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Colouring Outside the Lines: How AI-Driven Personalization Reshapes the Experience–Value Pathway in Human–AI Co-Creation

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Abstract **Original Research Article**

Artificial intelligence (AI) is reshaping the way users and systems jointly generate value, yet little is known about how AI-driven personalization alters the experience–value pathway in human–AI co-creation. Drawing on the Stimulus–Organism–Response (S-O-R) paradigm and Service-Dominant Logic (SDL), this study examines personalization, trust in AI, perceived control, and interactivity as stimuli influencing two internal states—perceived value and co-creation experience—which in turn shape co-creation value. Data were collected from 343 Vietnamese AI users through a judgemental (purposive) sampling procedure and analysed using partial least squares structural equation modelling (PLS-SEM). The results confirm ten of the eleven hypotheses: personalization, trust in AI, perceived control, and interactivity significantly enhance perceived value, while personalization, trust in AI, and perceived control also strengthen the co-creation experience; interactivity, however, does not significantly affect the co-creation experience. Co-creation experience positively influences perceived value, and both constructs jointly drive co-creation value, supporting a cascading experience–value pathway. Theoretically, the study extends SDL and S-O-R to AI-mediated settings by reframing AI-driven personalization as an operant resource that triggers a dual internal mechanism. Practically, the findings guide AI developers and managers to design personalization features that balance algorithmic adaptivity with user agency to sustain meaningful value co-creation.

Keywords: AI-driven personalization, Co-creation experience, Co-creation value, Human–AI co-creation, Perceived value, PLS-SEM.

1. Introduction

The accelerating diffusion of artificial intelligence (AI) into everyday life has fundamentally redefined how individuals interact with digital systems (Haenlein & Kaplan, 2019). Generative and conversational tools such as ChatGPT, Gemini, and Adobe Firefly are no longer passive utilities; they increasingly act as adaptive collaborators that customise outputs in real time and co-construct value alongside their users (L. Huang & Zheng, 2023; Vallabhaneni et al., 2024). Within this landscape, AI-driven personalization has emerged as the central mechanism through which intelligent systems anticipate user intentions, tailor recommendations, and orchestrate interactive experiences (J. Chen, Liu, et al., 2024; Hathout Chaimae, 2025). As AI moves from instrumental automation toward context-aware collaboration, the boundaries between human creativity and algorithmic assistance blur, giving rise to a new paradigm of human–AI co-creation (Ramaswamy & Ozcan, 2020; Rezwana & Maher, 2022).

Traditional value co-creation theory, rooted in Service-Dominant Logic (SDL), conceptualises value as emerging from interpersonal interactions, resource integration, and reciprocal experiences between human actors (Vargo & Lusch, 2016; Chatterjee et al., 2022). However, the rise of AI as an active partner challenges several foundational assumptions of this framework. Unlike human co-creators, AI agents lack intentionality and emotional reciprocity, yet they exhibit learning, adaptation, and responsiveness that influence users' perceptions of shared control, trust, and experiential engagement (Bowen & Morosan, 2018; Richter, 2025). This paradigm shift raises a fundamental question: how does AI-driven personalization reshape the experiential mechanisms that facilitate value co-creation in human–AI dyads? Similar questions have been explored in adjacent domains where emerging technologies mediate consumer experience, such as metaverse retailing (Dang et al., 2024) and mobile payment ecosystems (Dang et al., 2023), both of which highlight trust, personalization, and interactivity as core drivers of user engagement.

Despite growing interest in AI and co-creation, three critical gaps remain in the literature. First, although prior research has extensively examined human–human value co-creation (Nangpiire et al., 2022; Palma et al., 2019), few studies have systematically connected AI-driven personalization to the co-creation experience–value pathway. Second, while explainability and technical aspects of AI have attracted scholarly attention (Vereschak et al., 2021), the relational and meaning-making dimensions—such as how users internalise trust, exercise control, and derive value through personalised interactions—remain underexplored (Behera et al., 2024). Third, most empirical work has focused on Western or highly digitised markets, leaving emerging economies such as Vietnam largely absent from the discourse on human–AI co-creation (Nguyen et al., 2025; Phan et al., 2025). This omission is significant because cultural orientation, digital maturity, and technology adoption patterns in Southeast Asia may shape AI-driven value co-creation in distinctive ways (Dang et al., 2024).

To address these gaps, the present study adopts the Stimulus–Organism–Response (S-O-R) paradigm, combined with SDL, to examine how AI-driven personalization—operationalised through personalization, trust in AI, perceived control, and interactivity—shapes two organismic states (perceived value and co-creation experience), which in turn drive co-creation value. Drawing on survey data from 343 Vietnamese AI users and partial least squares structural equation modelling (PLS-SEM), the study seeks to answer three research questions: (1) How do the four stimuli of AI-driven personalization influence users' perceived value and co-creation experience? (2) How does the co-creation experience translate into co-creation value through perceived value? (3) What theoretical and managerial implications emerge from understanding AI-driven personalization as an operant resource in Service-Dominant Logic?

This research contributes to the literature in three ways. Theoretically, it extends S-O-R and SDL to AI-mediated settings by reconceptualising AI-driven personalization as an operant resource that triggers a dual internal mechanism of cognition (perceived value) and experience (co-creation experience). Methodologically, it provides empirical evidence from an emerging Southeast Asian market, complementing prior studies on technology-mediated consumer behaviour in Vietnam (Dang et al., 2023, 2024; Nguyen et al., 2025). Practically, it offers actionable guidance for AI designers and managers to cultivate personalization features that sustain user agency and experiential richness. The remainder of the paper is structured as follows. Section 2 develops the literature review and hypotheses. Section 3 presents the methodology. Section 4 reports the results. Section 5 discusses the findings, implications, limitations, and avenues for future research.

2. Literature Review, Theoretical Foundation, and Hypotheses Development

2.1. Literature Review

This study investigates human–AI co-creation, with particular emphasis on AI-driven personalization, trust in AI, interactivity, and perceived control as key mechanisms influencing co-creation value. Viewing AI as an operant resource, scholars have argued that intelligent systems can discern, interpret, and anticipate consumer needs, thereby co-creating value with users rather than simply serving as passive tools (Akaka & Vargo, 2014; Lusch & Nambisan, 2015; Polese & Tartaglione, 2012). AI-driven customisation extends beyond static user profiles, integrating continuous behavioural monitoring, predictive analytics, and dynamic content distribution that evolves with each interaction (T. Li, 2024). The present study consolidates these elements into a unified framework for examining how AI-driven personalization generates co-creation value.

Prior research has highlighted the multidimensional nature of AI-driven co-creation. Y. Zhang and Lee (2022) showed that engaging experiential elements enhance co-creation experiences and perceived value, reinforcing favourable behavioural intentions. Wen et al. (2022) demonstrated that AI customisation enriches both the functional and experiential aspects of user engagement within digital platforms. S. K. Roy et al. (2019) similarly argued that smart servicescapes leverage AI-driven adaptation to foster immersive co-creation experiences and deeper emotional engagement. In B2B contexts, Fehrenbach et al. (2024) found that combining human creativity with AI capabilities produces more innovative and effective outcomes when aligned with human judgment. Rezwana and Maher (2022) further emphasised that bidirectional human–AI communication enhances user control, trust, and creative experience. These studies collectively position AI-driven personalization as a critical enabler of co-creation, yet they also reveal a fragmented theoretical landscape in which the mediating role of perceived value and the cascading effect toward co-creation value remain underexamined. Complementary research on technology-mediated consumer experiences—such as interactive mobile advertising (Nguyen et al., 2025), mobile payment loyalty (Dang et al., 2023), and metaverse retail (Dang et al., 2024)—further underscores the importance of personalization, interactivity, and trust as recurring antecedents of value formation, motivating the integrative approach adopted in this research.

2.2. Theoretical Background

2.2.1. AI-Driven Personalization

AI-driven personalization is conceptualised as a transformative strategy that delivers tailored experiences aligned with individual preferences (Mustafa Ayobami Raji et al., 2024). It reflects the evolution of human–computer interaction from static, uniform interfaces toward dynamic and anticipatory customisation powered by real-time data and machine learning (J. Chen, Liu, et al., 2024; Klein & Martinez, 2023). Three conceptual pillars underpin AI-driven personalization: chatbot anthropomorphism, which enhances engagement through human-like attributes (R. Roy & Naidoo, 2021; Tsai et al., 2021); trustworthy AI, which emphasises transparency, reliability, and ethics (Mcknight et al., 2011; Shin, 2021); and perceived control, which captures users' capacity to shape AI-generated outputs (Arantes, 2024). Together, these dimensions shape how users evaluate the functional, relational, and ethical qualities of AI-mediated experiences.

2.2.2. Co-Creation Experience and Co-Creation Value

Under Service-Dominant Logic (SDL), value is not embedded in products or services but is co-created through the active engagement of participants during service interactions (Vargo & Lusch, 2004, 2016). The co-creation experience refers to the interactive process through which humans and AI jointly generate tangible outcomes and intangible relational value (Lavin & Ramona Riehle, 2025; Rezwana & Maher, 2022). In AI-mediated contexts, virtual agents and conversational interfaces shape user engagement through personalised, culturally-attuned exchanges (Baek, 2023), guiding how individuals interpret and derive meaning from collaboration. Scholars have theorised co-creation experience through emotional, interpersonal, and cognitive dimensions (Alben, 1996; Lallemand et al., 2015), emphasising experiential benefits as a form of psycho-cognitive outcome (Bhattacherjee et al., 2004).

Co-creation value, in contrast, captures the mutual value generated through collaborative interactions between human creativity and agentic non-human actors (Lavin, 2025; Saha et al., 2022; Sawyer & DeZutter, 2009). In AI-mediated environments, operand resources (e.g., data, platforms, interfaces) and operant resources (e.g., AI algorithms, user expertise) combine to produce co-created value (Bartelheimer et al., 2025; M.-H. Huang & Rust, 2018). By integrating these perspectives, the co-creation experience captures the process and emotional–cognitive dynamics of human–AI interaction, whereas co-creation value reflects the outcomes of that collaboration. Consistent with the value-in-use premise (Antón et al., 2018), the richer and more user-aligned the co-creation experience, the greater the resulting co-creation value.

2.2.3. Perceived Value Theory

Perceived value denotes a user's overall evaluation of the utility of a product or service based on a cost–benefit comparison (Pal & Triyason, 2018). Within the Technology Acceptance Model (TAM), perceived value has been shown to influence users' adoption and continued use of AI systems through dimensions such as novelty, enjoyment, and interest (Moon & Kim, 2001). Building on this foundation, H.-L. Yang and Lin (2014) categorised perceived value into hedonic, social, and cognitive dimensions, while Gusti et al. (2018) established that perceived utilitarian and hedonic values shape users' sustained engagement with AI systems. This study adopts perceived value as a central organismic state that mediates the relationship between AI-driven personalization and co-creation value.

2.3. Hypotheses Development

The Stimulus–Organism–Response (S-O-R) paradigm provides the theoretical scaffolding for linking AI-driven personalization to users' cognitive, affective, and behavioural responses. In this study, personalization, trust in AI, perceived control, and interactivity serve as stimuli (S), while perceived value and co-creation experience act as internal states (O), ultimately driving co-creation value (R). This framework aligns with recent applications of S-O-R in technology-mediated consumer research (Dang et al., 2024; Duc et al., 2024) and offers a systematic lens for analysing how AI system attributes and user perceptions jointly foster meaningful co-created value.

2.3.1. Personalization

Personalization enables AI systems to align content, recommendations, and interface dynamics with individual user preferences (J. Chen, Liu, et al., 2024). By reducing cognitive load and retrieval time, personalization enhances perceived value through a sense of distinctiveness and relevance (Hatami et al., 2025; Neuhofer et al., 2012). When users perceive that AI systems acknowledge and respond to their needs, they are more likely to evaluate the service as worthwhile and rewarding (Minkiewicz et al., 2014). Moreover, personalization strengthens the collaborative dynamic by making user contributions more impactful and reciprocal (S. K. Roy et al., 2019). Accordingly:

> *H1: Personalization has a significant positive impact on perceived value.*
>
> *H2: Personalization has a significant positive impact on co-creation experience.*

2.3.2. Trust in AI

Trust in AI is a foundational element of human–AI interaction, enabling users to anticipate system behaviour and tolerate uncertainty (Hoff & Bashir, 2015; Jacovi et al., 2021). As AI systems embed deeper into decision-making, trust is cultivated through transparency, fairness, explainability, and robustness (Y. Li et al., 2024). Users with higher trust perceive AI outputs as more reliable and aligned with their interests, thereby enhancing perceived value (Mcknight et al., 2011). Trust also reduces relational barriers, encouraging users to treat AI as a collaborative partner and enriching the co-creation experience (Lam et al., 2020; Rezwana & Maher, 2022). Recent research on AI-mediated commerce further confirms trust as a pivotal driver of engagement and perceived value across digital platforms (Dang et al., 2023, 2024). Thus:

H3: Trust in AI is positively related to perceived value.

H4: Trust in AI is positively related to co-creation experience.

2.3.3. Perceived Control

Perceived control refers to the extent to which users believe they can influence, modify, or terminate AI-generated interactions (Mathieson, 1991; Maedche et al., 2019). In AI-driven personalization, user control aligns with reactive personalization, where users actively opt-in to customised content rather than passively receiving algorithmic pushes (B. Zhang & Sundar, 2019). A heightened sense of control reduces uncertainty, reinforces confidence, and enhances users' capacity to evaluate AI outputs (Hui & Bateson, 1991). Conversely, diminished control engenders unease and reduces perceived benefits (Nabavi & Sadegh Bijandi, 2012). Empirical studies show that users with greater control exert more effort, derive more enjoyment, and rate co-creation outcomes as higher quality (Füller & Bilgram, 2017; Salma et al., 2025). Hence:

H5: Perceived control has a significant positive impact on perceived value.

H6: Perceived control has a significant positive impact on co-creation experience.

2.3.4. Interactivity

Interactivity captures the dynamic, reciprocal communication between users and AI systems (Stromer-Galley, 2004). Active engagement enhances perceived value, as users perceive AI outputs as more aligned with their goals (J. Chen, Guo, et al., 2024; S.-C. Chen & Lin, 2019). Interactive features—such as voice interfaces, visual cues, and avatars—facilitate idea exchange, real-time feedback, and collaborative refinement (Raees et al., 2024). Prior work on interactive mobile advertising and metaverse retail similarly identifies interactivity as a driver of consumer engagement and perceived value (Dang et al., 2024; Nguyen et al., 2025). By fostering shared ownership of outcomes, interactivity transforms passive users into active collaborators (Hanaysha & Alhyasat, 2025; Wang et al., 2007). Accordingly:

H7: Interactivity substantially enhances perceived value.

H8: Interactivity substantially enhances co-creation experience.

2.3.5. Co-Creation Experience, Perceived Value, and Co-Creation Value

Within SDL, value is always co-created through the beneficiary's participation (Vargo & Lusch, 2008). In AI-mediated contexts, users serve as co-producers who actively shape and refine their experiences (Grönroos, 2008). The value-in-experience perspective contends that value resides in the experiential realm emerging from co-created interactions rather than in the offering itself (Minkiewicz et al., 2014). Favourable co-creation experiences yield richer value perceptions (Y. Zhang & Lee, 2022), while perceived value in turn motivates users to invest effort, time, and resources in subsequent co-creation (Abror et al., 2023; Itani et al., 2019). Beyond this mediated pathway, co-creation experience can also directly stimulate co-creation value through engagement, knowledge sharing, and resource integration (Grönroos, 2011; Prahalad & Ramaswamy, 2004). Consistent with relational and experiential views of value (Heinonen & Strandvik, 2015; Vargo & Lusch, 2016), this study posits:

H9: Co-creation experience is positively associated with perceived value.

H10: Perceived value is positively associated with co-creation value.

H11: Co-creation experience is positively associated with co-creation value.

3. Methodology

3.1. Data Collection

A structured questionnaire was developed to operationalise the constructs in the proposed model. The instrument was divided into two sections: the first captured demographic information (gender, age, frequency of AI-tool use, and primary usage purpose), while the second contained measurement items for the seven constructs. A 7-point Likert scale was adopted to minimise neutral responses, enhance response dispersion, and improve discriminant sensitivity compared to 5-point scales (Bass et al., 1974; Dang et al., 2024). All scales were adapted from prior validated studies: personalization from Baek and Morimoto (2012) and Xu et al. (2008); trust in AI from Helal et al. (2023) and Jaradat et al. (2018); perceived control from Fan et al. (2017), C.-H. Lee and Wu (2017), and Webster et al. (1993); interactivity from Alalwan (2018) and Jiang et al. (2010); perceived value from Al-Debei et al. (2022) and Liu et al. (2015); co-creation experience from Lei et al. (2020) and Mathis et al. (2016); and co-creation value from Peña-García et al. (2021), Savitha et al. (2022), and Sthapit et al. (2019). Measurement items are presented in Appendix A.

3.2. Sampling and Sample Size

A non-probability judgemental (purposive) sampling procedure was employed to recruit Vietnamese AI users with sufficient exposure to AI tools such as ChatGPT, Gemini, and similar generative platforms. Purposive sampling is appropriate when the research requires respondents with specific experiential characteristics (Dang et al., 2023; Phan et al., 2025). The minimum sample size was determined using G*Power 3 (Erdfelder & Buchner, 1996). With an anticipated medium effect size ($f^2 = 0.15$), significance level $\alpha = 0.05$, statistical power $(1 - \beta) = 0.80$, and six predictors, the minimum required sample was 98. A total of 343 valid responses were obtained, well exceeding the threshold and providing adequate statistical power for PLS-SEM estimation (Hair et al., 2021).

4. Results

4.1. Demographic Profile

Table 1 presents the demographic profile of 343 respondents. The sample comprised 58.02% female and 41.98% male participants. Regarding age, 48.69% were aged 18–23, 23.32% aged 23–29, 16.33% aged 29–35, and 11.66% over 35. In terms of AI tool usage frequency, 41.69% used AI daily, 32.94% several times a week, 14.29% about once a week, and 11.08% a few times a month. Regarding primary purpose, 48.69% used AI for educational and research tasks, 35.28% for professional duties, and 16.03% for entertainment purposes such as content creation, image generation, and storytelling.

Table 1. Demographic Profile of Respondents

Characteristic	Category	Frequency	Percentage (%)
Age	18 – 23 years old	167	48.69
	23 – 29 years old	80	23.32
	29 – 35 years old	56	16.33
	Over 35 years old	40	11.66
Gender	Female	199	58.02
	Male	144	41.98

Characteristic	Category	Frequency	Percentage (%)
AI tools usage frequency	Every day	143	41.69
	Several times a week	113	32.94
	About once a week	49	14.29
	A few times a month	38	11.08
Primary usage purpose	Education / Research	167	48.69
	Working / Professional tasks	121	35.28
	Entertainment	55	16.03

4.2. Measurement Model Assessment

Before testing the structural hypotheses, the measurement model was evaluated for reliability and validity following Hair et al. (2017, 2021). Construct reliability was examined using Cronbach's Alpha (CA), composite reliability (CR), and Dijkstra–Henseler's rho (ρA). As shown in Table 2, all values exceeded the recommended 0.70 threshold (CA ≥ 0.898; CR ≥ 0.925; ρA ≥ 0.899), confirming adequate internal consistency (Foo et al., 2018; Tan & Ooi, 2018). Convergent validity was evaluated through factor loadings (FL) and average variance extracted (AVE). All factor loadings ranged from 0.831 to 0.894, above the 0.70 benchmark, and all AVE values exceeded 0.50, with the lowest AVE being 0.711 (Hair et al., 2016, 2021).

Discriminant validity was assessed using the Fornell and Larcker (1981) criterion and the cross-loading approach (Henseler et al., 2015). As presented in Table 3, the square root of AVE for each construct exceeded its inter-construct correlations, confirming discriminant validity. Multicollinearity was examined through variance inflation factor (VIF) values, which ranged from 2.199 to 3.212—well below the 5.00 threshold (Hair, 2014)—indicating no collinearity concerns.

Table 2. Convergent Validity and Construct Reliability

Construct	Items / FL	CA	ρA	CR	AVE	VIF Range
AAP	AAP1/0.883; AAP2/0.873; AAP3/0.894; AAP4/0.874; AAP5/0.867	0.926	0.927	0.944	0.772	2.707 – 3.212
CAE	CAE1/0.875; CAE2/0.875; CAE3/0.865;	0.921	0.922	0.941	0.761	2.569 – 3.165

Construct	Items / FL	CA	ρA	CR	AVE	VIF Range
	CAE4/0.856; CAE5/0.890					
CAV	CAV1/0.883; CAV2/0.862; CAV3/0.883; CAV4/0.878; CAV5/0.873	0.924	0.924	0.943	0.766	2.578 – 2.957
IAA	IAA1/0.872; IAA2/0.875; IAA3/0.854; IAA4/0.860; IAA5/0.864	0.916	0.916	0.937	0.748	2.472 – 2.844
PAC	PAC1/0.848; PAC2/0.865; PAC3/0.877; PAC4/0.872; PAC5/0.881	0.919	0.919	0.939	0.755	2.402 – 2.921
PAV	PAV1/0.841; PAV2/0.831; PAV3/0.852; PAV4/0.834; PAV5/0.858	0.898	0.899	0.925	0.711	2.199 – 2.536
TAI	TAI1/0.858; TAI2/0.874; TAI3/0.875; TAI4/0.878; TAI5/0.862	0.919	0.919	0.939	0.756	2.531 – 2.882

Note: AAP = AI-driven personalization; CAE = Co-creation experience; CAV = Co-creation value; IAA = Interactivity; PAC = Perceived control; PAV = Perceived value; TAI = Trust in AI.

Table 3. Discriminant Validity (Fornell–Larcker Criterion)

	AAP	CAE	CAV	IAA	PAC	PAV	TAI
AAP	0.878						
CAE	0.725	0.872					
CAV	0.867	0.762	0.875				
IAA	0.746	0.665	0.739	0.865			
PAC	0.592	0.626	0.599	0.513	0.869		
PAV	0.783	0.791	0.767	0.828	0.626	0.843	

	AAP	CAE	CAV	IAA	PAC	PAV	TAI
TAI	0.558	0.756	0.557	0.747	0.516	0.782	0.869

Note: Diagonal values (bold) represent the square root of AVE; off-diagonal values are inter-construct correlations.

4.3. Structural Model Assessment

The structural model was evaluated using 5,000 bootstrapping subsamples with no sign change (Hair et al., 2021). A path was considered significant when $t > 1.96$ and $p < 0.05$. Table 4 summarises the results of the eleven hypotheses. Personalization (AAP) significantly enhanced perceived value ($\beta = 0.238$, $t = 2.899$, $p = 0.004$) and co-creation experience ($\beta = 0.438$, $t = 6.262$, $p < 0.001$), supporting H1 and H2. Trust in AI (TAI) also exhibited positive effects on both perceived value ($\beta = 0.239$, $t = 3.836$, $p < 0.001$) and co-creation experience ($\beta = 0.538$, $t = 7.811$, $p < 0.001$), confirming H3 and H4. Perceived control (PAC) positively predicted perceived value ($\beta = 0.095$, $t = 2.716$, $p = 0.007$) and co-creation experience ($\beta = 0.165$, $t = 3.714$, $p < 0.001$), supporting H5 and H6. Interactivity (IAA) significantly enhanced perceived value ($\beta = 0.307$, $t = 3.986$, $p < 0.001$), supporting H7, but did not significantly influence co-creation experience ($\beta = -0.149$, $t = 1.841$, $p = 0.066$); H8 was therefore rejected. Co-creation experience positively affected perceived value ($\beta = 0.174$, $t = 2.501$, $p = 0.012$), supporting H9. Finally, perceived value ($\beta = 0.438$, $t = 5.623$, $p < 0.001$) and co-creation experience ($\beta = 0.416$, $t = 4.877$, $p < 0.001$) both significantly drove co-creation value, supporting H10 and H11.

Table 4. Results of Hypotheses Testing

Hypothesis	Path	β	SD	t-value	p-value	95% CI	Decision
H1	AAP → PAV	0.238	0.082	2.899	0.004	[0.088, 0.405]	Supported
H2	AAP → CAE	0.438	0.070	6.262	<0.001	[0.301, 0.573]	Supported
H3	TAI → PAV	0.239	0.062	3.836	<0.001	[0.120, 0.364]	Supported
H4	TAI → CAE	0.538	0.069	7.811	<0.001	[0.391, 0.658]	Supported
H5	PAC → PAV	0.095	0.035	2.716	0.007	[0.025, 0.162]	Supported
H6	PAC → CAE	0.165	0.044	3.714	<0.001	[0.084, 0.257]	Supported
H7	IAA → PAV	0.307	0.077	3.986	<0.001	[0.148, 0.450]	Supported

Hypothesis	Path	β	SD	t-value	p-value	95% CI	Decision
H8	IAA → CAE	−0.149	0.081	1.841	0.066	[−0.305, 0.015]	Not supported
H9	CAE → PAV	0.174	0.069	2.501	0.012	[0.034, 0.307]	Supported
H10	PAV → CAV	0.438	0.078	5.623	<0.001	[0.284, 0.590]	Supported
H11	CAE → CAV	0.416	0.085	4.877	<0.001	[0.246, 0.580]	Supported

Predictive relevance was assessed through Stone–Geisser's Q^2 (Hair et al., 2021), with all Q^2 values exceeding zero, confirming the model's predictive utility (Q^2CAE = 0.714; Q^2CAV = 0.807; Q^2PAV = 0.647). The coefficient of determination (R^2) reached 0.825 for perceived value (substantial), 0.729 for co-creation experience (substantial), and 0.653 for co-creation value (moderate-to-substantial), indicating strong explanatory power (Table 5).

Table 5. Predictive Relevance (Q^2) and R^2

Dependent Variable	Q^2	Interpretation	R^2	RMSE	MAE
CAE	0.714	$Q^2 > 0$ (Predictive)	0.729	0.537	0.379
CAV	0.807	$Q^2 > 0$ (Predictive)	0.653	0.441	0.304
PAV	0.647	$Q^2 > 0$ (Predictive)	0.825	0.596	0.429

Effect sizes (f^2) were evaluated using Cohen's (2013) benchmarks: 0.02 (small), 0.15 (medium), and 0.35 (large). For perceived value, interactivity exerted a medium effect ($f^2 = 0.149$), while personalization (0.097), trust in AI (0.093), co-creation experience (0.047), and perceived control (0.029) produced small effects. For co-creation experience, trust in AI had a large effect ($f^2 = 0.442$), personalization a medium effect (0.270), and perceived control (0.060) and interactivity (0.023) small effects. For co-creation value, perceived value (0.207) and co-creation experience (0.186) both generated medium effects (Table 6).

Table 6. Effect Size (f^2)

Predictor → Outcome	PAV	CAE	CAV
AAP	0.097 (small)	0.270 (medium)	—
TAI	0.093 (small)	0.442 (large)	—
PAC	0.029 (small)	0.060 (small)	—
IAA	0.149 (medium)	0.023 (small)	—
CAE	0.047 (small)	—	0.186 (medium)
PAV	—	—	0.207 (medium)

5. Discussion and Implications

5.1. Discussion of Findings

This study advances understanding of how AI-driven personalization shapes the experience–value pathway in human–AI co-creation by integrating Service-Dominant Logic, the Stimulus–Organism–Response paradigm, and perceived value theory. The findings yield four key insights that extend and refine existing knowledge on AI-mediated co-creation.

First, the results confirm that all four stimuli of AI-driven personalization—personalization, trust in AI, perceived control, and interactivity—positively shape perceived value, consistent with earlier work on AI-mediated consumer experiences (Hanaysha & Alhyasat, 2025; Hatami et al., 2025; Murillo-Zegarra et al., 2020). Personalised content delivery reduces cognitive load and increases contextual relevance (Gursoy et al., 2019), trust in AI diminishes uncertainty and boosts confidence (Choung et al., 2023), perceived control reinforces user autonomy (Ooge et al., 2023), and interactivity cultivates engagement and reciprocal meaning-making (Voorveld et al., 2018). These findings align with prior evidence from technology-mediated consumer behaviour research in Vietnam, where trust, interactivity, and personalization have consistently emerged as core value drivers (Dang et al., 2023, 2024; Nguyen et al., 2025).

Second, personalization, trust in AI, and perceived control significantly enhance co-creation experience (H2, H4, H6), reinforcing the view that users engage more actively when AI systems flexibly adapt to their needs. Personalization enables reciprocal learning between users and AI (J. Chen, Liu, et al., 2024), trust reduces perceived risk and fosters collaborative reliance (Bach et al., 2024), and perceived control empowers users to co-shape outputs (Ooge et al., 2023). This triadic mechanism corroborates recent work on AI-mediated engagement in emerging markets (Dang et al., 2024; Phan et al., 2025), suggesting that cognitive assurance and agency form the bedrock of meaningful human–AI collaboration.

Third, and contrary to expectations, interactivity did not significantly enhance the co-creation experience (H8), a finding that warrants careful interpretation. One plausible explanation lies in the contextual character of AI-mediated interactivity in Vietnam. Vietnamese users—particularly the younger cohort that dominates our sample—are digitally literate but tend to engage with AI tools in task-oriented, utilitarian ways, primarily for education, work, or content retrieval (Dang et al., 2024; Nguyen et al., 2025). In such contexts, interactivity may be perceived as a functional affordance rather than a relational or exploratory dimension, leading users to value interactive features for efficiency rather than co-creative expression (Lam et al., 2020). By contrast, studies conducted with Australian retail consumers—who possess high technical competence and engage with digital platforms in richer experiential ways—show strong positive effects of interactivity on co-creation (S. K. Roy et al., 2019). Additionally, users with limited depth of engagement may experience cognitive overload when interacting with complex AI interfaces, dampening the experiential quality of interactivity (Burin et al., 2018). This divergence suggests that the co-creative potential of interactivity is culturally and contextually contingent, and is shaped by both users' digital fluency and their interpretive framing of AI interactions.

Fourth, co-creation experience positively influences both perceived value (H9) and co-creation value (H11), while perceived value serves as a significant driver of co-creation value (H10). These results empirically validate the experience–value pathway central to SDL (Vargo & Lusch, 2008, 2016) and confirm that active user engagement with AI—through iterative feedback, content adaptation, and personalised recommendations—transforms into tangible co-created value. The dual route from co-creation experience to co-creation value (directly and via perceived value) suggests that users derive both experiential gratification and cognitive appraisal benefits from human–AI collaboration, reinforcing the synergistic nature of this partnership (S. K. Roy et al., 2019). These results echo emerging evidence from mobile payment ecosystems and metaverse retail, where the cascading effect of personalization, trust, and experiential engagement drives sustained user value (Dang et al., 2023, 2024).

5.2. Theoretical Implications

This study makes three theoretical contributions to the literature on AI-mediated co-creation. First, it extends Service-Dominant Logic by reconceptualising AI-driven personalization as an operant resource that activates dual internal mechanisms—perceived value (cognitive) and co-creation experience (experiential)—which jointly shape co-creation value. This reframing advances prior SDL research (Grönroos, 2008, 2011; Vargo & Lusch, 2016) by explicitly theorising the role of algorithmic agency in value co-creation processes, complementing efforts to integrate emerging technologies into SDL frameworks (Bartelheimer et al., 2025; Riikkinen et al., 2018).

Second, the study enriches the S-O-R paradigm by operationalising AI-driven personalization as a multidimensional stimulus that triggers cognitive and experiential organismic states. This dual-mediation structure advances recent S-O-R applications in technology-mediated consumer research (Dang et al., 2024; Duc et al., 2024) by showing that personalization, trust in AI, and perceived control exert parallel effects on both cognition and experience, whereas interactivity exerts an asymmetric effect—strengthening cognitive appraisal but not experiential engagement. This refinement underscores the need for more granular theorisation of stimulus–response dynamics in AI contexts, where users' interpretive frames may vary by cultural and digital-maturity context (Nguyen et al., 2025; Phan et al., 2025).

Third, the study provides a theoretical distinction between co-creation experience and co-creation value (Q. Yang & Lee, 2024; P. Zhang et al., 2021), positioning experience as the process dimension and value as the outcome dimension of human–AI collaboration. Drawing on experiential frameworks (Alben, 1996; Chemi & Krogh, 2017; Lallemand et al., 2015), this study contributes a validated measurement scheme that captures the multidimensional nature of co-creation in AI-mediated settings—addressing a persistent measurement gap and enabling more precise empirical investigations in future research.

5.3. Managerial Implications

For AI developers and platform managers, the findings suggest a move toward human-centred personalization design that prioritises transparency, user agency, and context sensitivity. Because trust in AI exerts the largest effect on co-creation experience, AI systems should embed cues that signal reliability, such as explainable recommendations, confidence indicators, and transparent data-use disclosures (Glikson & Woolley, 2020). Features that support perceived control—editable prompts, user-adjustable filters, and the ability to accept, revise, or reject AI outputs—further empower users to shape their experience and deepen co-creation (Ooge et al., 2023; Westphal et al., 2023). Recommender and intelligent-support systems should continuously adapt to users' evolving preferences while allowing users to retain final decision authority, consistent with the "AI as augmentation, not substitution" principle observed in practical settings such as Google Workspace (Akcil et al., 2021; Cao et al., 2024).

For platforms operating in emerging markets such as Vietnam, the non-significant effect of interactivity on co-creation experience highlights a distinct managerial opportunity. Rather than assuming that richer interactivity automatically translates into deeper engagement, managers should design interactive features that align with users' predominantly task-oriented motivations. This may include guided prompts, contextual onboarding, and progressive disclosure mechanisms that gently expand users' interactive repertoire over time, transforming utilitarian usage into more exploratory and co-creative engagement (Dang et al., 2024; Nguyen et al., 2025). Investment in digital literacy initiatives and user education can further amplify the co-creative potential of interactive AI features, particularly among users with limited prior experience with advanced AI tools (Burin et al., 2018).

Finally, managers should leverage the dual experience–value pathway to drive sustained engagement. Because both perceived value and co-creation experience independently fuel co-creation value, AI platforms should design for both cognitive and experiential payoffs—offering functional benefits (time saving, accuracy, personalised recommendations) alongside experiential rewards (feelings of empowerment, creativity, and collaborative ownership). Governance frameworks that ensure algorithmic transparency, data ethics, and responsible AI use can further reinforce user confidence and prevent value co-destruction (Glikson & Woolley, 2020; Zhu et al., 2022).

5.4. Conclusions

This study advances understanding of human–AI co-creation by demonstrating how AI-driven personalization reshapes the experience–value pathway between users and intelligent systems. The findings position AI not merely as a technological enabler but as an active co-creator that customises experiences, enhances perceived value, and sustains reciprocal value creation. By integrating SDL, S-O-R, and perceived value theory, the study clarifies how personalization, trust in AI, and perceived control underpin meaningful co-creation experiences, while interactivity produces context-dependent effects. The results emphasise the importance of designing AI systems that combine transparency, adaptivity, and emotional intelligence to sustain long-term user engagement and value co-creation in emerging digital economies.

5.5. Limitations and Future Research

Although this study provides meaningful insights, several limitations warrant acknowledgement. First, the cross-sectional design captures user perceptions at a single point in time and does not fully reflect the evolving nature of human–AI interactions. Longitudinal and experimental designs are encouraged to examine how trust, perceived value, and co-creation experience develop through repeated AI encounters (Dang et al., 2023, 2024). Second, the sample is drawn exclusively from Vietnam; while this offers valuable evidence from an emerging Southeast Asian economy, cross-cultural comparisons would shed light on how digital maturity, cultural orientation, and institutional context shape AI-driven value co-creation (Nguyen et al., 2025).

Third, future research might integrate additional organismic mediators such as emotional engagement, flow experience, and ethical concerns, as well as examine the moderating role of AI literacy, privacy sensitivity, and age cohorts on the experience–value pathway. As AI systems become more autonomous and context-aware, scholars should investigate the boundaries of shared decision-making and human–AI complementarity, including the potential dark sides of AI-driven personalization such as algorithmic dependence and value co-destruction (Nguyen et al., 2025). Finally, comparative studies across AI application domains—generative content creation, conversational commerce, metaverse retail, and smart city services—would enrich theoretical generalisability and provide domain-specific managerial insights.

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