boundary conditions under which workforce composition disclosures influence consumer responses. Prior studies indicate that attitudes toward AI (Schepman & Rodway, 2020; Castelo et al., 2019) and product involvement (Zaichkowsky, 1985) systematically shape how consumers evaluate automation, yet these moderators have rarely been integrated into experimental investigations of production framing.

Given these three gaps, the present study seeks to experimentally examine how different workforce composition framings in advertising human-only, AI-only, and human–AI hybrid shape consumer perceptions of authenticity, trust, innovation, and efficiency in an artisan product context. In addition, it investigates whether these effects are moderated by consumers' general attitudes toward AI and their level of product involvement.

Research Questions

RQ1: How do advertisements emphasizing human, AI, or hybrid production influence consumers' perceptions of authenticity, trust, innovation, and efficiency?

RQ2: Does a human–AI hybrid production narrative lead to more balanced overall evaluations (e.g., purchase intention) than purely human or purely AI production narratives?

RQ3: Are these effects moderated by consumers' attitudes toward AI and their level of product involvement with coffee?

2. Literature Review and Hypotheses Development

2.1 Coffee and AI

2.1.1 Importance and Dual Nature of Coffee

Coffee occupies a distinctive position in consumer markets due to its simultaneous economic importance and deep cultural embeddedness, making it a particularly suitable product category for studying consumer perceptions of production narratives (Thompson & Arsel, 2004). From an economic perspective, coffee is one of the most widely traded agricultural commodities worldwide, forming the basis of a global industry that spans cultivation, processing, retail, and service sectors (International Coffee Organization [ICO], 2023. Prior research in consumer behavior emphasizes that products integrated into habitual routines tend to acquire meanings that extend beyond their functional utility, shaping identity, social interaction, and emotional attachment (Belk, 1988; Wood & Neal, 2009).

A central reason coffee is theoretically relevant for advertising and branding research is its dual nature as both a utilitarian and a hedonic product. On the utilitarian dimension, coffee is primarily consumed for its functional benefits, most notably its stimulating effects derived from caffeine. Extensive research in psychology and neuroscience demonstrates that caffeine consumption enhances alertness, attention, and cognitive performance, which explains coffee's strong association with productivity and daily performance management (Dews et al., 2002; Smith, 2002). For many consumers, coffee consumption is routinized and instrumental, serving as a reliable means to regulate energy levels throughout the day (Wood & Neal, 2009). In such contexts, consumers tend to value attributes such as consistency, reliability, and efficiency, which reduce cognitive effort and uncertainty in repeated decision-making (Hamilton & Wagner, 2014).

At the same time, coffee clearly transcends purely functional consumption. A substantial body of consumer research conceptualizes coffee as a hedonic and symbolic good, particularly within the growing specialty and artisan segments (Beverland, 2005; Thompson & Arsel, 2004). In these contexts, consumers evaluate coffee not only based on physiological outcomes but also on sensory qualities such as aroma, taste complexity, and mouthfeel, as well as experiential elements related to preparation and consumption rituals (Carvalho et al., 2020). Research on experiential consumption shows that such multisensory engagement enhances emotional responses and deepens consumers' attachment to products (Holbrook & Hirschman, 1982).

Coffee consumption, especially in specialty contexts, is therefore frequently associated with pleasure, indulgence, and personal reward rather than mere functionality.
Importantly, the hedonic dimension of coffee is closely intertwined with symbolic meaning and identity expression. Prior work in consumer culture theory demonstrates that consumers use everyday products to construct, communicate, and reinforce aspects of their self-concept (Belk, 1988; Arnould & Thompson, 2005). Specialty coffee consumption has been shown to signal taste sophistication, ethical awareness, and alignment with values such as sustainability and craftsmanship (Thompson & Arsel, 2004; Beverland, 2005). Narratives surrounding origin, artisanal roasting, and human expertise play a central role in shaping these meanings, allowing consumers to perceive coffee as authentic, meaningful, and socially embedded rather than anonymous or mass-produced (Napoli et al., 2014).
The importance of human labor and craftsmanship in this symbolic construction has been repeatedly emphasized in branding research. Beverland (2005) demonstrates that cues of manual skill, tradition, and passion are critical for sustaining perceptions of authenticity in food and beverage brands. Similarly, research on the "handmade effect" shows that human involvement in production increases perceived sincerity, emotional investment, and uniqueness, even when objectively identical outcomes could be achieved through automation (Fuchs et al., 2015). In the context of coffee, the visibility of farmers, roasters, and baristas reinforces perceptions of care and expertise, strengthening consumers' beliefs that the product reflects genuine effort and commitment (Napoli et al., 2014).
The coexistence of utilitarian and hedonic meanings positions coffee as a hybrid product category in which functional performance and symbolic value are simultaneously salient. Prior research suggests that such hybrid products are particularly sensitive to production cues because consumers evaluate them along multiple dimensions at once (Batra & Ahtola, 1991). While functional considerations may lead consumers to appreciate technological precision and consistency, symbolic considerations may increase sensitivity to cues of human involvement, tradition, and authenticity (Beverland, 2005). As a result, changes in production narratives, such as the introduction of automation or AI, are likely to have multifaceted effects on consumer perceptions rather than uniformly positive or negative outcomes (Batra & Ahtola, 1991).

This dual evaluative structure makes coffee an especially appropriate empirical context for examining how workforce composition in advertising influences brand perceptions. Human-centered production narratives may strengthen perceptions of authenticity and trust by aligning with the symbolic and experiential meanings attached to coffee, whereas AI-driven production narratives may enhance perceptions of efficiency and technological sophistication by appealing to utilitarian expectations of consistency and optimization. The tension between these dimensions creates a theoretically rich setting for investigating how consumers respond to human, AI, and hybrid production claims, and how these responses translate into broader brand evaluations and behavioral intentions.

2.1.2 The Definition of AI

AI is commonly defined as the field of computer science concerned with the design of systems capable of performing tasks that normally require human intelligence, such as learning, reasoning, perception, and decision-making (Russell & Norvig, 2016). In management and social science research, AI is therefore treated as a general-purpose technology whose scope extends across domains and applications (Brynjolfsson & McAfee, 2017).

Early academic work on AI primarily distinguished between *strong* (or general) AI and *weak* (or narrow) AI. Strong AI refers to hypothetical systems with human-like general intelligence, whereas weak AI describes systems designed to perform specific tasks within predefined boundaries (Searle, 1980; Russell & Norvig, 2016; Floridi et al., 2018). This distinction is crucial, as most real-world applications of AI rely on task-specific models trained on large datasets rather than human-like cognition.

More recent literature further refines the concept of AI by differentiating between *predictive* and *generative* systems. Predictive AI refers to algorithms that analyze historical data to classify information, detect patterns, or forecast outcomes, typically using machine learning techniques such as supervised or unsupervised learning (Shmueli & Koppius, 2011; Jordan & Mitchell, 2015). In contrast, generative AI describes models capable of producing novel outputs, such as text, images, or designs, by learning underlying data structures rather than merely predicting predefined categories (Goodfellow et al., 2014; Huang & Rust, 2021).

Across definitions, a shared characteristic of AI systems is their reliance on data-driven learning processes. Machine learning, a central subfield of AI, enables systems to improve performance through experience rather than explicit programming (Mitchell, 1997). As AI systems become more adaptive and autonomous, they increasingly operate with limited direct human intervention, which raises important conceptual questions regarding agency, responsibility, and control (Floridi et al., 2018).

In organizational and marketing research, AI is therefore conceptualized not merely as a technical tool but as a socio-technical system that interacts with human actors, institutional structures, and decision-making processes (Rai et al., 2019). Scholars emphasize that AI should be understood in relation to the tasks it performs, the degree of autonomy it possesses, and the extent to which its actions are visible or attributable within organizational settings (Kaplan & Haenlein, 2019). This task- and context-dependent understanding of AI provides a foundation for examining how AI is subsequently integrated into production processes and how such integration may be interpreted by stakeholders.

2.1.3 The Role of AI in Production

The use of artificial intelligence in production contexts is commonly situated within the broader transformation of industrial systems driven by digitalization and data-intensive technologies (Kagermann et al., 2013; Frank et al., 2019).

A defining characteristic of AI-driven production is the replacement of rule-based logic with data-driven learning mechanisms. Traditional automation systems execute predefined instructions and respond identically across contexts, whereas AI systems rely on machine learning algorithms that continuously update their behavior based on incoming data (Jordan & Mitchell, 2015). This learning capability allows production systems to adapt dynamically to changes in demand, input quality, and environmental conditions, thereby improving operational flexibility and system resilience (Wamba et al., 2021).

One of the most widespread applications of AI in production lies in intelligent automation, particularly through AI-enabled robotics and computer vision technologies. These systems are frequently deployed in tasks requiring high levels of precision, speed, and consistency, such as quality inspection, assembly, and sorting (Choi et al., 2018). Empirical evidence suggests that AI-supported automation can substantially reduce error rates and performance variability relative to purely human-operated processes, especially in high-volume or high-complexity production environments (Baryannis et al., 2019).

Beyond physical execution, AI increasingly supports coordination and decision-making within production systems. Predictive algorithms are used to forecast equipment failures, optimize maintenance schedules, and manage inventory and logistics flows by processing large volumes of real-time operational data (Kamble et al., 2020). These capabilities enable firms to anticipate disruptions and intervene proactively rather than reactively, fundamentally altering managerial control over production processes (Rai et al., 2019).

More recent developments further extend AI's role into domains traditionally associated with expert judgment and creative problem-solving. Generative AI systems are now capable of producing design alternatives, simulating production outcomes, and optimizing process configurations under varying constraints (Davenport et al., 2020). This expansion challenges established distinctions between technical execution and creative authorship, as AI systems increasingly contribute to activities that were once considered uniquely human (Huang & Rust, 2021).

Importantly, the literature emphasizes that AI adoption in production rarely results in fully autonomous systems. Instead, most organizations implement hybrid socio-technical arrangements in which humans and AI systems collaborate (Autor, 2015). Human workers remain essential for defining objectives, supervising algorithms, interpreting outputs, and resolving ambiguous or ethically sensitive situations (Rai et al., 2019). This perspective highlights that AI-driven production should be understood as a reconfiguration of human roles rather than their wholesale replacement.

As AI systems become increasingly embedded in production infrastructures, they also gain strategic relevance beyond internal operations. Management research notes that AI-enabled production practices may be selectively disclosed or emphasized in external communication, thereby shaping stakeholder interpretations of how products are created and what values guide the firm's production philosophy (Kaplan & Haenlein, 2019; Rindfleisch et al., 2021). Such disclosures position AI not only as a technical resource but also as a symbolic element of production, with implications for how products and brands are perceived by external audiences.

2.1.4 AI Integration in the Coffee Value Chain

Although coffee is traditionally associated with craftsmanship, manual expertise, and human care, the contemporary coffee industry increasingly incorporates artificial intelligence and automation across multiple stages of production. Recent research shows that AI-based systems are now used in areas such as agricultural monitoring, quality control, roasting optimization, and service delivery within the coffee sector (Issa & Hammoud, 2022; Park et al., 2023). This development is particularly relevant because it introduces advanced technologies into a product category that carries strong symbolic associations with human skill, authenticity, and artisanal value (Beverland, 2005; Motta et al., 2025).

To contextualize the growing relevance of artificial intelligence within the coffee industry, Table 1 summarizes key points at which AI technologies are currently integrated across the coffee value chain. This overview is intended to illustrate the objective presence of AI in contemporary coffee production, rather than to suggest that consumers possess detailed knowledge of these specific applications.

Table 1: AI Integration Across the Coffee Value Chain and Consumer Perceptions

Stage	**AI/Automation Application**	**Likely Consumer Perception Implication**
Sourcing & Sorting	Computer vision; automated defect detection	↑ Competence, ↑ Precision
Roasting	Machine learning for roast optimization	↑ Efficiency, ↑ Innovation
Brewing & Service	Robotic baristas; automated brewing systems	↑ Efficiency, ↑ Novelty, ↓ Warmth

Importantly, consumers are typically not exposed to technical information regarding the specific stages at which AI is applied (Longoni & Cian, 2022). Instead, AI involvement is most often communicated in abstract or symbolic terms through brand narratives and marketing messages, leading consumers to rely on generalized inferences rather than detailed process knowledge (Longoni & Cian, 2022).

Prior research suggests that AI involvement tends to signal enhanced competence, efficiency, and technological advancement, particularly when associated with backend production processes that emphasize precision and consistency (Granulo et al., 2019; Longoni et al., 2019). These inferences align with broader consumer associations between automation and reliable performance.

At the same time, the visibility of AI in production raises potential concerns when applied to product categories that are symbolically linked to human care and craftsmanship. Coffee, especially in its specialty and artisan segments, is often valued not only for functional quality but also for the human labor embedded in its production, including farming expertise, roasting skill, and service interactions (Beverland, 2005; Motta et al., 2025). When AI becomes salient in such contexts, consumers may perceive a tension between technological efficiency and the preservation of human involvement. Research on human–technology interaction indicates that while automation enhances perceptions of competence, it may simultaneously reduce perceived warmth, emotional connection, and authenticity, particularly in consumer-facing contexts (Cuddy et al., 2008; Longoni et al., 2019).

Crucially, these consumer inferences do not require explicit knowledge of the specific production stage at which AI is applied. Rather, the mere disclosure of AI involvement can activate broader cognitive schemas related to standardization, impersonality, and reduced human agency (Puntoni et al., 2021). In contrast, emphasizing human labor tends to evoke associations with care, intentionality, and craftsmanship, which are especially valued in hedonic and identity-relevant product categories such as coffee (Napoli et al., 2014). Hybrid human–AI production narratives may occupy an intermediate position, potentially preserving signals of technological competence while maintaining a perceived locus of human oversight.

2.2 Brand Perceptions: Theoretical Foundations

Brand perceptions constitute a central construct in marketing and consumer psychology, as they shape how consumers interpret, evaluate, and respond to market offerings. One influential approach is brand personality theory, which proposes that consumers attribute human-like characteristics to brands and evaluate them along personality dimensions such as sincerity, competence, excitement, sophistication, and ruggedness (Aaker, 1997). Production-related cues, including whether products are made by humans or automated systems, may therefore shape brand personality inferences by signaling warmth, sincerity, or technical competence (Freling & Forbes, 2005).

A second prominent perspective is consumer–brand relationship theory, which conceptualizes brands as relationship partners with whom consumers form enduring, quasi-social bonds (Fournier, 1998). Subsequent research has demonstrated that relational constructs, particularly trust and authenticity, are essential for sustaining long-term brand relationships and fostering loyalty (Aggarwal, 2004; Veloutsou, 2009). Within this lens, brand actions and communications are evaluated not only for their outcomes but also for their perceived intentions and moral character, making cues of sincerity, benevolence, and human involvement especially salient.

In addition to these approaches, branding research has also drawn on signaling theory, which explains how consumers rely on observable cues to infer unobservable product and brand qualities under conditions of information asymmetry (Spence, 1973; Kirmani & Rao, 2000). Similarly, social cognition frameworks suggest that consumers rely on fundamental dimensions of judgment, such as warmth and competence, to evaluate brands as intentional entities (Aaker et al., 2010; Fiske et al., 2007).

While each of these theoretical lenses offers valuable insights into specific aspects of consumer evaluation, the present research adopts Customer-Based Brand Equity (CBBE) as its primary integrative framework. According to Keller's conceptualization, brand equity exists not in the objective features of the product but in the differential consumer response that arises from brand knowledge. This brand knowledge consists of brand awareness and a network of brand associations, which vary in strength, favorability, and uniqueness.

The CBBE framework is particularly relevant for this thesis because it explicitly links extrinsic cues to changes in brand associations without requiring alterations to the physical product. Prior research demonstrates that marketing communications, narratives, and symbolic cues can significantly reshape consumers' associative networks by activating meanings related to values, competence, or authenticity (Erdem & Swait, 2004; Keller, 2013). Workforce composition claims in advertising function precisely as such extrinsic cues, as they highlight the perceived "source" of value creation and invite consumers to infer underlying brand qualities. Whether production is framed as human-driven, AI-driven, or hybrid may therefore alter both functional associations (e.g., efficiency, reliability, technological sophistication) and symbolic associations (e.g., authenticity, trustworthiness, moral integrity).

Importantly, CBBE accommodates both cognitive and affective components of brand perception. This dual structure aligns closely with the objectives of the present study, which examines how different production narratives shape perceptions that vary in their functional versus symbolic orientation. Authenticity and trust capture affective and moral dimensions of brand equity, whereas perceived innovation and efficiency capture competence-related and performance-oriented dimensions.

By adopting the CBBE framework, this study integrates insights from brand personality theory, consumer–brand relationship research, and signaling perspectives into a single coherent structure. Rather than treating authenticity, trust, innovation, and efficiency as isolated outcomes, they are conceptualized as interconnected brand associations that jointly shape consumer responses. This approach allows for a nuanced examination of how human, AI, and hybrid production narratives reorganize brand meaning in consumers' minds, ultimately influencing evaluative judgments and behavioral intentions.

2.2.1 Brand Authenticity and Trust

Brand authenticity and brand trust are closely related yet conceptually distinct constructs that play a central role in how consumers evaluate brands, particularly in categories characterized by symbolic meaning and craftsmanship. Authenticity refers to the extent to which a brand is perceived as genuine, true to its values, and faithful to its origins (Beverland, 2005). Rather than being an objective attribute, authenticity is a consumer perception that emerges from interpretive processes through which consumers assess whether a brand's actions, communications, and values appear sincere and non-instrumental (Napoli et al., 2014; Morhart et al., 2015). In contemporary markets saturated with standardized offerings, authenticity has become a critical differentiator, especially in artisanal and premium segments where consumers actively seek products that convey human care, tradition, and meaning (Beverland & Farrelly, 2010).

Scholars generally conceptualize brand authenticity as a multidimensional construct. Morhart et al. (2015) identify dimensions such as continuity, credibility, integrity, and symbolism, emphasizing that authentic brands are perceived as consistent over time, honest in their claims, morally grounded, and culturally meaningful. Relatedly, Napoli et al. (2014) distinguish between credibility, defined as the perceived truthfulness and reliability of brand communications, and integrity, referring to the extent to which brands adhere to their stated values and principles. This distinction is important, as a brand may communicate credibly while still being perceived as opportunistic or value-inconsistent, thereby undermining authenticity. In this sense, authenticity is not solely about technical accuracy but about perceived motivation and moral alignment.

In artisanal product categories, authenticity is often closely associated with the presence of human labor and craftsmanship. Research on the "handmade effect" demonstrates that consumers attribute greater authenticity, emotional value, and moral worth to products perceived as crafted by human hands rather than produced by machines (Fuchs et al., 2015). This effect is driven by inferences about effort, care, and personal investment, which consumers symbolically transfer from the producer to the product itself. As a result, human involvement functions as a powerful authenticity cue, particularly in categories where production is traditionally linked to skill, tacit knowledge, and passion (Beverland, 2005).

Brand trust, while closely related to authenticity, represents a distinct evaluative judgment. Trust is commonly defined as a consumer's willingness to rely on a brand under conditions of uncertainty and vulnerability, based on expectations that the brand will behave reliably, honestly, and benevolently (Delgado-Ballester, 2004; Mayer et al., 1995). Trust reduces perceived risk and facilitates long-term relationships, making it a foundational element of consumer–brand relationships (Chaudhuri & Holbrook, 2001; Sirdeshmukh et al., 2002). Importantly, trust is not a unitary construct. Marketing and organizational research consistently distinguishes between cognitive trust and affective trust (McAllister, 1995; Delgado-Ballester & Munuera-Alemán, 2001).

Cognitive trust is grounded in perceptions of competence, reliability, and predictability. Consumers develop cognitive trust when they believe a brand has the technical ability and resources necessary to deliver consistent performance (Erdem & Swait, 2004). Affective trust, by contrast, reflects emotional bonds and perceptions of benevolence, care, and moral intention. It emerges when consumers believe that a brand genuinely cares about their well-being rather than acting purely out of self-interest (Chaudhuri & Holbrook, 2001; Aaker et al., 2010). While both forms of trust contribute to positive brand evaluations, affective trust is particularly important in categories involving identity expression, symbolic meaning, or ethical considerations.

Authenticity and trust are deeply intertwined because perceptions of genuineness and value alignment provide the psychological foundation upon which trust is built. Authentic brands are more likely to be perceived as honest, morally grounded, and benevolent, thereby fostering both cognitive and affective trust (Napoli et al., 2014; Fritz et al., 2017). Empirical research shows that authenticity enhances trust by reinforcing perceptions of integrity and sincerity, which in turn strengthen consumers' willingness to rely on the brand (Eggers et al., 2013). In artisanal categories such as specialty coffee, authenticity cues related to craftsmanship, ethical sourcing, and human expertise are therefore especially potent in cultivating trust, as they signal both competence and moral intent (Beverland & Farrelly, 2010; Choi & Burnham, 2020).

The increasing presence of artificial intelligence in production contexts introduces a complex tension in how authenticity and trust are formed. From a social cognition perspective, consumers evaluate agents whether human or non-human along two fundamental dimensions: competence and warmth (Fiske et al., 2007; Aaker et al., 2010). Competence captures perceptions of ability, efficiency, and intelligence, whereas warmth reflects perceived intentions, benevolence, and moral character. AI systems are consistently perceived as highly competent due to their precision, consistency, and data-processing capabilities, but low in warmth because they lack emotional capacity, moral intuition, and human intentionality (Castelo et al., 2019; Longoni et al., 2019).

This asymmetry has important implications for brand trust. AI-driven processes may enhance cognitive trust by signaling technical reliability and error reduction, particularly in tasks involving optimization and standardization (Dietvorst et al., 2015; Longoni & Cian, 2022). However, the same processes may undermine affective trust, as consumers struggle to attribute benevolent intentions or moral responsibility to algorithmic systems. Research shows that consumers are more reluctant to place trust in AI when decisions involve ethical judgment, care, or accountability, domains traditionally associated with human agency (Bigman & Gray, 2018; Castelo et al., 2019).

In symbolic product categories such as coffee, where authenticity and trust are tightly linked to human care and craftsmanship, this competence–warmth imbalance becomes particularly salient. The perception that production is driven primarily by algorithms may introduce doubts about sincerity, accountability, and value alignment, even when functional quality is assured. Consequently, AI-related cues have the potential to simultaneously strengthen cognitive trust while weakening affective trust, creating an ambivalent trust profile that differs fundamentally from trust grounded in human labor (Dietvorst et al., 2015; Longoni & Cian, 2022).

Hybrid arrangements, which combine human agency with technological support, may therefore occupy an intermediate position, preserving elements of authenticity and affective trust while signaling modern competence.

Although prior research distinguishes between cognitive and affective dimensions of trust, the present study treats trust as a unidimensional construct, consistent with common practice in brand trust research.

2.2.2 Perceived Innovation and Efficiency

Perceived innovation and perceived efficiency capture the functional and performance-oriented dimensions of brand evaluation and represent core components of how consumers assess a firm's capability to deliver value in competitive markets. Unlike authenticity and trust, which are closely tied to emotional meaning and moral inference, innovation and efficiency primarily reflect beliefs about a brand's technical sophistication, problem-solving capacity, and operational excellence. These perceptions are particularly important in contexts where production processes are complex or technologically mediated, as consumers often rely on indirect cues to infer a brand's capabilities (Keller, 1993; Henard & Dacin, 2010).

Perceived innovation refers to the extent to which consumers view a brand as novel, forward-looking, and technologically advanced in its products or processes (Garcia & Calantone, 2002). Innovation perceptions function as symbolic signals of progressiveness and leadership, shaping expectations about future performance and the brand's ability to deliver superior solutions (Chandy & Tellis, 1998; Kunz et al., 2011). Importantly, innovation does not require radical changes to the core product itself (Keller, 2013). In categories characterized by relatively stable product forms such as food and beverages innovation is often inferred from process-related cues, including production methods, technological integration, and scientific optimization

(Shams et al., 2020). Consumers therefore use information about how a product is made as a heuristic for judging whether a brand is modern, adaptable, and capable of improvement.
The marketing literature consistently shows that technological cues play a central role in shaping innovation perceptions. Technologies associated with data analytics, automation, and artificial intelligence are strongly linked to cultural narratives of scientific advancement and rational optimization, which consumers readily associate with innovativeness (Verganti, 2008; Huang & Rust, 2021). The presence of advanced technology activates a "science-based" schema, leading consumers to infer that a brand relies on objective analysis, experimentation, and continuous improvement rather than intuition alone (Longoni et al., 2019). As a result, brands that communicate the use of AI or advanced algorithms are often perceived as more innovative, even when the underlying product remains unchanged (Verganti, 2008).

Perceived efficiency complements innovation by focusing on how effectively a brand converts inputs into desirable outcomes. Efficiency reflects beliefs about speed, reliability, consistency, and the minimization of waste or error in production and delivery (Parasuraman et al., 1988). From a consumer perspective, efficiency reduces uncertainty by signaling operational control and predictability, thereby lowering perceived risk associated with product performance (Sirdeshmukh et al., 2002). Brands perceived as efficient are assumed to be better equipped to maintain quality standards, meet demand reliably, and respond effectively to changing conditions (Grönroos, 1984).
AI has become a dominant symbolic cue for efficiency because of its association with precision, scalability, and data-driven decision-making. Research shows that consumers widely believe algorithmic systems outperform humans in tasks requiring consistency, monitoring, and optimization, particularly when errors are costly or outcomes must be standardized (Dietvorst et al., 2015; Gursoy et al., 2019). AI-driven processes are perceived as less prone to fatigue, bias, or inconsistency, reinforcing impressions of operational mastery and technical competence (Longoni & Cian, 2022). Consequently, the disclosure of AI-supported production often leads consumers to expect reliable quality, faster execution, and streamlined processes.

At the same time, the emphasis on innovation and efficiency introduces a tension that is well documented in consumer research. While technological sophistication enhances perceptions of competence, it may also shift attention away from experiential and symbolic attributes that consumers value in hedonic or tradition-rich categories (Huang & Rust, 2018). Prior studies indicate that when technology becomes salient, consumers tend to prioritize functional performance over emotional resonance, leading to trade-offs between efficiency-oriented benefits and experiential meaning (Newman & Smith, 2016; Suh & Lee, 2022). This does not imply that innovation and efficiency are undesirable rather, it suggests that their positive impact depends on how well they align with category expectations and consumer values.

2.3 Consumer Responses to AI Production

Consumer responses to AI in firms' value creation are often ambivalent rather than uniformly positive or negative. In an experiential account, consumers can perceive AI as *empowering* (e.g., enabling speed, accuracy, and personalization) while simultaneously experiencing replacement concerns that are psychological as much as economic (Puntoni et al., 2021). When AI is disclosed as part of "how a product is made," this disclosure can therefore change not only beliefs about performance, but also the *meaning* consumers assign to the product and the brand behind it (Puntoni et al., 2021).

2.3.1 The Competence–Warmth Trade-Off in Consumer Responses to AI Production

Consumer responses to the increasing integration of artificial intelligence in organizational and production contexts are complex and often ambivalent rather than uniformly positive or negative. Prior research emphasizes that consumers simultaneously experience AI as a source of functional enhancement and as a potential threat to human distinctiveness (Puntoni et al., 2021). On the one hand, AI-enabled systems offer clear instrumental benefits, such as increased speed, precision, personalization, and consistency. On the other hand, their growing presence in domains traditionally associated with human judgment, care, or creativity can elicit psychological discomfort and resistance. This ambivalence suggests that consumer reactions to AI production are shaped by more than simple evaluations of efficiency or performance.

Puntoni et al. (2021) conceptualize this tension as a trade-off between feelings of *empowerment* and *replacement*. While AI may empower consumers by improving functional outcomes, it can simultaneously evoke concerns about the erosion of uniquely human qualities. Research indicates that consumers may experience a more existential form of unease when AI performs tasks previously interpreted as requiring human intuition, emotional sensitivity, or moral judgment (Puntoni et al., 2021). As a result, the disclosure of AI involvement in production does not merely communicate a change in technique; it can alter the symbolic meaning of the product itself, shifting it from something perceived as humanly crafted to something optimized by impersonal systems.

This evaluative tension can be systematically understood through the Stereotype Content Model (SCM), a foundational framework in social psychology. The SCM proposes that social judgments across a wide range of targets are structured along two universal dimensions: *competence* and *warmth* (Fiske et al., 2007). Competence refers to perceived ability, skill, and effectiveness, whereas warmth reflects perceived intentions, including benevolence, sincerity, and moral orientation. Although originally developed to explain interpersonal and intergroup perceptions, subsequent research demonstrates that consumers apply the same cognitive framework when evaluating brands, organizations, and non-human agents such as AI systems (Aaker et al., 2010; Bigman & Gray, 2018).

Within this framework, AI systems are typically perceived as high in competence. They are associated with attributes such as precision, consistency, objectivity, and technological sophistication, which signal strong functional capability (Longoni et al., 2019). When consumers learn that a product is produced or supported by AI, they are therefore likely to infer high levels of technical mastery and process optimization. At the same time, AI systems are consistently perceived as low in warmth. They are commonly viewed as lacking emotional capacity, empathy, moral sensitivity, and benevolent intentions, which are central to warmth judgments (Goodman et al., 2017; Bigman & Gray, 2018).

In contrast, human labor is strongly associated with warmth-related qualities. Human producers are perceived as capable of care, emotional investment, and sincere intention, even when their performance may be viewed as less consistent or less efficient than that of machines (Fuchs et al., 2015). These warmth inferences are particularly salient in product categories where craftsmanship, personal effort, and moral accountability are symbolically important. As a result, production cues emphasizing human involvement tend to elicit stronger feelings of authenticity, emotional connection, and trust, whereas AI-driven production cues tend to emphasize technical competence at the expense of perceived warmth.

This competence–warmth asymmetry creates a structural trade-off in consumer evaluations of production disclosures (Fiske et al., 2007; Longoni & Cian, 2022). When production is attributed to AI, consumers may infer superior functional performance while simultaneously experiencing emotional distance and reduced relational connection to the product or brand. Conversely, when production is framed as human-driven, consumers may perceive greater sincerity and authenticity but may also question scalability, consistency, or efficiency. Importantly, this trade-off is not inherently evaluative; rather, it reflects a cognitive pattern through which consumers organize social meaning when interpreting production sources (Fiske et al., 2007; Longoni & Cian, 2022).

The competence–warmth framework thus provides a critical theoretical foundation for understanding how consumers interpret human versus AI production narratives. It explains why AI production may simultaneously enhance perceptions of innovation and efficiency while undermining authenticity and trust, and why human production may generate the opposite pattern.

2.3.2 Algorithm Discount: Aversion to Automated Production

While the competence–warmth framework explains the fundamental structure of consumer evaluations, it does not fully capture the systematic penalties consumers impose on algorithmic agents. A complementary stream of research documents a robust phenomenon known as algorithm aversion, which describes consumers' tendency to distrust and devalue algorithmic output relative to human judgment, even when algorithms demonstrably outperform humans (Dietvorst et al., 2015). This bias persists across a range of domains, including forecasting, creative tasks, and evaluative decision-making, and provides an important extension to competence–warmth theory in the context of AI production.

Dietvorst et al. (2015) show that consumers are particularly sensitive to algorithmic errors. Even minor mistakes by algorithms are often interpreted as evidence of fundamental incompetence, whereas comparable human errors are more readily forgiven and attributed to situational factors. This asymmetry leads consumers to apply harsher evaluative standards to AI systems than to human agents. Crucially, algorithm aversion does not require repeated failures; a single visible imperfection can trigger disproportionate distrust. In production contexts, this implies that AI involvement may increase perceived efficiency while simultaneously heightening perceived risk and skepticism.

Subsequent research extends algorithm aversion beyond error sensitivity to broader concerns about agency, transparency, and accountability. Algorithms are frequently described as "black boxes," whose decision-making processes are opaque and difficult to interpret for non-experts (Castelo et al., 2019). This lack of transparency undermines consumers' ability to attribute intentionality, moral responsibility, or corrective capacity to the system. As a result, when outcomes are uncertain or emotionally consequential, consumers prefer human agents whom they perceive as capable of learning, caring, and taking responsibility for mistakes (Bigman & Gray, 2018).

This tendency gives rise to what more recent literature terms the algorithm discount: a systematic devaluation of products, services, or outputs associated with algorithmic production, independent of objective quality (Gong et al., 2025). The algorithm discount reflects not merely functional skepticism but a symbolic response to the absence of human intention and moral agency. Consumers often perceive algorithmic producers as lacking sincerity, passion, or intrinsic motivation, which are central cues in categories characterized by experiential or symbolic value (Newman & Smith, 2016).

Attribution theory further clarifies why algorithm discount is particularly persistent. Research suggests that consumers attribute algorithmic failures to stable, internal characteristics of the system, perceiving the algorithm itself as flawed or incapable of meaningful improvement (Dietvorst et al., 2018). In contrast, human failures are more likely to be attributed to temporary or external factors, such as fatigue or contextual constraints. This attributional asymmetry results in a more enduring penalty for AI-driven production, even when algorithms statistically improve over time.

Importantly, algorithm discount is not limited to domains involving high error costs or technical complexity. Studies show that consumers exhibit similar resistance in creative and symbolic domains, where the value of output is closely tied to perceived intention, effort, and emotional investment (Castelo et al., 2019; Newman & Smith, 2016). In such contexts, algorithmic production can be perceived as undermining the authenticity of the outcome, regardless of functional quality. This is particularly relevant for product categories in which production narratives contribute substantially to perceived meaning, such as artisan foods or culturally embedded consumption goods.

The literature on algorithm aversion, attribution bias, and perceived agency suggests that consumer skepticism toward AI production extends beyond isolated performance concerns. Prior research indicates that algorithmic systems are evaluated not only on output quality but also on their perceived capacity for intentionality, accountability, and moral judgment (Dietvorst et al., 2015; Bigman & Gray, 2018; Castelo et al., 2019). As a result, even when AI signals superior competence, consumers may hesitate to fully endorse products associated with algorithmic production, particularly in contexts characterized by uncertainty or symbolic value.

This stream of research further indicates that algorithm discount operates at a symbolic and relational level rather than a purely functional one. When production is attributed to AI, consumers may infer a reduced presence of human intention, emotional investment, and moral responsibility qualities that are central to authenticity and trust judgments in experiential product categories (Newman & Smith, 2016; Gong et al., 2025). Building on attribution theory, these perceptions may persist even in the absence of objective performance failures, as algorithmic agents are often viewed as inherently less capable of learning, caring, or taking responsibility compared to human producers (Dietvorst et al., 2018).

In combination with the competence–warmth framework, the algorithm discount literature highlights why AI-only production narratives may systematically struggle to elicit positive evaluations on warmth-related dimensions, despite signaling efficiency and innovation (Fiske et al., 2007; Longoni & Cian, 2022). These theoretical insights underscore the importance of considering how production disclosures activate both cognitive evaluations of capability and deeper symbolic concerns about agency and meaning. Such dynamics are particularly relevant when contrasting AI-only production with hybrid human–AI configurations, which may partially restore perceived human oversight and accountability, an issue addressed in the following section.

2.3.3 Impact of Workforce Composition on Authenticity, Trust, Innovation, and Efficiency

Building on the competence–warmth framework and the literature on algorithm discount, prior research provides converging evidence that the disclosure of production workforce composition systematically shapes consumer evaluations of core brand perceptions. In particular, authenticity and trust tend to be associated with perceived human agency and moral intention, whereas innovation and efficiency are more strongly linked to perceptions of technical competence and process optimization. These perceptual asymmetries are especially pronounced when consumers are explicitly informed about whether production is carried out by humans, AI systems, or a combination of both.

Authenticity is widely conceptualized as the perception that a brand is genuine, sincere, and guided by intrinsic values rather than purely instrumental motives (Beverland, 2005; Napoli et al., 2014). In experiential and artisanal product categories, authenticity judgments are closely tied to perceptions of human involvement, effort, and craftsmanship, as these cues signal intentionality, care, and moral accountability (Fuchs et al., 2015; Newman & Smith, 2016). Human labor is therefore consistently associated with higher perceived authenticity because it embodies warmth-related traits such as sincerity, empathy, and ethical commitment (Fiske et al., 2007; Aaker et al., 2010).

Trust, while conceptually distinct from authenticity, is closely related and similarly grounded in perceptions of benevolence and integrity. Trust reflects a consumer’s willingness to rely on a brand under conditions of uncertainty, based on expectations that the brand will behave competently, honestly, and with good intentions (Delgado-Ballester, 2004; Mayer et al., 1995). Prior research suggests that affective trust, in particular, is strengthened when brands are perceived as acting with human concern and moral responsibility, attributes that are more readily ascribed to human agents than to algorithmic systems (Chaudhuri & Holbrook, 2001; Bigman & Gray, 2018).

AI-driven production narratives tend to weaken authenticity and trust perceptions because algorithms are commonly viewed as lacking intentionality, emotional capacity, and moral judgment (Castelo et al., 2019; Goodman et al., 2017). The algorithm discount literature further suggests that consumers penalize products associated with automated systems not because of inferior output, but because of the perceived absence of human agency and accountability (Dietvorst et al., 2015; Gong et al., 2025). Taken together, these findings indicate that production framed as human-driven should elicit higher perceived authenticity and trust than production framed as AI-driven, particularly in categories where symbolic meaning and craftsmanship are salient.

H1: Advertisements emphasizing human production will yield significantly higher perceived authenticity and trust compared to the AI and hybrid conditions.

In contrast to authenticity and trust, perceived innovation and efficiency are primarily competence-based evaluations. Perceived innovation refers to the extent to which consumers view a brand as technologically advanced, forward-looking, and capable of delivering novel solutions (Garcia & Calantone, 2002; Henard & Dacin, 2010). Efficiency reflects perceptions of operational mastery, including consistency, precision, speed, and resource optimization (Parasuraman et al., 1988; Grönroos, 1984). Both constructs are closely aligned with the competence dimension of social judgment (Fiske et al., 2007).

AI systems are strongly and unambiguously associated with competence-related traits. Extensive research shows that consumers perceive algorithms as superior to humans in tasks involving data processing, optimization, and consistency, particularly when performance criteria are objective or technical in nature (Longoni et al., 2019; Huang & Rust, 2021). As a result, merely disclosing the use of AI in production can activate a technological schema that emphasizes scientific rigor, process optimization, and innovation leadership (Verganti, 2008; Shams et al., 2020).

Empirical evidence across service, manufacturing, and creative domains indicates that AI involvement increases perceived efficiency by signaling reduced error rates, standardized output, and predictive control over production processes (Gursoy et al., 2019; Longoni & Cian, 2022). While these efficiency gains may come at the expense of warmth-related perceptions, they nonetheless represent a clear functional advantage of AI-based production. Consequently, brands emphasizing AI-driven production are expected to benefit from elevated perceptions of innovation and efficiency relative to human-centered production narratives.

H2: Advertisements emphasizing AI production will yield significantly higher perceived innovation and efficiency compared to the human and hybrid conditions.

2.3.4 Consumer Reactions to Hybrid Production

Thus far, the literature has highlighted two contrasting production extremes: purely human production, which is strongly associated with warmth-related perceptions such as authenticity and trust, and purely AI-driven production, which is predominantly associated with competence-related perceptions such as innovation and efficiency. Recent scholarship, however, increasingly emphasizes that many real-world production systems do not rely exclusively on either humans or algorithms, but instead operate through hybrid human–AI collaborations (Raisch & Krakowski, 2021; Kares et al., 2023). These hybrid configurations are explicitly designed to combine the functional strengths of AI with the moral, emotional, and interpretive capacities of human agents.

From a consumer psychology perspective, hybrid production models are theorized to mitigate the perceptual trade-offs identified in the competence–warmth framework. By retaining visible human involvement alongside algorithmic support, hybrid systems may preserve warmth-related inferences such as sincerity, accountability, and care, while simultaneously benefiting from AI's competence-related advantages in consistency, optimization, and speed (Longoni & Cian, 2022). This dual signaling function distinguishes hybrid production from AI-only production, which often suffers from reduced perceptions of benevolence and authenticity due to the perceived absence of human intention (Castelo et al., 2019; Bigman & Gray, 2018).

A central mechanism underlying favorable reactions to hybrid systems is the restoration of perceived human control. Research on human–AI collaboration suggests that consumers are more comfortable with algorithmic involvement when humans retain supervisory authority, decision rights, or veto power over automated outputs (Dietvorst et al., 2018; de Almeida, 2024). This human oversight signals moral accountability and ethical responsibility, reducing concerns associated with algorithmic opacity and error attribution. As a result, hybrid production can attenuate the algorithm discount that typically applies to fully automated systems, particularly in contexts where subjective judgment or symbolic value is salient (Gong et al., 2025).

Moreover, hybrid configurations may resolve ambiguity surrounding agency attribution. Whereas AI-only production raises questions about who is responsible for outcomes, hybrid production clarifies the presence of a human agent who can be held accountable, thereby strengthening trust and legitimacy perceptions (Kares et al., 2023). At the same time, the inclusion of AI continues to signal technological sophistication and process excellence, maintaining perceptions of innovation and efficiency. This balance is especially relevant in experiential product categories, such as specialty coffee, where consumers simultaneously value craftsmanship and technical quality.

Importantly, existing research cautions that hybrid systems do not necessarily outperform human or AI systems on all dimensions. Instead, their value lies in their ability to reduce extreme perceptual penalties associated with either production mode alone (Raisch & Krakowski, 2021). Hybrid production is therefore expected to generate more moderate, integrated evaluations rather than dominating both warmth- and competence-related judgments. In advertising contexts, emphasizing human–AI collaboration may communicate a narrative of responsible innovation one that acknowledges technological progress while respecting human values and expertise.

The literature suggests that hybrid production narratives may elicit more balanced consumer evaluations by partially preserving authenticity and trust while simultaneously enhancing perceptions of innovation and efficiency (Raisch & Krakowski, 2021).

H3: Advertisements emphasizing hybrid (human + AI) production will yield the most balanced overall evaluations, outperforming the pure AI condition on authenticity and trust and the pure human condition on innovation and efficiency.

2.4 Moderators: Attitudes Toward AI and Product Involvement

Although workforce composition cues are expected to shape brand perceptions in systematic ways, prior research cautions against assuming uniform consumer responses to technological innovation. Consumer evaluations of AI-driven production are highly contingent on individual difference variables, which act as boundary conditions for acceptance or resistance to automation (Puntoni et al., 2021; Longoni et al., 2019). To account for this heterogeneity and to avoid a deterministic interpretation of AI effects, the present study incorporates two theoretically grounded moderators: consumers' attitudes toward AI and their level of product involvement.

H4: The effects of workforce composition framing (human vs. AI vs. hybrid) on brand perceptions and overall evaluations are significantly moderated by consumers' attitudes toward AI and their level of product involvement.

2.4.1 Attitudes Toward AI

Attitudes toward AI reflect consumers' general evaluations of intelligent technologies, ranging from optimism and openness to skepticism and resistance (Schepman & Rodway, 2020; Fast & Horvitz, 2017). These attitudes shape how individuals interpret the role of AI in production and whether algorithmic involvement is perceived as a signal of progress or as a threat to human agency and values.

Consumers with more favorable attitudes toward AI are more likely to associate AI-enabled production with innovation, efficiency, and technological sophistication. Prior research shows that such individuals are more accepting of algorithmic decision-making and automated systems, perceiving them as competent, objective, and performance-enhancing (Logg et al., 2019; Castelo et al., 2019). In marketing contexts, positive AI attitudes have been linked to higher acceptance of AI-driven services and reduced discomfort with diminished human involvement (Gursoy et al., 2019). Accordingly, AI-only and hybrid production narratives are expected to elicit more positive evaluations among consumers with favorable AI attitudes, particularly with respect to innovation- and efficiency-related perceptions. Conversely, consumers with negative attitudes toward AI tend to associate automation with dehumanization, loss of moral accountability, and erosion of social values (Bigman & Gray, 2018). Prior research demonstrates that such skepticism intensifies algorithm aversion, leading consumers to discount AI-produced offerings even when objective performance is high (Dietvorst et al., 2015; Longoni et al., 2019). For these consumers, disclosures of AI involvement may exacerbate concerns related to authenticity, trust, and benevolence, thereby amplifying resistance to AI-based production framings.

2.4.2 Product Involvement

Highly involved consumers, such as specialty coffee enthusiasts, typically possess strong category knowledge and well-defined expectations regarding appropriate production practices. In such contexts, attributes related to authenticity, craftsmanship, and human expertise function as central evaluative criteria (Beverland, 2005; Fuchs et al., 2015). When AI involvement is made salient, highly involved consumers may perceive a violation of category norms, particularly if AI is framed as replacing human judgment or care. Prior research indicates that high involvement amplifies sensitivity to authenticity cues and increases resistance to automation in domains associated with symbolic meaning and identity expression (Napoli et al., 2014; Mende et al., 2019). In contrast, low-involvement consumers tend to rely more heavily on functional and heuristic cues, such as efficiency, consistency, and convenience. According to the Elaboration Likelihood Model, these consumers engage less deeply with symbolic meanings and are therefore less sensitive to potential authenticity losses associated with AI disclosure (Petty & Cacioppo, 1986). For this group, AI-enabled production may enhance evaluations by signaling reliability and technological advancement.

Taken together, product involvement is expected to moderate the impact of workforce composition framing on brand perceptions and purchase intentions, such that AI-based production narratives elicit stronger resistance among highly involved consumers and weaker resistance among less involved consumers.

2.5 Conceptual Framework and Hypotheses

Workforce composition framing in advertising constitutes the independent variable. Drawing on the competence–warmth trade-off and research on algorithmic production, this framing is expected to influence core brand perceptions, namely authenticity, trust, innovation, and efficiency. These perceptions represent the primary psychological mechanisms through which production cues shape consumer evaluations.

In line with prior research on consumer decision-making, brand perceptions are expected to aggregate into an overall brand evaluation, operationalized in this study as purchase intention. More favorable brand perceptions are therefore expected to translate into stronger purchase intentions.

The framework further incorporates two individual-level moderators: attitudes toward AI and product involvement. These moderators are not assumed to be directly influenced by the advertising manipulation but are expected to condition the strength and direction of the relationships between workforce composition and brand perceptions. Specifically, consumers' predispositions toward AI and their level of engagement with the product category may amplify or attenuate the perceived benefits and drawbacks of human, AI, and hybrid production narratives.

H1: Advertisements emphasizing human production will yield significantly higher perceived authenticity and trust compared to the AI and hybrid conditions.

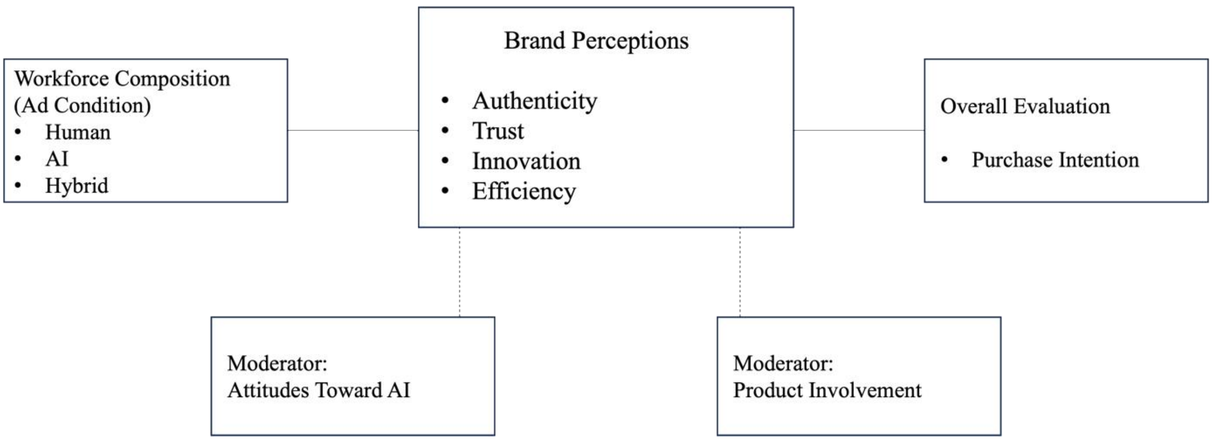
H2: Advertisements emphasizing AI production will yield significantly higher perceived innovation and efficiency compared to the human and hybrid conditions.

H3: Advertisements emphasizing hybrid (human + AI) production will yield the most balanced overall evaluations, compared to the pure human and pure AI conditions.

H4: The effects of advertising condition on brand perceptions and overall evaluations are moderated by consumers' attitudes toward AI and their level of product involvement.

Figure 1 presents the conceptual framework guiding the present study. The framework integrates the key theoretical arguments developed in the preceding sections and visually summarizes the hypothesized relationships among the study variables.

Figure 1. Conceptual framework of workforce composition effects on brand perceptions



3. Methodology

3.1 Research Design

This study employed a between-subjects experimental survey design administered online via Qualtrics. The experimental manipulation focused on workforce composition framing in a coffee brand advertisement, with participants exposed to one of three production narratives: human-only production, AI-only production, or a human–AI hybrid production model. The design allows for causal inference regarding the effects of workforce composition disclosure on key brand perceptions.

Participants were randomly assigned to one of the three conditions. After exposure to the stimulus advertisement, respondents completed measures of brand perceptions, followed by scales assessing individual difference variables and demographic information. The study followed a single-factor, three-level experimental structure, with continuous moderators incorporated analytically through interaction-based regression models.

3.2 Procedure

The survey was distributed digitally using Qualtrics and was accessible on desktop and mobile devices. Upon accessing the survey, participants were presented with an informed consent form outlining the general purpose of the study, voluntary participation, anonymity, and data protection procedures.

After providing consent, participants were randomly assigned to one of the three experimental conditions using Qualtrics' built-in randomization function with equal allocation across conditions. Participants then viewed a coffee brand advertisement created specifically for the study. All versions of the advertisement were identical in visual design, layout, and brand elements, differing only in the textual description of the production process. The stimuli were intentionally minimalistic to isolate the effect of workforce composition framing.

Following exposure to the advertisement, participants completed a series of validated multi-item scales measuring brand authenticity, brand trust, perceived innovation, perceived efficiency, and purchase intention. Subsequently, participants responded to measures assessing attitudes toward AI and product involvement. Finally, demographic information was collected, including age, gender, education level, country of residence, and coffee consumption habits. The survey required approximately five to eight minutes to complete and did not collect any personally identifiable information.

3.3 Participants

Participants were recruited through a combination of online distribution channels, including social media, personal networks, and survey exchange platforms. The survey targeted adults aged 18 years and older, with no restrictions regarding nationality, gender, or occupation. Participation was voluntary and anonymous, and all respondents provided informed consent prior to beginning the study.

A total of 264 responses were initially collected. Following data-quality screening procedures, including the exclusion of repeated submissions identified through IP address checks, the final analytical sample consisted of $N = 130$ valid and complete responses. This approach was adopted to ensure data integrity and is consistent with common quality-control practices in online survey research.

The final sample consisted of 59% female and 41% male participants. With regard to age, 36% of respondents were between 18 and 24 years old, 43% between 25 and 34 years old, 12% between 35 and 44 years old, 4% between 45 and 54 years old, and 5% were aged 55 or above. This distribution indicates a predominantly young to middle-aged adult sample.

Participants reported relatively high educational attainment. Approximately 13% indicated a high school diploma or equivalent as their highest completed level of education, 15% reported college or university education, 32% held a bachelor's degree, 27% held a master's degree, and 4% reported a doctoral degree or higher.

In terms of nationality, the sample was predominantly German (83%), followed by smaller proportions of Spanish (3%) and Portuguese (2%) respondents, with the remaining participants reporting other nationalities.

Participants also reported frequent engagement with the product category. Coffee consumption was high, with 54% indicating that they drink coffee multiple times per day, 16% once per day, and the remainder reporting consumption several times per week or less frequently. In addition, respondents indicated moderate to high familiarity with artificial intelligence–based products and services ($M = 4.71$, $SD = 1.36$), suggesting that the sample was sufficiently exposed to AI-related technologies to meaningfully evaluate AI-related production claims.

Overall, the demographic composition and consumption habits of the sample indicate that participants were well suited for evaluating advertising messages related to specialty coffee and the communication of human, AI, and hybrid production processes.

3.4 Measurement Variables

3.4.1 Dependent Variables

All dependent variables were measured using multi-item seven-point Likert scales (1 = strongly disagree, 7 = strongly agree). Items were averaged to form composite scores, with higher values indicating stronger endorsement of the respective construct. Established scales were used without substantive adaptation beyond contextual wording.

Brand authenticity was measured using five items adapted from Napoli et al. (2014), capturing perceptions of genuineness, value congruence, and sincerity. A sample item is: *"This brand seems genuine."*

Brand trust was assessed with five items drawn from established brand trust research (Delgado-Ballester, 2004), measuring perceived honesty, reliability, and dependability. A sample item is: *"I feel that I can trust this brand."*

Perceived innovation was measured using five items adapted from Garcia and Calantone (2002) and Henard and Dacin (2010), reflecting perceptions of technological advancement and forward-thinking orientation. A sample item is: *"This brand is innovative."*

Perceived efficiency was assessed using three items derived from prior research on technological competence and process optimization (Huang & Rust, 2021). A sample item is: *"This production process seems efficient."*

Purchase intention was measured using four items adapted from Dodds et al. (1991), capturing consumers' likelihood of purchasing or recommending the product. A sample item is: *"I would consider buying this coffee."*

3.4.2 Explanatory Variables

The primary explanatory variable was workforce composition framing, manipulated as a categorical variable with three levels: human-only production, AI-only production, and hybrid human–AI production. The human-only condition served as the reference category in subsequent analyses.

Two moderator variables were included. Attitudes toward AI were measured using four items adapted from prior research on technology readiness and consumer responses to AI (Parasuraman, 2000; Schepman & Rodway, 2020). The scale captured general comfort with AI, perceived benefits of AI in product creation, and openness to technologically advanced products. One item reflecting concern about AI reducing the "human touch" was reverse-coded prior to aggregation. Higher values indicated more positive attitudes toward AI.

Product involvement was assessed using items adapted from Zaichkowsky's (1985) Personal Involvement Inventory, tailored to the context of coffee consumption. The scale measured the personal relevance and importance of coffee to each participant, with higher scores reflecting greater involvement.

Several control variables were included to account for potential confounding effects, including age, gender, education level, and coffee consumption frequency.

4. Results

4.1 Scale Assessment

Internal consistency of all multi-item scales was assessed using Cronbach's α, applying the commonly accepted threshold of $\alpha \geq .70$ (Nunnally, 1978; Streiner, 2003). All constructs demonstrated excellent internal reliability. Cronbach's α values, rounded to two decimal places, are reported in Table 2.

Table 2. *Reliability Analysis of Study Constructs*

Construct	**Items**	**Cronbach's α**
Perceived Authenticity	5	.95
Perceived Innovation	5	.95
Perceived Efficiency	3	.88
Perceived Trust	5	.96
Purchase Intention	3	.94
Product Involvement	2	.91
Attitude Toward AI	4	.73

All scales exceeded recommended reliability thresholds and were therefore retained for subsequent analyses.

4.2 Descriptive Statistics

Means and standard deviations were computed for all continuous composite variables. All measures were assessed on seven-point Likert scales ranging from 1 (strongly disagree) to 7 (strongly agree). Descriptive statistics are reported in Table 3.

Table 3. *Means and standard deviations*

Variable	M	SD
Perceived authenticity	4.58	1.51
Perceived innovation	4.78	1.71
Perceived efficiency	4.96	1.64
Perceived trust	4.50	1.51
Purchase intention	4.36	1.52
Attitude toward AI	5.07	0.96
Product involvement	4.96	1.51

4.3 Correlation Analysis

Bivariate Pearson correlations were computed among all main study variables to examine their associations prior to hypothesis testing. The full correlation matrix is reported in Appendix C.

Several strong and theoretically meaningful relationships emerged. Perceived authenticity was strongly correlated with perceived trust ($r = .89$, $p < .001$) and with purchase intention ($r = .83$, $p < .001$). Perceived innovation and perceived efficiency were also strongly correlated ($r = .90$, $p < .001$), reflecting their shared competence-based dimension.

Attitude toward AI was positively correlated with perceived innovation ($r = .21$, $p = .015$) and perceived efficiency ($r = .19$, $p = .028$). Product involvement showed small to moderate positive correlations with authenticity, trust, and purchase intention. Given the artisan product context, where authenticity constitutes a central evaluative signal, strong associations among authenticity, trust, and purchase intention are theoretically plausible. These correlations are reported for descriptive purposes only. All hypotheses were formally tested using multiple regression analyses..

4.5 Hypothesis Testing

To test the proposed hypotheses, a series of multiple linear regression analyses was conducted. Workforce composition was operationalized using two dummy variables representing the AI-only and hybrid production conditions, with the human-production condition serving as the reference category. All regression models included the same set of predictors: the AI dummy, the hybrid dummy, mean-centered attitude toward AI, mean-centered product involvement, and the interaction terms between each production dummy and the two moderators. Separate regression models were estimated for each dependent variable: perceived authenticity, perceived trust, perceived innovation, perceived efficiency, and purchase intention. This analytical strategy allows for a systematic examination of both the direct effects of workforce composition and the moderating influence of individual consumer characteristics.

The regression results are reported in Tables 4 and 5. Table 4 presents the results for emotionally grounded brand evaluations (authenticity, trust, and purchase intention), while Table 5 reports the results for functional brand evaluations (innovation and efficiency). Collinearity diagnostics indicated no violations of regression assumptions. Full regression outputs are provided in Appendix A.

Table 4. Multiple Regression Results for Emotional Outcomes

Predictor	Authenticity (B, SE)	Trust (B, SE)	Purchase Intention (B, SE)
AI dummy	−1.92*** (.22)	−2.18*** (.21)	−2.06*** (.22)
Hybrid dummy	−0.42† (.22)	−0.23 (.21)	−0.18 (.22)
AI × AI attitude	0.03 (.26)	0.08 (.24)	−0.05 (.26)
Hybrid × AI attitude	−0.08 (.23)	0.09 (.22)	0.20 (.23)
AI × Product involvement	−0.21 (.15)	−0.55*** (.14)	−0.37* (.15)
Hybrid × Product involvement	0.05 (.14)	−0.02 (.13)	−0.04 (.14)
AI attitude (c)	0.66*** (.18)	0.45* (.17)	0.44* (.18)
Product involvement (c)	0.27** (.10)	0.27** (.09)	0.32*** (.10)

Note. Human-only condition is the reference category. † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

4.5.1 Emotional Brand Evaluations: Authenticity, Trust and Purchase (H1, H3, H4)

The first set of analyses examined how workforce composition influenced emotionally driven brand perceptions, namely perceived authenticity, perceived trust, and purchase intention. These outcomes capture consumers' affective and moral responses to production narratives and are central to Hypotheses 1 and 3.

Across all three emotional outcomes, workforce composition exerted a strong and consistent effect. Relative to the human-production condition, the AI-only production narrative was associated with a substantial reduction in perceived authenticity ($B = −1.92$, $p < .001$), perceived trust ($B = −2.18$, $p < .001$), and purchase intention ($B = −2.06$, $p < .001$). These results provide clear support for Hypothesis 1, demonstrating that emphasizing human production yields more favorable emotional evaluations than emphasizing AI production. The hybrid production condition also produced lower authenticity evaluations than the human condition; however, this effect was only marginally significant ($B = −0.42$, $p = .055$). For trust and purchase intention, the hybrid condition did not differ significantly from the human condition, suggesting that the inclusion of human oversight may partially mitigate the emotional penalties associated with full automation.

Beyond these main effects, individual differences played an important role in shaping emotional responses. Product involvement significantly moderated the relationship between workforce composition and emotional evaluations. Specifically, higher product involvement intensified the negative effect of the AI-only condition on authenticity ($B = −0.21$, $p = .168$), trust ($B = −0.55$, $p < .001$), and purchase intention ($B = −0.37$, $p = .015$). Although the interaction for authenticity did not reach conventional significance levels, the direction of the effect was consistent across all three outcomes. This pattern indicates that highly involved consumers were particularly sensitive to the removal of human craftsmanship and care, reacting more negatively when the product was framed as fully AI-produced.

Attitude toward AI also exhibited consistent positive main effects on emotional evaluations. Respondents with more favorable attitudes toward AI reported higher perceived authenticity ($B = 0.66$, $p < .001$), trust ($B = 0.45$, $p = .010$), and purchase intention ($B = 0.44$, $p = .018$), independent of production condition. However, attitude toward AI did not significantly interact with workforce composition for these emotional outcomes. Together, these findings suggest that while general openness toward AI increases baseline acceptance, it does not fully offset the emotional costs of removing human involvement in production.

Overall, the results for emotional brand evaluations indicate that human production narratives remain particularly powerful in shaping authenticity, trust, and purchase intention. Hybrid production narratives partially alleviate, but do not entirely eliminate, the emotional disadvantages associated with AI-only production, providing partial support for Hypothesis 3.

4.5.2 Functional Brand Evaluations: Innovation and Efficiency (H2, H4)

Table 5. Multiple Regression Results for Functional Outcomes

Predictor	Innovation (B, SE)	Efficiency (B, SE)
AI dummy	2.45*** (.24)	2.00*** (.25)
Hybrid dummy	2.49*** (.24)	2.15*** (.24)
AI × AI attitude	0.30 (.28)	0.26 (.29)
Hybrid × AI attitude	0.58* (.25)	0.44† (.26)
AI × Product involvement	0.54** (.16)	0.83*** (.17)
Hybrid × Product involvement	0.31* (.15)	0.43** (.16)
AI attitude (c)	0.13 (.20)	0.17 (.20)
Product involvement (c)	−0.08 (.10)	−0.23* (.11)

Note. Human-only condition is the reference category. † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

The second set of regression analyses focused on functional brand evaluations, specifically perceived innovation and perceived efficiency. These outcomes reflect competence-based consumer judgments and are central to Hypothesis 2.

In contrast to the emotional outcomes, workforce composition exerted a reversed pattern of effects on functional evaluations. Relative to the human-production condition, both the AI-only and hybrid production narratives significantly increased perceived innovation (AI-only: $B = 2.45$, $p < .001$; Hybrid: $B = 2.49$, $p < .001$) and perceived efficiency (AI-only: $B = 2.00$, $p < .001$; Hybrid: $B = 2.15$, $p < .001$). These findings provide strong support for Hypothesis 2, demonstrating that AI involvement—whether autonomous or collaborative functions as a powerful signal of technological advancement and operational competence.

Moderation analyses further revealed that product involvement amplified functional evaluations when AI was present. Higher product involvement strengthened perceptions of innovation in both the AI-only ($B = 0.54$, $p = .001$) and hybrid conditions ($B = 0.31$, $p = .042$). A similar pattern emerged for perceived efficiency, where product involvement significantly intensified positive evaluations under both AI-only ($B = 0.83$, $p < .001$) and hybrid production narratives ($B = 0.43$, $p = .007$). This suggests that highly involved consumers are particularly attentive to efficiency and optimization cues when evaluating technologically framed production processes.

Attitude toward AI showed a more limited role in shaping functional perceptions. While it did not exert a significant main effect on perceived efficiency, it positively moderated perceived innovation in the hybrid condition ($B = 0.58$, $p = .021$). This indicates that consumers with favorable AI attitudes are especially receptive to innovation cues when AI is framed as complementing, rather than replacing, human expertise.

4.5.3 Summary of Hypothesis Testing

Taken together, the regression analyses provide strong support for Hypotheses 1 and 2. Advertisements emphasizing human production generated significantly higher perceived authenticity, trust, and purchase intention, whereas advertisements emphasizing AI involvement yielded significantly higher perceived innovation and efficiency. Hypothesis 3 received partial support, as the hybrid production condition consistently produced intermediate evaluations rather than the most favorable outcomes across all dimensions. Finally, Hypothesis 4 was supported, as both attitudes toward AI and product involvement moderated several of the observed relationships, highlighting important boundary conditions in consumer responses to AI-based production narratives.

5. Discussion

This study examined how different workforce composition narratives human-only, AI-only, and human–AI hybrid shape consumer responses to a specialty coffee brand. Building on prior research on authenticity, automation, trust, and technology acceptance, the findings provide a coherent picture of how consumers navigate the symbolic and functional implications of AI involvement in product creation.

5.1 Interpretation of Key Findings

The findings reveal a consistent and theoretically meaningful pattern across all dependent variables, reflecting a fundamental trade-off between emotional and functional evaluations when AI is introduced into production narratives. This pattern aligns closely with prior work on the competence–warmth framework, which suggests that social targets perceived as highly competent are often simultaneously viewed as low in warmth (Fiske et al., 2007; Cuddy et al., 2008), as well as with research on algorithm-related consumer responses (Longoni & Cian, 2022).

Advertisements emphasizing human production elicited the strongest perceptions of authenticity, trust, and purchase intention. This pattern confirms that human labor remains a powerful symbolic cue in categories where craftsmanship, care, and moral intention are central to value creation. Prior authenticity research demonstrates that consumers associate human effort with sincerity, intentionality, and moral value, which in turn foster trust and positive brand evaluations (Beverland, 2005; Napoli et al., 2014; Fuchs et al., 2015). In contrast, AI-based production narratives weakened these emotional evaluations, reinforcing evidence that algorithmic agency disrupts the attribution of sincerity and moral responsibility to brands (Longoni & Cian, 2022; Castelo et al., 2019).

In contrast to the emotional outcomes, AI-based production narratives generated the highest perceptions of innovation and efficiency. This inverse pattern reflects the strong association between AI and technical competence, optimization, and progress. Consumers appear to rely on a performance-oriented evaluation logic when interpreting AI involvement, associating algorithmic processes with precision, consistency, and technological sophistication. Prior research shows that AI functions as a salient innovation cue, particularly in traditional product categories where technological advancement is otherwise less visible (Henard & Dacin, 2010; Longoni et al., 2019; Huang & Rust, 2021). Together, these findings reinforce the existence of a functional–emotional trade-off in AI-related brand communication.

The hybrid human–AI condition consistently occupied an intermediate position across all outcomes. Compared to AI-only production, hybrid narratives improved authenticity, trust, and purchase intention, while still retaining higher levels of perceived innovation and efficiency than purely human production. This pattern suggests that consumers respond more favorably when AI is framed as augmenting, rather than replacing, human expertise. Such framing aligns with conceptualizations of “augmented intelligence,” in which human oversight preserves accountability and value alignment while benefiting from technological efficiency (Huang & Rust, 2021; Guzman & Lewis, 2020). However, the hybrid condition did not outperform both extremes simultaneously, indicating that it operates as a compromise rather than a universally optimal solution.

Consumer responses were further shaped by individual-level characteristics. Attitudes toward AI were associated with greater receptiveness to AI-only and hybrid production narratives, particularly with respect to perceived innovation and efficiency. In contrast, product involvement more consistently intensified negative reactions to AI-based production on emotional outcomes such as authenticity and trust This finding is consistent with prior work showing that general technology readiness and AI attitudes systematically influence acceptance of automated systems (Parasuraman, 2000; Schepman & Rodway, 2020). In contrast, high product involvement intensified resistance to AI-based production. Highly involved coffee consumers appeared especially sensitive to violations of craftsmanship norms, responding more negatively to AI involvement across emotional outcomes. This pattern aligns with involvement theory, which posits that consumers with stronger category engagement apply stricter evaluative standards and place greater emphasis on intrinsic cues such as origin, process, and human agency (Zaichkowsky, 1985; Fuchs et al., 2015).

5.2 Theoretical and Managerial Implications

This research contributes to the literature in several ways. First, it extends authenticity theory by demonstrating that AI-related disruptions to authenticity are not confined to luxury or heritage goods but also apply to everyday yet symbolically rich categories such as specialty coffee (Beverland, 2005; Napoli et al., 2014). Second, the findings provide empirical support for the competence–warmth trade-off in AI production contexts, showing that functional and emotional evaluations follow distinct cognitive pathways (Fiske et al., 2007; Cuddy et al., 2008). Third, by explicitly examining hybrid production narratives, the study moves beyond the dominant human-versus-AI dichotomy and clarifies the psychological role of human oversight in restoring trust and authenticity (Guzman & Lewis, 2020; Huang & Rust, 2021). Finally, the moderation effects highlight important boundary conditions for technology acceptance, demonstrating that both AI attitudes and product involvement systematically shape consumer responses to AI disclosures (Parasuraman, 2000; Schepman & Rodway, 2020).

From a managerial perspective, the findings offer clear guidance for brands navigating AI communication. Emphasizing human craftsmanship remains critical in high-involvement and authenticity-driven markets, where AI disclosure can trigger strong negative reactions. AI-centric positioning may be effective when performance, efficiency, or innovation constitute the primary value proposition and when target audiences are technologically receptive. Hybrid production narratives represent a pragmatic risk-mitigation strategy, allowing brands to signal modernity while maintaining human accountability and care. Importantly, the results underscore the necessity of audience segmentation: using AI-focused messaging for highly involved consumers in artisanal categories is likely to backfire, whereas the same message may succeed among more technology-oriented segments.

5.3 Limitations and Future Research

Several limitations should be acknowledged. The use of a fictitious brand enhances internal validity but limits generalizability to established brands with strong reputations or heritage. The focus on a single product category restricts conclusions to contexts where authenticity and sensory experience are central. Reliance on self-reported purchase intention does not capture actual behavior, and future research should incorporate behavioral or economic outcome measures. The cross-sectional design prevents assessment of long-term dynamics, such as whether initial authenticity penalties diminish over time. Finally, moderator variables were measured rather than manipulated, which constrains causal interpretation.

Although prior literature distinguishes between cognitive and affective dimensions of trust, the present study measured trust as a unidimensional construct. Future research could examine whether AI and hybrid production narratives differentially affect these components.

Future research could address these limitations by testing AI production narratives across diverse product categories, manipulating price or quality signals, adopting longitudinal designs, and experimenting with alternative AI framings. Incorporating behavioral choice measures or willingness-to-pay experiments would further strengthen understanding of the economic implications of AI disclosure in marketing communication.

6. Conclusion

This research demonstrates that the way brands communicate their workforce composition constitutes a powerful strategic signal that systematically shapes consumer evaluations. Across all analyses, a clear functional–emotional trade-off emerged. Advertisements emphasizing human production maximized perceptions of authenticity, trust, and purchase intention, whereas AI-based production narratives enhanced perceived innovation and efficiency while incurring substantial emotional penalties. Hybrid human–AI narratives consistently occupied an intermediate position, mitigating but not eliminating the negative effects associated with full automation while retaining functional benefits.

Importantly, these effects were not uniform across consumers. More favorable attitudes toward AI were associated with stronger innovation- and efficiency-related evaluations of AI and hybrid production, while high product involvement consistently intensified resistance to AI-only narratives in this artisanal context. Taken together, the findings indicate that AI integration is not merely an operational decision but a communicative choice that determines which dimensions of brand value are foregrounded. For managers, the results underscore the necessity of aligning AI-related messaging with both category symbolism and audience characteristics, particularly when operating in domains where human craftsmanship and authenticity remain central to consumer value perceptions.

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8. Appendix

Appendix A: Scale Reliability

Perceived Authenticity:

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Perceived Authenticity - This brand feels authentic	18,36	35,442	,912	,903
Perceived Authenticity - This brand stays true to its value	18,30	39,219	,878	,914
Perceived Authenticity - This brand reflects real craftsmanship	18,75	33,613	,851	,918
Perceived Authenticity - This brand communicates honestly	17,81	40,808	,665	,948
Perceived Authenticity - I feel this brand has a genuine identity	18,44	36,372	,864	,912

Perceived Innovation:

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
For each of the statements below, please rate the extent to which you disagree or agree regarding how this ad made you feel towards the brand's innovation. - This brand is innovative	19,13	45,866	,921	,944
For each of the statements below, please rate the extent to which you disagree or agree regarding how this ad made you feel towards the brand's innovation. - This brand uses cutting-edge methods	19,23	46,675	,900	,947
For each of the statements below, please rate the extent to which you disagree or agree regarding how this ad made you feel towards the brand's innovation. - This brand is forward-thinking	19,05	47,300	,923	,943
For each of the statements below, please rate the extent to which you disagree or agree regarding how this ad made you feel towards the brand's innovation. - This brand often introduces new ideas	19,12	51,861	,803	,963
For each of the statements below, please rate the extent to which you disagree or agree regarding how this ad made you feel towards the brand's innovation. - This brand embraces technology	18,98	44,705	,893	,949

Perceived Efficiency:

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
For each of the statements below, please rate the extent to which you disagree or agree regarding how this ad made you feel towards the brand's efficiency. - I think this coffee is produced efficiently	9,96	12,611	,810	,925
For each of the statements below, please rate the extent to which you disagree or agree regarding how this ad made you feel towards the brand's efficiency. - The production process seems advanced	9,85	11,366	,890	,860
For each of the statements below, please rate the extent to which you disagree or agree regarding how this ad made you feel towards the brand's efficiency. - This ad makes the brand appear technologically capable	9,97	9,379	,874	,884

Purchase Intention:

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Now, for the statements below, please rate your intentions regarding the product: - I would consider buying this coffee	8,43	9,689	,899	,942
Now, for the statements below, please rate your intentions regarding the product: - I would recommend this coffee to others	8,75	9,199	,937	,914
Now, for the statements below, please rate your intentions regarding the product: - I would choose this brand over competitors	8,96	9,464	,888	,951

Attitude Toward AI:

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Now, for each of the statements below, please rate the extent to which you disagree or agree: - I feel comfortable with companies using AI to improve products	12,4923	5,957	,550	,525
Now, for each of the statements below, please rate the extent to which you disagree or agree: - I think AI can make some products better than humans can	12,6462	6,153	,563	,516
AIatt3_R	15,2231	8,376	,232	,731
Now, for each of the statements below, please rate the extent to which you disagree or agree: - I enjoy trying products that use new technologies	12,2769	7,613	,488	,585

Appendix B: Descriptive Statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Authenticity_Mean	130	1,00	6,80	4,5831	1,51028
Innov_Mean	130	1,00	7,00	4,7754	1,71035
Eff_Mean	130	1,00	7,00	4,9641	1,63681
Trust_Mean	130	1,00	6,60	4,5015	1,50704
Pi_Mean	130	1,00	6,67	4,3564	1,52057
Prodinv_Mean	130	1,00	7,00	4,9615	1,51429
Alatt_Mean	130	1,00	7,00	5,0744	,96472
Valid N (listwise)	130				

Appendix C: Correlation Matrix

Correlations

		Authenticity_Mean	Innov_Mean	Eff_Mean	Trust_Mean	Pi_Mean	Prodinv_Mean
Authenticity_Mean	Pearson Correlation	1	,060	,087	,889**	,833**	,316**
	Sig. (2-tailed)		,498	,328	<,001	<,001	<,001
	N	130	130	130	130	130	130
Innov_Mean	Pearson Correlation	,060	1	,899**	-,003	,002	,213*
	Sig. (2-tailed)	,498		<,001	,973	,978	,015
	N	130	130	130	130	130	130
Eff_Mean	Pearson Correlation	,087	,899**	1	,048	,064	,193*
	Sig. (2-tailed)	,328	<,001		,586	,469	,028
	N	130	130	130	130	130	130
Trust_Mean	Pearson Correlation	,889**	-,003	,048	1	,916**	,192*
	Sig. (2-tailed)	<,001	,973	,586		<,001	,028
	N	130	130	130	130	130	130
Pi_Mean	Pearson Correlation	,833**	,002	,064	,916**	1	,280**
	Sig. (2-tailed)	<,001	,978	,469	<,001		,001
	N	130	130	130	130	130	130
Prodinv_Mean	Pearson Correlation	,316**	,213*	,193*	,192*	,280**	1
	Sig. (2-tailed)	<,001	,015	,028	,028	,001	
	N	130	130	130	130	130	130

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Appendix D: Regression Results

Perceived Authenticity:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,763[a]	,581	,554	1,00882

a. Predictors: (Constant), Prodinv_c, hybrid_x_Aiatt, ai_dummy, ai_x_Aiatt, hybrid_dummy, ai_x_Prodinv, hybrid_x_Prodinv, Aiatt_c

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	171,099	8	21,387	21,015	<,001[b]
	Residual	123,143	121	1,018		
	Total	294,243	129			

a. Dependent Variable: Authenticity_Mean

b. Predictors: (Constant), Prodinv_c, hybrid_x_Aiatt, ai_dummy, ai_x_Aiatt, hybrid_dummy, ai_x_Prodinv, hybrid_x_Prodinv, Aiatt_c

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	5,354	,158		33,837	<,001		
	ai_dummy	-1,920	,222	-,600	-8,667	<,001	,721	1,388
	hybrid_dummy	-,422	,218	-,134	-1,936	,055	,720	1,388
	ai_x_Aiatt	,027	,256	,009	,106	,916	,438	2,282
	hybrid_x_Aiatt	-,076	,229	-,032	-,329	,743	,360	2,776
	ai_x_Prodinv	-,210	,152	-,111	-1,389	,168	,539	1,857
	hybrid_x_Prodinv	,054	,139	,031	,384	,702	,519	1,927
	Aiatt_c	,657	,183	,419	3,585	<,001	,253	3,959
	Prodinv_c	,268	,096	,269	2,797	,006	,374	2,676

a. Dependent Variable: Authenticity_Mean

Perceived Innovation:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,788[a]	,620	,595	1,08819

a. Predictors: (Constant), Prodinv_c, hybrid_x_Aiatt, ai_dummy, ai_x_Aiatt, hybrid_dummy, ai_x_Prodinv, hybrid_x_Prodinv, Aiatt_c

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	234,079	8	29,260	24,710	<,001[b]
	Residual	143,282	121	1,184		
	Total	377,361	129			

a. Dependent Variable: Innov_Mean

b. Predictors: (Constant), Prodinv_c, hybrid_x_Aiatt, ai_dummy, ai_x_Aiatt, hybrid_dummy, ai_x_Prodinv, hybrid_x_Prodinv, Aiatt_c

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3,088	,171		18,088	<,001		
	ai_dummy	2,445	,239	,675	10,231	<,001	,721	1,388
	hybrid_dummy	2,491	,235	,699	10,592	<,001	,720	1,388
	ai_x_Aiatt	,301	,276	,092	1,089	,278	,438	2,282
	hybrid_x_Aiatt	,577	,247	,218	2,331	,021	,360	2,776
	ai_x_Prodinv	,538	,163	,251	3,289	,001	,539	1,857
	hybrid_x_Prodinv	,310	,150	,160	2,058	,042	,519	1,927
	Aiatt_c	,134	,198	,076	,680	,498	,253	3,959
	Prodinv_c	−,082	,104	−,073	−,792	,430	,374	2,676

a. Dependent Variable: Innov_Mean

Perceived Efficiency:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,747[a]	,558	,529	1,12371

a. Predictors: (Constant), Prodinv_c, hybrid_x_Aiatt, ai_dummy, ai_x_Aiatt, hybrid_dummy, ai_x_Prodinv, hybrid_x_Prodinv, Aiatt_c

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	192,821	8	24,103	19,088	<,001[b]
	Residual	152,789	121	1,263		
	Total	345,610	129			

a. Dependent Variable: Eff_Mean

b. Predictors: (Constant), Prodinv_c, hybrid_x_Aiatt, ai_dummy, ai_x_Aiatt, hybrid_dummy, ai_x_Prodinv, hybrid_x_Prodinv, Aiatt_c

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3,549	,176		20,137	<,001		
	ai_dummy	2,001	,247	,578	8,110	<,001	,721	1,388
	hybrid_dummy	2,148	,243	,630	8,848	<,001	,720	1,388
	ai_x_Aiatt	,262	,285	,084	,919	,360	,438	2,282
	hybrid_x_Aiatt	,436	,256	,172	1,704	,091	,360	2,776
	ai_x_Prodinv	,831	,169	,405	4,921	<,001	,539	1,857
	hybrid_x_Prodinv	,428	,155	,231	2,753	,007	,519	1,927
	Aiatt_c	,168	,204	,099	,825	,411	,253	3,959
	Prodinv_c	-,234	,107	-,216	-2,185	,031	,374	2,676

a. Dependent Variable: Eff_Mean

Perceived Trust:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,788[a]	,621	,596	,95842

a. Predictors: (Constant), Prodinv_c, hybrid_x_Aiatt, ai_dummy, ai_x_Aiatt, hybrid_dummy, ai_x_Prodinv, hybrid_x_Prodinv, Aiatt_c

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	181,834	8	22,729	24,744	<,001[b]
	Residual	111,146	121	,919		
	Total	292,980	129			

a. Dependent Variable: Trust_Mean

b. Predictors: (Constant), Prodinv_c, hybrid_x_Aiatt, ai_dummy, ai_x_Aiatt, hybrid_dummy, ai_x_Prodinv, hybrid_x_Prodinv, Aiatt_c

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	5,281	,150		35,125	<,001		
	ai_dummy	-2,182	,210	-,684	-10,369	<,001	,721	1,388
	hybrid_dummy	-,225	,207	-,072	-1,086	,280	,720	1,388
	ai_x_Aiatt	,082	,243	,029	,338	,736	,438	2,282
	hybrid_x_Aiatt	,094	,218	,040	,433	,666	,360	2,776
	ai_x_Prodinv	-,554	,144	-,294	-3,848	<,001	,539	1,857
	hybrid_x_Prodinv	-,019	,133	-,011	-,146	,884	,519	1,927
	Aiatt_c	,453	,174	,290	2,604	,010	,253	3,959
	Prodinv_c	,269	,091	,270	2,949	,004	,374	2,676

a. Dependent Variable: Trust_Mean

Purchase Intention:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,770[a]	,592	,565	1,00238

a. Predictors: (Constant), Prodinv_c, hybrid_x_Aiatt, ai_dummy, ai_x_Aiatt, hybrid_dummy, ai_x_Prodinv, hybrid_x_Prodinv, Aiatt_c

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	176,688	8	22,086	21,981	<,001[b]
	Residual	121,576	121	1,005		
	Total	298,264	129			

a. Dependent Variable: Pi_Mean

b. Predictors: (Constant), Prodinv_c, hybrid_x_Aiatt, ai_dummy, ai_x_Aiatt, hybrid_dummy, ai_x_Prodinv, hybrid_x_Prodinv, Aiatt_c

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	5,082	,157		32,322	<,001		
	ai_dummy	-2,064	,220	-,641	-9,377	<,001	,721	1,388
	hybrid_dummy	-,177	,217	-,056	-,816	,416	,720	1,388
	ai_x_Aiatt	-,048	,255	-,016	-,187	,852	,438	2,282
	hybrid_x_Aiatt	,198	,228	,084	,868	,387	,360	2,776
	ai_x_Prodinv	-,370	,151	-,195	-2,461	,015	,539	1,857
	hybrid_x_Prodinv	-,041	,139	-,024	-,297	,767	,519	1,927
	Aiatt_c	,437	,182	,277	2,402	,018	,253	3,959
	Prodinv_c	,323	,095	,321	3,384	<,001	,374	2,676

a. Dependent Variable: Pi_Mean

Appendix E: Qualtrics Survey

Welcome and thank you for considering participating in this experiment on the automation of the workplace. I am conducting this experiment as part of my Master Thesis at Católica Lisbon School of Business and Economics, under the supervision of *Cristina Mendonça* whose contact details are available on the *Católica Lisbon School of Business and Economics* website.   The study consists of answering individual opinion tasks. And it will take about 5 minutes to complete. The purpose of the study is to understand how people perceive different ways companies describe their production processes and workforce. Please answer as honestly as possible. All answers will be kept strictly confidentially and are anonymous. This means that it will not be possible to link your responses to your identity. The data collected will be used for research purposes only and may be presented in my thesis or disseminated in academic journals, always in an aggregated form, never about any individual response. I ask you to take the study in one go, without interruptions. There are no expected side effects of participating in this study beyond those associated with looking at a computer screen for circa 5 minutes. You may change your mind and drop out at any point of the study during its completion. If you have any questions about this study, please email *Leonie Kaiser* (s-lckaiser@ucp.pt). By continuing you agree to participate. Thank you!

Q1 **Brand Introduction** Maison Nova Coffee is a fictional artisan coffee brand created for this study. The brand positions itself as premium, sustainable, and quality-focused.

Instruction Imagine that you are visiting your favorite coffee shop or browsing for coffee online. You come across the following ad from the brand Maison Nova Coffee. Please take a few moments to look carefully at the advertisement and product image before continuing to the next questions.

Show this question:
If Condition = human-only

Advertisement Introduction Every cup of Maison Nova Coffee is handcrafted by skilled artisans — tradition you can taste

Show this question:
If Condition = hybrid

Advertisement Introduction Every cup of Maison Nova Coffee combines human craftsmanship with AI precision — the best of both worlds

Show this question:
If Condition = AI-only

Advertisement Introduction Every cup of Maison Nova Coffee is perfected by advanced AI systems — innovation in every sip

For each of the statements below, please rate the extent to which you disagree or agree regarding how this ad made you feel towards the brand's authenticity.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)

This brand feels authentic (1)	○	○	○	○	○	○	○
This brand stays true to its value (2)	○	○	○	○	○	○	○
This brand reflects real craftsmanship (3)	○	○	○	○	○	○	○
This brand communicates honestly (4)	○	○	○	○	○	○	○
I feel this brand has a genuine identity (5)	○	○	○	○	○	○	○

Perceived Innovation For each of the statements below, please rate the extent to which you disagree or agree regarding how this ad made you feel towards the brand's innovation.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
This brand is innovative (1)	○	○	○	○	○	○	○
This brand uses cutting-edge methods (2)	○	○	○	○	○	○	○
This brand is forward-thinking (3)	○	○	○	○	○	○	○
This brand often introduces new ideas (4)	○	○	○	○	○	○	○
This brand embraces	○	○	○	○	○	○	○

technology (5)

Perceived Efficiency For each of the statements below, please rate the extent to which you disagree or agree regarding how this ad made you feel towards the brand's efficiency.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I think this coffee is produced efficiently (1)	○	○	○	○	○	○	○
The production process seems advanced (2)	○	○	○	○	○	○	○
This ad makes the brand appear technologically capable (3)	○	○	○	○	○	○	○

Perceived Trust For each of the statements below, please rate the extent to which you disagree or agree regarding how this ad made you trust the brand.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I believe this brand is trustworthy (1)	○	○	○	○	○	○	○
I feel confident relying on this brand (2)	○	○	○	○	○	○	○
I think this brand keeps its	○	○	○	○	○	○	○

promises (3)							
I believe this brand acts with integrity (4)	○	○	○	○	○	○	○
This brand has my best interests in mind (5)	○	○	○	○	○	○	○

Purchase Intention Now, for the statements below, please rate your intentions regarding the product:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I would consider buying this coffee (1)	○	○	○	○	○	○	○
I would recommend this coffee to others (2)	○	○	○	○	○	○	○
I would choose this brand over competitors (3)	○	○	○	○	○	○	○

Attitude toward AI Now, for each of the statements below, please rate the extent to which you disagree or agree:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I feel comfortable with companies using AI to improve products (1)	○	○	○	○	○	○	○
I think AI can make some products better than humans can (2)	○	○	○	○	○	○	○
I worry that AI reduces the "human touch" in products (3)	○	○	○	○	○	○	○
I enjoy trying products that use new technologies (4)	○	○	○	○	○	○	○

AI experience Please indicate your prior experience with AI products or services:

	Not at all familiar (1)	Slightly familiar (2)	Somewhat familiar (3)	Moderately familiar (4)	Fairly familiar (5)	Very familiar (6)	Extremely familiar (7)
How familiar are you with products or services	○	○	○	○	○	○	○

that use AI? (1)

Product Involvement Please indicate your level of agreement with the following statements about your interest in coffee:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I consider myself interested in specialty coffee (1)	○	○	○	○	○	○	○
I often try new coffee brands (2)	○	○	○	○	○	○	○

Habits How often do you drink coffee?:

○ Never (1)

○ Less than once a week (2)

○ 1-2 times per week (3)

○ 3-4 times per week (4)

○ Once a day (5)

○ Multiple times per day (6)

Attention Check The ad emphasized that the product was primarily produced by:

○ Mostly humans (1)

○ Mostly AI/systems (2)

○ Both humans and AI equally (3)

Brand Perception Please indicate your level of agreement with the following statements about the Maison Nova Coffee brand:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I think this coffee would be high quality (1)	○	○	○	○	○	○	○
The brand feels warm and friendly (2)	○	○	○	○	○	○	○

Age Please indicate your age group:

○ 18-24 (1)

○ 25-34 (2)

○ 35-44 (3)

○ 45-54 (4)

○ 55-64 (5)

○ 65 or older (6)

Gender Please indicate your gender:

○ Female (1)

◯ Male (2)

◯ Prefer not to say (3)

Level of Education Please indicate your highest completed level of education:

◯ High school or equivalent (1)

◯ College or university (2)

◯ Bachelor's degree (3)

◯ Master's degree (6)

◯ Doctorate or higher (4)

◯ Other (5)

Nationality Please indicate your nationality:

◯ German (1)

◯ Portugese (2)

◯ Spanish (3)

◯ Italian (4)

◯ French (5)

◯ Other (6) ____

Comments If you have any comments or feedback about this survey, please write them below:

____

____

____

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Disclosure Thank you very much for your participation in this survey! Your responses have been recorded anonymously and are a crucial contribution to our academic research project. Please be assured that the data will be used solely for the purposes of this study. If you have any questions or concerns regarding the present questionnaire, the research project, or your rights as a participant, please feel free to reach out to: Leonie Kaiser (s-lckaiser@ucp.pt)