From Infrastructure to Impact: Modeling the Path from AI-Enabled CRM to Customer Loyalty in B2B Firms

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Abstract: - This study aimed to investigate the impact of AI-enabled customer relationship management systems on customer experience, customer satisfaction, and customer loyalty in Turkish B2B companies. While previous literature has focused largely on developed markets and the B2C level, this study examines the Turkish B2B sector, providing both a B2B assessment and an example of an emerging market experience. A conceptual model linking digital infrastructure, the integration of AI and customer relationship management systems, and customer experience, satisfaction, and loyalty was tested using data collected through a survey from 200 CRM professionals. SEM analysis results showed that a strong digital infrastructure supports the adoption of AI-enabled CRM, significantly improving customer experience and satisfaction. Furthermore, customer satisfaction is the most important determinant of customer loyalty and mediates the link between experience and loyalty. The measured effects were found to be consistent when compared across sectors and company sizes. The study provides applicable feedback for companies in similar markets and highlights the need for aligned investments in AI-enabled CRM strategies.

Key-Words: AI-CRM, B2B, customer satisfaction, customer loyalty, SEM.

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1 Introduction

Technological and digital solutions utilized in customer relationship management (CRM) are at the forefront of businesses' digital transformation efforts in pursuit of competitive advantage. The core activities of conventional CRM systems are to accumulate and process customer data in order to deliver customer satisfaction and loyalty, track interactions, and improve after-sales processes. However, CRM solutions today, which are driven by Artificial Intelligence (AI), include machine learning (ML), natural language processing (NLP), and predictive analytics in their solutions, enabling data-driven decision-making and facilitating personalized customer experience solutions, [1], [2], [3], [4], [5], [6], [7]. Companies utilizing these AI-powered solutions can monitor customer trends in real-time, predict sales opportunities, and automate decision-support processes. Finally, they are able to provide consistent experiences across various touchpoints (e.g., websites, social media, call centers) with CRM infrastructures that can predict customer behavior, [8], [9], [10].

Empirical research conducted over the last five years shows that AI-enabled CRM use has achieved ubiquitous popularity with widespread expansion across technology-leading industries such as retail, banking, and telecommunications, [11]. Several studies reported an increase in the level of customer loyalty and ensuing buying behavior after the introduction of AI in CRM functions, [12]. Besides, [13], ascertained that the estimation of customer lifetime value through AI-powered predictive models in Business-to-Business (B2B) companies was much more accurate than with manual methods. Irrespective of the current level of technology and its pervasiveness, literature focuses predominantly on Europe and North America. Empirical studies on the implementation of AI in companies that function

in emerging economies like Turkey are limited [14], [15]. However, advanced CRM solutions, particularly cloud-based and AI-driven platforms, have seen strong demand in Türkiye since 2020.

According to statistics cited in [16], as of 2023, 5.5% of businesses in Türkiye are estimated to have used AI technologies, and 4.4% as of 2024. The result suggests that, although there has been increasing interest, the uptake is low. Further, usage is concentrated mainly in large businesses. Yet, there are extremely limited academic research studies examining the overall application of AI-enabled CRM systems in Turkish B2B companies from both the technological infrastructure and human resource capacity perspectives. [14] also demonstrated the application of AI technologies in certain areas of operations in the Turkish banking sector. However, it is stated that research studies with a focus like this in the B2B context are nonexistent. Thus, there is a need to identify the determinants of the adoption of AI-based CRM applications in this context and investigate their impact on customer loyalty and satisfaction.

This study aims to fill a literature gap by presenting one of the first empirical research studies investigating the use of AI-enabled CRM software in B2B firms in Türkiye with a particular reference to the level of customer satisfaction and loyalty. The study proposes a conceptual model that connects digital infrastructure, AI-enabled CRM applications, and customer experience and investigates their impact on customer loyalty. Here, the data from a sample of 200 people are analyzed with the assistance of Structural Equation Modeling (SEM) to see how the integration of AI-enabled CRM functionalities in existing digital infrastructure(s) affects customer experience and satisfaction, and ultimately how they culminate in customer loyalty. The study attempts to validate the theoretically derived research model using data-driven approaches. The research provides novel insights into the mechanisms through which the utilization of AI-enabled CRM applications creates value in B2B contexts in Türkiye, an emerging economy, both a strategic and practical roadmap for digital transformation leaders and a foundation for additional research in this understudied domain as well. The remainder of the article is organized as follows: The following section provides a theoretical review of CRM evolution and CRM integration with AI.

Section 3 summarizes the methodology, including an introduction to the sample and explanations of the measurement scales. Section 4 gives the complete report and interpretation of the SEM analysis results. The final section discusses the implications of the findings to the extant literature and provides theoretical and practical recommendations for researchers and practitioners.

2 Theoretical Background

2.1 Evolution of CRM

CRM software has also evolved and developed significantly since it began in the 1990s. The software was initially conceived to be a computer program applied in the automation of sales processes. Its definition later progressed to encompass sales and marketing procedures as well as post-sales service operations by the beginning of the 2000s. As illustrated in [17], focusing on current applications, two significant outcomes are proposed to result from the integration of AI into CRM. The first is the ability of CRM managers to offer advanced personalization solutions in real-time segmentation; the second is predictive support for decisions based on trend modeling and lead scoring. Empirical evidence from literature also supports this theoretical model. For example, [18] investigated how the deployment of AI CRM integration and big data analysis capabilities affected firm performance in Thai large firms. A study based on data collected from 450 managers across 10 companies shows that a company's integration of AI-CRM has a highly effective capability to enhance team collaboration and company performance. Competitive advantages of a company are positively influenced by big data analytics expertise as well as the degree of teamwork in a team but do not impact integration capabilities. These results suggest that sophisticated technologies support internal ability and competitiveness, but to obtain quantifiable performance gains from them requires a higher level of strategic association and execution. The work [19], based on a similar design set out above, validates data obtained from 308 employees of large multinational companies and SMEs in India to investigate behavioral intentions to adopt system solutions infused with CRM and AI. The study, grounded in the Technology Acceptance Model (TAM), concluded that employee attitudes regarding the system's usefulness and ease of use have direct and important influences on employee behavioral intentions. It is also emphasized that companies should make it a point to stimulate positive attitudes among employees so that systems they employ turn out to be useful, helpful, and easy to use to employees, and adoption is increased. Internal leadership support and compliance have proved to

be significant enablers in this regard. The study, [20], carry out a systematic review of 72 empirical studies between 2013 and 2023 to identify five key mechanisms through which AI-based CRM systems drive customer retention and business performance: (i) delivering personalized experiences based on behavioral analysis to personalize interaction, (ii) enabling real-time decision-making based on predictive modeling to forecast customer demand, (iii) optimizing the productivity of services based on automated processes and AI-based chatbots, (iv) optimizing customer segmentation and targeting strategies, and (v) utilizing proactive churn management strategies to prevent customer loss.

Drawing on the Resource-Based View, the review finds firm-level empirical evidence that is consistent in the sense that these mechanisms are positively related to customer satisfaction, lifetime value, retention, and profitability for the firm. Overall, these studies reveal the importance of sequentially testing digital infrastructure, AI-enabling functionality, and resultant customer outcomes.

2.2 B2B CRM and AI Adoption in Emerging Markets

Most existing AI-CRM studies are focused on B2C environments of developed economies. In developing economies, certain institutional, infrastructural, and cultural conditions moderate the adoption of AI-CRM and the effectiveness of AI-CRM. Infrastructural challenges of undependable internet connectivity and short skillsets in AI, revealed by the study, [21], to result in low AI-CRM penetration in developing economies. The study, [22], examines firms in Türkiye's Technology Development Zones (TDZs) and empirically examines whether the adoption of AI has an impact on perceived business performance. Survey data indicate a statistically significant but weak positive correlation between AI adoption and perceived performance. The study also investigates AI strategy variations among AI adopter and non-adopter firms using existing AI business strategy perspectives—finding that adopters embrace more strategic, forward-looking AI strategies than non-adopters. The study, [23], employ service-dominant logic to empirically test the impact of salesperson's personal characteristics—expertise, ethicality, service quality, and value co-creation shared—on relationship quality (satisfaction and trust) that in turn shapes customer loyalty in Asian B2B contexts. Questioning 266 B2B account managers across numerous industries, their structural equation modeling results reveal that expertise is most influential on trust and satisfaction, followed closely by ethics, service quality, and shared value. Greater trust and satisfaction ultimately strongly predict greater customer loyalty.

In Within Türkiye, there exists a limited but growing corpus of research that has started to explore ICT adoption within B2B contexts. For instance, [24], explores the influence of CRM adoption on customer satisfaction and organizational performance in Turkish B2B markets based on a sample of 113 organizations. They find that CRM adoption has a very positive effect on customer satisfaction and organizational marketing performance but does not lead to substantial improvement in financial performance. Second, higher customer satisfaction is an excellent performance driver of organizational performance. Importantly, environmental dynamism and competition are opposite moderators that weaken the satisfaction–performance relationship. Overall, the study revolves around the premise that while CRM can enhance marketing achievement and satisfaction within B2B relationships, these may or may not be brought about by financial performance in turbulent market conditions. The findings of [25], indicate that although there has been a significant growth in the application of ICT among Turkish firms, there remain significant gaps to be addressed relative to their counterparts in member countries of the European Union. Larger firms, particularly firms operating in sectors like manufacturing and information and communication technology (ICT) industries, are more digitally advanced because they are exposed more to resources, infrastructure, and human resources. On the other hand, small and medium-sized enterprises (SMEs), particularly the legacy industries, are faced with limited capital, low digital competency, and substandard technology infrastructure, which make them unable to take advantage and adopt digital technology to its maximum.

2.3 B2B Research Gaps and Contributions

Summing up the above, three primary gaps emerge:

1. Sectoral and Geographic Coverage: North American and Western European B2C settings are the subject of most AI-CRM studies, whereas B2B studies—particularly in emerging economies such as Türkiye—are few.

2. Chronological Processes: Although digitalization → AI implementation → customer consequence has been empirically established for established markets, how accurately it holds in Turkish B2B settings has yet to be tested empirically.

3. Customer Outcomes: Existing Turkish work predominantly places emphasis on operational or monetary metrics (e.g., revenue from cross-sell, cost reduction) but does not incorporate customer satisfaction and loyalty as mediating or dependent variables.

Accordingly, this research tries to fill such gaps in the literature by (a) examining explicitly AI-enabled CRM implementation in Turkish B2B firms; (b) probing a sequential digitalization, AI integration, customer experience, and customer loyalty model; and (c) employing SEM to examine these relationships based on a trustworthy sample of Turkish B2B practitioners. In so doing, the study both theoretically—by validating or expanding extant models within an emerging market context—and practically—by providing evidence-based recommendations to Turkish B2B managers regarding how to use AI-CRM for better customer results.

3 Methodology

This section details the research design, sampling procedure, measurement instruments, and data analysis techniques employed to examine AI-enabled CRM adoption and its effects on customer satisfaction and loyalty within Turkish B2B firms.

3.1 Research Design

A quantitative, cross-sectional survey design was employed to test the conceptual model linking digital infrastructure, AI-CRM integration, customer experience, customer satisfaction, and customer loyalty. Such a design is appropriate for assessing relationships among latent constructs and testing hypotheses with SEM, [26], [27]. Data were gathered at a single point in time to facilitate analysis of both measurement validity and structural paths.

3.2 Sample and Data Collection

The target population comprised managers and senior employees responsible for CRM functions (e.g., CRM managers, marketing directors, IT managers) in Turkish B2B firms. A purposive, non-probability sampling technique was used to ensure that respondents had direct experience with AI-enabled CRM, [28]. Between March and May 2025, an online survey was distributed. A preliminary contact list of 450 B2B firms was obtained from the Turkish Exporters Assembly and industry associations. Invitations containing a secure survey link were emailed to CRM contacts identified via official company sites and LinkedIn. Out of 450 invitations, 215 completed responses were received (response rate = 47.8%). After removing cases with more than 20 % missing data or inconsistent response patterns, 200 valid questionnaires remained. This sample size satisfies the 10:1 respondent-to-parameter ratio recommended for [26]. Table 1 summarizes the demographic characteristics of the final sample.

3.3 Measurement Instruments

All constructs were measured via multi-item scales adapted from well-established academic sources. A forward-backward translation procedure ensured linguistic and contextual equivalence for Turkish respondents, [28]. A pilot test (n = 30 CRM professionals) confirmed item clarity and internal consistency (Cronbach's $\alpha \geq 0.80$ for all scales).

Digital Infrastructure is measured using the "Information Technology Infrastructure" scale adapted from [29]. AI-CRM Integration is assessed with the "AI Capability in CRM" scale developed in [30]. Customer Experience: Captured using "Customer Experience" scale from [31]. Customer Satisfaction is measured via the "Customer Satisfaction" scale from [32]. Customer Loyalty is assessed with the "Customer Loyalty" scale adapted from [33]. Control variables are (1) Firm Size: Measured as the number of employees (categorical: 50–249; 250–499; 500+). (2) Industry / Sector: Coded as Manufacturing, Wholesale/Distribution, Information Technology, or Other.

Table 1. Sample Demographics

Specs	Demographics		
	Category	*Frequency*	*%*
Gender	Male	128	64.0
	Female	72	36.0
Age	25–34	46	23.0
	35–44	98	49.0
	45–54	40	20.0
	55+	16	8.0
Industry / Sector	Manufacturing	86	43.0
	Wholesale/ Distribution	54	27.0
	Information Technology	32	16.0
	Other	28	14.0
Firm Size-Employees	50–249	64	32.0
	250–499	74	37.0
	500+	62	31.0

Source: created by the authors

3.4 Data Analysis

Data analysis followed a four-stage approach using AMOS 24.0, [34], and SPSS 27.0, [35]:

Preliminary Analysis: Missing data were evaluated via Little's MCAR test; data were MCAR ($p > .05$) and imputed using Expectation–Maximization, [36]. Univariate skewness and kurtosis fell within ±1; Mardia's coefficient (1.83, $p > .05$) indicated multivariate normality, [37]. Variance Inflation Factors (VIFs) were below 3, confirming no multicollinearity, [38].

Measurement Model (Confirmatory Factor Analysis-CFA): A CFA assessed construct validity. Standardized factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR) were examined. Fit indices (CFI, TLI, RMSEA, SRMR) were evaluated against Chen's cutoffs, [39]: CFI/TLI ≥ 0.90; RMSEA ≤ 0.08; SRMR ≤ 0.08. Convergent validity was confirmed by standardized loadings ≥ 0.70 and AVE ≥ 0.50. Discriminant validity was verified using the Fornell–Larcker criterion, [40].

Structural Model (Hypothesis Testing): SEM tested hypothesized paths among latent constructs. Path coefficients (β), significance levels (p), and R^2values were reported. Indirect effects (e.g., customer satisfaction mediating between customer experience and loyalty) were examined via bias-corrected bootstrapping (5,000 resamples) to generate 95% confidence intervals, [41]. Control variables were incorporated to account for potential confounds.

Additional Analyses: Multiple-group SEM examined the moderating effects of firm size and industry sector. Measurement invariance across groups was evaluated by comparing constrained versus unconstrained models with $\Delta\chi^2$ tests, [42]. All tests were two-tailed with $\alpha = 0.05$.

4 Results

This section presents the findings from the CFA, SEM tests of hypothesized relationships, and additional analyses.

4.1 Research Design

Descriptive statistics and internal consistency estimate for all constructs are summarized in Table 2.

All constructs demonstrated Cronbach's α values above the commonly accepted threshold of .70, [43]. Composite reliabilities exceeded .80, confirming satisfactory internal consistency. AVE values for all constructs exceeded .50, indicating adequate convergent validity, [40]. A five-factor measurement model (DI, AI-CRM, CE, CSat, CLoy) was tested via CFA to assess construct validity. The initial model exhibited acceptable fit indices: $\chi^2 = 921.74$, $p < .001$, $\chi^2/df = 4.63$, CFI = .946, TLI = .940, RMSEA = .057 (90% CI = .053–.061), SRMR = .042.

All standardized factor loadings were significant ($p < .001$) and exceeded .70, ranging from .72 to .89. Convergent validity was supported by AVE values above .50 (Table 2).

Discriminant validity was examined by comparing the square root of each construct's AVE with its correlations with other constructs, [40]. As shown in Table 3, the square root of AVE for each construct exceeded its correlations with all other constructs, confirming discriminant validity.

Table 2. Descriptives, Reliability, and Convergent Validity

Construct	Statistics				
	Mean	SD	α	CR	AVE
DI: Digital Infrastructure	3.78	0.64	0.88	0.89	0.56
AI-CRM: AI-CRM Integration	3.52	0.71	0.90	0.91	0.60
CE: Customer Experience	3.61	0.68	0.92	0.93	0.58
CSat: Customer Satisfaction	3.49	0.74	0.85	0.86	0.57
CLoy: Customer Loyalty	3.45	0.77	0.87	0.88	0.59

Source: created by the authors

Table 3. Interconstruct Correlations and Discriminant Validity

Construct	Correlations[a]				
	DI	*AI-CRM*	*CE*	*CSat*	*CLoy*
DI	0.75				
AI-CRM	0.52*	0.77			
CE	0.48*	0.61*	0.76		
CSat	0.35*	0.54*	0.68*	0.75	
CLoy	0.29*	0.47*	0.63*	0.72*	0.77

[a]*Diagonal elements represent the square root of AVE; off-diagonal elements are inter-construct correlations.*
**p < 0.01.*
Source: created by the authors

4.2 Structural Model and Hypothesis Testing

Model evaluation employed multiple fit indices and nested model comparisons. Fit indices reported include χ^2, χ^2/df, CFI, TLI, RMSEA (with 90% CI), and SRMR. Cutoff criteria followed, [37], [39], recommendations (CFI/TLI ≥ .90 acceptable, RMSEA ≤ .08 acceptable, SRMR ≤ .08 acceptable).

Nested model testing included: (a) a model with direct AI-CRM → CLoy path constrained to zero vs. unconstrained, (b) an alternative ordering model with CSat preceding CE, and (c) reduced models omitting the DI → CE direct path. For each nested comparison, we report $\Delta\chi^2$ and corresponding p-values; preferred models were those with lower AIC/BIC and non-significant χ^2 increases when imposing theoretically justified constraints.

Structural Model Fit: Place The hypothesized structural model—linking DI → AI-CRM → CE → CSat → CLoy, with direct paths from DI to CE and AI-CRM to CSat—was evaluated. Fit indices indicated good model fit: χ^2= 935.63, p < .001; CFI = .943; TLI = .937; RMSEA = .059 (90% CI = .055–.063); SRMR = .045.

Table 4. Standardized Path Coefficients and Significance

Hypothesized Path	Coefficients			
	β	***SE***	***p***	***Supported?***
H1: DI → AI-CRM	.54	.06	<.001	Yes
H2: DI → CE	.28	.05	<.001	Yes
H3: AI-CRM → CE	.48	.05	<.001	Yes
H4: AI-CRM → CSat	.22	.07	<.01	Yes
H5: CE → CSat	.62	.04	<.001	Yes
H6: CSat → CLoy	.71	.03	<.001	Yes

Source: created by the authors

Direct Effects: Standardized path coefficients and significance levels are displayed in Table 4 and Figure 1.

DI → AI-CRM Integration: β = .54, p < .001. Firms with more advanced digital infrastructure reported greater AI-CRM integration.

DI → CE: β = .28, p < .001. Direct digital capabilities also positively influenced overall customer experience.

AI-CRM Integration → CE: β = .48, p < .001. Higher levels of AI-CRM integration were associated with enhanced customer experience.

AI-CRM Integration → CSat: β = .22, p < .01. AI-driven CRM functionalities had a direct, positive effect on customer satisfaction.

CE → CSat: β = .62, p < .001. Customer experience exerted a strong positive influence on satisfaction.

CSat → CLoy: β = .71, p < .001. Higher customer satisfaction reliably predicted greater customer loyalty.

The model explained substantial variance in endogenous constructs: AI-CRM Integration (R^2 = .29), Customer Experience (R^2 = .45), Customer Satisfaction (R^2 = .62), and Customer Loyalty (R^2 = .51).

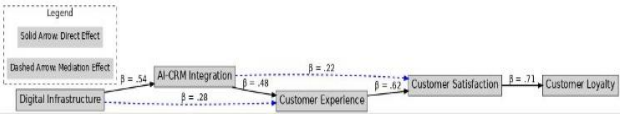

Fig. 1: Structural Model with Standardized Coefficients
Source: created by the authors

Figure 1 shows the theoretical model tested in the study. The model shows that digital infrastructure affects AI-supported CRM integration (AI-CRM Integration); this integration creates direct and indirect effects on customer experience, customer satisfaction, and customer loyalty. Solid lines represent direct effects; dashed lines represent mediator (indirect) effects. All path coefficients (β) were obtained as a result of SEM analyses.

To complement the SEM estimates for computational validation, we implemented two robustness checks: (1) a Monte Carlo simulation using the observed sample-based parameter estimates to assess parameter recovery under reduced sample sizes (n = 100, 150, 200) and (2) nested-model comparisons to test alternative causal orderings (e.g., AI-CRM → CSat direct vs. AI-CRM → CE → CSat). The Monte Carlo simulation (5,000 replications per condition) confirmed stable parameter recovery for the principal paths at n ≥ 150, supporting the reliability of our reported coefficients. Nested-model comparisons favored the hypothesized sequential model (DI → AI-CRM → CE → CSat → CLoy) based on AIC/BIC and significant chi-square differences in alternative specifications.

4.3 Mediation Analyses

To examine the multiple indirect effects (i.e., DI → AI-CRM → CE; AI-CRM → CE → CSat; CE → CSat → CLoy; AI-CRM → CE → CSat → CLoy) hypothesized, bootstrapping (5,000 resamples) was employed, [41]. Results are summarized in Table 5.

Indirect Effect of DI on CE via AI-CRM: Indirect effect = .26; 95% CI = [.17, .35]; p < .001. The direct effect (β = .28, p < .001) and the indirect effect were both significant, indicating partial mediation.

Indirect Effect of AI-CRM on CSat via CE: Indirect effect = .30; 95% CI = [.22, .39]; p < .001. The direct effect (β = .22, p < .01) remained significant, indicating complementary partial mediation.

Indirect Effect of CE on CLoy via CSat: Indirect effect = .43; 95% CI = [.34, .53]; p < .001. The direct effect of CE on CLoy (without mediation) was not specified a priori; this analysis confirms that CE influences loyalty primarily through satisfaction.

Indirect Effect of AI-CRM Integration on CLoy (via CE and CSat): Sequential mediation effect = .21; 95% CI = [.14, .29]; p < .001. This chain indicates that AI-CRM Integration enhances loyalty indirectly through CE and CSat.

Table 5. Bootstrapped Indirect Effects (5,000 Resamples)

Path	Coefficients			
	Ind Eff	*95% CI*	*p*	*Mediation Type*
DI → AI-CRM → CE	.26	[.17, .35]	<.001	Partial
AI-CRM → CE → CSat	.30	[.22, .39]	<.001	Partial
CE → CSat → CLoy	.43	[.34, .53]	<.001	Full
AI-CRM → CE → CSat → CLoy	.21	[.14, .29]	<.001	Sequential

Source: created by the authors

4.4 Multiple-Group Analysis

To assess potential moderation by firm size and industry sector, multiple-group SEM was conducted following established invariance testing procedures (configural → metric → scalar) following, [42]. Two grouping variables were tested separately: (1) Firm Size (50–249 vs. 250–499 vs. 500+ employees) and (2) Industry Sector (Manufacturing vs. Wholesale/Distribution vs. IT vs. Other). Baseline (configural) models for all groups showed acceptable fit (CFI ≥ .92, RMSEA ≤ .065). Constraining factor loadings (metric invariance) did not significantly worsen model fit ($\Delta\chi^2/\Delta df$ non-significant, p > .05), and constraining intercepts (scalar invariance) likewise produced no significant fit deterioration. ($\Delta\chi^2$ difference test non-significant, p > .05). After establishing measurement invariance, structural path coefficients were compared across groups.

To further clarify group-level behavior, we performed group-specific estimation and formal invariance tests for the structural model. Although small numerical differences are observable in some group-specific point estimates, formal tests indicate these differences are not statistically significant: constraining structural paths across the three firm-size categories yielded $\Delta\chi^2(12) = 13.24$, p = .35, and across the four industry sectors yielded $\Delta\chi^2(18) = 21.11$, p = .28. These non-significant $\Delta\chi^2$ results support configural, metric and scalar invariance and imply that the hypothesized relationships operate equivalently across firm sizes and industry sectors in our Turkish B2B sample. Practically, this invariance suggests that the managerial implications derived from the model—namely, that investments in digital infrastructure facilitate AI-CRM capabilities which, in turn, improve customer experience and satisfaction and ultimately foster loyalty—are broadly applicable across small, medium, and large firms and across the examined sectors. While point estimates show minor numerical variation (for example, slightly larger AI-CRM → CE coefficients in IT firms), such differences fall within sampling variability and are not statistically meaningful.

5 Conclusion

This study aimed to explore the effect of digital infrastructure and AI-based CRM systems on customer experience, satisfaction, and loyalty in Turkish B2B firms. Empirical data from 200 firms and validated through SEM, this study supported a sequential model of digital infrastructure facilitating AI-CRM integration, leading to enhanced customer experience and satisfaction, which finally impact customer loyalty. This study makes several new contributions to AI-powered CRM literature. A lot of prior work has focused on B2C sectors (such as retail, banking, telecom) in mature, [11]. This study presents very little empirical data from the B2B sector of an emerging economy—Türkiye—whose digital infrastructure maturity and managerial practices also differ radically from high-income environments. By situating the analysis in this less-researched context, the study addresses a gap identified in more recent studies, [44]. Contrary to analyses of CRM adoption or AI implementation separately, the current study proposes and enables a holistic framework that is connected by digital infrastructure, AI-CRM capabilities, and customer-facing outcomes. The inclusion of customer satisfaction as a necessary mediating variable by the model makes it distinct from research studies that analyze loyalty or satisfaction alone as outcomes. The suggestion that AI-CRM's impact on loyalty is largely indirect, via enhanced customer experience and satisfaction, is a strategic consideration that suggests experience-based CRM design aligning with AI systems. Table 6 (Appendix) situates the present study within the available research on AI-CRM adoption and customer consequences in various settings.

The study's findings are in line with international findings. For example, [5], showed that the AI capabilities (e.g., machine learning and natural language processing) are positively related to CRM and organizational outcomes. Our findings affirm the connection in a Turkish B2B context. Moreover, [13], stated that customer satisfaction has a greater effect on loyalty methods in an AI capability environment. The present study confirmed this, indicating that satisfaction was the strongest predictor of loyalty, fully mediating the experience-loyalty relationship. In addition, while [45], discussed the role of omnichannel experience on customer retention, our study extends the discussion with personalization and AI automation in CRM platforms.

Table 6 (Appendix) provides a summary of the study, indicating our findings convergently support and extend previous empirical findings on the role of AI-CRM and associated digital capabilities in improving customer- and firm-level outcomes. Across various contexts and over time, research has consistently found favorable associations with AI-CRM, integration capabilities, collaboration, and firm and customer outcomes - and often mediated by customer satisfaction, organizational creativity and/or innovation. The present results support these links in the Turkish B2B context, showing that digital infrastructure enables AI-CRM capabilities, which facilitate customer experience and satisfaction, thereby enhancing loyalty.

In addition, unlike a number of earlier studies that evidenced context effects (for example, sectoral or size-based differences), our invariance testing demonstrated that the structural relationships in the hypothesized model were stable across size and industry groups. This adds to the generalizability of the model and our confidence in AI-CRM's influence on customer outcomes across a range of organizational contexts.

Apart from congruence with prior evidence, this study adds to the literature base in a unique way by addressing an essential void in existing literature: the absence of empirical work on AI-CRM skills and customer outcome patterns in the Turkish B2B market. Although previous work has focused on Western economies or international multi-sector samples, few have comprehensively examined the full structural model —i.e., digital infrastructure, AI-CRM, customer experience, satisfaction, and loyalty—within the B2B setting of emerging economies. With the inclusion of multi-group invariance testing, this study not only confirms the hypothesized relationships but also provides one of the first empirical illustrations of their generalizability across firm size and industry sector in the context of Türkiye. These findings contribute new context-specific findings to the global discussion on the uptake of AI-CRM, and theoretical and practical implications are generated for managers operating under such conditions in emerging markets.

For business professionals, the meaning of what the findings are is that effective CRM is more than the adoption of AI technologies alone but rather the digital infrastructure of the company. Investment in cloud infrastructures, systems interoperability, and streaming of real-time data are key success drivers for AI-CRM. Managers must focus on bringing AI modules for personalization, predictive analytics, and customer insight generation. Furthermore, the indirect route from AI to loyalty via satisfaction implies that companies need to focus on customer-driven process design as well as technical implementation.

Despite its findings, this study also has several limitations. First, the cross-sectional design limits causal inference. Longitudinal studies in the future would potentially indicate how AI-CRM system advantages happen over time and if and to what extent early satisfaction benefits lead to long-run loyalty. Second, while the sample comes from different B2B firms in Türkiye, the results cannot be generalized to other emerging markets. Cross-sectional studies across regions such as Southeast Asia, Eastern Europe, or Latin America are required to assess contextual dependencies. Third, this paper's research only takes into consideration customer-side effects. Future research could explore the effect of AI-CRM integration on internal organizational effects, e.g., process effectiveness, employee take-up, or ROI. Qualitative studies—e.g., case studies or CRM manager interviews—may also help bring more insights on implementation challenges and facilitators.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The authors wrote, reviewed and edited the content as needed and verifies that none utilized artificial intelligence (AI) tools were used. The authors take full responsibility for the content of the publication.

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APPENDIX

Table 6. Comparison with Key Empirical Studies on AI-CRM and Customer Outcomes

Study	N	Context	Key Paths Tested	Key Findings
[18]	450 managers across 10 firms	Large Thai enterprises (B2B context discussed)	AI-CRM adoption & Big Data capability → integration capability, collaboration, firm performance	AI-CRM adoption significantly enhances integration capability, team collaboration and firm performance; big-data capability improves collaboration and competitive advantage, but not integration capability
[6]	308 respondents	Employee behavioral intention toward AI-CRM (India)	Perceived usefulness / ease → Behavioral intention (via utilitarian/hedonic attitudes)	Perceived usefulness and ease significantly affect behavioral intention and attitudes; leadership/support is important for adoption
[20]	72 empirical studies (review)	Multiple sectors / international	Mechanisms linking AI-CRM → retention & performance	Identifies five mechanisms: personalization, real-time decisioning, automation/efficiency, refined segmentation, proactive churn management
[23]	266 B2B account managers	B2B across Asia	Salesperson attributes (expertise, ethics, service quality) → Relationship quality (trust, satisfaction) → Loyalty	Expertise is the strongest predictor of trust & satisfaction; trust/satisfaction drives loyalty
[24]	113 firms	Turkish B2B firms	CRM adoption → Customer satisfaction → Marketing & firm performance	CRM adoption increases customer satisfaction and marketing performance, but not significantly financial performance; satisfaction mediates gains; contextual moderators (dynamism, competition) weaken effects
[22]	100 professionals from Technology Development Zone companies	Turkish B2B firms	AI-driven CLV models (forecast accuracy)	AI-driven CLV forecasts are substantially more accurate than manual methods
[46]	202 respondents	Norway, CIOs/IT managers	AI capability → Org. creativity → Firm performance	Creativity mediates AI capability → performance
[47]	205 firms	India, manufacturing & supply chain	AI readiness index → Operational performance	Readiness boosts performance; top mgmt. & learning culture crucial
[48]	30 expert contributions	Global, multi-sector	AI adoption: challenges & opportunities	Ethical/data/privacy issues; need for human–AI collaboration
[49]	Not specified (mixed method)	SMEs, GCC countries	AI adoption in SMEs → Efficiency & competitiveness	AI boosts efficiency; barriers: resources & skills
[50]	178 firms + 10 exec interviews	Norway	Digital capabilities (incl. AI) → Perf. metrics	AI-linked capabilities improve financial & non-financial performance
[51]	Not reported	China, e-commerce	AI capability & mgmt. → Decision-making → Performance (moderated by marketing capability)	Multiple mediation; marketing capability moderates the AI effect
[52]	Review of 45 studies	Multi-sector	AI → Business performance	AI generally improves performance; the effect depends on readiness, data, and context
[53]	334 firms	Korea, manufacturing	AI → Performance (mediated by process/product innovation)	Both innovation types mediate AI → performance
[54]	398 firms	Multinational B2B	AI capabilities → Open innovation → Performance	Open innovation mediates the AI effect; environment moderates
[55]	6,300 firm-year obs.	China, industrial	AI-driven digital transformation → Performance	Mediated by green digital innovation; strengthened by human–AI collaboration
This study	200 CRM professionals	Turkish B2B firms	Digital infrastructure → AI-CRM → Customer experience → Customer satisfaction → Customer loyalty (+ multi-group/invariance tests)	Digital infrastructure supports AI-CRM; AI-CRM increases customer experience and satisfaction; satisfaction is strongest predictor of loyalty and mediates experience → loyalty; model invariance across firm size & industry

Source: created by the author

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