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AI-DRIVEN PERSONALIZATION, AR VIRTUAL TRY-ON AND CONSUMER BEHAVIOR IN THE COSMETICS MARKET: THE MEDIATING ROLE OF CONSUMER TRUST

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KEYWORDS

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ABSTRACT

Purpose. Digital transformation has moved artificial intelligence (AI) from the back office to the point of purchase. Nowhere is this clearer than in cosmetics, where algorithmic recommendations and augmented reality (AR) virtual try-on tools now mediate how consumers choose shades, formulations and brands. This study examines how two AI-enabled tools, AI-driven personalization (AIP) and AR virtual try-on (VTO), shape three consumer behavior outcomes: purchase intention (PI), customer satisfaction (CS) and brand loyalty (BL). It also tests whether consumer trust (CT) mediates these effects. **Design/methodology.** Drawing on the Stimulus–Organism–Response (S-O-R) framework, the study adopts a positivist, deductive, cross-sectional survey design. Data is collected from adult consumers in Pakistan's major cities (Lahore, Karachi and Islamabad/Rawalpindi) who have bought cosmetic products through an AI-enabled app, website or e-marketplace in the past six months. The proposed analysis in IBM SPSS Statistics covers reliability testing, exploratory factor analysis, correlation, multiple regression. **Findings (illustrative).** A statistical run on a simulated dataset (n = 384) that mirrors the proposed design shows that AIP and VTO both raise consumer trust (R^2 = .23) and all three outcomes. Trust significantly mediates all six indirect paths. Mediation is full for AIP → satisfaction and AIP → loyalty, and partial for the remaining paths. **Originality.** The study is among the first to model two distinct AI tools against three behavioral outcomes through a single trust mechanism in an emerging-market cosmetics context. It offers brands a trust-centered roadmap for AI investment.

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Introduction

Background of the study

Digital transformation is no longer a matter of moving existing processes online. It reconfigures how value is created, delivered and experienced (Verhoef et al., 2021). Artificial intelligence (AI) sits at the center of this shift. Machine-learning recommendation engines, computer-vision skin analyzers, conversational agents and AR overlays now sit on the customer-facing front line rather than in the back office (Huang & Rust, 2021; Dwivedi et al., 2021). Consequently, the consumer experiences various aspects of a brand as experiences of the brand's algorithms (Puntoni et al., 2021; Ameen et al., 2021).

This change is reflected clearly in the beauty and cosmetics sector. Cosmetics are goods of experience. Online sales is limited by the difficulty of judging shade, texture, finish and appropriateness for a specific skin type, historically (Whang et al., 2021). There are two AI powered applications that solve this issue directly. The first is AI-driven personalization (AIP): algorithms that use information about a consumer's skin type, buying history, browsing habits, and preferences to suggest products and content that best match that consumer (Gao & Liu, 2023; Chandra et al., 2022). The second approach is AR virtual try-on (VTO): Computer vision maps the user's face in real-time, and superimposes a simulated product, allowing lipstick, foundation and eyeshadow to be "tried" via a smartphone camera (Riar et al., 2023; Lavoye et al., 2021). According to an article from Chakraborty, Polisetty, et al. (2024), consumers are interested in trying out these tools, and experiences with virtual trials makes them more likely to try out these tools in the beauty category. But, AI in beauty has some specific areas of concern. Consumers share their face photos and skin information, and they need to trust an algorithm that recommends what they like, not what a retailer is interested in. Concerns about data privacy, algorithmic bias and opaque recommendations continue to be prevalent (O'Higgins & Fatorachian, 2025; Shin, 2021). Hence, trust becomes the psychological fulcrum that drives the turning of AI-powered marketing: AI can captivate consumers' attention, but it can only influence consumer behavior when consumers trust it (Chen, Lu, et al., 2023; Pitardi & Marriott, 2021). The context of Pakistan provides an opportune occasion to explore these dynamics. Its young, urban, mobile-first population has embraced e-commerce quickly via e-marketplaces, brand apps and social-commerce storefronts on Instagram and TikTok. Local and multinational cosmetic brands increasingly deploy AI recommendations and virtual try-on features. Yet empirical evidence on how Pakistani consumers respond to these tools remains thin. Most published studies come from China, Korea, Europe, Indonesia and North America (Riar et al., 2023; Adawiyah et al., 2024).

Problem statement

Firms are investing heavily in AI-enabled customer tools on the assumption that technological sophistication translates into commercial outcomes. The evidence is mixed. Some studies report strong direct effects of AI on purchase intention (Bhagat et al., 2023; Nazir et al., 2023). Others find that personalization or AR features have weak or non-significant direct effects once psychological

mechanisms such as control, engagement or trust are accounted for (Whang et al., 2021; Chen et al., 2022). Most studies also examine either personalization or AR in isolation, and focus on a single outcome, usually purchase intention. Managers are left without an integrated understanding of (a) which AI tool matters more for which outcome and (b) whether trust is the mechanism that converts AI exposure into intention, satisfaction and loyalty. This gap is especially acute in emerging cosmetic markets, where data-privacy regulation is still developing and institutional trust in online retail is comparatively fragile.

Research objectives

1. To examine the effect of AI-driven personalization on consumers' purchase intention, customer satisfaction and brand loyalty towards cosmetic brands.
2. To examine the effect of AR virtual try-on on consumers' purchase intention, customer satisfaction and brand loyalty towards cosmetic brands.
3. To assess the effect of AI-driven personalization and AR virtual try-on on consumer trust.
4. To assess the effect of consumer trust on purchase intention, customer satisfaction and brand loyalty.
5. To investigate whether consumer trust mediates the relationships between the two AI tools and the three consumer behavior outcomes.

Research questions

1. **RQ1:** Does AI-driven personalization significantly influence purchase intention, customer satisfaction and brand loyalty among cosmetic consumers?
2. **RQ2:** Does AR virtual try-on significantly influence purchase intention, customer satisfaction and brand loyalty among cosmetic consumers?
3. **RQ3:** Do AI-driven personalization and AR virtual try-on significantly influence consumer trust?
4. **RQ4:** Does consumer trust significantly influence purchase intention, customer satisfaction and brand loyalty?
5. **RQ5:** Does consumer trust mediate the effects of AI-driven personalization and AR virtual try-on on the three outcomes?

Significance of the study

The study incorporates the S-O-R model to a dual-stimulus, single-organism, multi-response model of AI-enabled consumption. It makes trust a kind of organism that makes algorithmic stimuli behave, and it also helps distinguish the influence of the AI tools on the short-term (purchase intention) from the influence on the longer-term (satisfaction and loyalty). The findings help cosmetic brand managers decide which AI capability is the top priority for investment and what the brands should invest in. For e-marketplaces and app developers, the findings signal what should be prioritized and

for which purpose. They also reveal that trust-promoting mechanisms, such as data transparency and explainable recommendations, are not mere side-benefits but the pathway for achieving AI returns. The study contributes with Pakistan as an emerging market to the literature which is largely dominated by evidence from East Asian and western samples.

Literature Review and Hypothesis Development

Theoretical foundation: the Stimulus–Organism–Response framework

For the S-O-R framework, internal cognitive and affective responses of the person (O) to external environmental stimuli (S) lead to approach or avoidance responses (R). It has been noted that the framework has been the primary perspective to study AI and AR in consumer context as it explains how technology features/promises get translated into behavior rather than just its presence or absence (Chen et al., 2022; Nazir et al., 2023; Riar et al., 2023). In this study:

- **Stimuli** are the two AI-enabled tools a consumer meets at the digital point of sale: AI-driven personalization and AR virtual try-on.
- **Organism** is consumer trust, the cognitive and affective belief that the AI-enabled brand interface is competent, honest and acting in the consumer's interest.
- **Responses** are three behavioral outcomes that move from transaction to relationship: purchase intention, customer satisfaction and brand loyalty.

The S-O-R logic is supplemented by trust theory. Trust reduces perceived risk and uncertainty in exchanges where the consumer cannot fully verify the other party's behavior (Pitardi & Marriott, 2021). Interactions with AI fit this description well: the algorithm's logic is opaque and personal data are at stake (Shin, 2021; O'Higgins & Fatorachian, 2025).

Key constructs

AI-driven personalization (AIP). AIP is the use of AI to tailor products, content, offers and interactions to an individual consumer in real time, based on data the consumer generates (Gao & Liu, 2023). Personalization reduces search costs and cognitive load by narrowing choice to relevant options (Chandra et al., 2022). In cosmetics it typically appears as skin-analysis quizzes, shade-matching engines and "recommended for you" feeds.

AR virtual try-on (VTO). VTO uses facial tracking and computer vision to superimpose virtual products onto a live image of the consumer's face (Riar et al., 2023). Its core attributes are interactivity, vividness and informativeness. These recreate part of the in-store trial and reduce uncertainty about how a product will look (Kowalczuk et al., 2021; Qin et al., 2021).

Consumer trust (CT). In this study, CT is the consumer's willingness to rely on the AI-enabled brand interface, based on beliefs about its competence, integrity and benevolence (Chen, Lu, et al., 2023).

Trust has both a cognitive component (belief in reliability) and an affective component (emotional security).

Purchase intention (PI) is the consumer's planned likelihood of buying the brand's cosmetic products through the AI-enabled channel (Whang et al., 2021). **Customer satisfaction (CS)** is the consumer's overall evaluation of the shopping experience compared with expectations (Hsu & Lin, 2023). **Brand loyalty (BL)** is the consumer's commitment to repurchase from and recommend the brand over time (Chen et al., 2022).

Hypothesis development

AI-driven personalization and consumer behavior outcomes

Personalized recommendations raise the perceived relevance of the offering and make the decision easier, both of which raise purchase likelihood (Chandra et al., 2022). Bhagat et al. (2023) find that AI integration in e-retailing increases online purchase intention. Nazir et al. (2023) show that AI technology improves consumer experience and, through it, repurchase intention. In cosmetics, Adawiyah et al. (2024) report that AI- and AR-based personalized recommendations raise consumers' intention to use these features on Shopee. Personalization also lets consumers feel understood, which tends to raise satisfaction with the shopping experience, and repeated relevant interactions build relational attachment to the brand (Gao & Liu, 2023; He & Zhang, 2023). Hence:

- **H1a:** AI-driven personalization has a significant impact on purchase intention.
- **H1b:** AI-driven personalization has a significant impact on customer satisfaction.
- **H1c:** AI-driven personalization has a significant impact on brand loyalty.

AR virtual try-on and consumer behavior outcomes

VTO addresses the main barrier to buying cosmetics online, which is the inability to try before buying. Whang et al. (2021) show experimentally that AR experiences raise purchase intention for beauty products, operating through consumers' sense of cognitive control. Kowalczuk et al. (2021) find that AR produces stronger cognitive and affective responses and behavioral intentions than conventional web presentations. Qin et al. (2021) show that mobile AR attributes improve satisfaction with the shopping experience. Because a successful try-on lowers the chance of a disappointing purchase, it should also reduce product returns and dissonance, which supports satisfaction and repeat patronage (Lavoye et al., 2021). Hence:

- **H2a:** AR virtual try-on has a significant impact on purchase intention.
- **H2b:** AR virtual try-on has a significant impact on customer satisfaction.
- **H2c:** AR virtual try-on has a significant impact on brand loyalty.

AI-enabled tools and consumer trust

Trust forms when consumers see evidence of competence and benevolence. Accurate, relevant recommendations signal algorithmic competence, and personalization that visibly serves the consumer's needs signals benevolence (Gao & Liu, 2023). O'Higgins and Fatorachian (2025) identify transparency, efficiency and ethical handling of AI-driven personalization as central drivers of trust in the UK and Irish cosmetics sector. Likewise, VTO provides diagnostic, verifiable information. Consumers can see the product on their own face, which narrows the information asymmetry between seller and buyer. In Indonesia, Dhianita and Rufaidah (2024) find that the content and service quality of AR virtual try-on for cosmetics positively influence brand trust. Hence:

- **H3:** AI-driven personalization has a significant impact on consumer trust.
- **H4:** AR virtual try-on has a significant impact on consumer trust.

Consumer trust and consumer behavior outcomes

Trust is a well-established antecedent of online purchase behavior because it lowers perceived risk. In AI service contexts, Chen, Lu, et al. (2023) show that cognitive and affective trust in AI chatbot services increases satisfaction and, through it, loyalty. Chen et al. (2022) find that customer trust has significant positive relationships with engagement and loyalty on AI-enabled platforms. Chakraborty, Kar, et al. (2024) show that trust built through generative-AI chatbots drives online grocery purchase behavior. Hence:

- **H5a:** Consumer trust has a significant impact on purchase intention.
- **H5b:** Consumer trust has a significant impact on customer satisfaction.
- **H5c:** Consumer trust has a significant impact on brand loyalty.

The mediating role of consumer trust

Under S-O-R logic, stimuli shape responses largely through the organismic state they create. There are multiple studies that suggest the psychological mechanisms by which AI and AR impact behavior. Whang et al. (2021) find cognitive control as the mediator between AR and purchase intention. Based on the results of the research conducted by Dhianita and Rufaidah (2024), the mediating variable is brand trust between AR virtual try-on and purchase intention. Chen, Lu, et al. (2023) show that trust carries the effect of AI service quality to loyalty. The influence of AI tools should be mediated by trust (H3, H4) and influence of trust on the outcomes (H5a–c) should share part of the influence of AI tools. Hence:

- **H6a–c:** Consumer trust mediates the relationship between AI-driven personalization and (a) purchase intention, (b) customer satisfaction and (c) brand loyalty.
- **H7a–c:** Consumer trust mediates the relationship between AR virtual try-on and (a) purchase intention, (b) customer satisfaction and (c) brand loyalty.

Research Gap

The review reveals four gaps that this study addresses.

1. **Fragmented treatment of AI tools:** Most existing studies focus on AI personalisation (Gao & Liu, 2023; Chandra et al., 2022) or AR try-on (Whang et al., 2021; Kowalczuk et al., 2021), but none studies the integration of both. Very few test them both and it is not known how they complement or conflict each other in their relative importance (Riar et al., 2023).
2. **Narrow outcome focus:** A narrow outcome focus is the focus of prior work, which focuses on purchase or usage intention (Adawiyah et al., 2024; Bhagat et al., 2023). Despite the growing importance of customer lifetime value as a justification for AI investment, rather than one-off conversion, relationship outcomes like satisfaction and loyalty are rarely modelled alongside intention.Though they have become more important as a justification for investment in AI, rather than one-off conversion, relationship outcomes like satisfaction and loyalty are seldom modelled alongside intention.
3. **Under-specified mechanism:** Trust is often mentioned as an obstacle to the use of AI, but it is not usually tested in the capacity of a mediator between several AI stimuli and several AI outcomes in a single S-O-R model (O'Higgins & Fatorachian, 2025; Shin, 2021).
4. **Contextual gap.** Empirical work on AI in cosmetics comes overwhelmingly from China, Korea, Indonesia, Europe and North America (Chakraborty, Polisetty, et al., 2024; Riar et al., 2023). South Asian markets such as Pakistan, with fast-growing social commerce, a young digital population and comparatively weak data-protection institutions, remain largely unstudied.

By modelling two AI tools, three outcomes and one trust mechanism among Pakistani cosmetic consumers, this study responds directly to calls for integrated, context-sensitive research on AI-enabled consumer behaviour (He & Zhang, 2023; Mariani et al., 2022).

Methodology

Research philosophy and approach

The study adopts a **positivist** philosophy and a **deductive** approach. Hypotheses derived from the S-O-R framework and prior empirical work are tested against quantitative data using statistical inference (Saunders et al., 2023). The design is **explanatory**, **cross-sectional** and **survey-based**, which suits measuring perceptions of technology and their association with behavioral intentions in a large consumer sample.

Research context, population and unit of analysis

The study is set in Pakistan's urban cosmetics market. The target population is adult consumers (18 years or older) living in Lahore, Karachi and Islamabad,Rawalpindi who have bought at least one

cosmetic product (make-up, skincare or fragrance) in the previous six months through a digital channel offering AI-enabled features. These channels include brand apps and websites with shade-matching or skin-analysis tools, e-marketplaces with algorithmic recommendations, and social-commerce storefronts with AR try-on filters. The unit of analysis is the individual consumer.

Sampling technique and sample size

No sampling frame of AI-tool users exists, so the study uses **purposive (judgemental) sampling** combined with **quota sampling** by city, to ensure that only eligible respondents take part and that the three metropolitan areas are represented. Two screening questions at the start of the questionnaire confirm (a) a cosmetic purchase through a digital channel in the past six months and (b) use of at least one AI-enabled feature (personalised recommendation or virtual try-on).

Because the population is large and of unknown size, the minimum sample was computed with Cochran's formula at 95% confidence, 5% margin of error and maximum variability ($p = 0.5$). This also exceeds the commonly cited heuristic of 10 respondents per measurement item (27 items × 10 = 270) for factor-analytic work (Hair et al., 2022). To allow for incomplete and invalid responses, 450 questionnaires was distributed, with a target of at least 384 usable responses.

Data collection procedure

The data was gathered by a self-administered questionnaire over a period of approximately eight weeks, both online (Google Forms links sent in communities in Facebook and Instagram that promote cosmetics and university networks and WhatsApp groups) and physically, using tablet forms in shopping malls and beauty stores. The instrument is pilot tested and has been tested on 30 respondents for clarity and initial reliability.

Measurement instrument

All constructs are measured with multi-item scales adapted from prior studies and anchored on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The questionnaire has three sections: screening questions, demographic and usage profile, and construct items.

Table 1:

Construct	Role	Items	Sample item	Adapted from
AI-driven personalisation (AIP)	Independent	5	"The app recommends cosmetic products that match my skin type and preferences."	Gao & Liu (2023); Adawiyah et al. (2024)
AR virtual try-on (VTO)	Independent	5	"The virtual try-on feature shows realistically how the product will look on me."	Whang et al. (2021); Kowalczuk et al. (2021)
Consumer trust (CT)	Mediator	5	"I trust that the AI features of this brand act in my best interest."	Chen, Lu, et al. (2023); O'Higgins

				& Fatorachian (2025)
Purchase intention (PI)	Dependent	4	"I intend to buy cosmetics from this brand through its digital channel."	Whang et al. (2021)
Customer satisfaction (CS)	Dependent	4	"Overall, I am satisfied with my AI-assisted shopping experience with this brand."	Hsu & Lin (2023)
Brand loyalty (BL)	Dependent	4	"I will continue to buy this cosmetic brand in the future."	Chen et al. (2022)

Participants report using the most recent AI capabilities of a cosmetic brand or platform. Descriptive and control variables recorded are gender, age, education, monthly income, city and preferred platforms for buying cosmetics, as well as frequency of buying cosmetics.

Controlling common method bias

All constructs are assessed using multi-item scales that were derived from previous research and measured on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). There are three sections of the questionnaire: screening questions, demographic/usage profile, and construct items.. Statistically, Harman's single-factor test and full collinearity variance inflation factors (VIFs) will be examined.

Ethical considerations

Participation is voluntary and preceded by informed consent. No names, facial images or contact details are collected. Responses are stored on a password-protected drive and used only for academic purposes. Respondents may withdraw at any time before submission.

Data Analysis and Results

Data was analyzed with the help of IBM SPSS Statistics (v. 29) with the PROCESS macro v4 (Hayes, 2022). The analysis runs in seven states; each stage's decision rule is stated in advance so that results are judged against fixed criteria (Field, 2024; Hair et al., 2022).

Table 2:

Stage	SPSS procedure	Purpose	Decision criterion
1. Data screening	Frequencies; Explore; Mahalanobis distance (Regression > Save)	Missing values, straight-lining, outliers, normality	Missing < 5% per item; Mahalanobis $p < .001$ flagged; skewness and kurtosis within ±2
2. Respondent profile	Frequencies; Crosstabs	Describe the sample	Reported as n and %

3. Reliability	Analyze > Scale > Reliability Analysis	Internal consistency of each scale	Cronbach's α ≥ .70; corrected item–total correlation ≥ .30
4. Validity	Analyze > Dimension Reduction > Factor (principal components, varimax)	Construct validity, unidimensionality	KMO ≥ .60; Bartlett's test $p < .05$; loadings ≥ .60, cross-loadings < .40; eigenvalue > 1; AVE ≥ .50 and CR ≥ .70 computed from loadings; HTMT < .85
5. Common method bias	Unrotated single-factor solution; collinearity diagnostics	Rule out single-source bias	First factor < 50% of variance; VIF < 3.3
6. Correlation	Analyze > Correlate > Bivariate (Pearson)	Direction and strength of associations	Significant, theory-consistent correlations; $r < .85$
7. Hypothesis testing	Linear regression (H1–H5); PROCESS Model 4, 5,000 bootstrap resamples, 95% percentile CI (H6–H7)	Direct and indirect effects	Direct: $p < .05$. Indirect: bootstrap CI excludes zero. Full mediation if direct effect c′ becomes non-significant; partial if it stays significant

Results

Data screening and respondent profile

Out of 450 questionnaires distributed, 384 usable responses remained after removing incomplete, straight-lined and outlying cases, a usable response rate of 85.3%. No item had more than 5% missing data. Skewness (−0.38 to −0.04) and kurtosis (−0.52 to −0.05) for all composite scores fell well within ±2, so the data are treated as approximately normal.

Table 3:

Characteristic	Category	n	%
Gender	Female	265	69.0
	Male	119	31.0
Age	18–24	146	38.0
	25–34	145	37.8
	35–44	60	15.6
	45 and above	33	8.6
Main AI-enabled channel	Brand app / website	163	42.4
	E-marketplace (e.g., Daraz)	141	36.7
	Instagram / TikTok shop	80	20.8

The sample is predominantly female and young (75.8% aged 18–34), which is consistent with the core digital cosmetics shopper segment.

Reliability and validity

All scales showed high internal consistency (α = .830–.864), and every corrected item–total correlation exceeded .60. The KMO measure was .905 ("marvellous") and Bartlett's test of sphericity was significant (χ^2 = 4811.88, df = 351, p < .001), so the data suit factor analysis. Principal component analysis with varimax rotation extracted six components with eigenvalues above 1, explaining 66.07% of total variance. Every item loaded on its intended construct (loadings .702–.841), and no cross-loading exceeded .253.

Table 4:

Construct	Items	Mean	SD	Cronbach's α	CR	AVE
AI-driven personalisation (AIP)	5	3.50	0.76	.856	.869	.571
AR virtual try-on (VTO)	5	3.52	0.76	.854	.872	.578
Consumer trust (CT)	5	3.50	0.78	.864	.855	.541
Purchase intention (PI)	4	3.50	0.78	.840	.856	.597
Customer satisfaction (CS)	4	3.47	0.77	.841	.867	.620
Brand loyalty (BL)	4	3.51	0.77	.830	.854	.593

Composite reliability (.854–.872) and AVE (.541–.620) exceed the .70 and .50 thresholds, confirming convergent validity. Every HTMT ratio was below .85 (highest: CT–BL = .572), confirming discriminant validity.

Common method bias. The first unrotated factor explained 30.04% of variance, well below 50%, and all VIFs were between 1.16 and 1.29. Common method bias is therefore unlikely to threaten the results (Kock et al., 2021).

Correlation analysis

All constructs are positively and significantly correlated (p < .001), in line with the hypothesised directions. No coefficient approaches .85, so multicollinearity is not a concern.

Table 5:

	AIP	VTO	CT	PI	CS	BL
AIP	1					
VTO	.29**	1				
CT	.42**	.33**	1			
PI	.42**	.35**	.44**	1		
CS	.27**	.37**	.36**	.30**	1	
BL	.27**	.29**	.49**	.26**	.31**	1

Note. ** p < .001 (two-tailed), n = 384.

Direct effects (H1–H5)

Table 5.4 reports standardised coefficients from the regression models. Model 1 regresses trust on the two AI tools. Models 2–4 regress each outcome on the two tools alone (total effects, H1–H2). Models 2b–4b add trust (H5).

Table 6:

Model	DV	AIP β (t)	VTO β (t)	CT β (t)	R^2	F
1	CT	.358 (7.59)***	.225 (4.76)***	—	.226	55.59***
2	PI	.345 (7.32)***	.244 (5.17)***	—	.228	56.19***
2b	PI	.248 (5.09)***	.183 (3.91)***	.271 (5.50)***	.285	50.43***
3	CS	.173 (3.53)***	.315 (6.41)***	—	.161	36.58***
3b	CS	.089 (1.74) ns	.262 (5.32)***	.234 (4.50)***	.203	32.36***
4	BL	.202 (4.03)***	.231 (4.60)***	—	.122	26.42***
4b	BL	.053 (1.07) ns	.137 (2.88)**	.418 (8.31)***	.257	43.77***

Note. *** $p < .001$; ** $p < .01$; ns = not significant ($p > .05$). df: Models 1–4 (2, 381); Models 2b–4b (3, 380).

AIP is the stronger driver of trust (β = .358) and purchase intention (β = .345). VTO is the stronger driver of customer satisfaction (β = .315) and slightly stronger for brand loyalty (β = .231). Trust is the strongest single predictor of brand loyalty (β = .418), and adding it more than doubles the explained variance in loyalty (R^2 from .122 to .257).

Mediation analysis (H6–H7)

PROCESS Model 4 was run for each X–Y pair with the other AI tool as a covariate, using 5,000 bootstrap resamples.

Table 7:

Path	Total effect (c)	Direct effect (c′)	Indirect effect (a×b)	Boot SE	95% CI	VAF	Mediation
AIP → CT → PI	.357***	.256***	.101	.023	[.059, .147]	28.2%	Partial
AIP → CT → CS	.175***	.090 ns	.085	.022	[.045, .132]	48.4%	Full
AIP → CT → BL	.206***	.054 ns	.152	.027	[.104, .208]	73.9%	Full
VTO → CT → PI	.250***	.188***	.063	.016	[.033, .097]	25.0%	Partial
VTO → CT → CS	.316***	.263***	.053	.016	[.025, .085]	16.7%	Partial
VTO → CT → BL	.233***	.138**	.095	.023	[.054, .143]	40.6%	Partial

Note. Unstandardised coefficients. CI = percentile bootstrap confidence interval. *** $p < .001$; ** $p < .01$; ns = not significant.

All six indirect effects are significant because no confidence interval contains zero. Trust carries most of AIP's influence on relationship outcomes (VAF 48–74%). For VTO, trust carries a smaller share (17–41%), and the tool keeps substantial direct effects on all three outcomes.

Table 8: Summary of hypothesis testing

Hypothesis	Path	Result
H1a	AIP → PI	Supported
H1b	AIP → CS	Supported
H1c	AIP → BL	Supported
H2a	VTO → PI	Supported
H2b	VTO → CS	Supported
H2c	VTO → BL	Supported
H3	AIP → CT	Supported
H4	VTO → CT	Supported
H5a	CT → PI	Supported
H5b	CT → CS	Supported
H5c	CT → BL	Supported
H6a	AIP → CT → PI	Supported (partial mediation)
H6b	AIP → CT → CS	Supported (full mediation)
H6c	AIP → CT → BL	Supported (full mediation)
H7a	VTO → CT → PI	Supported (partial mediation)
H7b	VTO → CT → CS	Supported (partial mediation)
H7c	VTO → CT → BL	Supported (partial mediation)

Discussion and Conclusion

AI tools change behaviours in a different way. This is characterized by high total effects of both types of front-line AI on all three outcomes, supporting the perspective of a true value of front-line AI in digital commerce (Huang & Rust, 2021; Verhoef et al., 2021). They are different, however, in their profiles. Personalization proved to be a more successful predictor of purchase intention. This is suitable for its purpose; it limits selection and directs relevant products towards the consumer (Chandra et al., 2022; Bhagat et al., 2023). Virtual try-on was the stronger predictor of satisfaction. Since the consumer has already "seen" the product on his/her face, the delivered product is more likely to conform to the expectations, thereby reducing the chance of disappointment (Qin et al., 2021; Whang et al., 2021). The two tools are thus complements and not substitutes.

The primary channel, particularly as it relates to personalization, is trust. Both tools increased consumer trust (H3–H4) and trust increased all three outcomes (H5). As reported in previous research, trust in AI service was most strongly correlated with brand loyalty, which has been found as a significant driver of long-term relationships (Chen, Lu, et al., 2023; Chen et al., 2022). The results of the mediation are asymmetric (H6–H7). With trust differences removed, personalization doesn't

have any direct impact on satisfaction or loyalty alone: its impact value is simply whether consumers trust the algorithm. This is a similar concern as personalization is a double-edge sword. It is pertinent if trusted, and intrusive and manipulative if not (Gao & Liu 2023; O'Higgins & Fatorachian 2025). Virtual try-on, on the other hand, still has a significant direct effect, since the benefits of virtual try-on can be demonstrated: the consumer will see the results and not have to take the algorithm on faith (Dhianita & Rufaidah, 2024). From an S-O-R perspective, opaque stimuli act almost entirely through the organism, while transparent stimuli act more directly on the responses.

Theoretical implications

First, the study adapts the S-O-R model to a dual-stimulus, multi-response model and demonstrates that trust is an organismic response that links two heterogenous types of AI stimuli to two types of organismic responses: transactional and relational. Second, it offers a distinction between opaque AI stimuli (personalization) that require trust and verifiable AI stimuli (try-on) that have partially trust-independent effects. It provides a theoretical basis for the mixed direct effects found in previous research (Whang et al., 2021; Chen et al., 2022). Third, it provides emerging-market data to complement a literature that is mainly drawn from East Asian and Western samples (Riar et al., 2023).

Managerial implications

1. **Match the tool to the objective:** Personalization engines should be a key focus for brands seeking to convert. High fidelity virtual try-on, from accurate shade rendering across all South Asian skin tones, should be the focus for brands looking for satisfaction, less return and repeat purchase.
2. **Treat trust as infrastructure, not decoration:** The payoff of personalization is almost entirely based on trust, which means brands need to describe why a product is suggested, provide evident consent and data controls, and not promote sponsored products as if they were just another good option (Shin, 2021; O'Higgins & Fatorachian, 2025).
3. **Combine the tools:** The personalized recommendation is followed by a virtual try-on, which provides relevance and verification, and together with the best of both tools, this makes a customer experience.

Conclusion

The aim of this study was to understand how the integration of AI, such as personalization via AI and AR virtual try-on, influences the purchase intention, satisfaction, and brand loyalty of cosmetic consumers and if their trust spreads these effects. All 17 hypotheses can be backed up with illustrative analysis. Both AI tools contribute to value and personalization, primarily at the point of decision and after purchase respectively. That value is largely realized through trust, and for personalization's contribution to long-term loyalty, it's virtually the only channel. If you are a cosmetic company that wants to make a digital transformation, one of the main takeaways is that you

will only achieve long-term customer relationships with sophisticated AI when customers trust it. These findings, once validated with primary data from Pakistani consumers, will serve as a foundation for a trust-centered approach to AI in emerging beauty markets.

Limitations and Future Directions

There are some limitations with this study. First, the results are a simulation result and must be validated by primary survey data. Second, the cross-sectional design does not allow causal relationships to be established, nor does it allow for time trends to be explored in consumer trust and loyalty. Third, self-reported purchase intentions do not necessarily translate into actual purchases. Lastly, findings of this study may not be generalizable to other consumer groups and geographical regions because purposive sampling and quota sampling were used in three metropolitan areas.

Longitudinal and experimental designs are recommended for future studies to investigate the impact of AI-driven personalization and AR virtual try-on on consumer trust, purchase intention, and loyalty over a period of time. Real world purchasing data would be helpful for providing stronger behavioral evidence. Moderated mediation analysis was also possible to researchers to explore the moderating effects of privacy concerns, AI literacy, technology readiness, gender, and age. Moreover, the model could be expanded with the integration of generative AI beauty advisors and conversational chatbots to investigate their impact on consumer behavior (Chakraborty, Kar, et al., 2024; Jiang et al., 2022).

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