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The Influence of AI-Powered Personalized Advertising on Consumer Purchase Intention: The Mediating Role of Brand Trust in Pakistan's E-Commerce Sector

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AI has helped e-commerce companies to create highly personalized ads, but it is still unknown if personalized advertising can lead to purchase intent in emerging markets. In this research, the effect of personalized ads using AI on purchase intention was assessed and brand trust was tested as mediator in the e-commerce market of Pakistan. The data collection process was based on a cross-sectional design and 280 online active consumers were selected using purposive sampling, where a new five-point Likert Scale questionnaire was used to measure the advertising personalization, perceived relevance, brand trust, and intent to purchase. Data were screened and described in SPSS and the hypothesized relationships were tested using partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4 with bootstrapping using 5000 resamples. The measurement model was found to be reliable and valid. Personalization of the advertisement and perceived relevance had significant direct effects on purchase intention ($\beta = .16$ and $.20$, respectively) and both advertising constructs predicted brand trust ($\beta = .28$ and $.45$, respectively). In turn, brand trust was the strongest predictor ($\beta = .45$) and partially mediated the impact of both the personalization of the advertising and the perceived relevance of advertising. The model accounted for 50% of the variance in purchase intention. The results show that the personalization is not enough: relevance has to be translated into trust in order to be of commercial value to advertisers.

Introduction

Artificial intelligence (AI) has revolutionized customer communication for brands. Browsing history, search history, purchase history, and situational factors are now fed into machine learning systems in real time to determine who will be shown which ad, which product, or which offer (Davenport et al., 2020; Huang & Rust, 2021). This change has been termed as a paradigm change from segment targeting to personalized engagement, where marketing messages are tailored and adjusted continually based on customer preferences that are deduced from the person (Kumar et al., 2019). The field of consumer research has seen a systematic review, suggesting it has become a key research area with the focus on personalized advertising and the personalization–privacy paradox (Chandra et al., 2022).

Relevance is the key to the commercial potential of personalization. Evidence in the field shows that ads that are tailored to consumers' interests elicit more responses than ads that are more generic (Bleier & Eisenbeiss, 2015b; Tucker, 2014), and

personalization is correlated with higher perceived informativeness, credibility, advertising value and purchase intention (Kim & Han, 2014). Meanwhile, the need for personalisation is linked to gathering and analysis of individual data, and this is not always a preferred approach by consumers. Several studies have examined the personalization paradox, revealing that personalized advertising can make consumers feel more vulnerable and make the ads less responsive (Aguirre et al., 2015); that the creation of personalized ads can trigger reactance among consumers (Chen et al., 2019); and that consumers can evaluate the pros and cons of personalized offers when deciding on their reaction (Boerman et al., 2017; Xu et al., 2011).

Many other reactions are competing for the success of personalized advertising, which is why it is vital that consumers trust the ads in this instance. Trust has been found to have a significant influence on the reactions of consumers to personalized online advertising (Bleier & Eisenbeiss, 2015a), and research on AI-powered shopping experiences shows that trust is a factor that affects the outcomes of the shopping experience with AI (Ameen et al., 2021). In the larger e-commerce literature, trust has been recognized as a factor in consumer decisions to embark on online purchasing behavior in the first place, as it mitigates the perceived uncertainty of online transactions (Pavlou & Fygenson, 2006). The trust in the brand, which is in the form of consumers' confidence in the brand, is thus a plausible mechanism linking AI-powered personalization to purchase intention.

Despite the wealth of this new material, there are three ways in which evidence is uneven. First, the majority of the studies have been carried out in the Western or East Asian context, where the regulatory environment, the digital skills and confidence of the consumers in online platforms is both different and less developed than in emerging economies. The e-commerce industry has been growing at a rapid pace in Pakistan, with the increasing availability of smartphones and internet, and online retailers so far have depended on algorithmic advertising but little research has been conducted to understand the impact of algorithmic advertising on Pakistani consumers. Secondly, many studies consider personalization as simply one stimulus without separating the personalization that the advertiser uses from the perceived relevance by the consumer. Third, the role of brand trust as a mediator to explain how personalization influences intention is not always explored as a mediating process, but rather as an outcome.

This study explored how personalized advertising through AI can impact consumer purchase intention and investigated the potential mediating effect of brand trust on online shoppers in Pakistan to fill these gaps. Specifically, the study aimed to identify the direct impact of personalization in advertising and perceived advertising relevance on purchase intention as well as on brand trust, as well as the extent to which brand trust mediated the relationship of the two advertising constructs and purchase intention. Partial least squares structural equation modeling (PLS-SEM), a variance-based method, was used to analyze the data of 280 active online shoppers, which is suitable for the predictive model with the mediating relationships (Hair et al., 2019). The study makes a unique contribution to the literature by explaining how AI advertising creates commercial value in this nascent market and provides advertisers with actionable steps to achieve relevance while also building trust. The rest of the paper synthesizes the literature and formulates the hypotheses, explains methodologies, shares analyses, explains results, provides discussion, and offers conclusions and recommendations.

Literature Review

Personalized advertising using AI – When a company uses machine learning and related data-driven methods to choose, create and present advertisements that are customized to the assumed attributes, tastes, and activities of a particular customer. Davenport et al. (2020) suggested that AI will transform marketing strategy and customer behaviour throughout the customer journey and Huang and Rust (2021) theorized a strategic framework where mechanical, thinking and feeling AI will assist marketing in three stages: market research, marketing strategy and marketing action. Similarly, Kumar et al. (2019) highlighted how AI can facilitate personalised interaction by analysing customer data and tailoring offers to the individual level, on a large scale. Chandra et al. (2022) conducted a systematic review of 383 publications and identified personalized recommendation, personalized relationship, the personalization–privacy paradox, and personalized advertising as the key themes in the area, highlighting the need for more research on the personalization of AI across channels.

The empirical evidence of the impact of personalized advertising has largely been positive. In a field experiment with a social network, Tucker (2014) has reported that offering users more personal control over their information resulted in them being more receptive to receiving personalised advertisements, indicating that personalisation is most effective where consumer privacy is respected. Personalization is not always an effective thing as it depends on the type of content presented, the time of the presentation and its location in the user's environment, as demonstrated by Bleier and Eisenbeiss (2015b). In the smartphone context, Kim and Han (2014) found that personalization positively influences the informativeness, credibility and entertainment value of an ad and negatively influences irritation, and that the advertising value and flow experience have a positive influence on purchase intention. As a whole, these studies indicate that personalization impacts on purchase intention both directly and via an intermediate process of assessing the advertisement and the advertiser.

Perceived relevance is consumers' assessment of whether the ad matches their needs, interests, and situation and it is the most sought-after benefit that personalization aims to provide consumers. However, relevance is important in advertising response models (Kim & Han, 2014), as less effort is needed in finding relevance and it makes the advertising useful, which explains its significant role. But relevance is a perception, not a technical characteristic of an algorithm: ads that are technically "highly personalized" can easily be perceived as irrelevant or intrusive if the consumer doesn't understand or accept how they were selected (Aguirre et al., 2015; Xu et al., 2011). To understand the difference between the personalization advertisers actually use and the relevance consumers feel is key in the explanation of the varying results of personalization across different contexts and individual consumers.

The personalization paradox concerns the trade-off between the advantages of personalized communication and the intrusion on privacy that enables this form of communication. Xu et al. (2011) investigated this tension when considering location-aware marketing and demonstrated that consumers' decisions were based on a balance between the expected personalization benefit and concerns regarding privacy. Aguirre et al. (2015) showed that, when consumers were aware that their information was collected covertly, they felt more vulnerable, were more resistant to personalized advertising, and explored ways to build trust to alleviate this reaction. Consumer reactance emerged as one of the most significant deterrents to the acceptance of online personalized advertising according to Chen et al., (2019), and it was found that consumers' evaluations were influenced by their perceived vulnerability and curiosity. Boerman et al. (2017) analyzed the available literature on online behavioral advertising and concluded that the reaction to targeted advertising is influenced by several antecedents and psychological processes, including consumers' privacy concerns. The results suggest that personalization can have both reinforcing and reinforcing effects on consumer reaction and that a psychological process that is able to buffer consumers' uncertainty must be identified to account for the overall effect.

The most common construct identified as the solution to this tension is trust. Bleier and Eisenbeiss (2015a) showed that trust is a pivotal factor in determining the response of a consumer to personalization in online advertisements, suggesting that there is a relationship between the presence of personalization and its reception by consumers. Ameen et al. (2021) constructed their model based on the theory of trust-commitment and service quality model, and obtained the mediation result of trust and perceived sacrifice as well as the direct result of relationship commitment influencing the AI-enabled customer experience. Pavlou and Fygenson (2006) expanded the theory of planned behavior to the context of electronic commerce adoption and emphasized the need for the beliefs of the electronic commerce consumer regarding the electronic commerce vendor and the transaction environment in determining the intention to purchase through electronic commerce. These studies collectively argue that brand trust is an evaluative judgment that entails consumers' evaluations of relevance as well as risk and advertiser intentions, and that this evaluation judgment relates to favorable advertising evaluations that turn into purchase intentions.

Based on this evidence, hypotheses were generated for the present study. There is a reason to expect that personalization would boost purchase intention: personalizing marketing creates a closer fit between the offering and the consumer's needs, and makes the advertising seem more valuable to the recipient (Kim & Han, 2014; Tucker, 2014). Similarly, perceived relevance (consumer's own perception of fit) was predicted to have a positive influence on purchase intention. Advertising personalization and perceived relevance were hypothesized to increase brand trust because if the brand is personalizing an ad and making it relevant to consumers, they feel the brand is paying attention to them and so they are less vulnerable (Aguirre et al., 2015; Bleier & Eisenbeiss, 2015a). Based on the above, it was hypothesized that brand trust would help to decrease uncertainty in online exchanges and thereby boost purchase intention (Pavlou & Fygenson, 2006; Ameen et al. 2021). Lastly, the impact of personalisation and perceived relevance of advertising was hypothesized to be mediated by brand trust to purchase intention. The following hypotheses were thus put forward:

H1: When presented with ads customized to their specific needs, consumers are more likely to make a purchase.

H2: The perceived relevance is positively related to the purchase intention.

H3: Personalization in advertising positively influences the trust in a brand.

H4: Perceived relevance has a positive effect on brand trust.

H5: Customer satisfaction has a positive effect on purchase intention.

H6: Brand trust is a mediator between advertising personalization and purchase intention.

H7: There is a mediating role between perceived relevance and purchase intention for brand trust.

An analytic approach is needed to test such a model, as it estimates multiple relationships and to test the indirect effects rigorously. Considering the separate paths alone is not enough to test mediation, and Preacher and Hayes (2008) suggested

bootstrapping the indirect effect due to the sampling distribution of a product of coefficients being typically asymmetric. PLS-SEM can be used for models that are predictive and that contain latent constructs measured by several indicators, as long as the measurement model and structural model are evaluated and reported systematically (Hair et al., 2019). Conceptually related constructs, such as personalization, relevance and trust should be checked for discriminant validity using the heterotrait-monotrait ratio (Henseler et al., 2015), and common method bias should be examined in survey research by full collinearity assessment (Kock, 2015). The present study was designed based on these considerations.

Methodology

The method used in this study was a quantitative approach with a cross-sectional design and explanatory research design based on the positivist approach. The study was designed as a quantitative study because the study was intended to test hypothesized relationships among constructs that could be measured, and a cross-sectional survey, because it enabled data on all constructs to be efficiently collected from a large number of consumers at one time.

The target population was adults, who used to do online shopping in Pakistan. The respondents were eligible to participate if they were 18 years of age or older and had placed at least one purchase on an e-commerce platform over the last three months, and had seen personalised ads (including 'product ads retargeted after viewing', 'recommended offers' or 'algorithm curated promotions') on shopping platforms, social media or search engines. The research question demanded that the respondents have firsthand experience with personalized online advertising, so no complete sampling frame of active online shoppers was available and the purpose of the sampling was to get the required sample of respondents with experience in the research phenomenon for which the validity of their responses to the measure items would have been reduced by including those who had no experience of personalized online advertising. While this type of sampling does not allow for statistical generalization, it has been accepted in theory testing consumer research, where the population of interest is well-defined. There were two ways of estimating the required sample size. The power analysis of multiple regression with three predictors and a medium effect size ($f^2 = .15$) and a significance level of .05 and a statistical power of .80 yielded a minimum of 77 cases, and the ten times rule, based on the most number of structural paths pointing to the most constructs, yielded 30 cases. The final sample of 280, therefore, surpassed the thresholds and ensured sufficient precision for the estimation and bootstrapping of PLS-SEM (Hair et al., 2019). A total of 340 questionnaires were sent out, and 280 of the returned questionnaires (82.4%) were completed for analysis.

Structured and self-administered questionnaire was used to obtain primary data. The instrument was divided into four sections (advertising personalization, perceived relevance, brand trust and purchase intention) and one demographic section, with each section containing multiple items. The items were adapted from existing scales used in the fields of personalized advertising, trust and purchase intentions and rephrased to explicitly address e-commerce based advertisements. Some of the representative items were "The online ads I see on shopping platforms seem to be the ads I would be interested in" (advertising personalisation), "The ads I see from online stores are relevant to what I need" (perceived relevance), "I feel that I can rely on the brands that advertise to me online" (brand trust) and "I intend to purchase from brands that advertise to me online in the near future" (purchase intention). Each item was rated using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The questionnaire was in English as it is the language of higher education and most of the e-commerce interfaces in Pakistan. The questionnaire was checked for content and face validity by three experts in the field of marketing who are professors. A pilot test was then conducted with 30 online shoppers not included in the final sample to test the clarity and reliability, with Cronbach's alpha scores for all scales above .70, and the wording of some items changed slightly based on feedback from the respondents.

This study was conducted over a period of six weeks using an online questionnaire, which was sent out through social media, messaging groups, university and professional networks in the major urban centers of Pakistan. The purpose of the study was explained with a cover page and the meaning of the concept personalized advertising was described. Screening questions at the beginning of the questionnaire clarified that each respondent fulfilled the eligibility criteria. Since all data was collected from one source, procedural remedies to control for common method bias were used including assuring anonymity, neutral wording of items, separation of predictor and outcome sections, and an instruction that there were no right or wrong answers.

The study was conducted in accordance with the ethical principles for studies on human subjects, and the study was approved by the relevant institutional review committee prior to data collection. Respondents were told about the nature of the research, the time likely to be needed to complete the questionnaire, and that they could withdraw from the study without penalty. Prior to respondents accessing the questionnaire, they obtained informed consent electronically. No identifying information was gathered, including names, e-mail addresses, or contact numbers; responses were reported in a general way only and data were kept in password protected files and files were available only for the research team. Participation was not encouraged by offering incentives that might bias participation.

The data were analyzed in two stages. The first stage of the data screening process used IBM SPSS Statistics to identify missing values, outliers, and normality tests, to calculate frequencies and descriptive statistics for demographic variables and constructs, and to perform Harman's single factor test as a preliminary common method bias test. The second stage applied SmartPLS 4 to estimate the measurement model and structural model using PLS-SEM based on the suggestion of Hair et al. (2019). To assess the measurement model, indicator loadings were examined, internal consistency reliability was calculated with a Cronbach's alpha (ρ_A) and composite reliability (ρ_C) of at least .70 and .95 respectively, were considered satisfactory, convergent validity was assessed by average variance extracted (AVE) values of .50 or more, and discriminant validity was assessed by the heterotrait-monotrait (HTMT) ratio below .85 (Henseler et al., 2015). To ensure that common method bias was not a threat, full collinearity variance inflation factors (VIFs) were used and were all below 3.3 (Kock, 2015). This structural model was then evaluated by checking for collinearity between predictors ($VIF < 3$), coefficient of determination (R^2), effect sizes (f^2), predictive relevance ($Q^2_{predict}$), and the standardized root mean square residual ($SRMR < .08$). The significance of the path coefficients was determined by bootstrapping with 5,000 resamples, two-tailed tests at .05 level with 95% percentile confidence intervals. Specific indirect effects (Preacher & Hayes, 2008) were bootstrapped to test for the mediating role; mediation was concluded when the indirect effect was significant (and confidence interval did not include zero) and partial or full mediation by the mediator variable occurred according to whether the direct effect remained significant. Variance accounted for (VAF) was also calculated to demonstrate the percentage of the overall effect that goes through brand trust.

Data Analysis and Results

Data Screening and Sample Profile

The 280 cases used were without any missing values and also without any multivariate outliers of concern were found by screening. Although normally distributed data is not required to perform PLS-SEM, the univariate normality was found to be acceptable with Skewness values ranging from -0.84 to -0.21 and Kurtosis values ranging from -0.62 to 0.71 being within the ± 1 range. Harman's single factor test resulted in a percentage of variance explained by a single factor of less than 50%, and all full collinearity VIFs were below the critical value of 3.3 (Kock, 2015), suggesting that common method bias was not a serious concern. Table 1 provides an overview of the sample's characteristics, which were relatively balanced by gender (54.3% male), dominated by a short age span of 25 to 34 years (40.0%), and well educated (87.9% of all respondents had at least a bachelor's degree). The majority of the respondents (68.6%) made shopping online two or three times a month. The mean scores on the four constructs varied from 3.69 (brand trust) to 3.88 (purchase intention) with a generally favorable perceptions as illustrated by the standard deviations ranging from 0.68 to 0.74 (Table 2).

Table 1

Demographic Profile of Respondents (N = 280)

Characteristic	Category	n	%
Gender	Male	152	54.3
	Female	128	45.7
Age (years)	18-24	96	34.3
	25-34	112	40.0
	35-44	52	18.6
	45 or above	20	7.1
Education	Intermediate or below	34	12.1
	Bachelor's degree	138	49.3
	Master's degree	92	32.9
	MPhil/PhD	16	5.7

Characteristic	Category	n	%
Online shopping frequency	Weekly or more	74	26.4
	2-3 times per month	118	42.1
	Once per month	62	22.1
	Less than once per month	26	9.3

Note. Percentages may not sum to 100 because of rounding.

Measurement Model

The measurement model was evaluated prior to the structural model. Table 2 presents all 18 indicator loadings which ranged from .741 to .884 with all values greater than .70, as well as all indicator VIFs which were less than 3. Cronbach's alpha ranged from .842 to .889, ρ_A from .848 to .893 and composite reliability from .894 to .916, which were within recommended range from .70 to .95, thus indicating satisfactory internal consistency reliability. AVE scores were between .656 and .698 with values above .50, which were indicative of convergent validity. HTMT criterion (Table 3) was used to determine discriminant validity, and in all cases, the ratio is lower than .85 (the highest ratio between brand trust and purchase intention is .75) while the upper limits of the bootstrapped confidence intervals are also lower than .85.

Table 2

Descriptive Statistics, Reliability, and Convergent Validity of the Constructs

Construct	Items	M	SD	Loadings	α	ρ_A	CR	AVE
Advertising personalization (AP)	5	3.74	0.71	.741-.862	.871	.878	.905	.656
Perceived relevance (PR)	4	3.82	0.68	.768-.871	.842	.848	.894	.680
Brand trust (BT)	5	3.69	0.74	.752-.884	.889	.893	.916	.685
Purchase intention (PI)	4	3.88	0.70	.779-.880	.862	.866	.902	.698

Note. $N = 280$. Items were rated on a five-point Likert scale. α = Cronbach's alpha; ρ_A = reliability coefficient rho_A; CR = composite reliability; AVE = average variance extracted.

Table 3

Discriminant Validity: Latent Variable Correlations and HTMT Ratios

Construct	1	2	3	4
1. Advertising personalization	—	.68	.61	.60
2. Perceived relevance	.58	—	.71	.67
3. Brand trust	.54	.61	—	.75
4. Purchase intention	.52	.57	.66	—

Note. Values below the diagonal are latent variable correlations (all $p < .001$); values above the diagonal are heterotrait-monotrait (HTMT) ratios. All HTMT values are below .85.

Structural Model

Inner VIFs ranged from 1.51 to 1.85 indicating that collinearity of the predictors was not a concern. Moderate explanatory power was found with the model, accounting for 42% of the variance in brand trust ($R^2 = .42$) and 50% of the variance in purchase intention ($R^2 = .50$). The Q^2_{predict} values of .29 for brand trust and .34 for purchase intention were adequate to show high levels of predictive relevance and the SRMR value of .047 was under .08, which was below the acceptable limit for model fit. The results of the bootstrapped structural model are presented in Table 4. The H1 was supported: Personalization advertising was found to have a positive and significant direct effect on purchase intention ($\beta = .16$, $t = 2.62$, $p = .009$) with a small effect size ($f^2 = .03$). H2 was also confirmed and purchase intention was significantly predicted by perceived relevance ($\beta = .20$, $t = 3.13$, $p = .002$, $f^2 = .04$). The effects of both advertising personalization ($\beta = .28$, $t = 4.83$, $p < .001$, $f^2 = .09$) and perceived relevance ($\beta = .45$, $t = 8.18$, $p < .001$, $f^2 = .23$) were positive on brand trust, thus supporting H3 and H4, the latter having the strongest influence. Brand trust was the strongest predictor of purchase intention ($\beta = .45$, $t = 7.50$, $p < .001$, $f^2 = .23$), supporting H5.

Table 4

Structural Model Results: Direct Effects (5,000 Bootstrap Resamples)

Hypothesis and path	β	SE	t	p	95% CI	f^2	Decision
H1: AP $\rightarrow$ PI	.16	.061	2.62	.009	[.04, .28]	.03	Supported
H2: PR $\rightarrow$ PI	.20	.064	3.13	.002	[.08, .33]	.04	Supported
H3: AP $\rightarrow$ BT	.28	.058	4.83	< .001	[.17, .39]	.09	Supported
H4: PR $\rightarrow$ BT	.45	.055	8.18	< .001	[.34, .56]	.23	Supported
H5: BT $\rightarrow$ PI	.45	.060	7.50	< .001	[.33, .57]	.23	Supported

Note. $N = 280$. AP = advertising personalization; PR = perceived relevance; BT = brand trust; PI = purchase intention; CI = percentile bootstrap confidence interval. $R^2 = .42$ for BT and .50 for PI.

Mediation Analysis

The outcomes of mediation are summarized in Table 5. The specific indirect effect of advertising personalization on purchase intention through brand trust was positive and significant ($p < .05$, $\beta = .126$, 95% CI [.065, .189]) and as was the specific indirect effect of perceived relevance ($p < .05$, $\beta = .203$, 95% CI [.134, .272]). Given that the direct effects of both advertising constructs on purchase intention also persisted (Table 4) and with the same sign as the indirect effects, brand trust was categorized as a complementary partial mediator for both relationships, thus supporting H6 and H7. Both effects of advertising personalization and perceived relevance were significant and the total effects were $\beta = .286$ and $\beta = .403$, respectively where 44.1% and 50.3% of the total were attributable to the effects of brand trust.

Table 5

Mediating Effect of Brand Trust: Specific Indirect Effects (5,000 Bootstrap Resamples)

Hypothesis and path	Indirect effect	SE	t	p	95% CI	Total effect	VAF (%)
H6: AP $\rightarrow$ BT $\rightarrow$ PI	.126	.032	3.94	< .001	[.065, .189]	.286	44.1
H7: PR $\rightarrow$ BT $\rightarrow$ PI	.203	.035	5.80	< .001	[.134, .272]	.403	50.3

Note. $N = 280$. AP = advertising personalization; PR = perceived relevance; BT = brand trust; PI = purchase intention; CI = percentile bootstrap confidence interval; VAF = variance accounted for. Both mediations were complementary (partial).

Discussion

This study investigated the effect of personalized advertising using AI on purchase intention of online shoppers in Pakistan and if the brand trust explained the relationship between the two variables. All seven hypotheses were supported by the results.

Both the personalization of ads and perceived relevance of ads directly increased purchase intention, with a significant portion of such effects also being indirect via brand trust, which was the strongest predictor of purchase intention.

This small direct effect of personalization on purchase intention ($\beta = .16$) is in line with studies showing that personalization does not always increase consumer response, and that its impact is contingent upon context and personalization's evaluation by the consumer (Bleier & Eisenbeiss, 2015b; Kim & Han, 2014). This larger effect of perceived relevance on both brand trust and purchase intention reinforces the idea that value is added not by the technical sophistication of the targeting but by what the consumers think is relevant to them, as suggested in previous research on the personalization paradox (Aguirre et al., 2015; Xu et al., 2011). Experiential relevance appears to convey that the brand is meeting the needs of the consumer, while the same message but perceived as irrelevant can seem to be adding little and can even elicit reactance (Chen et al., 2019).

The results that brand trust partially mediated both relationships builds on existing research that looked at trust as a partial mediator between the two relationships when using personalized advertising (Bleier & Eisenbeiss, 2015a) and as a mechanism in AI-driven customer experiences (Ameen et al., 2021). The study demonstrated that personalization and relevance is a part of its effect on purchase intention because it increases consumers' brand trust, and not just because it moderates or results in brand trust. This finding is in line with other e-commerce evidence pointing to the role of trust in reducing uncertainty surrounding online transactions, which help drive e-commerce intentions (Pavlou & Fygenson, 2006). The partial mediation suggests that personalization and relevance continue to have a direct effect, consistent with advertising response models such as perceived value and engagement having an independent effect on intention over and above the influence of trust (Kim & Han, 2014).

In Pakistan the role of trust might have been heightened. Consumers in emerging e-commerce markets can be left to their own devices to determine the authenticity of products, delivery methods, and the way their personal information is treated, and as a result will often depend heavily on a brand's level of trust when making decisions about whether or not to follow an ad. The present design was not able to directly test this explanation, but it is consistent with the robust role of brand trust found here, and implies that the personalization-privacy trade-off that has been demonstrated in other markets (Boerman et al., 2017; Tucker, 2014) could be different in markets with less developed institutional structures.

Theoretically, the results align with strategic and engagement-based views of AI in marketing, which suggest that the usefulness of AI goes beyond just prediction to how consumers experience it (Huang & Rust, 2021; Kumar et al., 2019). They also provide evidence that the impact of AI-driven personalisation on consumer behaviour takes the form of a psychological assessment, as per the theory that AI alters consumer behaviour as well as marketing strategy (Davenport et al., 2020). Last, the study showed that it is not only necessary but also useful to differentiate between personalisation and perceived relevance and to consider both in relation to trust, rather than personalisation alone.

Conclusion and Recommendations

The findings of this research revealed that AI personalised advertising has significant direct and indirect effects on the purchase intent in the e-commerce industry in Pakistan, indirectly by impacting the trust of the brand. Perceived relevance was more powerful than personalisation itself and brand trust was the most likely to influence intention to purchase. This suggests, however, that personalization is only able to create commercial value when it is felt to be relevant to the consumer and when it builds, not undermines, their sense of trust in the brand.

Here are a few recommendations for practitioners. E-commerce companies and advertisers need to assess personalization by relevance instead of targeting accuracy, considering consumer feedback, advertising relevance ratings, and frequency controls to ensure better alignment of personalized ads to real user needs. Second, since a large proportion of the impact of personalization was transferred through trust, advertising firms ought to spend more on building trust along with advertising, such as through clear explanations of the reason an ad is being shown; preference and privacy controls that are easy to find; reliable delivery and after-sales services; and consistent brand communication. Third, platforms should not engage in deceptive or unethical data collection, as other markets have demonstrated that such actions make consumers more vulnerable and less responsive (Aguirre et al., 2015).

There should be clear advertising transparency and data protection standards for consumers to differentiate between legitimate personalisation and intrusive data usage, which should be supported by policymakers and regulators. Educating consumers on the functioning of algorithmic advertising can also enable them to take informed decisions and foster trust in digital commerce.

There are some caveats to be noted. The cross sectional design makes it difficult to make causal inferences and the use of purposive sampling restricts generalizations to the wider population of Pakistani consumers. Data presented are collected by self-report and so may be subject to social desirability biases and intention to purchase does not necessarily lead to actual

purchase. Future research may take advantage of longitudinal or experimental research designs and involve probability samples across regions and platform types, as well as behavioral measures including click-through and conversion, and other mediators and moderators including privacy concern, perceived intrusiveness, reactance, and digital literacy. Comparisons of the emerging markets and multigroup analysis by age, gender and shopping frequency would also provide a framework for defining the boundaries of the model.

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