International Journal of Organizational Innovation

CONSUMER PREFERENCES IN AI PRODUCT DESIGN: A COMPARATIVE STUDY OF SOCIAL INFLUENCE AND ANTHROPOMORPHIC APPEAL IN EASTERN AND WESTERN CULTURES

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Abstract

AI smart products, seen as innovations by professionals, also spark concerns among certain consumers and ethicists. Despite differing opinions, the advancement of AI applications is inexorable. This study delves into consumer preferences for AI product attributes and their adoption intent, emphasizing social influence and trust. We analyzed 663 responses—260 from Western English speakers and 403 from Taiwanese individuals. Square structural equation modeling revealed that greater body-self evaluation enhances user comment searches, moderated by social media attachment. User comments correlate with a preference for warm materials and anthropomorphic designs. While material preference doesn't strongly impact usage intention, anthropomorphism does. This research breaks new ground in understanding body-self and societal effects on AI product preferences and intentions, offering insights into Eastern vs. Western consumer behaviors.

Keywords: Anthropomorphism, Artificial intelligence, Comment search, Product preference, Social influence

Introduction

"We are not thinking machines that feel; rather, we are feeling machines that think" - Antonio Damasio (2010), a Neuroscientist

Understanding consumers' product preferences for new technologies is essential for both sellers and scholars (Chang & Feng, 2022; Ghani et al., 2019; Kulakli & Osmanaj, 2020; Miller, 2019; Tsai et al., 2021). AI and big data technologies have emerged in fields like healthcare and virtual reality gaming. However, concerns about privacy and AI's decision-making capabilities present challenges (Arnold et al., 2019; Berkel et al., 2022; Miller, 2019; Rai, 2020). Determining the factors influencing AI product adoption is now imperative.

The presence or actions of others readily affect individual attitudes and behaviors (Barrett, 2017; Izuma, 2017). Advances in ICT have amplified social influence (Izuma, 2017). Though extensively researched, gaps remain in the literature, notably regarding user comments' effects on consumer behavior towards AI products (Book et al., 2018; Hu et al., 2019). This research aims to address these gaps, considering cultural factors such as individualism and collectivism (Bagozzi & Lee, 2002; Hsieh & Tseng, 2018).

Literature

Social influence

Historically, social influence theories have been applied in various domains (Asch & Guetzkow, 1951; Hu et al., 2019). Social influence is the result of an individual's interaction with his or her social environment (Hu et al., 2019). In marketing, social influence helps understand consumer behavior (Hsieh & Tseng, 2018). This research intends to explore the application of such theories to AI products, especially those dealing with sensitive health data and so involve more concerns. A significant research gap has been found around the body-self relation in the age of digital networking (Tiggemann, 2014). Body-self relationship refers to how an individual evaluates and likes his/her own body and is greatly impacted by social influences through digital networking today. Social influences are often categorized into normative (approval-based conformity) and informational (accuracy-based conformity) (Hsieh & Tseng, 2018; Hu et al., 2019). Both intersect within the self-concept realm, which operates at personal, interpersonal, and collective levels (Knoll & Schramm, 2015). A good self-concept encompasses a positive self-defining relationship as well as a positive self-defining group membership. Moreover, according to Damasio (2010), normative influence precedes informational influence. In sum, a person who cares how he/she looks may care to be likable and confirmed right in the eyes of one's own as well as others. In that sense, a person who pursues a nice body-self relation is likely to care what other people comment on a certain thing before further consideration.

H1. Body-self relation positively correlates with user comment search.

Social media attachment

The advent of social media platforms has fostered new cyber social norms (VanMeter et al., 2018). However, the excessive use of these platforms can manifest addiction-like symptoms (Altuwairiqi et al., 2019). Individuals lacking satisfactory attachment to their significant ones may resort to social media (Trub & Barbot, 2016). Deep attachments can reshape behaviors, especially around validation and information-seeking. User comments, providing insights into peer actions and sentiments, thus gain importance (Altuwairiqi et al., 2019). Thus, such individuals are more susceptible to both informational and normative social influences.

H2. Social media attachment strengthens the relationship between body-self relation and user comment search.

User comment search, product preference, and intention to use

"User comment search" pertains to seeking user-generated content about products rather than official marketing content. To reduce decision ambiguity, people often seek others' opinions (Book et al., 2018). Online word-of-mouth (WOM) is shown to be considerably influential, often more than traditional marketing (Trusov et al., 2009; Lee et al., 2011). Chu and Kim (2011) associated eWOM with several factors, including social influences and trust. User comments or eWOM play a crucial role in consumer evaluations, often surpassing price considerations (Book et al., 2018).

Regarding product aesthetics, research often neglects utilitarian services like health advice, focusing more on hedonic services (Abdulrahman Al Moosa et al., 2022). There is also limited exploration on design aspects like color and material warmth. The few studies find warm materials convey comfort and cold ones suggest discomfort (Labrecque & Milne, 2012; Coelho, 2016). Warm materials in healthcare contexts promote positive patient experiences (Shafieyoun, 2016). In that vein, this study posits that socially driven consumers, who are more influenced by user comments, shall prefer warm materials.

H3. User comment search positively correlates with a preference for warm materials over cold ones.

Furthermore, consumers engaging with user comments may favor anthropomorphic AI that embodies social warmth. Anthropomorphism embeds human characteristics in products and shapes user experiences (Yang et al., 2020). Research indicates perceived control (Yang et al., 2022) and self-blame mechanisms (Fan et al. 2020) can affect preferences for anthropomorphism. User comments contrastingly reduce uncertainty while increasing perceived control and the likelihood of blaming the product commenters (instead of self-blame).

H4. User comment search is positively linked to a preference for anthropomorphic products.

Most material research is based on natural science or architecture. Wong and Aziz (2021) found a consistent preference for warm materials like wood in homes over cold ones like concrete. Warm materials, especially in medical settings, enhance sociability and reduce stress (Shafieyoun, 2016). Regarding trust, prior research also finds a halo effect carried over first impressions involving the aesthetics cues to other non-observable attributes of products and environment (Tractinsky & Lowengart, 2007). Consequently, design aesthetics generate a quick and lasting system trust (Tuch et al., 2012) in favor of adopting a utilitarian AI application (Abdulrahman Al Moosa et al., 2022).

H5. A preference for warmer materials has a positive correlation with the intent to use the AI product.

Studies on material choice in terms of AI product adoption are sparse, yet the anthropomorphism-AI acceptance relationship is well-explored, albeit with conflicting findings. Some argue anthropomorphic designs threaten human uniqueness (Gursoy, 2019), while others claim they enhance product affability (Kim et al., 2019). On the social influence front, Gursoy et al. (2019) linked positive relationships between social influence, performance expectancy, and anthropomorphic designs affecting user emotions, subsequently influencing AI product acceptance. Trust also plays a role; attributes conveying human- likeness boost interpersonal trust (Lankton et al., 2015). System trust and interpersonal trust are two distinct kinds of trust concerning human-technology interaction (Wang et al., 2023), While system trust focuses on functionality and is highlighted by aesthetics, interpersonal trust hinging on benevolence and competence (Lankton et al., 2015) is underscored here. Figure 1 illustrates our research model.

H6. Anthropomorphism preference is tied to AI product use intention.

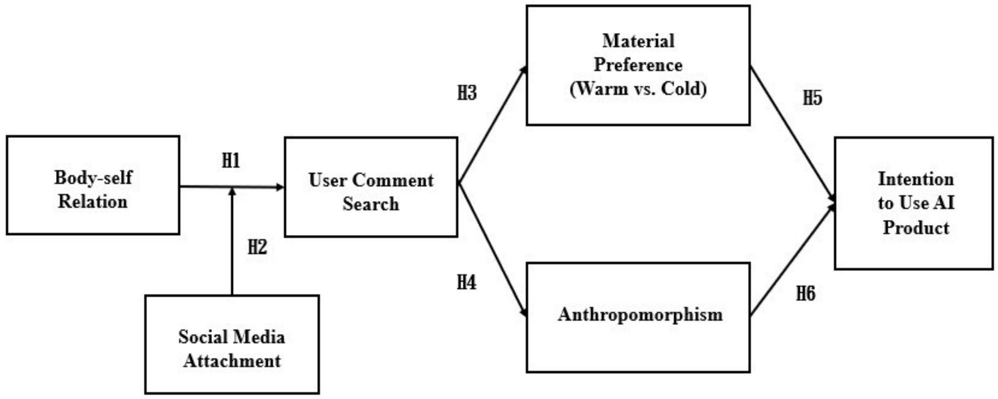

Figure 1. Research Model

Methodology

Sample and data collection

We employed online surveys through professional platforms after obtaining ethical approval from the Institutional Review Board in Taiwan. For Western samples, MTurk was used, but due to challenges in sourcing Chinese participants, we collaborated with a local survey firm. Online surveys, particularly via MTurk, have been recognized for their cost-effectiveness and reliability, especially post-COVID-19 (Maulana, 2020; Kees et al., 2017). After a pilot in early May 2022 and refinements, our main data collection in late May yielded 260 valid MTurk responses and 403 from Taiwan. Using ANOVA, we found no significant differences between early and late responses, allowing unified data analysis. Common method variance tests confirmed its non-issue (Podsakoff et al., 2012)

Measures

Our multilingual survey incorporated validated items tailored to our study's context. Items were rated on a 7-point Likert scale unless stated otherwise.

Body-self relation. Derived from Nabi and Keblusek (2014), we utilized the 7-item appearance and satisfaction subscales from the MBSRQ (Brown et al., 1990).

Social media attachment. After gauging participants' social media activity, we used adapted socioemotional questions from Rom and Alfasi (2014) to be platform-neutral.

User comment search. Three items, informed by Book et al. (2018), assessed the value placed on user comments versus product price.

Product attribute preferences. Participants expressed material preferences for AI products and their likeliness for anthropomorphic AI features, based on Noor et al. (2021).

Intention to use. Participants' intent to use an AI health system was gauged using items from Chen et al. (2022).

Control variables. We integrated factors like age, gender, education, and cultural dimensions to validate results (Bagozzi & Lee, 2002; Hsieh & Tseng, 2018).

Results

Data analysis

Utilizing SmartPLS 3.3.9 software and PLS-SEM, our study evaluated constructs' quality using metrics prescribed by Hair et al. (2017). Through a PLS bootstrapping method of 5,000 samples (Hair et al., 2017), we validated our hypotheses. Mediators and the dual impact of body-self relation and social media attachment on AI product intention were examined. All latent variables recorded VIFs between 1.000 and 3.662, meeting the criteria set by Kock (2015).

Measurement Model

Table 1 demonstrated significant factor loadings. Item loadings exceeded the 0.7 benchmark, and constructs surpassed the 0.7 threshold in both composite reliability and Cronbach’s alpha (Fornell and Larcker, 1981; Nunnally and Bernstein, 1994). AVEs for each construct were above 0.5. Table 2 and the Heterotrait-monotrait ratio conformed to discriminant validity standards (Kline, 2011).

Structural model

Table 3 presents our structural model's evaluation, considering path coefficients and predictive metrics like R^2, adjusted R^2, Q^2, and f^2 values. Q^2 values were positive, indicating reliable predictive relevance. Bootstrapping with 5,000

Table 1. Validity and reliability of first-order constructs

First-order constructs	Items	Western sample				Eastern sample			
		Loadings	CR	AVE	Cronbach α	Loadings	CR	AVE	Cronbachα
Body-self Relation (BSR)	BSR1	0.822	0.961	0.672	0.956	0.762	0.939	0.565	0.931
	BSR2	0.823				0.838			
	BSR3	0.842				0.764			
	BSR4	0.746				0.694			
	BSR5	0.781				0.664			
	BSR6	0.852				0.780			
	BSR7	0.723				0.692			
	BSR8	0.835				0.769			
	BSR9	0.844				0.764			
	BSR10	0.859				0.712			
	BSR11	0.808				0.689			
	BSR12	0.890				0.864			
Social Media Attachment (SMA)	SMA1	0.835	0.882	0.652	0.823	0.773	0.855	0.598	0.786
	SMA2	0.852				0.897			
	SMA3	0.786				0.688			
	SMA4	0.753				0.718			
User Comment Search (UCS)	UCS1	0.768	0.849	0.652	0.737	0.727	0.835	0.629	0.704
	UCS2	0.843				0.853			
	UCS3	0.809				0.794			
Material Preference (MP)	MP1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Anthropomorphism (ANT)	ANT1	0.818	0.896	0.682	0.846	0.774	0.901	0.695	0.854
	ANT2	0.835				0.850			
	ANT3	0.824				0.870			
	ANT4	0.826				0.839			
Intention to Use AI Product (IUAIP)	IUAIP1	0.790	0.923	0.751	0.893	0.905	0.945	0.813	0.924
	IUAIP2	0.883				0.922			
	IUAIP3	0.911				0.877			
	IUAIP4	0.879				0.901			

Table 2. Inter-correlations of first-order constructs

	BSR	SMA	UCS	ANT	IUAIP
BSR	**0.820**(W) **0.752**(E)				
SMA	0.618(W) 0.346(E)	**0.808**(W) **0.773**(E)			
UCS	0.305(W) 0.201(E)	0.328(W) 0.256(E)	**0.807**(W) **0.793**(E)		
ANT	0.499(W) 0.207(E)	0.505(W) 0.285(E)	0.548(W) 0.458(E)	**0.826**(W) **0.834**(E)	
IUAIP	0.085(W) 0.085(E)	0.280(W) 0.007(E)	0.275(W) 0.220(E)	0.269(W) 0.156(E)	**0.867**(W) **0.901**(E)

BSR: body-self relation; SMA: social media attachment; UCS: user comment search; ANT: anthropomorphism; IUAIP: intention to use AI product.

W: Western, E: Eastern.

The diagonal represents the square root of the AVE.

Table 3. Structural equation model results

Independent variables	Dependent variables			
	UCS	MP	ANT	IUAIP
BSR	.246(3.352) ***[0.045] (W)			
	.117(2.536) **[0.013] (E)			
SMA	.241(3.096) ***[0.045] (W)			
	.219(4.618) ***[0.047] (E)			
BSR x SMA	.271(2.440) **[0.104] (W)			
	.148(1.819) **[0.030] (E)			
UCS		-.023(0.395) [0.001] (W)	.548(10.065) ***[0.428] (W)	
		-.117(2.228) **[0.014] (E)	.458(10.347) ***[0.266] (E)	
MP				.003(0.058) [0.000] (W)
				.005(0.103) [0.000] (E)
ANT				.269(3.593) ***[0.078] (W)
				.156(2.665) ***[0.025] (E)
R^2	0.207 (W)	0.001 (W)	0.300 (W)	0.072 (W)
	0.107 (E)	0.014 (E)	0.210 (E)	0.024 (E)
Adjusted R^2	0.198 (W)	0.003 (W)	0.297 (W)	0.065 (W)
	0.100 (E)	0.011 (E)	0.208 (E)	0.020 (E)
Q^2	0.102 (W)	0.009 (W)	0.196 (W)	0.048 (W)
	0.051 (E)	0.008 (E)	0.143 (E)	0.016 (E)

BSR: body-self relation; SMA: social media attachment; UCS: user comment search; MP: material preference; ANT: anthropomorphism; IUAIP: intention to use AI product. W: Western, E: Eastern.

Number of observations (*N*) for W= 260 and for E=403; t-values are presented in parentheses (); f^2 values are presented in brackets []; * $p < .1$, ** $p < .05$, *** $p < .01$.

resamples confirmed the significance of path model relationships (Cohen, 1988).

For Western samples, Table 3 supported H1 and H2 while rejecting H3. Positive correlations were found between user comment search and anthropomorphism (supporting H4) and between anthropomorphism preference and AI product intention (supporting H6). H5 was rejected.

For Eastern samples, H1, H2, and H4 were supported. H3 was rejected due to a negative correlation between user comment search and material preference. H5 was dismissed, while a preference for anthropomorphism positively influenced AI product intention, supporting H6.

Discussion and Conclusion

As technology evolves, AI-infused products are becoming increasingly prevalent. Yet, the nuances of their design aesthetics, particularly material choice, are often overlooked. Understanding which AI products appeal to specific customers is now crucial. This study investigates product preferences from the perspective of one's body-self relation to AI design, providing insights into the roles and relationships of these factors.

Theoretical insights

This research addresses the increasing importance of interpersonal influences and determinants affecting intentions toward AI product usage (Chang & Feng, 2022; Ghani et al., 2019). Three main contributions emerge:

First. This study highlights the link between the adoption of AI products and one's body-self relation, clarifying the sequential relationship between normative and informational social influences. Notably, a significant interaction effect exists between body-self relation and social media attachment on user comments search.

Second, the relationship between user comments and AI product intention varies based on cultural environmental characteristics. For instance, user comment search correlates negatively with a preference for warm materials in Eastern cultures but not in Western ones. This distinction suggests consumers from collectivist societies favor cooler materials, potentially for their unassuming nature (Abdulrahman Al Moosa et al., 2022; Wong & Aziz, 2021).

Finally, while prior literature offers mixed results on anthropomorphism's influence on AI product intention (Blut et al., 2021; Yang et al., 2022), our findings suggest that those with strong body-self relationships, social media attachment, and user comment search tendencies have a positive inclination towards anthropomorphic AI products.

Managerial insights

This research provides actionable insights for managers. When investing in AI products, understanding the target market's cultural nuances is paramount. Western firms should prioritize anthropomorphic designs, while Eastern firms should balance anthropomorphism with a preference for cooler materials. This study emphasizes that marketing strategies should be tailored, focusing on consumers' body-self relationships and their attention to user comments. Collaborating with internet influencers, marketers can spotlight the significance of body-self relationships and anthropomorphic designs to target the right consumer segments effectively.

Future research directions

The global response to COVID-19 has reshaped consumer behavior, with a marked shift towards online consumption and social media shopping. This shift offers a new avenue for research on marketing strategies and their effectiveness during such transformative periods. With increased reliance on agile marketing strategies due to changing consumer behaviors, future studies should investigate their impact on AI adoption rates. Exploring additional factors, like enhanced AI-focused education, can also provide a comprehensive understanding of consumer adoption patterns. As AI continues to evolve, this research serves as a foundational step, encouraging more in-depth studies in the domain.

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