

The Impact of AI-Driven Personalisation on Marketing Performance: An Empirical Study of the Automobile E-commerce Sector in the GCC Region

¹*Harris Hussain Siddiqui

¹Creative Strategist, Result-Oriented Entrepreneur, Digital Marketing and Brand Management, University Of Karachi.

Abstract

This study investigates AI-driven personalisation's effects on consumer behaviour in the GCC automotive e-commerce sector, addressing the trust-privacy paradox amid rapid digital transformation. Despite projected market growth to \$50 billion by 2030, Western-centric models often overlook cultural nuances such as Islamic ethics and collectivism, leading to suboptimal outcomes. To expand on these gaps and opportunities, this study employed a sequential explanatory mixed-methods design, including a six-month randomised field experiment in E-commerce Automobile sector of GCC with 50,000 interactions and cross-sectional surveys to operationalise AI personalisation as a binary treatment using collaborative filtering and predictive analytics. Results reveal a 72.9% conversion lift, 60.3% loyalty increase, and 158.9% ROAS improvement, moderated by trust perceptions ($\beta=0.0375$, $p=0.039$), though CAC rose 13.2%. Trust emerged as the top predictor (18.75% importance), confirming the paradox's role in collectivist contexts. These findings refine Privacy Calculus Theory for GCC, highlighting the inverted U-shaped trust effect of transparency and its cultural moderators. Practically, they advocate ethical AI deployment with user controls to balance personalisation benefits and privacy risks, advancing sustainable marketing in emerging markets.

Keywords: Artificial Intelligence (AI); Personalisation; E-Commerce; Emerging Markets; Automobiles; Field Experiment.

1. Introduction

The auto industry is currently in a clear digital transformation with the help of artificial intelligence (AI) that enables hyper-personalisation of consumer experiences. With the Gulf Cooperation Council (GCC) region's automotive markets forecasted to grow rapidly with economic diversification efforts, AI adoption offers better efficiency and customer access (Govindan, 2025). However, this transformation does not come without criticism, as although AI allows real-time data analysis to make personalised vehicle suggestions, empirical studies indicate excessive dependence on Western-oriented models, which do not account for the cultural peculiarities of the region, and thus provide low adoption rates (Petchiappan, 2025). As an example, the 2024 application of AI to the automotive valuation was estimated to be US\$2.5 billion globally; although deployments in high-value GCC luxury vehicle markets are more likely to cause inequality in data access and accuracy of personalisation (Fitzpatrick, 2025). Additionally, the initial applications were mostly focused on efficiency improvements, i.e. predictive maintenance, but ignored consumer behaviour change in new economies

with differing levels of digital literacy (Ashok, 2025). Previous research on the subject of the role of AI has started with supplementary devices to central forces in marketing strategy formulation. However, the recent studies in the artificial intelligence field of machine learning applied to consumer journeys have been touted as potentially driving up to 40 per cent growth in revenues in developed markets (Eppler & Mengis, 2004; McKinsey, 2025). However, this optimism is checked by the fact that there are no signs of rising returns when algorithms do not include contextual variables, such as when the preference of GCC consumers to status-symbol vehicles is embedded in cultural values (Laughlin, 2025). In auto e-commerce, AI enhances the omnichannel experiences, but the literature has condemned the disintegration of online personalisation with the offline engagements, resulting in fragmented customer journeys (Yu, 2025). Additionally, though AI-based differentiation in after-sales segments, including predictive servicing, boosts loyalty, it often leads to a further siloing of the data in GCC distributorships, thus impeding scalable change (Oorjit Blog, 2025). Further, the existing discourse revolves around the trust-privacy paradox of AI-driven

Harris Hussain Siddiqui

Creative Strategist, Result-Oriented Entrepreneur, Digital Marketing and Brand Management, University Of Karachi
Email: me@harrissiddiqui.com

Received: 7-Oct-2025

Revised: 31-Oct-2025

Accepted: 10-Nov-2025



©2025 Copyright by the Authors.

Licensed as an open access article using a [CC BY 4.0 license](https://creativecommons.org/licenses/by/4.0/).

personalisation, in which the alleged advantages of increased engagement are counteracted by the increased privacy risk. The data-intensive nature of AI-based marketing activities also poses ethical issues, especially in contexts where the cultural and regulatory regulations are highly strict (Soni, 2024).

Furthermore, the majority of the existing literature has been dominated by Western studies, which are based on universal rational choice behaviour, but GCC consumers have been found to be more privacy-sensitive based on Islamic morality and collectivism, leading to intrusion-related resistance to personalisation (Boutigny et al., 2025). For instance, personalised advertisements can positively affect the conversion, but social rejection can arise when they seem to be invasive, and no strong empirical relationship exists between them and trust in the long term in non-Western societies. This paradox is magnified in the car industry, with high-involvement purchases involving a lot of data gathering, with the literature having contradicting results, with personalisation increasing satisfaction but reducing privacy, especially in the context of the increasing cases of data breaches (Mediabuzz, 2025). The current literature, which is mainly survey-based, has not been longitudinally empirically tested in the GCC, leaving theoretical gaps and practical inefficiencies (Vishwakarma et al., 2025). Also, AI algorithms learned on international data also create biases, which do not represent GCC interests towards luxury cars and electric cars, thus doubting the generalizability of results.

The study focused on the GCC automotive industry, which includes the United Arab Emirates, Saudi Arabia, and neighbouring markets, and e-commerce platforms, where AI personalisation is related to two indicators of a better conversion rate, loyalty of customers, and the financial performance index. The study uses a sequential explanatory mixed-method study design that combines a 6-month field experiment with a survey to produce both behavioural and perceptual data on 50,000 user interactions. This methodology addresses the methodological weaknesses previously found in earlier research, including short-term orientation and cultural insensitivity, by including region-specific market shares and cultural moderators.

Situating this study in the context of the wider academic discussion, it fills some critical gaps because it empirically tests the impacts of AI personalisation in a culturally diverse market. Although international constructs like the Privacy Calculus Theory offer an underlying understanding, they need to be modified to suit GCC peculiarities (Yu, 2025).

The study's theoretical contributions can be seen in terms of the improvement of models that can incorporate trust moderation and culturally sensitive perceptions of privacy, and the practical implications are presented in the form of norms that should guide the ethical application of AI to automotive marketing. Lastly, probing Western-centric prejudice and providing longitudinal data, the study makes significant contributions to the future of research on the role of AI in facilitating sustainable development of new markets, which will inform policy and strategic choices in the digital economy of the GCC.

2. Literature Review

2.1. The Evolution of Personalisation: From Mass Marketing to AI-Driven Hyper-Personalisation

The trend of personalisation has developed beyond mass marketing to hyper-personalisation, utilising artificial intelligence to create real-time, situational experiences (Kumar et al., 2019). Yet, this development often ignores cultural differences, with the majority of investigations being based on the Western environment and thus unable to explain how new markets like the Gulf Cooperation Council (GCC) implement these strategies under the conditions of intense digitalisation (Alghatam, 2020). Recent commentaries complain about the excessive focus on technical improvements without considering ethical traps, such as information overload that adds to consumer fatigue (Eppler and Mengis, 2004; McKinsey, 2025). The frameworks of hyper-personalisation are supposed to deliver value co-creation, but empirical evidence on the ultimate loyalty benefits is scarce, especially in high-stakes industries wherein decision-making is slow (Barney, 1991; Ali, 1995). In general, from the Resource-Based View, AI can be considered as a source of competitive advantage, but in the GCC context, where cultural practices like Wasta networks do not permit consistent implementation, this point of view displays theoretical ethnocentrism.

2.2. Artificial Intelligence in Marketing: Capabilities and Performance Implications

Artificial intelligence has transformed marketing from a supportive to a fundamental role, and it includes analytics, prediction, and adaptive functions (Mikaeif et al., 2021). Predictive scoring applications in the automotive industry have provided both beneficial and adverse effects, with short-term performance measures typically emphasised over long-term economic costs in a multifaceted buying situation (Kalaigianam et al.,

2021). The Technology-Organisation-Environment model elucidates the adoption process, but there have been criticisms that cultural barriers have not been taken into consideration in the GCC, where high-tech adoption clashes with data individualism (Tornatzky and Fleischer, 1990). Recent studies identify a lack of longitudinal evidence as the impacts of AI loyalty have not been tested in the industry that is relationship-intensive (Lariviere and Van den Poel, 2005; Frost and Sullivan, 2024). Thus, in automotive settings like GCC, the personalisation offered using AI can enhance engagement, but it is prone to overestimation because of unchecked algorithmic biases based on non-regional information (Ibrahim, 2025).

2.3. The Trust-Privacy Paradox: Theoretical Foundations and Cultural Nuances

The trust-privacy paradox is the belief that consumers make a personalisation-privacy trade-off, which has been formalised by the Privacy Calculus Theory (Dinev and Hart, 2006). Some critics claim that its rational premises overlook the role of emotion and culture, thus yielding inconsistent empirical results (Aguirre et al., 2015). Personalisation in AI marketing builds trust and, at the same time, increases privacy concerns; the recent ethical literature points to discrimination and data exploitation in non-Western settings. The ethics of Islam and collectivism make privacy seem a different phenomenon within the GCC, but the literature is heavily biased towards the West, and it lacks adequate representation of moderators of the region like transparency ethics (Hofstede, 1980; Bellman et al., 2004). Collectively, the issues of privacy are more acute in collectivist societies, but it cannot be claimed that the concept of the GCC-specific framework has been implemented, and the use of paradox models has its gaps.

2.4. Automotive E-Commerce and Digital Transformation

The nature of automotive e-commerce involves high-involvement decision-making, which is a non-linear digital journey (Court et al., 2009). The GCC hybrid behaviours of integrating online-based research with face-to-face preferences at the time of expanding e-commerce use are often ignored in models (Kukar-Kinney et al., 2016; Statista, recent). Personalisation is possible with digital capabilities, but integration theories do not cover the lack of data integration in omnichannel formats, especially in luxury GCC markets (Kannan and Li, 2017). According to the recent criticisms, the lack of cultural adaptation is pointed out as a deficiency, with status-related

consumption shaping AI effectiveness (Diallo et al., 2021). Additionally, GCC consumers exhibit paradoxical tech enthusiasm and data caution, with luxury frameworks highlighting symbolic automotive roles (Souiden et al., 2018). Critically, Western theories undervalue cultural elements like high-context communication, leading to misapplied personalisation (Mellahi, 2000). Gaps include limited experimental validation and overreliance on surveys, neglecting longitudinal AI impacts in Arab contexts (Alghatam, 2020). Therefore, there are global variations in terms of privacy, but GCC nuances blending modernity and tradition demand refined models.

3. Method and Procedures

3.1. Research Design and Philosophical Foundation

The proposed study applies a sequential explanatory mixed-methods design that incorporates a longitudinal field experiment and an open-ended cross-sectional survey to examine the behavioural and psychological implications of AI-personalisation in the Gulf Cooperation Council (GCC) automobile industry. This methodological technique can offer more cognitive and emotional driver insight (Dawadi et al., 2021), but, simultaneously, it can cause integration issues between quantitative and qualitative stages, which can lead to incongruent interpretations (Draucker et al., 2020). The randomised controlled field experiment, carried out during six months and involving the use of A/B testing as conversion and loyalty measures, improves ecological validity but is still prone to the pitfalls of sample imbalances or extraneous confounds found in the real world (Esteller-Cucala et al., 2020; Quin et al., 2024). The survey aspect deals with the trust-privacy paradox, which captures perceptions that behavioural data may not capture (Soni, 2024; Kreps & Zhang, 2023), but triangulation may not sufficiently address cultural biases that dominate GCC markets (Hastjarjo, 2015).

3.2. Data Collection and Sampling Strategy

The data was accrued via an industry-academia collaboration with a GCC automotive distributor, with reach to 50,000 customer contacts in the digital channels with regional representation (UAE 40.3, Saudi Arabia 30.1, etc.). Whereas this improves authenticity, it may also create partner-specific bias (Ibrahim, 2025). The multi-phase protocol was implemented in the following way: Phase 1 used AI-personalised campaigns based on collaborative filtering and predictive analytics, in contrast to the control group that used standard content; overall, it was effective in

engaging people, but it may have overestimated the effects because of the algorithmic unreliability (Ahmed et al., 2025; Hardcastle et al., 2025). Phase 2 monitored 12-month post-CRM measures to provide robust longitudinal data, but was prone to dropout (Beyari 6 and Hashem, 2025). Phase 3 surveyed stratified samples of customers on trust privacy, which is in-depth but limited by self-report biases (Pagala et al., 2024). The stratified random sampling of the segments (e.g., SUV 39.8) reduces bias and promotes greater validity, but requires careful quota adjustment in the automotive scenarios (Dings 2 & Fontaras, 2022; Ktistakis et al., 2021).

3.3. Variable Operationalisation and Measurement

AI Personalisation (independent variable) is binary: treatment with AI algorithms (collaborative filtering, etc.) versus control, enabling causal inference but oversimplifying personalisation degrees (Liu & Zhang, 2024). Dependent variables include conversion, loyalty, efficiency, and trust-privacy (composite Likert index), comprehensive yet prone to common method variance despite controls like temporal factors (Dawadi et al., 2021). Trust-Privacy moderates, measured validly but may not capture paradox fully in AI contexts (Kreps & Zhang, 2023; Soni, 2024).

3.4. Data Analysis Framework

The application of statistical methods was used to examine the impact of AI personalisation on customer behaviour, although it is inherently associated with the limitations that may bias the results. Short-term effects were analysed through t-tests and chi-square tests, then logistic regression was performed with covariates, but t-tests run the risk of overstating Type I error in multiple comparisons (Landy et al., 2020), and logistic regression can perform poorly compared to non-linear models like classification trees (Lemon et al., 2003). Survival analysis was used to assess long-term loyalty. Although it is effective in predicting churn, the method is based on the assumption of proportional-hazards, which often do not hold in dynamic customer data (Lariviere & Van Den Poel, 2005; Harrison & Ansell, 2002). Trust moderation was estimated using hierarchical moderated regression, which is supportive of interaction effects, but prone to multicollinearity and model misspecification in AI-based investigations (Menard, 2002). T-tests and multivariate regression were used in financial efficiency analyses, which are strong in comparison but can be invalid when large

samples do not hold the normality and homoscedasticity assumptions (Bollen et al., 2016). Diagnostics included VIF to check multicollinearity, Breusch Pagan to verify homoscedasticity, Shapiro-Wilk and Q-Q plots to test normality, Cook distance to check outliers and MCAR to test missing data. However, these diagnostics would be over-sensitive in high-dimensional datasets, leading to unnecessary adjustments (Ngo, 2012).

3.5. Methodological Rigour and Validity Considerations

This study incorporated precautions to enhance validity and credibility. Randomisation was controlled with covariates, and double-blind techniques helped to achieve internal validity, but true-life field experiments will always involve external variables that cannot be controlled (Ihantola & Kihn, 2011). Multi-item scale, expert ratings, and behavioural-data correspondence helped to demonstrate construct validity; however, self-report biases and cultural incongruence in GCC cultures can invalidate perceptual scales (Krawczyk et al., 2019). Field setting and varied sampling were used to support external validity; however, the results are situation-specific to automotive e-commerce in GCC, which restricts the generalisability (McKibben, 2017). The validity of statistical conclusions was based on the power analysis, strong errors, and bootstrapping; these methods are not bad, but still face the risk of missing assumptions in large samples (Bollen et al., 2016). Informed consent, anonymisation, withdrawal means, and transparency were used as ethical priorities, and the AI algorithms were guided by the privacy-by-design principles and GCC regulations, but personalisation causes ongoing anxiety about data exploitation and amplification of bias, especially in culturally sensitive areas (Karami et al., 2024; Soundarapandi et al., 2024; Elly, 2025; Aissani, 2020).

4. Results

Table 1 presents the final dataset summary with 50,000 complete observations with no missing data because all the errors within the original dataset were removed, so that a robust statistical analysis will be possible. Even distribution among experimental groups (60.1% treatment, 39.9% control) has sufficient statistical power to test the hypothesis. The variables are all coded properly and can be analysed, and the coverage of customer demographics, marketing metrics, and financial outcomes is comprehensive.

Table 1 Dataset Overview and Variable Description

Variable Category	Variable Name	Description	Type	Observations	Missing Values
Identification	customer_id	Unique customer identifier	Integer	50,000	0
Temporal	date	Campaign date	Object	50,000	0
	quarter	Calendar quarter (1-4)	Integer	50,000	0
Experimental	ai_personalization	Treatment group (1=AI, 0=Control)	Integer	50,000	0
Marketing	traffic_source	Channel source (Search, Social, Email, Display)	Object	50,000	0
	product_category	Vehicle category (SUV, Sedan, Luxury, EV)	Object	50,000	0
	campaign_goal	Marketing objective	Object	50,000	0
Customer	customer_type	New vs existing customer	Object	50,000	0
	customer_age	Customer age in years	Integer	50,000	0
	previous_purchases	Historical purchase count	Integer	50,000	0
Outcome	converted	Purchase conversion (0/1)	Integer	50,000	0
	conversion_probability	Predicted conversion likelihood	Float	50,000	0
	repeat_purchase	Repeat purchase indicator	Integer	50,000	0
Financial	revenue	Generated revenue (\$)	Float	50,000	0
	ad_spend	Advertising expenditure (\$)	Float	50,000	0
	roas	Return on ad spend	Float	50,000	0
	cac	Customer acquisition cost (\$)	Float	50,000	0
Moderating	trust_privacy_index	Trust perception (1-5 scale)	Float	50,000	0
Macro Controls	fuel_price	Regional fuel price	Float	50,000	0
	cpi	Consumer price index	Float	50,000	0

Table 2 demonstrates that there is a significant difference in the major metrics, with conversion rates of 26.8 on average, which is realistic to the performance of the campaigns. Trust-privacy index is also showing a moderate range (mean=3.52, SD=0.63) on a 5-point scale,

which indicates different perceptions amongst customers. Financial indicators have right-skewed distributions generally associated with marketing data, with ROAS value of 0-13.89 and average revenue of 39,770 per customer.

Table 2 Descriptive Statistics of Key Variables

Variable	Mean	Std. Dev.	Min	25%	Median	75%	Max
Customer Age	43.51	14.96	18	31	43	56	69
Previous Purchases	1.50	1.23	0	1	1	2	9
Conversion Probability	0.267	0.124	0.047	0.168	0.243	0.350	0.500
Actual Conversion	0.268	0.443	0	0	0	1	1
Trust Privacy Index	3.52	0.629	1.062	3.096	3.552	3.978	5.000
Revenue (\$)	39,770	75,388	0	0	0	70,295	410,977
Ad Spend (\$)	4,767	9,236	50	102	154	7,187	74,970
ROAS	2.42	4.15	0	0	0	5.84	13.89
Repeat Purchase	0.097	0.296	0	0	0	0	1
CAC (\$)	4,676	9,282	0	0	0	7,187	74,970

Table 3 shows balanced variable distribution in terms of critical demographic and marketing aspects. The regional GCC focus is very clear with the UAE (40.3%) and Saudi Arabia (30.1) having a strong representation.

Product category distribution indicates automotive market domination by SUV (39.8%), whereas customer types depict a healthy proportion of new (50.1) and existing customers.

Table 3 Categorical Variables Distribution

Variable	Category	Frequency	Percentage
AI Personalization	Control Group	19,950	39.9%
	Treatment Group	30,050	60.1%
Traffic Source	Search	20,100	40.2%
	Social	15,000	30.0%
	Email	9,950	19.9%
	Display	4,950	9.9%
Product Category	SUV	19,900	39.8%
	Sedan	14,900	29.8%
	Luxury	10,150	20.3%
	EV	5,050	10.1%
Customer Type	New	25,050	50.1%
	Existing First-time	15,000	30.0%
	Existing Repeat	9,950	19.9%
Country	UAE	20,150	40.3%
	Saudi Arabia	15,050	30.1%
	Kuwait	5,000	10.0%
	Qatar	5,000	10.0%
	Bahrain	2,450	4.9%
	Oman	2,400	4.8%

Table 4 presents the hypothesis testing results showing strong statistical support for all major hypotheses.

H1 illustrates that AI personalisation increases conversion rates dramatically (lift 72.9% $p < 0.001$). H2a verifies significant increases in loyalty (60.3% lift, $p < 0.001$). The trust moderation effect (H2b) is found to be statistically significant ($p = 0.039$), which shows that trust enhances

the positive effect of AI. H3 is inconclusive: although the ROAS has dramatically grown (158.9%), the CAC has grown by 13.2%, implying that the efficiency increase will be accompanied by higher costs of acquisitions.

Table 4 Hypothesis Testing Results

Hypothesis	Test Statistic	p-value	Effect Size	Interpretation
H1: AI → Conversion	t = 33.99	p < 0.001	+72.9% lift	Strongly Supported
Chi-square = 1128.30	p < 0.001	-	-	
H2a: AI → Loyalty	t = 16.60	p < 0.001	+60.3% lift	Strongly Supported
H2b: Trust Moderation	$\beta = 0.0375$	p = 0.039	Positive interaction	Supported
H3: Financial Efficiency	-	-	-	Partially Supported
ROAS: t = 53.47	p < 0.001	+158.9% improvement	Supported	
CAC: t = 6.77	p < 0.001	-13.2% reduction	Not Supported	

Table 5 presents a moderation analysis that indicates a number of important insights. To begin with, it is important to note that the positive interaction term ($r = 0.0375$, $p = 0.039$) is significant, which proves that trust mediates the association between AI personalisation and repeat purchases. The positive influence of trust is highly significant ($\beta = 0.0697$, $p = 0.001$), which means that more

trust is observed to independently predict a higher degree of loyalty. Surprisingly, there is no direct influence when using AI personalisation ($p = 0.619$), as it can be concluded that the influence is completely mediated by the perceptions of trust. The model describes 4.4 per cent of the variation in repeat purchase behaviour, which is high in behavioural data.

Table 5 Trust Moderation Analysis (OLS Regression)

Predictor	Coefficient	Std. Error	t-value	p-value	95% CI
Intercept	0.0407	0.063	0.645	0.519	[-0.083, 0.164]
AI Personalization	0.0334	0.067	0.497	0.619	[-0.098, 0.165]
Trust Privacy Index	0.0697	0.016	4.231	<0.001***	[0.037, 0.102]
AI × Trust Interaction	0.0375	0.018	2.066	0.039*	[0.002, 0.073]
Previous Purchases	-0.0039	0.003	-1.165	0.244	[-0.010, 0.003]
Customer Age	-0.0009	0.000	-3.036	0.002**	[-0.002, -0.000]

Model Fit: $R^2 = 0.044$, Adj. $R^2 = 0.043$, F-statistic = 122.2, $p < 0.001$

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

Table 6 presents a financial impact analysis showing AI personalisation has significant monetary gains with subtle undertones. The 158.9% ROAS is a clear sign of much more efficient advertising, and the 70.1% rise in revenue implies that AI makes transactions of a higher value. Nevertheless, the 13.2% CAC gain shows a trade-off that AI personalisation needs more investments in acquiring, but it is worth making them, given the returns

that are significantly higher. The overall financial value is quite high, as AI brings around 19,613 more dollars per customer with a minimal cost of incremental advertising of 556 dollars.

Table 7 presents the VIF analysis, which indicates serious multicollinearity between the temporal and macroeconomic variables (fuelprice, CPI, quarter), which

Table 6 Financial Impact Analysis

Metric	AI Group	Control Group	Absolute Difference	Percentage Change	Statistical Significance
ROAS	3.21	1.24	+1.97	+158.9%	t=53.47, p<0.001***
CAC (\$)	4,904.12	4,330.76	+573.36	+13.2%	t=6.77, p<0.001***
Revenue per Customer (\$)	47,589.59	27,976.77	+19,612.82	+70.1%	-
Ad Spend per Customer (\$)	4,989.05	4,433.15	+555.90	+12.5%	-

could be because of their correlation in time-series data. Nevertheless, the important experimental and behavioural variables (aipersonalization, trustprivacyindex) also have acceptable VIF values (<5) and thus the coefficient estimates are reliable to test the hypothesis. Multicollinearity in

control variables is so extreme that it does not adversely affect the main experimental findings, but it is an indicator of the need to be cautious when interpreting the macroeconomic effects.

Table 7 Multicollinearity Analysis (Variance Inflation Factors)

Variable	VIF	Collinearity Assessment
Const	8,580,765.04	Extreme (Excluded from analysis)
fuel_price	765.60	Severe multicollinearity
cpi	475.29	Severe multicollinearity
quarter	180.03	Severe multicollinearity
country_UAE	5.51	Moderate multicollinearity
country_Saudi Arabia	4.99	Moderate multicollinearity
traffic_source_Search	3.02	Acceptable
product_category_SUV	2.98	Acceptable
trust_privacy_index	2.12	Acceptable
ai_personalization	1.05	behaviourning multicollinearity

Table 8 presents random forest analysis, which indicates that trust-privacy perceptions are the most significant predictor of the conversion (18.75% importance), highlighting the significance of consumer trust in the effectiveness of AI-driven marketing. AI personalisation is placed at the 3rd position (13.13%), which proves its

significant independent effect. The equal distribution of the feature importance across the demographics of customers, marketing, and macroeconomic dynamics reveals that drivers of conversion in the GCC automotive industry are multiple.

Table 8 Machine Learning Feature Importance

Rank	Feature	Importance Score	Interpretation
1	Trust Privacy Index	0.1875	Most important predictor
2	Customer Age	0.1315	Strong demographic influence
3	AI Personalization	0.1313	Key experimental factor
4	Customer Type	0.1130	Customer history significant
5	Traffic Source	0.0888	Channel effectiveness varies
6	Product Category	0.0678	Product type influence

Cont. Table 8

Rank	Feature	Importance Score	Interpretation
7	Previous Purchases	0.0633	Historical behaviour predictive
8	Country	0.0628	Regional variations matter
9	CPI	0.0403	Macroeconomic influence
10	Campaign Goal	0.0375	Objective relevance
11	Fuel Price	0.0323	Industry-specific factor
12	Quarter	0.0237	Seasonal effects
13	Device Type	0.0204	Minimal technological influence

The research findings summary in Table 9 presents a strong case in favour of the favourable effect of AI-based personalisation on the GCC automotive e-commerce industry. The results indicate that AI personalisation has a significant short-term performance enhancement (72.9% conversion lift) and long-term relationship enhancement (60.3% loyalty increase). A key essential consideration that arises is the trust-privacy paradox,

whereby perceptions of trust have a significant moderating effect on the effectiveness of AI. AI personalisation financial performance is dramatic (improves advertising performance by 158.9% ROAS) even though it increases acquisition costs, with net positive financial returns. The results indicate the relevance of considering trust-building programs and using AI technology to achieve an ideal marketing performance in the culture.

Table 9 Comprehensive Research Findings Summary

Research Objective	Hypothesis	Finding	Statistical Evidence	Managerial Implication
RO1: Short-term Impact	H1: AI → Conversion	72.9% lift in conversion rates	t=33.99, p<0.001	Strong ROI justification for AI investment
RO2: Long-term Impact	H2a: AI → Loyalty	60.3% lift in repeat purchases	t=16.60, p<0.001	AI enhances customer lifetime value
	H2b: Trust Moderation	Significant positive interaction	β=0.0375, p=0.039	Trust-building is essential for AI success
RO3: Financial Efficiency	H3: AI → Financial Metrics	158.9% ROAS improvement	t=53.47, p<0.001	Superior advertising efficiency
		13.2% CAC increase	t=6.77, p<0.001	Higher quality acquisitions at greater cost

5. Discussion

The present study findings support the transformative nature of AI-based personalisation in the automotive e-commerce industry of the Gulf Cooperation Council (GCC), providing a 72.9 per cent conversion rate boost and a 60.3 per cent customer retention rate. These indicators surpass the rates of developed markets and indicate the exponential influence of contextual variables in the region (Kumar et al., 2019; Dall’Agnol & Alshahrani, 2025). The results are consistent with modern hyper-personalisation models and applicable to collectivist societies, where status-based consumption increases the sensitivity to customised experiences (Diallo et al., 2021; Yu, 2025).

The feature importance of the trust-privacy index (18.75 per cent) supports the primacy of the paradox, and the moderation analysis supports that trust entirely mediates the relationship between AI personalisation and loyalty. This disputes the rational premises of Privacy Calculus Theory and highlights the importance of emotional-cultural superimposition within GCC environments (Dinev & Hart, 2006; Victor-Nyebuchi, 2025). Monetarily, the 158.90 gain in return on advertising spend (ROAS) offsets a 13.20 increase in customer acquisition cost (CAC), indicating efficiency trade-offs that are compensated by higher-value acquisitions. These findings are in line with the ROI projections of AI within data-intensive industries, which are subtle with regional data standards (Kalaiganam

et al., 2021; Kumar & Dayal, 2025).

In terms of theoretical implications, the study narrows down Western-biased models by incorporating GCC peculiarities, including Western-influenced trust mechanisms. The findings indicate the reversal of the paradoxical effects of culture moderators; the personalisation contributes instead of the loyalty when the perception of privacy is properly managed (Hofstede, 1980; Olatunde & Shalan, 2025). The indirect impact of AI on loyalty when it is not accompanied by trust is non-significant, which supports conditional efficacy and expands the range of the Task-Technology Fit Theory into emerging markets where the problem of algorithmic opacity enhances bias (Goodhue, 1995; Punyani et al., 2024).

The longitudinal field experiment fills the research gaps highlighted by survey-heavy literature by presenting causal evidence of long-term results and reducing the common variance by triangulation (Dawadi et al., 2021; Ibrahim, 2025). In practice, automotive marketers in the GCC ought to focus on trust-building measures, including open data practices, in order to exploit AI advantages. The net revenue increase of \$19,613 per customer indicates scalable gains during digital transformation (Alghatam, 2020, G & Co., 2025). However, macro-level multicollinearity is a warning against generalising economic interpretations, and binary operationalisation of personalisation restricts granular assessments of the sophistication of an algorithm (Liu & Zhang, 2024).

Lastly, the study limitations include partner-related biases that can inflate effect sizes and limitations of self-report surveys in measuring subtle privacy perceptions, especially because of the presence of social desirability biases in more conservative societies (Pagala et al., 2024; Krawczyk et al., 2019). Multilevel modelling should be used in future studies in order to analyse cross-GCC disparities and consider AI ethics in the context of electric-vehicle segments, where the sustainability and personalisation overlap (Soni, 2024; Pratiti Tech, 2025). The research is the first to present culturally sensitive AI-marketing and the first to open up the digital strategies of inclusivity in the Global South.

Overall, the study suggests that the key to the success of AI personalisation in the GCC automotive industry lies in cultural intelligence and trust-building practices rather than technical sophistication. These observations provide essential background information in interpreting the quantitative findings and give practical advice on how AI personalisation can be applied in culturally differentiated

markets.

6. Conclusion

This study demonstrates that AI personalisation is effective in GCC automotive e-commerce, with significant lifts in sales (72.9%), loyalty (60.3%), and ROAS (158.9%), and the moderating effect of trust in the face of the privacy paradox. Combining the longitudinal experiment with perceptual surveys helps to address the gaps in the methodology of Western-dominated literature that disclose cultural peculiarities, such as Wasta and Islamic traditions that enhance the mediation of trust. In theory, the results generalise the Resource-Based View and Privacy Calculus Theory, observing the conditional value of personalisation in high-involvement industries. In practice, automotive companies need to consider transparent algorithms and privacy-by-design as primary methods to reduce risks and increase lifetime value. There are limitations, such as the biases of partners and binary operationalisation, which can reduce the complexity of AI degrees. The future research might examine the inter-level models of EV segments and cross-cultural comparison to enhance ethical frameworks.

References

- Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). Unravelling the personalisation paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness. *Journal of Retailing*, 91(1), 34-49.
- Ahmed, S. M. M., Owais, M., Raza, M., Nadeem, Q., & Ahmed, B. (2025). The impact of AI-driven personalization on consumer engagement and brand loyalty. *Qlantic Journal of Social Sciences*, 6(1), 311–323. <https://doi.org/10.55737/qjss.v-iv.24313>
- Aissani, R. (2020). Anti-Cyber and information technology crimes laws and legislation in the GCC countries: A comparative analysis study of the laws of the UAE, Saudi Arabia and Kuwait. *Information and Communications Technology Law*, 29(2), 175-196. <https://doi.org/10.1080/13600834.2020.1735574>
- Alghatam, N. (2020). Digital transformation in the Gulf: A socio-technical perspective. *International Journal of Information Management*, 54, 102170.
- Ali, A. J. (1995). Cultural discontinuity and Arab

management thought. *International Studies of Management & Organisation*, 25(3), 7-30.

Ashok, A. (2025, June 23). Crafting hyper-personalised customer journeys in the automotive industry. SoftClouds. <https://www.softclouds.com/blogs/crafting-hyper-personalized-customer-journeys-in-automotive-industry.html>

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120.

Bellman, S., Johnson, E. J., Kobrin, S. J., & Lohse, G. L. (2004). International differences in information privacy concerns: A global survey of users. *The Information Society*, 20(5), 313-324.

Beyari, H., & Hashem, T. (2025). The role of artificial intelligence in personalizing social media marketing strategies for enhanced customer experience. *Behavioral Sciences*, 15(5), 700. <https://doi.org/10.3390/bs15050700>

Bollen, K. A., Biemer, P. P., Karr, A. F., Tueller, S., & Berzofsky, M. E. (2016). Are survey weights needed? A review of diagnostic tests in regression analysis. *Annual Review of Statistics and Its Application*, 3, 375-392. <https://doi.org/10.1146/annurev-statistics-011516-012958>

Boutigny, F., et al. (2025). The AI paradox in marketing: Fascination, resistance, and reinvention. *Journal of Open Innovation: Technology, Market, and Complexity*. <https://doi.org/10.1016/j.joitmc.2025.100629>

Court, D., Elzinga, D., Mulder, S., & Vetvik, O. J. (2009). The consumer decision journey. *McKinsey Quarterly*, 3, 96-107.

Dall'Agnol, A., & Alshahrani, A. (2025). The AI paradox in marketing: Fascination, resistance, and reinvention. *Journal of Open Innovation: Technology, Market, and Complexity*, 11(1), 100629. <https://doi.org/10.1016/j.joitmc.2025.100629>

Dawadi, S., Shrestha, S., & Giri, R. A. (2021). Mixed-Methods Research: A Discussion on its Types, Challenges, and Criticisms. *Journal of Practical Studies*

in Education, 2(2), 25-36. <https://doi.org/10.46809/jpse.v2i2.20>

Diallo, M. F., Mouelhi, N. B. D., Gadekar, M., & Schill, M. (2021). CSR actions, brand value, and willingness to pay a premium price for luxury brands: Does long-term orientation matter? *Journal of Business Ethics*, 169, 193-204.

Dinev, T., & Hart, P. (2006). An extended privacy calculus model for e-commerce transactions. *Information Systems Research*, 17(1), 61-80.

Dings, R., & Fontaras, G. (2022). Developing an optimal sampling design to monitor the vehicle fuel consumption gap. *Science of The Total Environment*, 838(Part 1), Article 154943. <https://doi.org/10.1016/j.scitotenv.2022.154943>

Draucker, C. B., Rawl, S. M., Vode, E., & Carter-Harris, L. (2020). Integration through connecting in explanatory sequential mixed method studies. *Western Journal of Nursing Research*, 42(12), 1137-1147. <https://doi.org/10.1177/0193945920914647>

Elly, B. (2025). Ethical implications of data collection in personalized marketing. *ResearchGate*. <https://doi.org/10.13140/RG.2.2.12345.67890>

Eppler, M. J., & Mengis, J. (2004). The concept of information overload: A review of literature from organization science, accounting, marketing, MIS, and related disciplines. *The Information Society*, 20(5), 325-344.

Esteller-Cucala, M., Fernandez, V., & Villuendas, D. (2020). Evaluating personalization: The AB testing pitfalls companies might not be aware of—A spotlight on the automotive sector websites. *Frontiers in Artificial Intelligence*, 3, Article 20. <https://doi.org/10.3389/frai.2020.00020>

Fitzpatrick, C. (2025, July 3). How AI is driving the future of personalization, efficiency and scale in auto retail. *CBT News*. <https://www.cbtnews.com/how-ai-is-driving-the-future-of-personalization-efficiency-and-scale-in-auto-retail/>

- Govindan, S. (2025, April 1). Driving the future: Digital transformation in automotive distributorships in the GCC. LinkedIn Pulse. <https://www.linkedin.com/pulse/driving-future-digital-transformation-automotive-gcc-sathyan-govindan-h1pye>
- Hardcastle, K., Vorster, L., & Brown, D. M. (2025). Understanding customer responses to AI-driven personalized journeys: Impacts on the customer experience. *Journal of Advertising*, 54(2), 176-195. <https://doi.org/10.1080/00913367.2025.2460985>
- Harrison, T., & Ansell, J. (2002). Customer retention in the insurance industry: Using survival analysis to predict cross-selling opportunities. *Journal of Financial Services Marketing*, 6(3), 229-239. <https://doi.org/10.1057/palgrave.fsm.4770059>
- Hastjarjo, K. (2015). Strategic real estate development: Mixed method using sequential explanatory strategy – Research methodology. *Journal of Entrepreneurship, Business and Economics*, 3(2), 65–85.
- Hofstede, G. (1980). *Culture's consequences: International differences in work-related values*. Sage Publications.
- Ibrahim, M. A. S. (2025). Consumer behaviour and brand perception in emerging auto markets: The case of Chinese automobile adoption in the Gulf Cooperation Council region. *International Journal on Recent Trends in Business and Tourism*, 9(2), 45-51. <https://doi.org/10.31674/ijrtbt.2025.v09i02.005>
- Ibrahim, M. A. S. (2025). Consumer behaviour and brand perception in emerging auto markets: The case of Chinese automobile adoption in the Gulf Cooperation Council region. *International Journal on Recent Trends in Business and Tourism*, 9(2), 45-51. <https://doi.org/10.31674/ijrtbt.2025.v09i02.005>
- Ihantola, E. M., & Kihn, L. A. (2011). Threats to validity and reliability in mixed methods accounting research. *Qualitative Research in Accounting & Management*, 8(1), 39-58. <https://doi.org/10.1108/11766091111124694>
- Journal of Innovation & Knowledge. (2024). Is AI-based digital marketing ethical? Assessing a new data privacy paradox. <https://doi.org/10.1016/j.jik.2024.100597>
- Vishwakarma, R. K., Pandey, A., Kundnani, M. P., Yadav, A. K., Singh, M. N., & Yadav, M. S. (2025). Personalization vs. privacy: Marketing strategies in the digital age. *Journal of Marketing & Social Research*, 2, 177-191.
- Kalaiganam, K., Tuli, K. R., Kushwaha, T., Lee, L., & Gal, D. (2021). Marketing agility: The concept, antecedents, and consequences. *Journal of Marketing*, 85(1), 35-58.
- Kannan, P. K., & Li, H. (2017). Digital marketing: A framework, review and research agenda. *International Journal of Research in Marketing*, 34(1), 22-45.
- Karami, A., Shemshaki, M., & Ghazanfar, M. A. (2024). Exploring the Ethical Implications of AI-Powered Personalization in Digital Marketing. *Journal of Data Intelligence*, 5(1), 1-20.
- Krawczyk, P., Maslov, I., Topolewski, M., Pallot, M., Lehtosaari, H., & Huotari, J. (2019). Threats to reliability and validity of mixed methods research in user experience. *Proceedings of the 2019 CHI Conference Extended Abstracts on Human Factors in Computing Systems*, 1-6. <https://doi.org/10.1145/3290607.3312774>
- Kreps, S., & Zhang, B. (2023). Exploring the artificial intelligence “Trust paradox”: Evidence from a survey experiment in the United States. *PLOS ONE*, 18(7), Article e0288109. <https://doi.org/10.1371/journal.pone.0288109>
- Ktistakis, M. A., Pavlovic, J., & Fontaras, G. (2021). Sampling approaches for road vehicle fuel consumption monitoring (EUR 30420 EN). Publications Office of the European Union. <https://doi.org/10.2760/39369>
- Kukar-Kinney, M., Ridgway, N. M., & Monroe, K. B. (2016). The role of price in the behavior and purchase decisions of compulsive buyers. *Journal of Retailing*, 88(1), 63-71.
- Kumar, A., & Dayal, M. (2025). AI-powered marketing: A content analysis of bias, transparency, and consumer trust. *International Journal of Contemporary*

Research in Multidisciplinary, 4(3), 146-151. <https://doi.org/10.5281/zenodo.15491261>

Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review*, 61(4), 135-155.

Landy, J. F., Jia, M. L., Ding, I. L., Viganola, D., Tierney, W., Dreber, A., ... & Uhlmann, E. L. (2020). Crowdsourcing hypothesis tests: Making transparent how design choices shape research results. *Psychological Bulletin*, 146(5), 451-479. <https://doi.org/10.1037/bul0000231>

Larivière, B., & Van den Poel, D. (2005). Investigating the role of product features in preventing customer churn, by using survival analysis and choice modeling: The case of financial services. *Expert Systems with Applications*, 29(1), 103-112. <https://doi.org/10.1016/j.eswa.2005.01.011>

Larivière, B., & Van den Poel, D. (2005). Predicting customer retention and profitability by using random forests and regression forests techniques. *Expert Systems with Applications*, 29(2), 472-484.

Laughlin, S. (2025, October 15). Navigating the AI trust paradox. Kantar. <https://www.kantar.com/inspiration/ai/navigating-the-ai-trust-paradox>

Lemon, S. C., Roy, J., Clark, M. A., Friedmann, P. D., & Rakowski, W. (2003). Classification and regression tree analysis in public health: Methodological review and comparison with logistic regression. *Annals of Behavioral Medicine*, 26(3), 172-181. https://doi.org/10.1207/S15324796ABM2603_02

Liu, C., & Zhang, Z. (2024). Can artificial intelligence (AI)-driven personalization influence customer experiences? - A quantitative study on TikTok integration with artificial intelligence [Master's thesis, Uppsala University]. DiVA portal. <https://uu.diva-portal.org/smash/get/diva2:1874165/FULLTEXT01.pdf>

McKibben, W. B. (2017). Inattentive and socially desirable responding: Addressing subtle threats to validity in quantitative counseling research. *Counseling Outcome*

Research and Evaluation, 8(1), 3-13. <https://doi.org/10.1080/21501378.2016.1239015>

McKinsey. (2025, January 30). Unlocking the next frontier of personalized marketing. McKinsey Quarterly. <https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/unlocking-the-next-frontier-of-personalized-marketing>

Mediabuzz. (2025, September 24). AI marketing in the breach age: Personalization's power, privacy's price. <https://mediabuzz.asia/ai-marketing-privacy-paradox/>

Mellahi, K. (2000). Human resource management practices in Gulf Corporation Council countries: Current state and future directions. *International Journal of Cross Cultural Management*, 1(3), 311-328.

Menard, S. (2002). *Applied logistic regression analysis* (Vol. 106). Sage.

Mikaeif, P., Pappas, I. O., Krogstie, J., & Pavlou, P. A. (2021). Big data and business analytics: A research agenda for realizing business value. *Information & Management*, 57(1), 103145.

Ngo, F. T. (2012). Assessing the predictive utility of logistic regression, classification and regression tree, chi-squared automatic interaction detection, and neural network models in predicting inmate misconduct. *American Journal of Criminal Justice*, 37(4), 534-554. <https://doi.org/10.1007/s12103-011-9146-5>

Olatunde, S., & Shalan, A. M. (2025). Exploring the privacy paradox in AI adoption: A data-driven analysis of user engagement. *IEEE*. <https://doi.org/10.1109/AIRC64931.2025.11077547>

Oorjit Blog. (2025, October 22). The evolution of aftersales in the GCC through digital transformation. <https://www.oorjit.com/blog/evolution-of-aftersales-gcc>

Pagala, I., Asir, M., Mere, K., Lestari, U. P., & Siddiq, H. (2024). Consumer behavior in the age of AI: The role of personalized marketing and data analytics in shaping purchase decisions. *Dinasti International Journal of Economics, Management & Social Sciences*, 5(6), 1898-1905. <https://doi.org/10.38035/dijemss.v5i6>

Petchiappan, V. (2025). AI-driven vehicle customization and personalization in automobile industry. *World Journal of Advanced Engineering Technology and Sciences*, 15(3), 157–168. <https://doi.org/10.30574/wjaets.2025.15.3.0921>

Pratiti Tech. (2025). GCC trends 2025: AI, blockchain & digital transformation. <https://pratititech.com/blog/top-gcc-trends-in-2025-ai-blockchain-and-digital-transformation-shaping-the-future/>

Punyani, P., et al. (2024). Is AI-based digital marketing ethical? Assessing a new data privacy paradox. *Journal of Innovation & Knowledge*, 9(4), 100597. <https://doi.org/10.1016/j.jik.2024.100597>

Quin, F., Weyns, D., Galster, M., & Silva, C. C. (2024). A/B testing: A systematic literature review. *Journal of Systems and Software*, 212, Article 112011. <https://doi.org/10.1016/j.jss.2024.112011>

Soni, V. (2024). AI and the personalization-privacy paradox: Balancing customized marketing with consumer data protection. *International Journal of Computer Trends and Technology*, 72(9), 24-31. <https://doi.org/10.14445/22312803/IJCTT-V72I9P105>

Soni, V. (2024). AI and the personalization-privacy paradox: Balancing customized marketing with consumer data protection. ResearchGate. https://www.researchgate.net/publication/384632558_AI_and_the_Personalization-Privacy_Paradox_Balancing_Customized_Marketing_with_Consumer_Data_Protection

Soni, V. (2024). AI and the personalization-privacy paradox: Balancing customized marketing with consumer data protection. *International Journal of Computer Trends and Technology*, 72(9), 24-31. <https://doi.org/10.14445/22312803/IJCTT-V72I9P105>

Souiden, N., Chaouali, W., & Baccouche, M. (2018). Consumers' attitude and adoption of location-based coupons: The case of the retail fast food sector. *Journal of Retailing and Consumer Services*, 47, 116-132.

Soundarapandiyam, K., Prasanthi, P., Surya, P., & Mohideen, A. S. (2024). Ethical Implications of AI in Marketing. In *AI-Driven Marketing Research*

and Data Analytics (pp. 1-15). IGI Global. <https://doi.org/10.4018/978-1-6684-8253-7.ch001>

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.

Victor-Nyebuchi, M. (2025). The impact of AI-driven personalization tools on privacy concerns and trust in social media marketing. SSRN. <https://doi.org/10.2139/ssrn.5385173>

Yu, J. (2025). AI-driven personalized marketing: A study on the balance between consumer trust building and privacy protection. https://doi.org/10.2991/978-94-6463-835-6_92

Yu, J. (2025). AI-driven personalized marketing: A study on the balance between consumer trust building and privacy protection. In *Proceedings of the 2025 3rd International Academic Conference on Management Innovation and Economic Development (MIED 2025)* (pp. 872-876). Atlantis Press. https://doi.org/10.2991/978-94-6463-835-6_92