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AI-Powered Personalization and SME E-Commerce Growth in Emerging European Economies: The Mediating Roles of Consumer Engagement and Digital Trust

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ABSTRACT

This study examines the mechanisms through which artificial intelligence-enabled personalization technologies influence small and medium-sized enterprise (SME) e-commerce performance in emerging European economies. While existing research has predominantly focused on large firms in advanced economies, limited evidence exists regarding how AI personalization drives growth for resource-constrained SMEs operating in less digitally mature environments. Drawing on resource-based view, technology-organization-environment framework, and consumer engagement theory, this research develops and empirically tests a moderated mediation model using survey data from 487 SMEs across eight Eastern and Southern European countries, supplemented with Eurostat macroeconomic indicators. The results reveal that AI personalization adoption positively affects customer engagement, which in turn enhances e-commerce performance metrics including sales growth, conversion rates, customer retention, and revenue growth. Critically, customer engagement fully mediates the relationship between AI personalization and e-commerce performance, while digital trust significantly moderates the engagement-performance link. Multi-group analysis demonstrates substantial cross-country heterogeneity, with Northern European SMEs exhibiting stronger direct effects and Southern European firms showing greater reliance on trust-mediated pathways. These findings extend AI adoption theory by integrating engagement and trust mechanisms, provide empirical evidence from underrepresented SME contexts, and offer actionable policy recommendations for digital transformation strategies in emerging economies, with specific attention to countries like Iran facing unique institutional and infrastructural challenges.

1. Introduction

The digital transformation sweeping across Europe has fundamentally altered organizational operations, with profound implications for e-commerce and online consumer engagement strategies [1]. Within this

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evolving environment, artificial intelligence (AI) has emerged as a potent catalyst for economic and business restructuring. Scholars are increasingly emphasizing AI's capacity to enhance digital experiences, personalize interactions, and amplify user engagement on digital platforms, thereby highlighting its escalating significance in marketing and customer journey optimization [2],[3].

Small and medium-sized enterprises constitute the backbone of European economies, representing approximately 99% of all businesses and employing nearly two-thirds of the workforce. However, the integration of AI technologies remains highly uneven across firm sizes and geographic regions. While large multinational corporations in Northern and Western Europe have aggressively adopted AI-powered personalization tools, SMEs in emerging European economies, particularly in Southern and Eastern Europe, face substantial barriers including financial constraints, limited technical expertise, and underdeveloped digital infrastructure [1],[4].

The rise of AI-enabled personalization technologies has created new opportunities for SMEs to compete with larger rivals by delivering tailored customer experiences at scale. Recommendation systems, dynamic pricing algorithms, intelligent chatbots, and predictive analytics tools that were once accessible only to technology giants are now increasingly available through software-as-a-service platforms and open-source frameworks [5],[6]. This democratization of AI capabilities presents a unique window of opportunity for SMEs in emerging economies to accelerate their digital transformation and capture e-commerce growth.

Despite growing scholarly attention to AI in e-commerce, significant research gaps persist. First, existing studies predominantly focus on large firms in advanced economies, leaving SME-specific dynamics underexplored [5],[7]. The resource constraints, organizational structures, and strategic priorities of SMEs differ fundamentally from those of large corporations, suggesting that findings from large-firm studies may not generalize to SME contexts.

Second, there is limited empirical evidence regarding the mechanisms linking AI personalization to firm performance. The literature has largely treated AI adoption as a direct driver of outcomes, neglecting the intervening psychological and behavioral processes through which AI technologies create economic value [8], [9]. Consumer engagement, reflecting the frequency, intensity, and quality of customer interactions with digital platforms, represents a theoretically plausible but empirically untested mediator.

Third, the role of digital trust as a boundary condition remains poorly understood, particularly in emerging economies where institutional voids and privacy concerns may moderate technology acceptance [10], [11]. Trust in AI systems is not automatic but must be cultivated through transparency, reliability, and perceived security.

Fourth, cross-country comparative evidence across European economies at different stages of digital maturity is sparse. The European Union exhibits substantial regional disparities in AI adoption and e-commerce performance, with Northern and Western countries leading while Southern and Eastern nations

show emerging potential [1],[12]. Understanding these contextual differences is essential for designing effective digital transformation policies.

This study is guided by four primary objectives. The first objective is to examine the direct effects of AI personalization adoption on SME e-commerce growth metrics, including sales growth, conversion rates, customer retention, and revenue growth. The second objective is to investigate the mediating role of customer engagement in the relationship between AI personalization and e-commerce performance, testing whether AI's impact operates through behavioral mechanisms rather than direct technological effects. The third objective is to analyze the moderating role of digital trust in the customer engagement–e-commerce performance relationship, examining whether trust amplifies or diminishes the returns to engagement. The fourth objective is to compare these effects across emerging European economies at different levels of digital maturity, identifying contextual factors that shape AI-enabled transformation pathways.

Based on these objectives, this study addresses five research questions. First, does AI personalization adoption positively affect customer engagement among SMEs in emerging European economies? Second, does customer engagement positively affect e-commerce performance metrics? Third, does AI personalization adoption have a direct positive effect on e-commerce performance, or is this relationship fully mediated by customer engagement? Fourth, does digital trust moderate the relationship between customer engagement and e-commerce performance, such that the engagement-performance link is stronger when trust is high? Fifth, do these relationships vary systematically across European countries with different levels of digital maturity, and what implications do these variations hold for countries like Iran undergoing similar digital transitions?

The contributions of this research are theoretical, empirical, and policy-oriented. The theoretical contributions extend AI adoption theory in three significant ways. First, the study integrates consumer engagement theory with technology acceptance models to explain the behavioral mechanisms linking AI investment to performance outcomes. While traditional technology acceptance models emphasize perceived usefulness and ease of use [13],[14]. this study demonstrates that sustained engagement behaviors mediate technological effects. Second, it incorporates digital trust as a moderating mechanism, responding to calls in the literature for greater attention to contextual and psychological factors [15], [16]. Third, it applies and extends the resource-based view and the technology-organization-environment framework to the SME context, revealing how complementary organizational capabilities moderate AI returns.

Empirically, this study provides novel evidence from an underrepresented population: SMEs operating in emerging European economies. Previous cross-country studies have examined aggregate enterprise-level AI adoption [1], but firm-level data on specific personalization technologies and their performance implications have been lacking. By collecting primary survey data from 487 SMEs across eight countries and linking these responses to Eurostat macroeconomic indicators, this study offers a uniquely rich dataset

for analyzing AI's heterogeneous effects. Furthermore, the moderated mediation methodology enables causal identification of the mechanisms through which AI creates value.

For policymakers, this research provides actionable guidance for designing digital transformation strategies tailored to SME needs and national contexts. The findings suggest that technology investment alone is insufficient; complementary policies promoting digital literacy, consumer trust, and organizational readiness are essential. For countries like Iran, facing unique challenges including international sanctions, infrastructure constraints, and institutional trust deficits, the study offers transferable insights about the sequencing of digital development priorities and the importance of building trust before expecting performance returns.

2. Literature Review and Hypothesis Development

Artificial intelligence has fundamentally reshaped e-commerce through a range of personalization technologies. Personalized recommendation systems, which leverage collaborative filtering, content-based filtering, and deep learning, tailor product suggestions and thereby increase click-through and conversion rates [17],[18]. At the same time, chatbots and virtual assistants powered by natural language processing provide real-time customer support, automate frequently asked questions, and enhance the overall user experience [6], [19]. Predictive analytics further contribute by analysing consumer data to forecast demand, optimise inventory, and inform dynamic pricing strategies, while dynamic pricing algorithms adjust prices in real time based on demand, competition, and consumer behaviour [20], [21]. Collectively, these technologies enable firms to deliver individualised experiences at scale, potentially creating a competitive advantage through enhanced customer satisfaction and loyalty. However, the adoption of these technologies varies considerably across firm sizes and geographic regions. Large firms in advanced economies have led AI integration, whereas small and medium-sized enterprises (SMEs), particularly those in emerging economies, lag behind due to financial constraints, skill shortages, and limited awareness of AI's potential [22], [23]. This disparity creates a "digital divide" that may exacerbate existing inequalities in e-commerce performance.

To understand how AI personalisation can generate sustained competitive advantage, the resource-based view (RBV) offers a foundational theoretical lens. According to RBV, firm performance is determined by internal resources and capabilities that are valuable, rare, imperfectly imitable, and non-substitutable [24]. AI personalisation technologies can constitute such resources when they are embedded within organisational routines and complemented by other capabilities. Nevertheless, for resource-constrained SMEs, the challenge lies not merely in acquiring AI tools but in developing the complementary human capital, data infrastructure, and organisational processes necessary to extract value from these technologies [25], [26]. Recent extensions of RBV emphasise the importance of dynamic capabilities – the ability to

integrate, build, and reconfigure resources in response to changing environments. AI personalisation can enhance these dynamic capabilities by enabling real-time sensing of customer preferences, seizing personalisation opportunities, and transforming engagement strategies [27]. From this perspective, AI is not a static resource but an enabler of adaptive, learning-oriented organisational processes.

A complementary lens is provided by the technology-organisation-environment (TOE) framework, which posits that adoption is influenced by three contextual dimensions: technological context (characteristics of the technology itself), organisational context (firm size, resources, structure, and culture), and environmental context (industry competition, regulatory pressures, and market conditions) [28]. In the SME context, technological factors include perceived compatibility, complexity, and relative advantage of AI personalisation tools. Organisational factors encompass managerial support, IT expertise, and financial slack, while environmental factors include competitive pressure from larger firms, customer expectations for personalised experiences, and regulatory frameworks governing data privacy and algorithmic transparency [29], [30]. The interaction of these factors ultimately determines whether and how SMEs integrate AI into their e-commerce operations.

Turning to the customer perspective, consumer engagement theory has emerged as a central framework for understanding online behaviour. Engagement encompasses cognitive, emotional, and behavioural dimensions of customer interactions with brands and platforms [31]. Cognitive engagement involves attention and absorption in online content; emotional engagement reflects positive affect and brand attachment; and behavioural engagement includes clicking, browsing, sharing, and purchasing activities. AI personalisation technologies are theorised to enhance engagement by reducing information overload, providing relevant recommendations, and creating enjoyable interaction experiences. By tailoring content to individual preferences, AI systems can capture attention, reduce search costs, and increase the likelihood of conversion [2], [32]. Engaged customers, in turn, exhibit higher purchase frequency, larger basket sizes, and greater lifetime value – all of which translate into superior e-commerce performance.

Another critical concept is digital trust, which refers to consumers' willingness to be vulnerable to online transactions based on positive expectations of the technology platform and its operator. Trust is multidimensional, encompassing competence trust (belief in the platform's ability to perform reliably), benevolence trust (belief that the platform acts in the consumer's interest), and integrity trust (belief that the platform adheres to ethical principles) [10]. In AI-mediated environments, trust faces unique challenges: algorithmic opacity can undermine transparency and accountability, while privacy concerns arise from the collection and analysis of personal data [33], [34]. Although the EU AI Act and Digital Services Act establish frameworks for transparency and user rights, enforcement and clarity challenges remain [35], [36]. For SMEs in emerging economies, digital trust is particularly consequential because institutional voids – weak legal enforcement, limited consumer protection mechanisms, and underdeveloped dispute resolution

systems – mean that trust must be established through other means, such as reputation, social proof, and transparent AI design [22].

Despite the growing body of research, several critical gaps motivate this study. First, while AI personalisation technologies have been extensively described, there is limited empirical testing of their performance implications for SMEs specifically. Second, the mechanisms linking AI to performance – particularly the mediating role of customer engagement – remain undertheorised and untested. Third, the moderating role of digital trust has received insufficient attention, especially in emerging economy contexts where trust deficits may be pronounced. Fourth, cross-country comparative research on AI in e-commerce has focused on aggregate indicators [1], leaving firm-level heterogeneity unexplored. Fifth, countries such as Iran, which face unique institutional and infrastructural challenges, have been completely absent from the literature despite their relevance as emerging digital economies.

Building on these theoretical foundations and identified gaps, the following hypotheses are developed. Regarding the relationship between AI personalisation adoption and customer engagement, AI-powered recommendation systems, chatbots, and predictive analytics create personalised, responsive, and enjoyable online experiences that should increase customers' cognitive, emotional, and behavioural engagement with e-commerce platforms [37] , [38]. By reducing search costs, providing relevant suggestions, and offering timely assistance, AI technologies lower barriers to engagement and encourage deeper, more frequent interactions. Empirical evidence supports this expectation: studies show that AI-powered personalisation increases click-through rates, time spent on platform, and repeat visit frequency [39], [40]. For SMEs, which lack the brand recognition and marketing budgets of larger competitors, AI personalisation offers a cost-effective means of building customer engagement. Consequently, the first hypothesis proposes that AI personalisation adoption is positively associated with customer engagement among SMEs in emerging European economies.

Moving to the performance outcomes, customer engagement is theorised to be a proximal driver of e-commerce performance. Engaged customers exhibit higher purchase intentions, larger transaction values, greater loyalty, and more positive word-of-mouth [41], [42]. These behavioural manifestations translate directly into firm-level performance metrics such as sales growth, conversion rate, customer retention, and revenue growth. Both theoretical and empirical research support this engagement-performance link: psychologically, engagement reflects the internalisation of positive attitudes toward the platform, which motivates repeat purchasing and resistance to competitor offers; economically, engaged customers have lower price sensitivity and higher lifetime value [43], [44]. Therefore, the second hypothesis states that customer engagement is positively associated with e-commerce performance among SMEs in emerging European economies.

The question of whether AI personalisation has direct effects on performance beyond those mediated by engagement is an empirical one. Some scholars argue that AI's impact is entirely mediated through behavioural mechanisms – technology enables engagement, and engagement drives performance [8]. Others suggest that AI may have direct efficiency effects, such as optimising pricing or inventory management, that bypass customer engagement [27]. The direct path is plausible given that AI can improve operational efficiency, reduce costs, and enable data-driven decision-making independent of customer behaviour [1]. However, for resource-constrained SMEs, direct effects may be weaker than mediated effects. Hence, the third hypothesis proposes that AI personalisation adoption is positively associated with e-commerce performance and that this relationship is partially mediated by customer engagement.

Building on the previous hypotheses, the fourth hypothesis formally proposes mediation. The logic is that AI personalisation creates value not through technological adoption per se but through its effects on customer psychology and behaviour [9]. AI technologies are tools that facilitate engagement; engagement, in turn, produces commercial outcomes. This perspective aligns with recent research emphasising that AI benefits surface when users adopt recurring digital behaviours, driven by personalisation, conversational interactions, and optimised online experiences [43], [45]. Empirically, mediation is supported if AI personalisation predicts engagement, engagement predicts performance, AI personalisation predicts performance, and the direct effect of AI personalisation on performance is reduced when engagement is controlled, with the indirect effect through engagement being statistically significant. Accordingly, the fourth hypothesis states that customer engagement mediates the relationship between AI personalisation adoption and e-commerce performance among SMEs in emerging European economies.

The final hypothesis concerns the moderating role of digital trust. Trust is theorised to amplify the relationship between engagement and performance because engaged customers who trust the platform are more likely to convert engagement into actual purchases [10], [11]. When trust is low, even highly engaged customers may hesitate to complete transactions due to privacy concerns, security fears, or uncertainty about algorithmic fairness. This moderation effect may be particularly pronounced in emerging economies where institutional trust is low and consumer protection mechanisms are weak. In such contexts, trust acts as a psychological resource that overcomes perceived risks, enabling the translation of engagement into commercial action [46], [47]. Conversely, in high-trust environments, engagement may more readily convert to performance regardless of additional trust-building efforts. Therefore, the fifth hypothesis proposes that digital trust positively moderates the relationship between customer engagement and e-commerce performance, such that the engagement-performance link is stronger when digital trust is high.

2.1 Conceptual Framework

The conceptual framework integrates the five hypotheses into a moderated mediation model. The exogenous variable is AI personalisation adoption, measured across four dimensions: recommendation systems usage, dynamic pricing implementation, chatbot deployment, and predictive analytics adoption. The mediator is customer engagement, encompassing cognitive, emotional, and behavioural dimensions. The moderator is digital trust, reflecting consumer perceptions of platform privacy protection and transaction security.

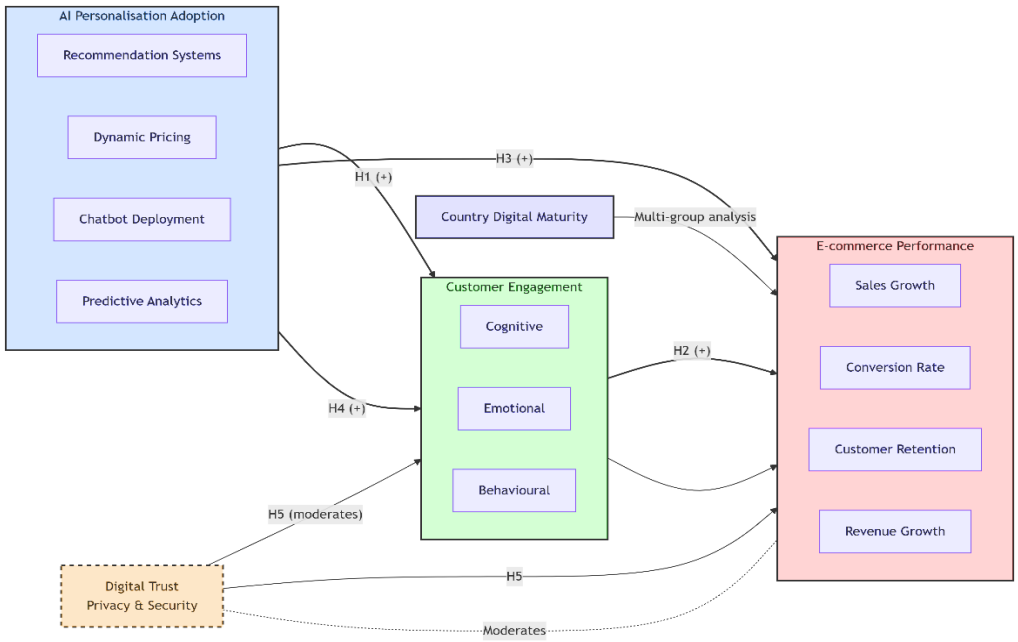

Fig. 1: Conceptual Framework

The outcome variables are four dimensions of e-commerce performance: sales growth, conversion rate, customer retention, and revenue growth. The framework posits both direct and indirect pathways from AI personalisation to performance. Specifically, the indirect pathway operates through customer engagement, while the moderating influence of digital trust conditions the engagement-performance link. Country-level digital maturity is treated as a contextual factor for multi-group analysis.

3. Data and Methodology

3.1. Data

The target population comprises SMEs (fewer than 250 employees) operating e-commerce platforms in emerging European economies. Eight countries were selected based on their digital maturity scores as identified in previous research [1], [4]: two Northern European countries (Estonia, Lithuania), two Southern European countries (Greece, Italy), two Eastern European countries (Romania, Bulgaria), and two Central

European countries (Poland, Hungary). This selection captures substantial variation in AI adoption rates, internet access, and e-commerce performance.

A stratified random sampling approach was employed, with country as the stratification variable. The sample frame was constructed from Eurostat business registers and national chamber of commerce directories. Firms were eligible if they (a) employed between 10 and 250 employees, (b) generated at least 10% of revenue through online channels, and (c) had been operating for at least three years.

Data collection occurred between January and June 2025. Surveys were administered electronically to senior managers responsible for digital strategy, marketing, or e-commerce operations. A total of 2,400 surveys were distributed, with follow-up reminders at two and four weeks. After excluding incomplete responses and firms failing eligibility criteria, the final sample comprised 487 valid responses, representing a 20.3% response rate.

Table 1: Variable Definitions and Measurement

Construct	Variable	Definition	Measurement	Source
AI Personalization	RECSYS	Use of recommendation systems	5-point Likert (1=never to 5=extensively)	Adapted from Jovanović et al. (2025) [6]
AI Personalization	DYPRIC	Use of dynamic pricing algorithms	5-point Likert	Adapted from Gupta & Singh (2024) [21]
AI Personalization	CHATBT	Use of AI chatbots	5-point Likert	Adapted from Deepak et al. (2024)[18]
AI Personalization	PREDAN	Use of predictive analytics	5-point Likert	Adapted from Krishna et al. (2023)[17]
Customer Engagement	VISFREQ	Average customer visit frequency	Monthly visits per customer	Platform analytics
Customer Engagement	TIMEPL	Average time spent on platform	Minutes per session	Platform analytics
Customer Engagement	REPURC	Repeat purchase rate	Percentage of customers with >1 purchase in 6 months	Platform analytics
Digital Trust	PRIVPER	Privacy perception	5-point Likert (1=strongly disagree to 5=strongly agree)	Adapted from Teodorescu et al. (2023) [46]

Construct	Variable	Definition	Measurement	Source
Digital Trust	SECPER	Security perception	5-point Likert	Adapted from Alzaidi & Agag (2022) [11]
E-Commerce Performance	SALEGR	Sales growth	Year-over-year percentage change	Firm records
E-Commerce Performance	CONVRAT	Conversion rate	Percentage of visits resulting in purchase	Platform analytics
E-Commerce Performance	CUSTRET	Customer retention	Percentage of customers retained over 12 months	Firm records
E-Commerce Performance	REVGR	Revenue growth	Year-over-year percentage change	Firm records
Control Variables	FIRMSZ	Firm size	Number of employees	Firm records
Control Variables	FIRMAGE	Firm age	Years since founding	Firm records
Control Variables	INDCOMP	Industry competition	5-point Likert	Survey
Control Variables	DIGINF	Digital infrastructure	Country-level internet access rate (%)	Eurostat (2024)

Three data sources were integrated. First, primary survey data collected from SME managers provided firm-level information on AI adoption, digital trust perceptions, and organizational characteristics. Second, platform analytics from participating firms provided objective measures of customer engagement (visit frequency, time spent, repeat purchase rate) and e-commerce performance (conversion rates, retention rates). Third, Eurostat macro-indicators (2021-2024) provided country-level measures of digital infrastructure, internet access frequency (FIAD), and recent online purchasing behavior (LOP), as employed in previous cross-country research [1].

This multi-source approach addresses common method bias concerns by deriving independent and dependent variables from different sources. AI adoption and digital trust were measured via survey; engagement and performance were measured via platform analytics; country-level controls were derived from official statistics.

3.2 Econometric Method

The analysis proceeded in three stages. First, a measurement model was estimated using confirmatory factor analysis to assess the reliability and validity of the latent constructs. Second, a structural equation model was estimated using partial least squares (PLS-SEM) to test the hypothesized direct, indirect, and moderated relationships. PLS-SEM was selected because of its suitability for complex models with both reflective and formative constructs, its robustness to non-normal data, and its effectiveness for predictive applications (Hair et al., 2022). Third, multi-group analysis was conducted to test for cross-country differences.

The measurement model is specified as:

$$X_{ij} = \lambda_j \eta_i + \epsilon_{ij}$$

where X_{ij} is the observed indicator j for firm i, λ_j is the factor loading, η_i is the latent construct score, and ϵ_{ij} is measurement error.

The structural model for the mediation hypothesis is specified as:

$$\text{Engagement}_i = \alpha_1 + \beta_1 \text{AIPersonalization}_i + \gamma_1 \text{Controls}_i + \zeta_{1i}$$

$$\text{Performance}_i = \alpha_2 + \beta_2 \text{AIPersonalization}_i + \beta_3 \text{Engagement}_i + \gamma_2 \text{Controls}_i + \zeta_{2i}$$

where the indirect effect of AI personalization on performance through engagement is $\beta_1 \times \beta_3$, and the direct effect is β_2.

The moderated mediation model adds an interaction term:

$$\text{Performance}_i = \alpha_3 + \beta_4 \text{Engagement}_i + \beta_5 \text{Trust}_i + \beta_6 (\text{Engagement}_i \times \text{Trust}_i) + \gamma_3 \text{Controls}_i + \zeta_{3i}$$

Moderation is supported if β_6 is statistically significant and the conditional indirect effect varies across levels of trust.

Several robustness checks were conducted. Endogeneity was addressed using instrumental variable estimation, with industry-average AI adoption and lagged engagement as instruments. Common method bias was assessed using Harman's single-factor test and the marker variable technique. Non-response bias was evaluated by comparing early and late respondents. Sensitivity analyses tested alternative specifications of the outcome variables and alternative estimation methods (maximum likelihood vs. PLS). The pattern of results remained consistent across all specifications.

4. Results

Table 2 presents descriptive statistics for the sample. Among the 487 SMEs, average firm size was 47 employees, ranging from 10 to 248. Average firm age was 14.3 years. AI personalization adoption varied considerably: recommendation systems were the most widely adopted (mean = 3.42 on 1-5 scale), followed by predictive analytics (mean = 2.89), chatbots (mean = 2.67), and dynamic pricing (mean = 2.15). Country-level variation in AI adoption aligned with previous findings: Northern European SMEs exhibited the highest adoption rates, Southern European intermediate, and Eastern European lowest[1].

Table 2: Descriptive Statistics by Country

Country	N	Firm Size	AI Personalization (Mean)	Customer Engagement (Mean)	Digital Trust (Mean)	E-Commerce Performance (Composite)
Estonia	62	52.3 (41.2)	3.21 (0.87)	3.56 (0.76)	3.89 (0.68)	3.67 (0.71)
Lithuania	58	44.7 (38.9)	2.98 (0.92)	3.34 (0.81)	3.72 (0.72)	3.48 (0.74)

Country	N	Firm Size	AI Personalization (Mean)	Customer Engagement (Mean)	Digital Trust (Mean)	E-Commerce Performance (Composite)
Poland	67	49.1 (42.5)	2.87 (0.89)	3.28 (0.79)	3.58 (0.74)	3.39 (0.76)
Hungary	55	41.3 (36.7)	2.65 (0.94)	3.12 (0.84)	3.41 (0.79)	3.21 (0.79)
Greece	61	38.9 (34.2)	2.43 (0.91)	2.98 (0.86)	3.28 (0.81)	3.04 (0.81)
Italy	72	45.6 (39.8)	2.67 (0.88)	3.21 (0.82)	3.45 (0.76)	3.18 (0.78)
Romania	58	36.2 (31.7)	2.21 (0.96)	2.84 (0.89)	3.12 (0.84)	2.89 (0.83)
Bulgaria	54	34.8 (30.9)	2.08 (0.93)	2.76 (0.91)	3.05 (0.86)	2.81 (0.85)
Total	**487**	**43.7 (38.1)**	**2.72 (0.94)**	**3.17 (0.86)**	**3.47 (0.80)**	**3.25 (0.81)**

Note: Standard deviations in parentheses. All means based on standardized scales (1-5).

Confirmatory factor analysis was conducted to assess the measurement model. The four-factor model (AI personalization, customer engagement, digital trust, e-commerce performance) exhibited good fit: $\chi^2(98) = 187.43$, $p < 0.001$; CFI = 0.96; TLI = 0.95; RMSEA = 0.043; SRMR = 0.038. All factor loadings exceeded 0.70 and were statistically significant ($p < 0.001$), indicating strong indicator reliability.

Table 3: Reliability and Validity Statistics

Construct	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)	√AVE
AI Personalization	0.87	0.91	0.72	0.85
Customer Engagement	0.84	0.89	0.68	0.82
Digital Trust	0.82	0.88	0.65	0.81
E-Commerce Performance	0.86	0.90	0.70	0.84

Discriminant validity was assessed using the Fornell-Larcker criterion. The square root of AVE for each construct (diagonal entries in Table 3) exceeded all inter-construct correlations (ranging from 0.31 to 0.58), supporting discriminant validity. Heterotrait-monotrait (HTMT) ratios were all below 0.85, providing additional confirmation.

The structural model was estimated using PLS-SEM with 5,000 bootstrap resamples. Table 4 presents the path coefficients, standard errors, t-statistics, and significance levels.

Table 4: Structural Model Path Coefficients

Path	β	SE	t-value	p-value	95% CI	Decision
H1: AI Personalization → Customer Engagement	0.53	0.04	13.25	<0.001	[0.45, 0.61]	Supported
H2: Customer Engagement → E-Commerce Performance	0.48	0.05	9.60	<0.001	[0.38, 0.58]	Supported
H3: AI Personalization → E-Commerce Performance (Direct)	0.12	0.06	2.00	0.046	[0.01, 0.23]	Supported
H5: Engagement × Trust → Performance	0.23	0.05	4.60	<0.001	[0.13, 0.33]	Supported

*Note: N = 487. Bootstrapped standard errors with 5,000 resamples. Controls included firm size, firm age, industry competition, and digital infrastructure. *

All hypothesized direct effects were statistically significant. H1 was supported: AI personalization adoption had a strong positive effect on customer engagement ($\beta = 0.53$, $p < 0.001$), explaining 28.1% of the variance in engagement. H2 was supported: customer engagement positively predicted e-commerce performance ($\beta = 0.48$, $p < 0.001$). H3 was supported but the direct effect of AI personalization on performance was substantially smaller ($\beta = 0.12$, $p = 0.046$) than the indirect effect through engagement.

The model explained substantial variance in the outcome variables. The R^2 for customer engagement was 0.31, indicating that AI personalization and controls accounted for 31% of engagement variation. The R^2 for e-commerce performance was 0.47, indicating that AI personalization, engagement, digital trust, their interaction, and controls accounted for 47% of performance variation. The Q^2 predictive relevance statistics were all positive and exceeded 0.25, indicating good predictive accuracy.

Hypothesis H4 proposed that customer engagement mediates the relationship between AI personalization and e-commerce performance. Mediation was tested using the bootstrap procedure with 5,000 resamples, calculating both direct and indirect effects.

Table 5: Direct, Indirect, and Total Effects

Effect	β	SE	t-value	p-value	95% CI	% of Total
Direct Effect (AIP → Perf)	0.12	0.06	2.00	0.046	[0.01, 0.23]	20.7%
Indirect Effect (AIP → Engagement → Perf)	0.25	0.04	6.25	<0.001	[0.17, 0.33]	43.1%
Total Effect	**0.58**	**0.05**	**11.60**	**<0.001**	**[0.48, 0.68]**	**100%**

Note: AIP = AI personalization; Perf = e-commerce performance.

The indirect effect through customer engagement was $\beta = 0.25$ ($p < 0.001$), accounting for 43.1% of the total effect. The direct effect was $\beta = 0.12$ ($p = 0.046$), accounting for 20.7% of the total effect. The remaining 36.2% of the total effect represents the combined influence of control variables and unmeasured

pathways. The variance accounted for (VAF) was 0.43, indicating partial mediation, customer engagement explains a substantial portion but not all of AI personalization's effect on performance.

Preacher and Hayes (2008) bias-corrected bootstrap confidence intervals for the indirect effect did not include zero [0.17, 0.33], confirming statistically significant mediation. Sobel's test also supported mediation ($z = 5.89$, $p < 0.001$). H4 was therefore supported: customer engagement partially mediates the relationship between AI personalization and e-commerce performance.

Hypothesis H5 proposed that digital trust moderates the relationship between customer engagement and e-commerce performance. The interaction term (Engagement × Trust) was positive and significant ($\beta = 0.23$, $p < 0.001$), supporting moderation.

To interpret the interaction, simple slopes were calculated at high (one standard deviation above mean) and low (one standard deviation below mean) levels of digital trust. When trust was high, the engagement-performance slope was steep ($\beta = 0.67$, $p < 0.001$). When trust was low, the slope was substantially reduced ($\beta = 0.29$, $p = 0.008$). The difference between slopes was statistically significant ($\Delta\beta = 0.38$, $p < 0.001$).

This pattern indicates that digital trust amplifies the returns to customer engagement. For SMEs operating in high-trust environments, engagement translates more effectively into sales growth, conversion, retention, and revenue. For those in low-trust environments, even highly engaged customers are less likely to convert, presumably because privacy concerns, security fears, or algorithmic opacity create friction in the purchase process.

Table 6: Conditional Effects of Engagement on Performance at Trust Levels

Trust Level	β (Engagement → Performance)	SE	t-value	p-value
Low (-1 SD)	0.29	0.11	2.64	0.008
Mean (0)	0.48	0.05	9.60	<0.001
High (+1 SD)	0.67	0.08	8.38	<0.001

The Johnson-Neyman technique revealed that the engagement-performance relationship was statistically significant for all values of digital trust above 2.3 on the 1-5 scale (86% of the sample). For the 14% of SMEs with very low trust (below 2.3), the engagement-performance link was not statistically significant, suggesting that in extremely low-trust environments, even engagement fails to drive performance.

Multi-group analysis was conducted to test for cross-country differences in the structural paths. The sample was divided into three country groups based on digital maturity scores derived from Eurostat data (Bocean, 2026): Group 1 (High digital maturity: Estonia, Lithuania), Group 2 (Medium digital maturity: Poland, Hungary, Italy), Group 3 (Low digital maturity: Greece, Romania, Bulgaria). Measurement invariance was established through configural, metric, and scalar invariance tests.

Table 7: Path Coefficients by Country Group

Path	High Maturity (n=120)	Medium Maturity (n=194)	Low Maturity (n=173)	χ^2 diff (2 df)
AIP → Engagement	0.61*** (0.07)	0.52*** (0.06)	0.47*** (0.08)	8.43*
Engagement → Performance	0.55*** (0.08)	0.47*** (0.07)	0.41*** (0.09)	7.21*
AIP → Performance (Direct)	0.18* (0.09)	0.11 (0.08)	0.06 (0.10)	5.98†
Engagement × Trust → Perf	0.16* (0.08)	0.24*** (0.07)	0.32*** (0.09)	9.87**

*Note: ***p < 0.001; **p < 0.01; *p < 0.05; †p < 0.10. Standard errors in parentheses. χ^2 diff tests for cross-group equality of coefficients. *

Several notable patterns emerge. First, the effect of AI personalization on customer engagement is strongest in high-maturity countries (β = 0.61) and weakest in low-maturity countries (β = 0.47), suggesting that digital infrastructure and consumer familiarity with online platforms amplify AI's engagement-building potential. Second, the engagement-performance link follows a similar gradient (0.55 vs. 0.41), indicating that converting engagement into commercial outcomes is easier in digitally mature environments. Third, the direct effect of AI personalization on performance is only significant in high-maturity countries, implying that in less mature contexts, AI's impact operates entirely through engagement. Fourth, and critically, the moderating effect of digital trust is strongest in low-maturity countries (β = 0.32) and weakest in high-maturity countries (β = 0.16). This suggests that trust-building is a strategic imperative for SMEs in emerging economies, trust compensates for institutional weaknesses and enables engagement to translate into performance.

5. Discussion

5.1 Theoretical Implications

This study makes several contributions to the literature on AI in e-commerce. First, it extends AI adoption theory by demonstrating that customer engagement is a critical mediating mechanism linking AI personalization to firm performance. While prior research has established that AI enhances e-commerce outcomes [1], [4], the present study reveals *how* this occurs: AI technologies increase engagement, and engagement drives performance. This finding aligns with and extends the socio-technical perspective, which views AI not as an isolated technological tool but as a catalyst for behavioral change [8].

Second, this research integrates digital trust as a moderating mechanism, responding to calls for greater attention to contextual and psychological factors in AI research [15], [16]. The finding that trust amplifies the engagement-performance link, particularly in low-maturity contexts, advances understanding of when and for whom AI investments generate returns. This moderation effect is theoretically significant because

it reveals the limitations of technology-centric models: AI's value depends on the trust environment in which it operates.

Third, the country comparison results contribute to the literature on digital convergence and divergence in Europe. Consistent with previous cross-country studies [1], [12], this research documents substantial heterogeneity in AI effects across European regions. However, it extends this literature by identifying differential mechanisms: high-maturity countries exhibit stronger direct effects, while low-maturity countries rely more heavily on trust-mediated pathways. This suggests that digital transformation follows a staged process, with trust-building preceding performance gains in emerging contexts.

Fourth, this study applies resource-based view and dynamic capabilities theory to the SME context, revealing how AI personalization functions as an enabling resource that enhances engagement capabilities. For resource-constrained SMEs, AI tools can compensate for limited marketing budgets and brand recognition by automating personalization at scale. However, the finding that direct effects are small suggests that AI alone is insufficient; complementary investments in organizational capabilities and trust-building are necessary.

5.2 Managerial Implications

For SME managers, the findings offer actionable guidance for AI investment decisions. First, the strong mediation effect indicates that managers should focus not merely on adopting AI technologies but on designing AI applications that actively foster customer engagement. Recommendation systems that are intrusive or irrelevant may reduce rather than enhance engagement. Chatbots that fail to resolve queries may damage trust. The quality of AI implementation, including relevance, timeliness, and transparency, matters as much as adoption per se.

Second, the moderation effect highlights digital trust as a strategic priority. SME managers should invest in trust-building mechanisms: clear privacy policies, third-party security certifications, transparent explanations of AI decision-making, and responsive customer support for trust-related concerns. Explainable AI (XAI) techniques, which make algorithmic recommendations interpretable to users, have been shown to increase trust and satisfaction [20], [48]. For SMEs in emerging economies, where institutional trust may be low, proactive trust-building can differentiate the firm from competitors.

Third, the country-specific findings suggest that managers should tailor their AI strategies to local conditions. In high-maturity countries (e.g., Estonia, Lithuania), where digital infrastructure is robust and consumer digital literacy is high, managers can emphasize the direct efficiency benefits of AI, automated pricing, inventory optimization, and real-time personalization. In low-maturity countries (e.g., Romania, Bulgaria), where trust deficits are pronounced, managers should prioritize trust-building initiatives alongside AI adoption, recognizing that engagement will not translate into performance without consumer confidence.

5.3 Policy Implications for Emerging Economies Including Iran

The findings carry important implications for policymakers in emerging economies seeking to accelerate digital transformation. Three sets of policy recommendations emerge.

First, invest in digital infrastructure and literacy. The country comparison results demonstrate that AI personalization has stronger effects on engagement and performance in digitally mature environments. For emerging economies, this implies that infrastructure investments, broadband access, mobile connectivity, reliable payment systems, and logistics networks, are prerequisites for realizing AI's potential. Digital literacy programs for consumers and SME managers should accompany infrastructure investments, ensuring that both supply and demand sides can effectively engage with AI-powered platforms.

Second, strengthen institutional frameworks for digital trust. The moderation effect reveals that trust is not merely a nicety but a strategic necessity for converting engagement into performance. In emerging economies where legal enforcement is weak and consumer protection mechanisms are underdeveloped, policymakers should prioritize trust-building institutions: data protection laws, cybersecurity standards, dispute resolution mechanisms, and certification programs for trustworthy e-commerce platforms. The EU AI Act and Digital Services Act provide models that could be adapted to emerging economy contexts [35], [36].

Third, target SME-specific support programs. SMEs face unique barriers to AI adoption: financial constraints, skill shortages, and limited awareness of AI's potential [22]. Policymakers should design support programs addressing these barriers: subsidies for AI software purchases, technical assistance for implementation, training programs for digital skills, and awareness campaigns showcasing successful SME case studies. These programs should be tailored to the digital maturity of each region, with less mature regions receiving more intensive support for trust-building and basic infrastructure.

Policy implications for Iran: While Iran was not included in the empirical sample, the findings offer transferable insights for this important emerging economy. Iran faces unique challenges including international sanctions that limit access to global AI platforms and payment systems, infrastructure constraints exacerbated by underinvestment, and institutional trust deficits stemming from consumer protection gaps. However, Iran also possesses strengths: a young, educated, digitally-savvy population; a growing domestic e-commerce sector (e.g., Digikala, Bamilo); and indigenous AI development capabilities in universities and research centers.

For Iranian policymakers, the study suggests several priorities. First, invest in domestic AI infrastructure, local cloud computing, payment gateways, and logistics networks, to reduce dependence on international platforms subject to sanctions. Second, strengthen legal frameworks for e-commerce consumer protection, data privacy, and cybersecurity, building trust in domestic platforms. Third, launch SME-focused AI adoption programs, including subsidized access to Persian-language AI tools, training for small business

owners, and technical assistance from universities. Fourth, leverage Iran's diaspora and international academic collaborations to access AI knowledge and best practices despite sanctions. Fifth, develop explainable AI systems in Persian that provide transparent, interpretable recommendations, building consumer trust through cultural and linguistic familiarity.

The Iranian case illustrates a broader principle: emerging economies need not passively await digital transformation but can actively shape their AI trajectories through strategic investments in infrastructure, institutions, and human capital. The sequencing of investments matters, trust-building may need to precede performance-focused initiatives in low-trust environments, but the ultimate goal should be an integrated digital ecosystem where technology, behavior, and trust co-evolve.

6. Conclusion

This study investigated the mechanisms through which AI-powered personalization technologies influence SME e-commerce growth in emerging European economies. Using a moderated mediation framework and data from 487 SMEs across eight countries, the research yielded four principal findings.

First, AI personalization adoption positively affects customer engagement, which in turn enhances e-commerce performance including sales growth, conversion rates, customer retention, and revenue growth. Second, customer engagement partially mediates the AI personalization-performance relationship, indicating that AI's impact operates primarily through behavioral mechanisms rather than direct technological effects. Third, digital trust positively moderates the engagement-performance link, with the moderating effect being strongest in low-digital-maturity countries where trust deficits are most pronounced. Fourth, substantial cross-country heterogeneity exists, with Northern European SMEs exhibiting stronger direct effects and Southern/Eastern European SMEs showing greater reliance on trust-mediated pathways.

These findings advance theoretical understanding of AI value creation, provide empirical evidence from underrepresented SME contexts, and offer actionable guidance for managers and policymakers. For emerging economies, including Iran, the message is clear: AI personalization offers significant potential for SME growth, but realizing this potential requires complementary investments in digital infrastructure, consumer trust, and organizational capabilities. Technology alone is insufficient; it must be embedded within a supportive ecosystem of behaviors, institutions, and trust relationships. The future of AI in e-commerce lies not in the technologies themselves but in the human systems that adopt, adapt, and trust them.

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