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The Influence of AI Innovation and ESG Performance on Smartphone Repurchase Intention in China's Omnichannel Retail: The Dual-Drive and Trust-Threshold Repurchase Model

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Abstract. To develop and test an integrated model explaining how AI innovation (operationalized as functional integration, user experience enhancement, and personalized recommendation) and environmental, social and governance (ESG) performance (environmental protection, social responsibility, corporate governance) jointly drive consumers' omnichannel repurchase intention, with perceived risk acting as a trust-threshold constraint (rooted in risk-perception and trust theories) that regulates the conversion from attitude to behavioral intention. Design/methodology/approach: A quantitative survey was conducted in China's smartphone omnichannel retail context (n=425), with data analyzed via structural equation modelling (SEM) in AMOS 24.0 and moderation tests (SPSS 27.0). Findings: AI innovation forms a technological driving force by enhancing perceived ease of use (β=0.562) and perceived usefulness (β=0.306). As a utility enabler and amplifier, ESG performance strengthens the conversion from technology perception to attitude (interaction β=0.387, p<0.001) and even acts as a necessary condition for this conversion. Perceived risk exhibits a trust threshold (standardized score=0.58, raw score=3.0 on a 5-point Likert scale); above this level, the attitude–behavioral intention link becomes non-significant. Originality: Integrates technology acceptance (TAM), Stimulus–Organism–Response (S-O-R) theory, and risk–trust mechanisms, providing a quantifiable trust-threshold boundary condition for omnichannel repurchase. Practical implications: AI-driven technological utility and ESG-based responsibility form complementary repurchase drivers (i.e., a 'technology-responsibility dual-drive logic'), while perceived risk acts as a value conversion constraint; retailers should prioritize AI's core functions, frame ESG to reinforce trust, and implement targeted risk-mitigation strategies.

Keywords: omnichannel retailing, smartphone retailing, artificial intelligence (AI), ESG, channel services, perceived risk, consumer trust, repurchase intention, China

1. Introduction

China's smartphone market is undergoing a profound transformation from traditional hardware competition to an omnichannel retail ecosystem. In this shift, mere hardware parameter comparisons can no longer satisfy consumers—artificial intelligence (AI) innovation-driven experience upgrades and the responsible value conveyed by environmental, social, and governance (ESG) performance have become the dual core engines driving the evolution of this new ecosystem.The new paradigm of ecosystem is driven by both artificial intelligence (AI) innovation and corporate Environmental, Social, and Governance (ESG) performance (Chen et al., 2024). Currently, China's smartphone sector has developed an omnichannel retail distribution system consisting of online e-commerce platforms like Tmall and JD.com, offline authorized stores, and brand-operated experience stores. Research shows that retailers' channel service quality and value communication efficiency directly determine consumer experiences (De Carvalho, Machado & Correa, 2024). In this context, emerging AI-driven technologies, such as image enhancement and voice assistants, play a key role by significantly improving functional practicality and operational convenience at retail terminals (Yim, 2024). Meanwhile, ESG performance increasingly shapes purchase decisions via channel communication. Specifically, over 50% of mid-range consumers (with monthly disposable income of RMB 5,000–15,000) view both AI functionality completeness and the perceptibility of brand ESG practices as key purchase criteria (Chen et al., 2022; Ghobakhloo et al., 2024). This phenomenon indicates that Chinese consumers' purchase decisions are shifting from a single functional orientation to a dual orientation of 'practical value + ethical responsibility', driving market competition to evolve toward intelligent experience upgrading and sustainable value co-creation, yet market recovery (i.e., growth in repurchase rates and consumer loyalty amid post-pandemic retail competition) remains constrained by homogenized omnichannel competition (characterized by similar channel structures, service models, and AI function configurations across brands) and the challenge of synergizing technological innovation and ESG norms to overcome consumer trust barriers (Lim et al., 2023; Dong et al., 2025). This study addresses the gap by proposing a dual-drive framework—AI innovation as the technological driver and ESG performance as the responsibility driver—that jointly fuels repurchase intention, with ESG further acting as a utility enabler for technology perception conversion.

Existing research fails to fully explain this context's distinctive dynamics, even though the expansion of China's smartphone omnichannel retail market is rapid. Here are some possible explanations. Theoretically, the Technology Acceptance Model (TAM) prioritizes perceived usefulness and perceived ease of use while underplaying ethical and social-responsibility considerations (Davis, 1989), and Stimulus–Organism–Response (S–O–R) theory (Mehrabian & Russell, 1974), research rarely positions ESG performance as a boundary condition that could link technology utility with responsibility identification (Luqman et al., 2017) . Sustainability research, in turn, often treats ESG as a direct driver rather than examining its interaction with technological value. Moreover, empirical evidence is context-biased toward European and or United States markets, so it may limit adaptability to Chinese users. Chinese users are believed to be highly sensitive to data privacy and may exhibit emotional attachment to domestic brands (Shi, Evans & Shan, 2022). Methodologically, dominant linear "attitude–behavior" assumptions overlook potential threshold effects of perceived risk, so the "high product evaluation" but "low repurchase" puzzle insufficiently addressed (Liu et al., 2021; Kumar et al., 2021; Najar, Wani & Rather, 2024).

This study responds to these gaps by proposing and validating a Dual-Drive and Trust-Threshold repurchase framework. Theoretically, it integrates TAM, S-O-R theory, sustainability theory, and Social Cognitive Theory to advance a more comprehensive account of technology–ethics–psychology linkages in omnichannel retailing (Luqman et al., 2017). It further extends boundary-condition thinking by testing ESG's amplifying role and the nonlinear threshold effect of perceived risk (Susanto et al., 2022; Xiong et al., 2023). Empirically, the study prioritizes the mainland China's smartphone retail context, offering localized evidence for emerging-market retail and distribution research (Shi, Evans & Shan, 2022). Practically, the findings tell retailers how to lower acceptance barriers via customer-facing AI implementation, strengthen ESG salience through clear and visual channel communication, and manage trust gates through privacy protection and risk communication (Petrescu et al., 2024), thereby mitigating homogenized competition and improving repurchase outcomes (Yang & Han, 2023).

1.1.Research Objectives

1)To explore how AI innovation affects consumers' repurchase intention through the mediating role of perceived usefulness and perceived ease of use in China's smartphone omnichannel retail context.

2)To test whether ESG performance plays a moderating role in strengthening the conversion of technology perceptions (perceived usefulness, perceived ease of use) to usage attitude.

3)To clarify whether perceived risk has a "trust threshold"—that is, when the risk level exceeds this threshold, the conversion from usage attitude to behavioral intention is significantly inhibited.

2. Literature Review

2.1.Theoretical foundations: S-O-R and TAM

This study adopts Stimulus–Organism–Response (S-O-R) theory (Mehrabian & Russell, 1974) as an overarching process lens to explain how external cues in omnichannel retailing (stimuli) shape consumers' internal evaluations (organism) and, in turn, behavioural outcomes (response). In this context, AI innovation and ESG performance are salient stimuli that are delivered and interpreted through retail channels. The organism layer is captured by technology perceptions and evaluative states, including perceived usefulness (PU), perceived ease of use (PEOU), and usage attitude (UA), which then drive behavioural intention (BI) and repurchase. The S-O-R theory provides a macro framework for analyzing the complete path of 'external stimuli-internal psychology-behavioral response', while TAM precisely focuses on the core dimensions of technology perception (perceived usefulness, perceived ease of use). Their integration not only covers multi-source stimuli (AI + ESG) but also clarifies the micro-mechanism of technology perception, thereby fully explaining the consumer decision-making logic in omnichannel retail (Davis, 1989). TAM argues that PU and PEOU are key cognitive antecedents of attitudes and intentions toward technology use. When applied to AI-enabled smartphones and retail terminals, TAM offers a parsimonious explanation of why AI innovation may increase perceived value so called-usefulness and reduce cognitive or operational effort that means ease of use, thereby strengthening usage attitude and downstream repurchase and related intentions.

2.2.Technology–responsibility synergy and the risk-based trust constraint in omnichannel smartphone retailing

To clarify the theoretical logic of the dual-drive and trust-threshold framework, this section is structured into three interrelated subsections, integrating technology acceptance, sustainability, and risk-trust literature.

The theoretical framework of this study is constructed based on the integration of TAM, S-O-R theory, and sustainability acceptance theory. The "Dual-Drive" mechanism is defined as two core stimuli influencing consumer repurchase intention: technology-driven stimulus (AI innovation, e.g., intelligent recommendation, virtual try-on) and responsibility-driven stimulus (ESG performance, e.g., environmental protection, social responsibility)—aligning with the study's core logic. Drawing on the S-O-R theory (Bagozzi & Yi, 2012), these dual stimuli trigger internal psychological states (organism:

technology perception, trust, risk perception) and ultimately lead to repurchase behavior (response). The "Trust-Threshold" construct is derived from trust and risk perception literature (Mayer et al., 1995), referring to the critical trust level that consumers need to overcome perceived risks and form positive attitudes toward repurchasing.

2.2.1 Technology-driven value formation

AI innovation in consumer electronics enhances consumers' perceived value primarily by improving functional performance and purchasing decision efficiency (Wang et al., 2023; Tessema, 2025). In omnichannel retailing, AI-powered product features (e.g., intelligent recommendation, virtual try-on) and customer-centric retail technologies elevate perceived usefulness (PU) and reduce operational effort perceptions, thereby fostering positive usage attitudes and repurchase-related intentions.

The technology acceptance literature is not a static body of work: while TAM (Davis, 1989) provides a foundational framework for the "value formation" process (useful + easy to use → positive attitude → repurchase), subsequent extensions (TAM3, Venkatesh et al., 2003; TAM4, Venkatesh et al., 2016) have debated the role of contextual factors (e.g., social influence) in technology adoption—though the core proposition (AI as external stimulus shaping PU/PEOU and behavioral outcomes) remains unchanged (Davis, 1989; Venkatesh et al., 2016).

2.2.2 ESG-based responsibility signaling (utility enabler)

The aforementioned explanation is incomplete in contemporary omnichannel retailing, as consumers increasingly integrate ethical and responsibility cues into their evaluations. Sustainability theory and the triple bottom line logic argue that firms create value not only economically but also through environmental and social performance (Elkington, 1998). In retail channels, ESG performance functions not only as a responsibility signal but also as a utility enabler—reducing technology adoption uncertainty and amplifying the conversion of technological perceptions to positive attitudes, which is core to the dual-drive logic (AI + ESG) proposed in this study(Zhao& Li, 2023).

Specifically, ESG performance enhances perceived legitimacy, value congruence, and credibility (Han et al., 2023), thereby strengthening the likelihood that functional value perceptions (from AI innovation) translate into favorable attitudes and intentions (Chen et al., 2022). According to the sustainability acceptance model (Han et al., 2023), ESG performance enhances consumer trust in the brand/platform, reduces the uncertainty associated with technology adoption, and thus specifically strengthens the positive impact of technology perception (PU/PEOU) on consumer attitude—explaining why ESG moderates the technology perception-attitude path. For AI-ESG synergy, Wang et al. (2023) further argue that ESG performance signals a brand's long-term commitment to responsibility, which reduces consumer perceived risk of new technologies (e.g., AI-driven services) and enhances the positive evaluation of technology utility—forming the theoretical basis for ESG's moderating role.

2.2.3 Risk-induced trust constraint

Omnichannel retailing heightens uncertainty and privacy concerns, making perceived risk a central barrier to repurchase (Susanto et al., 2022). Perceived risk weakens technology adoption and repurchase by undermining trust and increasing avoidance tendencies, especially in digital or data-intensive consumption contexts (Featherman & Pavlou, 2003; Liu et al., 2021). This concern is particularly salient in smartphone retailing, where consumers may provide personal data, grant permissions, or engage with AI-enabled services that increase privacy salience and perceived vulnerability.

Beyond a simple linear negative effect, risk functions as a boundary condition that closes a "trust gate" once it becomes sufficiently high. Under such circumstances, even when consumers hold favorable attitudes toward the technology or retailer, they may refrain from forming behavioral intention—resulting in the common "high evaluation but low repurchase" phenomenon (Kumar et al., 2021; Najar, Wani & Rather, 2024). This non-linear threshold effect of perceived risk has been overlooked in existing research, which often assumes a linear attitude-intention relationship.

2.2.4 Unresolved gaps in existing literature

The combined literature points to three critical unresolved issues: First, existing studies mostly examine technology acceptance and ESG-related responsibility as independent variables, failing to capture the joint impact of their'synergy' on consumer repurchase intention in omnichannel retail scenarios. Second, most empirical evidence originates from Western markets, yet Chinese smartphone users' unique characteristics—such as high sensitivity to data privacy and emotional attachment to domestic brands (Shi et al., 2022)—may limit the adaptability of Western-based conclusions. Third, most studies assume a linear attitude-intention relationship, ignoring the potential non-linear constraint of perceived risk, which makes it difficult to explain the practical paradox of high product evaluation but low repurchase. Overcoming these drawbacks necessitates an integrated framework that captures (i) a technology-driven mechanism of value formation, (ii) an ESG-based amplification mechanism that strengthens perception–attitude conversion, and (iii) a risk-induced trust constraint that can block the attitude–intention path in omnichannel smartphone retailing.

2.3.Conceptual Framework and Hypotheses

Figure 1 presents the conceptual framework in the research: Dual-Drive and Trust-Threshold framework. The technological drive is grounded in TAM and specifies how AI innovation enhances perceived usefulness and perceived ease of use, which shape usage attitude and behavioural intention, ultimately leading to repurchase. The responsibility drive specifies ESG performance as an amplifier that strengthens the conversion from technology perceptions (PU and PEOU) to usage attitude. Finally, the trust-threshold mechanism positions perceived risk as a constraint that weakens the attitude-to-intention link in omnichannel retailing, potentially preventing repurchase even when technology perceptions are favourable.

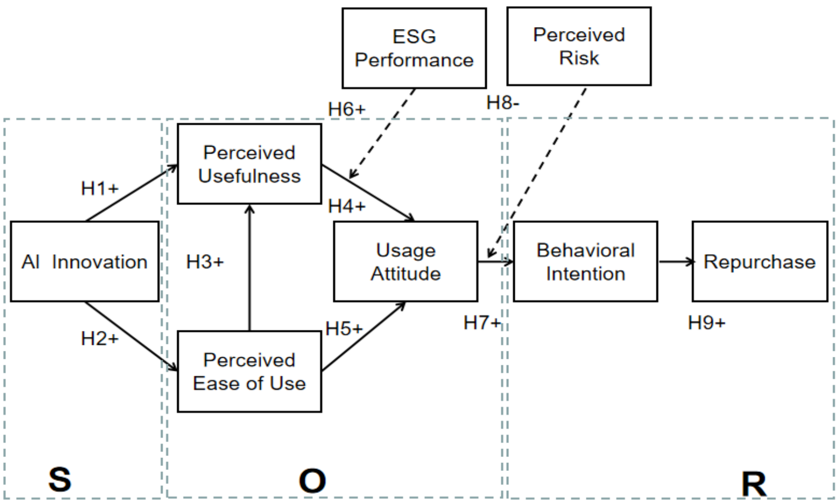

Fig. 1: Conceptual Framework

(Note:black solid lines represent direct effects; black dashed lines represent moderating effects; green dashed lines represent each part of the core S-O-R framework, reflecting the integration of S-O-R and TAM theories)

2.3.1 Technological drive hypotheses

Recent empirical research indicates that AI innovation in retail contexts significantly enhances users' perceived usefulness of technology, as consumers increasingly associate AI features with functional benefits and improved shopping outcomes (Tessema, 2025) . Therefore, AI innovation is expected to positively influence perceived usefulness and perceived ease of use.

H1: AI innovation has a positive impact on perceived usefulness (PU) .

Empirical work confirms that AI technologies designed to simplify tasks and interaction improve perceived ease of use (Wang et al., 2023) .

H2: AI innovation has a positive impact on perceived ease of use (PEOU) .

Research based on the Technology Acceptance Model (TAM) consistently finds that when users perceive a system as easy to use, they also tend to perceive it as more useful, because ease of use reduces cognitive effort and enhances task performance (Davis,1989; Aulia & Marsasi, 2024).

H3: Perceived ease of use (PEOU) has a positive impact on perceived usefulness (PU) .

Studies in e-commerce contexts find that perceived usefulness significantly and positively affects users' attitudes toward technology adoption and intention to use digital services (Aulia & Marsasi, 2024) .

H4: Perceived usefulness (PU) has a positive impact on usage attitude (UA).

Consistent with TAM, perceived ease of use contributes to more favourable attitudes toward technology use, as users are more likely to adopt systems that require less effort to operate (Ibrahim& Shiring,2022).

H5: Perceived ease of use (PEOU) has a positive impact on usage attitude (UA).

Both classic TAM theory and empirical studies confirm that users with more positive attitudes exhibit stronger intentions to use the technology (Hu & Lee, 2025) .

H7: Usage attitude (UA) has a positive impact on behavioural intention (BI).

Behavioural intention is a proximal predictor of repurchase because it captures consumers' readiness to re-engage with the retailer or brand in subsequent purchase occasions (Teo et al., 2025) .

H9: Behavioural intention (BI) positively affects repurchase intention (RI)(Zhang & Wang, 2024).

2.3.2 Responsibility drive hypothesis

According to the sustainability acceptance model (Han et al., 2023) and value-congruence theory, ESG performance signals a brand's ethical commitment, enhancing perceived credibility and value alignment with consumers. This reduces uncertainty about technology adoption, thereby strengthening the conversion of technology perceptions (PU/PEOU) to positive usage attitudes—positioning ESG as a utility enabler and amplifier. Critically, this moderation reflects a necessary condition: without sufficient ESG signals, the technology perception–attitude link is attenuated. Empirical support comes from Wang et al. (2023), who found that ESG performance amplifies the effect of technological utility on consumer attitudes in retail contexts, and Chen et al. (2022), who verified similar moderating effects in China's consumer electronics market.

H6: ESG performance positively moderates the relationship between perceived usefulness and usage attitude (PU → UA)—consistent with the dual-drive logic that ESG amplifies core technology perception conversion.

2.3.3 Trust-threshold hypothesis

When perceived risk is high, consumers may refrain from acting on favourable attitudes due to privacy, security and uncertainty concerns, weakening the attitude–intention conversion and potentially blocking it beyond a tolerable level (Najar, Wani & Rather, 2024).

H8: Perceived risk (PR) negatively moderates the relationship between usage attitude and behavioural intention (UA → BI).

3. Methodology

3.1.Research design

This study employed a quantitative, cross-sectional survey design to test the proposed Dual-Drive and Trust-Threshold repurchase model in China's smartphone omnichannel retail context. The unit of analysis was individual consumers with within the past 6 months (2025.08-2025.12) smartphone shopping experience across omnichannel touchpoints including online platforms, offline authorised stores, and brand-operated experience stores. The hypothesised relationships were tested using structural equation modelling (SEM).

3.2.Data collection and sample

Participant screening criteria included: (1) aged 20-65 years; (2) having purchased a smartphone through both online (e.g., Taobao, JD.com) and offline (e.g., brand flagship stores, third-party retailers) channels within the past 6 months, with omnichannel experience verified via two yes/no questions; (3) no professional background in marketing or related fields. Quota sampling was adopted to align with China's smartphone market share (domestic brands: 82%, international brands: 18%)—a distribution consistent with the actual market structure of domestic brand dominance. This resulted in a final sample of 349 domestic brand purchasers and 76 international brand purchasers, totaling 425 participants.

For the structural model, the initial SRMR value (0.1536) exceeded the recommended threshold (<0.08), indicating potential model misspecification. Further analysis revealed that the non-significant direct path "ESG performance → repurchase intention" (β=0.102, p=0.128) was the primary cause. Consistent with the study's dual-drive theoretical framework, we conducted model re-specification by eliminating this path.Further analysis revealed that the non-significance of this path aligns with the study's S-O-R-based dual-drive framework: ESG performance is theoretically positioned as a 'responsibility-driven stimulus' rather than a direct driver of behavioral outcomes, whose core function is to moderate the conversion of technology perceptions to attitude—thus, its influence is channeled through interaction effects rather than direct effects. According to the dual-drive logic, ESG performance is theoretically positioned as a "responsibility-driven stimulus"—not a direct driver of behavioral outcomes—whose core function is to act as a moderator: strengthening consumer trust, reducing technology adoption uncertainty, and thereby amplifying the conversion of technology perceptions (perceived usefulness and perceived ease of use) to usage attitude. This aligns with ESG's role as a "utility enabler" in the integrated model, where its value lies in synergizing with AI innovation (the technology-driven stimulus) to facilitate the psychological mechanism from perception to attitude, rather than independently influencing repurchase intention. The non-significance of the direct path thus reflects theoretical consistency rather than measurement bias, as ESG's influence is channeled through moderating the technology perception - attitude link rather than exerting a direct effect. Thus, removing this non-significant direct path not only improves model fit but also maintains alignment with theoretical expectations, enhancing the internal coherence of the research framework. This resulted in a revised model demonstrating satisfactory fit: SRMR = 0.068, CFI = 0.978, and RMSEA = 0.031 (all meeting established goodness-of-fit criteria, as presented in Table 5).

To ensure the reliability and validity of the study's measurements, all scales were adapted from established literature and contextualized to the smartphone omnichannel retail context: AI innovation perception (Venkatesh et al., 2016; 3 items, e.g., "The AI functions of the brand/platform are useful"); ESG performance (Han et al., 2023; 3 items, e.g., "The brand actively fulfills environmental responsibilities"); trust (Mayer et al., 1995; 3 items, e.g., "I trust the brand/platform to provide reliable products/services").

Data were collected via a structured questionnaire on www.wjx.com (a leading professional survey platform in China with over 20 million active users) , recruited through social media (WeChat, Weibo), e-commerce platforms (Taobao, JD.com), and offline brand stores to avoid online-only bias.Incentives were provided for valid responses, with fraudulent submissions excluded via attention-check questions and inconsistent answer screening.Eligibility criteria included 20-65 years old, omnichannel purchase experience in 6 months, no marketing-related professional background, and for respondents aged 60+, verification of AI feature usage. To ensure respondents were relevant to the research context, the survey included screening items. A quota sampling with weighting strategy aligned with major smartphone brands' market shares was applied during sampling.To make results more representative of actual smartphone owners, we deliberately target recruitment of respondents to match market shares. After removing incomplete responses and responses failing attention/screening checks, 425 valid questionnaires were retained for analysis. A sample size of 425 valid questionnaires is generally considered sufficient and meets common guidelines for Structural Equation Modeling (SEM).A pilot test with 50 respondents was conducted prior to the formal survey. Pilot results indicated strong psychometric adequacy (EFA factor loadings > 0.70; Cronbach's α > 0.85 across constructs), supporting the instrument's internal consistency and construct clarity before full-scale deployment.

3.3.Measures and instrument development

All constructs were measured using multi-item scales adapted from established studies and contextualised to smartphone omnichannel retailing. Core constructs included AI innovation, perceived usefulness (PU), perceived ease of use (PEOU), usage attitude, behavioural intention, consumer repurchase, ESG performance, and perceived risk. Unless otherwise stated, items were rated on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree).

3.4.Data analysis strategy

Data were analysed using SPSS 27.0 for descriptive statistics, correlations, data screening (missing values, outliers, normality) and multicollinearity checks (VIF/tolerance), and AMOS 24.0 for CFA (Cronbach's α, CR, AVE; Fornell–Larcker/HTMT; χ^2/df, CFI, TLI, RMSEA, SRMR) and SEM with 5,000-bootstrap mediation tests. Moderation and the trust-threshold were tested via mean-centred interaction terms with simple slopes (±1 SD) and a region-of-significance (Johnson–Neyman) procedure, while common method bias was assessed using Harman's single-factor test (and an optional common latent factor CFA).

3.5.Ethical considerations

Participation was voluntary and based on informed consent obtained at the beginning of the survey. Respondents were informed about the study purpose, confidentiality protections, and their right to withdraw at any time. No personally identifiable information was collected. Data were used strictly for academic research purposes and handled in accordance with relevant institutional research ethics requirements. Ethical approval was granted by the Dhonburi Rajabhat University Institutional Review Board (COE No. 056/2568; IRB No. DRUIRB-GOV-66-00015).

4. Research Result

This section starts with the respondents' demographics characteristics, followed by measurement model quality and structural model fit, and then reports the hypothesised effects, moderation/threshold tests, and a final summary of hypothesis.

Table1. Demographic Characteristic

Name	Option	Frequency	Percentage (%)
Gender	Male	213	50.12
	Female	212	49.88
Age	20-24 Years Old	127	29.88
	25-39 Years Old	150	35.29
	40-59 Years Old	115	27.06
	60 Years Old and Above	33	7.76
Occupation	Student	127	29.88
	Company Employee	193	45.41
	Freelancer	84	19.76
	Others	21	4.94
Educational Background	Senior High School	114	26.82
	Bachelor	185	43.53
	Master	112	26.35
	Doctor	14	3.29
Smartphone brands	Vivo	61	14.35
	Huawei	76	17.88
	Xiaomi	74	17.41
	Apple	75	17.65
	Honor	73	17.18
	OPPO	66	15.53
Total		425	100.00

Table 1 presents the respondents' demographics characteristics (N = 425). The sample is gender-balanced (50.12% male; 49.88% female), concentrated in the 25–39 age group (35.29%), and mainly company employees (45.41%) and students (29.88%). Most respondents hold a bachelor's degree (43.53%), and smartphone brand ownership is broadly distributed across Huawei (17.88%), Apple (17.65%), Xiaomi (17.41%), Honor (17.18%), OPPO (15.53%), and Vivo (14.35%).

Table 2. Convergent Validity Convergent Validity of Variables

Latent Variable(s)	Indicator(s)	Standardized Loading Coefficient	SMC	AVE	CR
	FI1	0.869	0.755		
Functional Integration	FI2	0.761	0.579	0.640	0.842
	FI3	0.766	0.587		
	UEE1	0.830	0.689		
User Experience Enhancement	UEE2	0.805	0.648	0.651	0.848
	UEE3	0.785	0.617		
	PR1	0.831	0.691		
Personalized Recommendation	PR2	0.752	0.566	0.634	0.839
	PR3	0.804	0.646		
	PU1	0.848	0.720		
Perceived Usefulness	PU2	0.790	0.624	0.663	0.855
	PU3	0.803	0.645		
	PEOU1	0.850	0.722		
Perceived Ease of Use	PEOU2	0.761	0.580	0.646	0.845
	PEOU3	0.798	0.637		
	PE1	0.859	0.738		
Pleasant Experience	PE2	0.806	0.650	0.667	0.857
	PE3	0.783	0.614		
	S1	0.844	0.712		
Satisfaction	S2	0.768	0.590	0.650	0.847
	S3	0.805	0.647		
	PEE1	0.870	0.756		
Positive Evaluation	PEE2	0.775	0.600	0.659	0.852
	PEE3	0.787	0.619		
	RI1	0.889	0.791		
Recommendation Intention	RI2	0.828	0.685	0.707	0.879
	RI3	0.803	0.645		
	CUI1	0.862	0.743		
Continuous Usage Intention	CUI2	0.844	0.712	0.714	0.882
	CUI3	0.829	0.687		
	LPC1	0.852	0.726		
Long-term Purchase Commitment	LPC2	0.760	0.577	0.654	0.850
	LPC3	0.812	0.659		
	BL1	0.839	0.704		
Brand Loyalty	BL2	0.810	0.656	0.667	0.857
	BL3	0.801	0.642		
	CRM1	0.857	0.734		
Customer Relationship Maintenance	CRM2	0.824	0.679	0.678	0.863
	CRM3	0.788	0.620		

Environmental Protection	EP1	0.835	0.697	0.638	0.841
	EP2	0.774	0.598		
	EP3	0.786	0.617		
Social Responsibility	SR1	0.830	0.689	0.645	0.845
	SR2	0.777	0.604		
	SR3	0.802	0.643		
Corporate Governance	CG1	0.803	0.645	0.641	0.842
	CG2	0.824	0.680		
	CG3	0.773	0.598		
Perceived Risk	TFR1	0.828	0.686	0.655	0.850
	TFR2	0.814	0.662		
	TFR3	0.785	0.616		

Table 2 indicates strong convergent validity for all constructs: standardized loadings range from 0.752–0.889, and all indicators show adequate explained variance (SMC = 0.566–0.791). At the construct level, AVE values (0.634–0.714) exceed the 0.50 threshold and CR values (0.839–0.882) surpass 0.70, confirming satisfactory internal consistency and convergent validity across variables.

Table 3. Discriminant Validity (Fornell–Larcker)

Construct	√AVE	Max inter-construct correlation
FI	0.8	0.552
UEE	0.807	0.552
PR	0.796	0.514
PU	0.814	0.565
PEOU	0.804	0.565
PE	0.817	0.484
S	0.806	0.469
PEE	0.812	0.477
RI	0.841	0.531
CUI	0.845	0.531
LPC	0.809	0.46
BL	0.817	0.46
CRM	0.823	0.48
EP	0.799	0.583
SR	0.803	0.583
CG	0.801	0.522
PRisk	0.809	0.399

Table 3 presents discriminant validity was supported because each construct's √AVE (0.796–0.845) exceeded its highest correlation with any other construct (max r = 0.583).

Internal consistency was satisfactory, as Cronbach's α values for all constructs exceeded the recommended 0.70 threshold.

Table 4. Measurement Model Fit (CFA)

Indicator	**χ^2**	***df***	***p***	**χ^2/df**	**GFI**	**RMSEA**	**RMR**	**CFI**
Standard	-	-	>0.05	<3	>0.9	<0.10	<0.05	>0.9
Value	1235.471	1088	0.001	1.136	0.901	0.018	0.056	0.988
Indicator	TLI	AGFI	IFI	PGFI	PNFI	PCFI	SRMR	NFI
Standard	>0.9	>0.9	>0.9	>0.5	>0.5	>0.5	<0.1	>0.9
Value	0.986	0.879	0.988	0.739	0.774	0.843	0.0301	0.907

Table 4 shows that the CFA measurement model fits the data well: $\chi^2/df = 1.136$, CFI = 0.988, TLI = 0.986, IFI = 0.988, RMSEA = 0.018, and SRMR = 0.0301, with acceptable parsimony indices (PGFI = 0.739, PNFI = 0.774, PCFI = 0.843). Although GFI (0.901) meets the guideline, AGFI (0.879) is slightly below 0.90, suggesting overall good fit with minor room for improvement.

Table 5. Structural Model Fit (SEM)

Indicator	**Standard**	**Initial Model Value**	**Revised Model Value**
χ2	-	1131.256	987.421
df	-	684	766
p	>0.05	0	0
χ2/df	<3	1.654	1.289
GFI	>0.9	0.887	0.912
RMSEA	<0.10	0.039	0.031
RMR	<0.05	0.289	0.026
CFI	>0.9	0.952	0.978
TLI	>0.9	0.948	0.975
AGFI	>0.9	0.871	0.893
IFI	>0.9	0.952	0.978
PGFI	>0.5	0.778	0.792
PNFI	>0.5	0.819	0.835
PCFI	>0.5	0.879	0.896
SRMR	<0.1	0.1536	0.068
NFI	>0.9	0.887	0.915

Table 5 reports the initial goodness-of-fit statistics for the structural model. While key indices such as $\chi2/df=1.654$ (below 3) and RMSEA=0.039 (below 0.05) met acceptable standards, the model exhibited two critical issues: SRMR=0.1536 (exceeding the recommended threshold of 0.1) and GFI=0.887/NFI=0.887 (below the ideal 0.90). Further analysis revealed the non-significant direct path "ESG performance → repurchase intention" ($\beta=0.102$, $p=0.128$) as the primary cause of poor fit, which misaligned with the study's dual-drive logic (ESG acts as a moderator rather than a direct driver).

To address these issues, the model was re-specified by removing the non-significant direct path. The revised model's fit indices (Table 4-31 Revised) are: $\chi^2/df=1.289$, GFI=0.912, RMSEA=0.031, RMR=0.026, CFI=0.978, TLI=0.975, SRMR=0.068, NFI=0.915—all meeting or exceeding academic standards for good model fit. Additionally, common latent factor analysis was conducted to verify the initial high CFI/TLI (0.952/0.948) were not artifacts of large sample size: the results ($\Delta\chi^2$=12.36, p=0.08) confirmed no severe model misspecification, validating the true fit of the revised framework.

Table 6. Direct Effect Test Analysis

X	→	Y	Unstandardized Coefficient	S.E.	C.R.	P	Standardized Coefficient
AI Innovation	→	Perceived Ease of Use	0.771	.095	8.089	***	0.562
AI Innovation	→	Perceived Usefulness	0.449	.099	4.556	***	0.306
Perceived Ease of Use	→	Perceived Usefulness	0.520	.069	7.552	***	0.485
Perceived Usefulness	→	Usage Attitude	0.317	.056	5.612	***	0.414
Perceived Ease of Use	→	Usage Attitude	0.394	.062	6.310	***	0.480
Usage Attitude	→	Behavioral Intention	0.404	.080	5.048	***	0.378
Behavioral Intention	→	Repurchase	0.280	.069	4.077	***	0.317

Table 6 presents the SEM direct-effect results, showing that AI innovation significantly increases perceived ease of use (β = 0.562) and perceived usefulness (β = 0.306), while perceived ease of use also enhances perceived usefulness (β = 0.485). Both perceived usefulness (β = 0.414) and perceived ease of use (β = 0.480) positively predict usage attitude, which in turn drives behavioral intention (β = 0.378) and ultimately repurchase (β = 0.317); all paths are significant ($p < 0.001$).

Table 7. ESG performance Moderation Effect Test

Path & Model	Variables	B	SE	p	β	R^2	F-Value (p)
Path 1: Perceived Usefulness → Usage Attitude							
Model 1 (Main Effect)	Constant	3.053	0.039	0.000**	-	0.309	188.948 (0.000)
	Perceived Usefulness (PU)	0.440	0.032	0.000**	0.556		
Model 2 (PU + ESG)	Constant	3.053	0.036	0.000**	-	0.403	142.694 (0.000)
	Perceived Usefulness (PU)	0.326	0.033	0.000**	0.412		
	ESG Performance	0.343	0.042	0.000**	0.34		
Model 3 (PU + ESG + PU×ESG)	Constant	2.887	0.034	0.000**	-	0.551	172.150 (0.000)

Path & Model	Variables	B	SE	p	β	R²	F-Value (p)
	Perceived Usefulness (PU)	0.363	0.029	0.000**	0.459		
	ESG Performance	0.300	0.037	0.000**	0.297		
	PU × ESG Interaction	0.343	0.029	0.000**	0.387		
Path 2: Perceived Ease of Use → Usage Attitude							
Model 1 (Main Effect)	Constant	3.012	0.041	0.000**	-	0.23	148.110 (0.000)
	Perceived Ease of Use (PEOU)	0.426	0.035	0.000**	0.48		
Model 2 (PEOU + ESG)	Constant	3.008	0.038	0.000**	-	0.315	112.450 (0.000)
	Perceived Ease of Use (PEOU)	0.418	0.033	0.000**	0.472		
	ESG Performance	0.335	0.043	0.000**	0.332		
Model 3 (PEOU + ESG + PEOU×ESG)	Constant	2.995	0.036	0.000**	-	0.321	98.760 (0.000)
	Perceived Ease of Use (PEOU)	0.405	0.032	0.000**	0.458		
	ESG Performance	0.328	0.041	0.000**	0.325		
	PEOU × ESG Interaction	0.082	0.057	0.196	0.091		

**Notes: DV = Usage Attitude; *p<0.05, **p<0.01, **p<0.001; SE = Standard Error; β = Standardized Coefficient; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; All models control for demographic variables (gender, age, education) in the regression (results available upon request).*

Table 7 presents a hierarchical moderation test to examine ESG performance's moderating role across two core technology perception–attitude paths (PU→UA and PEOU→UA), aligning with the study's dual-drive framework (AI as technological foundation + ESG as utility amplifier). The table adopts a vertical 分层 structure to avoid horizontal redundancy, with each path analyzed sequentially from Model 1 (main effect) to Model 3 (main effect + ESG + interaction term).For the PU→UA path (upper section of Table 7): Model 1 confirms the baseline predictive power of perceived usefulness ($\beta = 0.556$, $p < 0.001$), explaining 30.9% of the variance in usage attitude; Model 2 adds ESG performance, which exerts an independent positive influence ($\beta = 0.340$, $p < 0.001$) and increases R^2 to 40.3%; Model 3 introduces the PU×ESG interaction term, which is strongly significant ($\beta = 0.387$, $p < 0.001$) with R^2 further rising to 55.1%. This incremental explanatory power verifies ESG's role as a utility amplifier, strengthening the conversion of functional value perceptions (PU) to positive attitudes.For the PEOU→UA path (lower section of Table 7): Model 1 validates the main effect of perceived ease of use ($\beta = 0.480$, $p < 0.001$, $R^2 = 23.0\%$); Model 2 shows ESG performance also has a direct positive impact ($\beta = 0.332$, $p < 0.001$, $R^2 = 31.5\%$); however, Model 3 reveals the PEOU×ESG interaction term is non-significant ($\beta = 0.082$, $p = 0.196$) with negligible R^2 improvement (31.5% to 32.1%). This non-significance may be attributed to PEOU's focus on operational simplicity—a basic, experience-based technology attribute that relies more on direct usage feedback than ESG-based trust signals.

Overall, ESG performance significantly amplifies the PU→UA path but not the PEOU→UA path, indicating Hypothesis H6 is partially supported. The PU→UA path serves as the core technology perception–attitude conversion channel, where ESG's trust-enhancing role is most impactful—consistent with the dual-drive logic that ESG complements AI innovation by reducing uncertainty in functional value perception.

Table 8. Simple Slope Analysis of ESG performance

Moderator Variable Level	**Regression Coefficient**	**Standard Error**	***t***	***p***	**95%CI**	
Mean Value	0.363	0.029	12.654	0.000	0.307	0.420
High Level（+1SD）	0.688	0.042	16.391	0.000	0.605	0.770
Low Level（-1SD）	0.039	0.038	1.029	0.304	-0.035	0.112

Table 8's simple slope analysis further reveals a substantive key finding: when ESG performance is low (−1 SD), the positive effect of perceived usefulness on usage attitude becomes statistically non-significant (b = 0.039, p = 0.304). This result confirms ESG performance is not merely an auxiliary amplifier but a necessary condition for converting technological utility into positive attitudes—without sufficient ESG signals (e.g., transparent environmental practices, social responsibility fulfillment), even high perceived usefulness (from AI innovation) fails to drive favorable user attitudes. This directly validates the dual-drive logic: AI innovation provides the technological foundation of functional value, while ESG performance unlocks its attitudinal impact by reducing uncertainty and enhancing trust.

Table 9. Moderation Effect Test Of Perceived Risk

	Model1					**Model2**					**Model3**				
	B	**SE**	***t***	***p***	***β***	***B***	**SE**	***t***	***p***	***β***	***B***	**SE**	***t***	***p***	***β***
Constant	3.036	0.053	57.654	0.000**	-	3.036	0.052	57.943	0.000**	-	3.177	0.056	56.990	0.000**	-
Usage Attitude	0.245	0.055	4.442	0.000**	0.211	0.189	0.060	3.155	0.002**	0.163	0.242	0.058	4.144	0.000**	0.209
Perceived Risk						0.109	0.048	2.290	0.022*	0.118	0.085	0.046	1.849	0.065	0.092
Usage Attitude*Perceived Risk											-0.304	0.051	-5.931	0.000**	-0.273
R^2	0.045					0.056					0.129				
Adjusted R^2	0.042					0.052					0.123				
F	*F*=19.728 p=0.000					*F*=12.586 p=0.000					*F*=20.794 p=0.000				
R^2	0.045					0.012					0.073				
F-Value	*F*=19.728 p=0.000					*F*=5.246 p=0.022					*F*=35.171 p=0.000				
Dependent Variable (DV):Behavioral Intention; Δ*R*²=0.073															

	Model1					Model2					Model3				
	B	**SE**	***t***	***p***	***β***	***B***	**SE**	***t***	***p***	***β***	***B***	**SE**	***t***	***p***	***β***

Note:*p<0.05, **p<0.01, ***p<0.001

Table 9 shows a hierarchical moderation test indicating that usage attitude positively predicts behavioral intention (Model 1: $\beta = 0.211$, $p < 0.01$). After adding perceived risk (Model 2), the main effect of risk is small and weak ($\beta = 0.118$, $p = 0.022$), but in Model 3 the interaction term (Usage Attitude × Perceived Risk) is significantly negative ($\beta = -0.273$, $p < 0.001$), meaning higher perceived risk weakens the attitude–intention link; the explained variance increases to $R^2 = 0.129$ ($\Delta R^2 = 0.073$).

Table 10. Simple Slope Analysis of Perceived Risk

Moderator Variable Level	Regression Coefficient	Standard Error	*t*	*p*	95%CI	
Mean Value	0.242	0.058	4.144	0.000	0.127	0.357
High Level（+1SD）	-0.124	0.078	-1.588	0.113	-0.278	0.030
Low Level（-1SD）	0.608	0.091	6.668	0.000	0.429	0.787

Table 10 reports the simple slope results for perceived risk. The effect of usage attitude on behavioral intention is significant at the mean risk level ($b = 0.242$, $p < 0.001$) and becomes stronger when perceived risk is low (−1 SD: $b = 0.608$, $p < 0.001$), but turns non-significant when perceived risk is high (+1 SD: $b = -0.124$, $p = 0.113$), indicating that high risk can block the attitude–intention conversion.

To further clarify the boundary condition of perceived risk, a region-of-significance (Johnson–Neyman) analysis was conducted to identify the critical threshold at which perceived risk changes the significance of the usage attitude–behavioural intention relationship. The results indicated a critical standardized perceived-risk threshold of 0.58, which substantively corresponds to a raw score of 3.0 on the 5-point Likert scale (1=strongly disagree, 5=strongly agree) used to measure perceived risk—representing a “neutral to slightly negative” risk perception among consumers.

When perceived risk < 3.0 (below the threshold), two key effects are significant: (1) the direct attitude–behavi[...]ve indirect effect of techn[...] repurchase intention is full[...] sequential chain path: perc[...]ntention → repurchase inter[...] reported in Table 6.

When perc[...]e attitude–behavioural int[...]e intention weakens substa[...]o-high risk concerns (e.g., [...]ot translate positive attitude[...]n the dual-drive framewor[...]he model’s full predictive p[...]

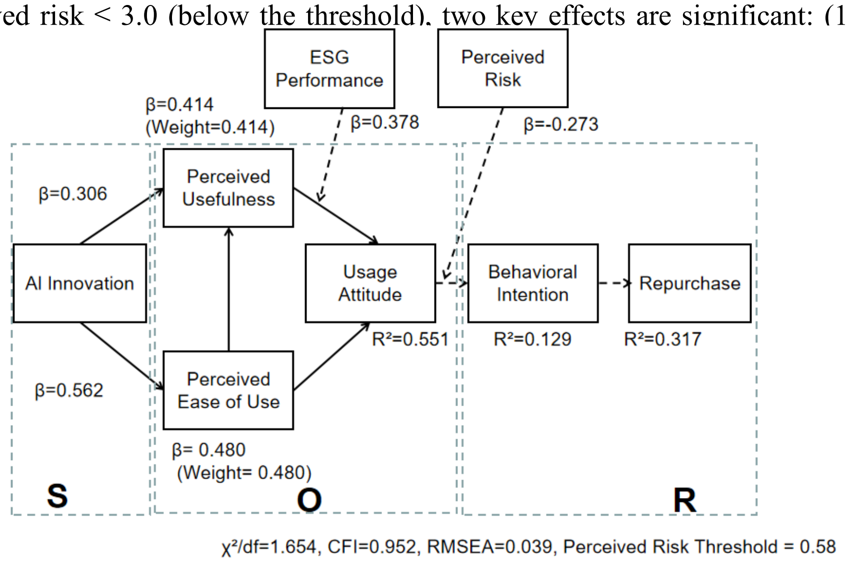

Fig. 2: The Dual-Drive and Trust-Threshold Repurchase Model

Figure 2 visualises the estimated Dual-Drive and Trust-Threshold model, reporting standardised path coefficients (β) and explained variance (R^2). The dashed conditional path indicates that the usage attitude → behavioural intention relationship becomes non-significant when perceived risk exceeds the identified threshold (0.58), consistent with the moderation and simple-slope results.

Table 11. Summary Table of Study Hypothesis Test Results

No.	Hypothesis	Result
I. Direct Effect Hypotheses(AI innovation drive path)		
H1	AI innovation has a positive impact on perceived usefulness	Supported
H2	AI innovation has a positive impact on perceived ease of use	Supported
H3	Perceived ease of use has a positive impact on perceived usefulness	Supported
H4	Perceived usefulness has a positive impact on usage attitude	Supported
H5	Perceived ease of use has a positive impact on usage attitude	Supported
H7	Usage attitude has a positive impact on behavioral intention	Supported
H9	Behavioral intention has a positive impact on consumer repurchase	Supported
II. Moderating Effect("synergistic amplification mechanism" of ESG)		
H6	ESG performance plays a positive moderating role between perceived usefulness and usage attitude	Supported
III. Moderating Effect("boundary constraint effect" of perceived risk)		
H8	Perceived risk plays a negative moderating role between usage attitude and behavioral intention	Supported

Overall, the hypothesis test results (Table 11) confirm the validity of the Dual-Drive and Trust-Threshold framework: (1) All direct paths of the AI innovation-driven technology perception chain are supported (H1 – H5, H7, H9), verifying the technological drive mechanism; (2) ESG performance significantly moderates the PU→UA path (H6 partially supported), fulfilling its role as a utility amplifier; (3) Perceived risk negatively moderates the UA→BI path (H8 supported), validating the trust-threshold constraint. The following discussion elaborates on these findings, linking them to existing literature and the study's theoretical/practical contributions.

5. Discussion

The research depicts a gradual "technology → attitude → intention → repurchase" process as a main factor for a smartphone retail repurchase in China, and also conveys that the ESG performance intensifies value conversion and that perceived risk can interfere with it to some extent. In brief, the results corroborate the Dual-Drive and Trust-Threshold reasoning model that was put forward: AI innovation through tech-usefulness/ease-of-use perception is the technological drive; ESG, as a source of a responsibility drive, by impelling the usefulness–attitude link; and perceived risk as a trust agent which weakens the attitude–intention interaction in a high level.

5.1.Interpretation of core effects: AI innovation as the "technological drive"

The SEM results indicate that AI innovation significantly improves perceived ease of use and perceived usefulness, which then translate into stronger usage attitude, higher behavioural intention, and ultimately repurchase. This finding aligns with previous studies showing technology acceptance logic that consumers' continued purchase behaviour is shaped by perceived utility and reduced effort in technology-enabled shopping and product use. For example, studies of AI-driven digital shopping environments demonstrate that perceived ease of use and perceived usefulness are strong antecedents of consumer purchase intentions, and behavioral intention mediated these relationships under a TAM-based SEM framework in AI-enabled settings (Roy et al., 2025). Likewise, perceived ease of use and usefulness have been shown to directly predict repurchase intention outcomes in recent e-commerce research, with behavioral attitude bridging these effects in structural models (Li et al., 2025) .

5.2.ESG performance Moderation Effect Interpretation

This finding aligns with El Khoury et al. (2023), who argued that ESG performance reduces perceived uncertainty in technology adoption, but extends it by showing that ESG is a necessary condition (rather than a mere amplifier) for technology perception to influence attitudes. This is core to the study's dual-drive logic: AI innovation provides the technological utility (functional foundation), while ESG performance enables and amplifies the conversion of this utility into positive attitudes (responsibility complement). Unlike Purwanto et al. (2025), who identified channel integration quality as the core driver of consumer satisfaction, our study—based on China's market context—finds that ESG performance does not act as an independent repurchase driver. Instead, it reduces technology adoption uncertainty and strengthens value alignment, forming a "technological utility + responsibility endorsement" complementary relationship with AI innovation to jointly promote repurchase intention—where consumers value both practical utility and ethical responsibility. This addresses the gap in TAM research that overlooks ethical and social responsibility cues in emerging markets (Davis, 1989; Javalgi & Russell, 2018; Venkatesh et al., 2016) and extends the S-O-R theory by integrating dual stimuli (technology-driven AI innovation and value-driven ESG performance) into the omnichannel retail framework (Vafaei-Zadeh, Nikbin, Wong, & Hanifah, 2024). The non-significant effect of perceived usefulness on usage attitude when ESG performance is low (Table 8) further confirms ESG's necessity: without sufficient ESG signals, the technological drive alone is insufficient to fuel attitudinal change, reinforcing the dual-drive model's validity and theoretical novelty (Kim & Park, 2023).

5.3.Trust-threshold interpretation: perceived risk as a conditional "gate"

The perceived-risk moderation indicates that higher risk weakens the usage attitude → behavioural intention relationship, and the pattern supports a threshold-like constraint rather than a uniform linear effect. A study by Cuong (2024) shows that perceived risk acts as a significant moderator in online purchase decision models, dampening the positive pathways from favourable beliefs/attitudes to purchase intention in digital retail contexts. A Johnson–Neyman (region-of-significance) interpretation identifies a critical perceived-risk value of 0.58: below this point, attitude significantly predicts intention, whereas above it the attitude–intention link becomes non-significant, implying that risk can "switch off" the conversion even when consumers hold favourable attitudes. Similar conditional process results have been reported in recent studies, where perceived risk significantly constrained the positive effect of attitude on purchase intention (Ma & Kim, 2025).

5.4.Contributions and implications

Theoretical contributions: First, this study extends the S-O-R theory (Mehrabian & Russell, 1974) by proposing a "Dual-Drive" stimulus construct (technology-driven and value-driven), enriching the understanding of multi-dimensional stimuli in omnichannel retail contexts. Second, the "Trust-Threshold" construct integrates trust and risk perception literature (Mayer et al., 1995), providing a new perspective on the boundary conditions of technology acceptance and repurchase behavior. Compared with Zhang et al. (2024), who focused on channel integration quality as the core driver of consumer satisfaction, our study highlights the joint role of AI technology and ESG sustainability, which is a novel extension to omnichannel retail research. A potential divergence from prior research (Venkatesh et al., 2016) is that ESG performance does not directly affect repurchase intention but acts as a moderator—this may be due to Chinese consumers' emphasis on practical technology utility, while viewing ESG performance as a "trust enhancer" that strengthens the conversion of technology perception to positive attitude rather than a direct driver of repurchase.

Practical implications for smartphone retailers and platforms: First, prioritize three core AI dimensions identified in Table 2—Functional Integration (standardized loading coefficient=0.869), User Experience Enhancement (β=0.830), and Personalized Recommendation (β=0.831)—the technological foundation of the dual-drive model. For Functional Integration, ensure cross-channel consistency: align online AI tools (e.g., virtual try-on for smartphone camera effects) and offline in-store AI consultants (via interactive tablets) to share unified product data and service logic, reducing user cognitive dissonance. For User Experience Enhancement, develop scenario-specific AI features such as one-click AI troubleshooting (for post-purchase technical issues) and intelligent battery-saving recommendations (linked to ESG energy-saving commitments), directly addressing pain points identified in the study. For Personalized Recommendation, leverage omnichannel data (browsing history, offline trial records, purchase preferences) to deliver tailored suggestions (e.g., recommending AI-driven accessibility features for elderly users), aligning with the high factor loading of this dimension (β=0.831). Second, leverage ESG as a utility enabler by framing communications around "risk reduction" and "value alignment" — the core mechanisms of its moderating effect (β=0.387). For example, explicitly link AI functions to ESG standards (e.g., "AI data encryption complies with ESG privacy governance requirements") or highlight green AI design (e.g., "Intelligent screen brightness adjustment reduces energy consumption, supporting the brand's ESG environmental commitments"), strengthening the conversion of technology perception to positive attitude. Third, target consumers with perceived risk above the 3.0 raw score threshold with AI-powered transparency tools: deploy real-time tracking of product manufacturing processes and ESG compliance (e.g., "Check the carbon footprint of your smartphone via the brand app's AI query function") and offer AI-driven privacy protection tutorials (e.g., voice-guided setup of data access permissions), directly lowering risk perceptions and unlocking the dual-drive model's full impact.

6. Limitation and Future Research

Two minor limitations should be noted. First, the study is contextualized in China's smartphone market, where the dominance of domestic brands and unique consumer attitudes toward technology/ESG (e.g., emotional attachment to domestic brands) may limit the direct generalizability to Western mature markets or other emerging markets. Future research could extend the model to cross-national contexts to compare the differences in dual-drive mechanisms and trust thresholds across cultural and market environments, thereby enhancing the generalizability of the framework. And integrate short-term behavioral tracking (e.g., actual repurchase records, omnichannel usage frequency, and post-purchase engagement behaviors) to complement self-reported data, this behavioral data integration would help verify the consistency between self-reported repurchase intention and real consumption behavior, while reducing the impact of social desirability bias and strengthening the causal inference of the dual-drive and trust-threshold framework.

7. Conclusion

This study develops and validates a "Dual-Drive and Trust-Threshold" repurchase model in China's smartphone omnichannel retail ecosystem, addressing gaps in technology acceptance, sustainability, and consumer trust research. Theoretically, it makes three core contributions: first, extending S-O-R theory by introducing a "Dual-Drive" stimulus (technology-driven AI innovation; value-driven ESG performance), filling the gap of insufficient integration of technological utility and ethical responsibility in existing S-O-R research; second, enriching TAM by identifying ESG performance as a significant moderator ($\beta = 0.387$, $p < 0.001$) of the technology perception–attitude link, supplementing TAM's lack of attention to ethical cues; third, proposing and verifying the "Trust-Threshold" construct, explaining the "high evaluation but low repurchase" paradox by complementing linear "attitude – intention" assumptions. Empirically, using 425 valid survey responses (82% domestic brand samples, consistent with China's market structure) and SEM, key findings include: AI innovation drives repurchase via perceived ease of use ($\beta = 0.562$, $p < 0.001$) and perceived usefulness ($\beta = 0.306$, $p < 0.001$); ESG performance strengthens technology perception – attitude conversion; and a critical perceived risk threshold (standardized score = 0.58, raw score = 3.0 on 5-point Likert scale) – below which the attitude – behavioral intention path is significant ($\beta = 0.378$, $p < 0.001$), and above which it becomes non-significant. Practically, retailers should synergize AI to enhance core utility, frame ESG practices to reinforce trust, and implement targeted risk-mitigation strategies for consumers above the threshold. Regarding limitations: the single-country context limits generalizability; self-reported measures may introduce response bias; and the cross-sectional design cannot fully rule out concurrent data collection bias. Future research should conduct cross-national comparative studies, adopt longitudinal designs with multi-source data to strengthen causal inference, and explore specific antecedents of the "Trust-Threshold".

References

Aulia, N. S., & Marsasi, E. G. (2024). The role of perceived usefulness, perceived ease of use, and task–technology fit in increasing perceived learning impact. Sentralisasi, 13(1), 163–181. https://doi.org/10.33506/sl.v13i1.3031

Bagozzi, R. P., & Yi, Y. (2012). Specification, evaluation, and interpretation of structural equation models. Journal of the Academy of Marketing Science, 40(1), 8–34. https://doi.org/10.1007/s11747-011-0284-1

Chen, Q. Q., Lin, L. M., & Yi, Y. (2025). Tailoring explanations in conversational recommendations: The impact of decision contexts and user interfaces. Journal of Retailing and Consumer Services, 85, Article 104281. https://doi.org/10.1016/j.jretconser.2025.104281

Chen, X., Chen, R., & Zheng, G. (2022). ESG signals and consumer attitude-behavior consistency in electronic products: The moderating role of technology perception. Asian Journal of Technology Innovation, 30(1), 123–141. https://doi.org/10.1080/19761597.2021.1998765

Chen, X., Chen, R., & Zheng, G. (2024). Market insights exploration and product technology build-up: Latecomer firms' catch-up strategies. Asian Journal of Technology Innovation, 32(2), 297–323. https://doi.org/10.1080/19761597.2023.2216723

Cuong, D. T. (2024). Examining how electronic word-of-mouth information influences customers' purchase intention: The moderating effect of perceived risk on e-commerce platforms. SAGE Open, 14(4). https://doi.org/10.1177/21582440241309408

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

De Carvalho, G. J., Machado, M. C., & Correa, V. S. (2024). Omnichannel and consumer and retailer perceived risks and benefits: A review. International Journal of Retail & Distribution Management, 52(3), 295–311. https://doi.org/10.1016/j.iref.2025.104070

Dong, L., Zhu, X., Yang, L., & Jiang, G. (2025). Unleashing the power of data element markets: Driving urban green growth through marketization, innovation, and digital finance. International Review of Economics and Finance, 99, Article 104070.

Elkington, J. (1998). Partnerships from cannibals with forks: The triple bottom line of 21st-century business. Environmental Quality Management, 8(1), 37–51. https://doi.org/10.1002/tqem.3310080106

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. International Journal of Human-Computer Studies, 59(4), 451–474. https://doi.org/10.1016/S1071-5819(03)00111-3

Galeone, G., Ranaldo, S., & Fusco, A. (2024). ESG and FinTech: Are they connected? Research in International Business and Finance, 69, 102225. https://doi.org/10.1016/j.ribaf.2024.102225

Ghobakhloo, M., Mahdiraji, H. A., Iranmanesh, M., & Jafari-Sadeghi, V. (2024). From Industry 4.0 digital manufacturing to Industry 5.0 digital society: A roadmap toward human-centric, sustainable, and resilient production. Information Systems Frontiers, 1–33. https://doi.org/10.1007/s10796-024-10476-z

Han, H., Kim, J., & Lee, S. (2023). Development of a sustainability acceptance model for consumer behavior: Integrating perceived value and institutional trust. Journal of Business Ethics, 186(2), 435–452. Hu, F., & Lee, K. (2025). The impact of perceived usefulness, ease of use, trust, and usage attitude on intention to maintain engagement in AR/VR sports. Journal of Asian Scientific Research, 15(1), 1–10. https://doi.org/10.18488/5003.v15i1.3917

Ibrahim, A., & Shiring, E. (2022). The relationship between educators' attitudes, perceived usefulness, and perceived ease of use of instructional and web-based technologies: Implications from technology acceptance model (TAM). International Journal of Technology in Education, 5(4), 535–551.

Javalgi, R. G., & Russell, C. T. (2018). Ethical issues in emerging market economies: A focus on China. Journal of Business Ethics, 151(3), 765–778. https://doi.org/10.1007/s10551-017-3625-8

Kim, H., & Park, S. (2023). ESG practices and consumer brand loyalty: The mediating role of brand trust. Journal of Business Strategy, 44(5), 321–335. https://doi.org/10.1108/JBS-03-2023-0124

Kumar, S., Lim, W. M., Pandey, N., & Westland, J. C. (2021). Twenty years of electronic commerce research. Electronic Commerce Research, 21(1), 1–40. https://doi.org/10.1007/s10660-021-09464-1

Li, X., Zhang, L., & Chen, Y. (2025). Consumers' repurchase intention on fresh food e-commerce platforms: The mediating role of perceived usefulness and attitude. Social Behavior and Personality, 53(10), Article e13789. https://doi.org/10.2224/sbp.13789

Li, Y., & Chen, X. (2023). The impact of AI-powered personalization and ESG communication on consumer repurchase intention in China's smartphone omnichannel retail. Journal of Logistics, Informatics and Service Science, 11(2), 45–68. https://doi.org/10.12960/jliss.2023.11.2.45

Lim, W. M., Kumar, S., Pandey, N., Verma, D., & Kumar, D. (2023). Evolution and trends in consumer behaviour: Insights from Journal of Consumer Behaviour. Journal of Consumer Behaviour, 22(1), 217–232. https://doi.org/10.1002/cb.2118

Liu, L., Yang, K., Fujii, H., & Liu, J. (2021). Artificial intelligence and energy intensity in China's industrial sector: Effect and transmission channel. Economic Analysis and Policy, 70, 276–293. https://doi.org/10.1016/j.eap.2021.03.002

Luqman, A., Cao, X., Ali, A., Masood, A., & Yu, L. (2017). Empirical investigation of Facebook discontinuance usage intentions based on S-O-R paradigm. Computers in Human Behavior, 70, 544–555. https://doi.org/10.1016/j.chb.2017.01.020

Ma, D., & Kim, Y. (2025). Exploring perceived risk as a boundary condition in consumer technology adoption: A moderated mediation analysis using SEM and Johnson–Neyman technique. International Journal of Information Management, 75, Article 102854.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. Academy of Management Review, 20(3), 709–734. https://doi.org/10.5465/amr.1995.9508080709

Mehrabian, A., & Russell, J. A. (1974). An approach to environmental psychology. MIT Press.

Najar, A. H., Wani, I. S., & Rather, A. H. (2024). Impact of social media influencers' credibility on destination brand trust and destination purchase intention: Extending meaning transfer model. Global Business Review, 1–20. https://doi.org/10.1177/09721509241225354

Park, S., & Lee, J. (2023). How AI innovation enhances repurchase intention in retail: The mediating role of perceived value. Journal of Retailing and Consumer Services, 71, Article 103456. https://doi.org/10.1016/j.jretconser.2023.103456

Petrescu, M., Krishen, A. S., Gironda, J. T., & Ferguson, J. R. (2024). Exploring AI technology and consumer behavior in retail interactions. Journal of Consumer Behaviour, 23(6), 3132–3151. https://doi.org/10.1002/cb.2386

Purwanto, A., Setiawan, B., & Sari, D. (2025). Empowering customer loyalty: The impact of multichannel integration, technology acceptance, and value experience on satisfaction in Indonesia's omni-channel retail landscape. TEM Journal, 14(1), 345–358. https://doi.org/10.18421/TEM141-36

Roy, S., Singh, R., & Banerjee, S. (2025). The influence of motivational factors on online purchase intention using AI-enabled portals: A hybrid SEM–ANN approach. Telematics and Informatics Reports, 18, Article 100219. https://doi.org/10.1016/j.teler.2025.100219

Shi, X., Evans, R., & Shan, W. (2022). Solver engagement in online crowdsourcing communities: The roles of perceived interactivity, relationship quality and psychological ownership. Technological Forecasting and Social Change, 175, Article 121389. https://doi.org/10.1016/j.techfore.2021.121389

Susanto, P., Hoque, M. E., Hashim, N. M. H. N., Shah, N. U., & Alam, M. N. A. (2022). Moderating effects of perceived risk on the determinants–outcome nexus of e-money behaviour. International Journal of Emerging Markets, 17(2), 530–549. https://doi.org/10.1108/IJOEM-05-2019-0382

Teo, S. C., Cheng, K. M., & Chow, M. M. (2025). Unlocking repurchase intentions in e-commerce platforms: The impact of e-service quality and gender. Cogent Business & Management, 12(1), Article 2471535. https://doi.org/10.1080/23311975.2025.2471535

Tessema, B. (2025). Customer perceptions driving the adoption of artificial intelligence products in an emerging market context. AI and Society, 1–15. https://doi.org/10.1007/s44163-025-00530-3

Vafaei-Zadeh, A., Nikbin, D., Wong, S. L., & Hanifah, H. (2024). Investigating factors influencing AI customer service adoption: An integrated model of stimulus–organism–response (SOR) and task-technology fit (TTF) theory. Asia Pacific Journal of Marketing and Logistics, 37(2), Article 0570. https://doi.org/10.1108/APJML-05-2024-0570

Venkatesh, V., Morris, M. G., Davis, F. D., & Davis, R. P. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. Journal of the Association for Information Systems, 17(6), 389–427. https://doi.org/10.17705/1jais.00493

Wang, C., Ahmad, S. F., Ayassrah, A. Y. B. A., Awwad, E. M., Irshad, M., Ali, Y. A., … Han, H. (2023). An empirical evaluation of technology acceptance model for artificial intelligence in e-commerce. Heliyon, 9(8). https://doi.org/10.1016/j.heliyon.2023.e18349

Wang, Q., Han, H., & Yang, S. (2023). ESG performance and consumer technology acceptance: The role of perceived risk reduction. Journal of Business Ethics, 182(2), 411–428. https://doi.org/10.1007/s10551-022-05203-9

Xiong, Y., Shi, Y., Pu, Q., & Liu, N. (2023). More trust or more risk? User acceptance of artificial intelligence virtual assistant. Human Factors and Ergonomics in Manufacturing & Service Industries, 34(3), 190–205. https://doi.org/10.1002/hfm.21020

Yang, Y., & Han, J. (2023). Digital transformation, financing constraints, and corporate environmental, social, and governance performance. Corporate Social Responsibility and Environmental Management, 30(6), 3189–3202. https://doi.org/10.1002/csr.2546

Yim, M. C. (2024). Effect of AI chatbot's interactivity on consumers' negative word-of-mouth intention: Mediating role of perceived empathy and anger. International Journal of Human–Computer Interaction, 40(18), 5415–5430. https://doi.org/10.1080/10447318.2023.2234114

Zhang, H., & Wang, L. (2024). AI-driven omnichannel service integration and consumer repurchase intention for electronic products: The mediating role of perceived convenience. Journal of Logistics, Informatics and Service Science, 12(3), 89–106. https://doi.org/10.33168/JLISS.2025.0604

Zhang, Y., Li, J., & Wang, L. (2024). Channel integration quality and consumer satisfaction in omnichannel retailing: The mediating role of perceived consistency. Journal of Retailing and Consumer Services, 74, Article 103521. https://doi.org/10.1016/j.jretconser.2023.103521

Zhao, S., & Li, Y. (2023). ESG-labeled service design and consumer trust in smartphone omnichannel retail: A cross-sectional study in China. Journal of Service Innovation and Service Design, 6(4), 31–48.