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The Impact of AI-Enabled Customer Relationship Management on Customer Satisfaction through Customer Engagement in the UAE Ministry of Interior

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Abstract

This study examined the impact of artificial intelligence in customer relationship management on customer satisfaction, with customer engagement as a mediating variable, to propose an AI-CRM framework for the Ministry of Interior, United Arab Emirates. The study focused on five AI-enabled CRM factors: predictive analytics, churn prediction and retention tools, chatbots and virtual assistants, personalization, and sentiment analysis. A quantitative approach was adopted, and data were collected from service users through an online questionnaire. Out of 500 questionnaires distributed, 351 valid responses were used for analysis after data screening. The findings revealed that predictive analytics, chatbots and virtual assistants, personalization, and sentiment analysis significantly influenced customer satisfaction. However, churn prediction and retention tools did not have a significant direct effect on customer satisfaction. The results also showed that customer engagement had a significant positive effect on customer satisfaction and significantly mediated the relationship between AI-enabled CRM factors and customer satisfaction. The study concludes that AI in CRM can enhance customer satisfaction when it strengthens customer engagement. Therefore, the proposed AI-CRM framework for the Ministry of Interior, UAE, should place customer engagement at the centre of AI implementation to support responsive, customer-centred, and technology-driven public service delivery.

Keywords: Artificial Intelligence, Customer Relationship Management, Customer Satisfaction, Customer Engagement, AI-CRM Framework, Ministry of Interior UAE

1. Introduction

In the modern technological landscape, both public and private sector organisations are increasingly adopting innovative approaches to understand, engage, and satisfy their customers. One of the most significant developments in this regard is the integration of artificial intelligence (AI) with Customer Relationship Management (CRM). AI-enabled CRM has become an important strategic tool because it allows organisations to collect, analyse, and apply customer data more effectively in order to improve service delivery, strengthen relationships, and enhance customer experience (Ahmad & Pande, 2024; Chatterjee et al., 2019; Sathyamoorthy & Pattabiraman, 2024). Traditionally, CRM focused on managing customer interactions, service communication, and relationship-building processes. However, with the emergence of AI, CRM has moved beyond basic record-keeping and communication management to more intelligent, predictive, and personalized forms of customer engagement (Ozay et al., 2024; Lukasik-Stachowiak, 2023).

Customer satisfaction remains one of the most important outcomes of effective CRM. It reflects the extent to which customers perceive that services meet their needs, expectations, and desired experiences. In CRM contexts, satisfaction is closely associated with service quality, customer value, continued engagement, trust, and long-term relationship development (Kumar & Reinartz, 2021; Lemon & Verhoef, 2022). In the private sector, customer satisfaction is often connected to retention, loyalty, and competitive advantage. Although the public sector does not pursue profit in the same way as private organisations, customer satisfaction is equally important because it reflects service quality, institutional credibility, public trust, and the ability of government agencies to meet citizens' expectations. In this regard, AI-enabled CRM can support public organisations in improving responsiveness, service accessibility, and customer-oriented decision-making (Dwivedi et al., 2021; Sathyamoorthy & Pattabiraman, 2024).

In public administration, CRM has become an essential approach for improving the relationship between government institutions and service users. Effective CRM practices enable public organisations to understand the diverse needs of citizens, respond quickly to inquiries and complaints, customize services, and improve overall service accessibility. As citizens increasingly expect faster, more transparent, and more personalized public services, government institutions are required to move beyond traditional bureaucratic service models and adopt more responsive digital systems. This shift has made AI an important enabler of public-sector CRM because it supports data-driven decision-making, service automation, proactive communication, and continuous monitoring of customer feedback (Almansoori & Al-Tahitah, 2021; Dwivedi et al., 2021; Ahmad & Pande, 2024).

The relevance of AI in CRM is particularly important in the United Arab Emirates, where citizens and residents increasingly expect high-quality government services. Within this environment, government organisations are expected to provide services that are timely, accessible, transparent, and responsive to the needs of diverse service users. Al-Mansoori (2023) emphasized the importance of improving customer service dynamics within the daily operations of the Ministry of Interior UAE, while Almansoori and Al-Tahitah (2021) highlighted the role of artificial intelligence in decision-making processes at the Ministry of Interior in the United Arab Emirates. Therefore, understanding how AI-enabled CRM contributes to customer satisfaction is highly relevant for UAE public institutions.

One of the most important public organisations in the UAE is the Ministry of Interior. The Ministry plays a central role in providing public services that require efficient communication, timely response, accurate information processing, and continuous customer support. Given the rapid development of the UAE and the increasing demand for high-quality public services, the Ministry of Interior has recognized the need to adopt modern CRM strategies to enhance service delivery and improve customer experiences. In this context, AI-enabled CRM provides an opportunity to improve daily service operations, support decision-making, and strengthen the relationship between the Ministry and its customers (Al-Mansoori, 2023; Almansoori & Al-Tahitah, 2021).

AI provides several opportunities for strengthening CRM within the Ministry of Interior UAE. In this study, AI in CRM is examined through five major factors: predictive analytics, churn prediction and retention tools, chatbots and virtual assistants, personalization, and sentiment analysis. Predictive analytics enables organisations to anticipate customer needs, identify behavioural patterns, forecast service demands, and support proactive decision-making (Choudhury, Singh, & Sharma, 2023; Davenport et al., 2020; Kumar & Reinartz, 2022; Zhang, 2023). Churn prediction and retention tools help identify customers or service users who may become dissatisfied or disengaged, allowing the organisation to intervene before dissatisfaction increases (Kumar, Singh, & Gupta, 2022; Ngai, 2022; Nguyen, Tran, & Hoang, 2023). Chatbots and virtual assistants provide immediate and automated support, reduce waiting time, and improve service accessibility (Kumar, Singh, & Gupta, 2023; Patel, 2023; Khneyzer, Boustany, & Dagher, 2024). Personalization enables services and communication to be tailored according to individual needs, preferences, and profiles (Choudhury, Gupta, & Singh, 2022; Kumar & Gupta, 2022; Zhang & Zhao, 2023). Sentiment analysis allows organisations to examine customer opinions, complaints, emotions, and feedback from different platforms in order to understand public perception and respond more effectively (Jiang, Xu, & Wang, 2022; Liu & Zhang, 2023; Kumar, Singh, & Sharma, 2023; Wang, Chen, & Zhang, 2023). Together, these AI-enabled CRM tools can support more responsive, proactive, and customer-centred public service delivery.

Previous studies have shown that AI-enabled CRM can improve service delivery, customer engagement, and customer satisfaction. AI-driven chatbots can enhance customer interaction by providing quick responses, continuous availability, and automated support for routine inquiries (Kumar, Singh, & Gupta, 2023; Patel & Verma, 2023; Khneyzer, Boustany, & Dagher, 2024). Similarly, AI-supported personalization can improve customer experience by enabling organisations to provide more relevant communication, recommendations, and service interactions (Choudhury, Gupta, & Singh, 2022; Kumar & Gupta, 2022; Lee & Kim, 2023). Predictive analytics can also support timely interventions by helping organisations anticipate customer needs, forecast service demand, and generate actionable insights for decision-making (Choudhury, Singh, & Sharma, 2023; Davenport et al., 2020; Zhang, 2023). These studies suggest that AI can improve customer satisfaction when it is implemented transparently, ethically, and in alignment with customer expectations (Binns, 2023; Miller & Johnson, 2023; Thompson & Williams, 2023).

Despite these benefits, the integration of AI into CRM is not without challenges. Organisations may face barriers such as resistance to AI adoption, limited technological integration, data privacy concerns, ethical risks, data quality problems, and difficulties in aligning AI systems with customer expectations (Garcia, Lee, & Kim, 2023; Garcia & Patel, 2023; Jeble, 2023; Binns, 2023). In the UAE public-sector context, these challenges are especially important because service users may have different expectations, languages, levels of digital literacy, and trust concerns. Therefore, the success of AI-enabled CRM depends not only on the availability of technology but also on user acceptance, transparency, data protection, ethical governance, and cultural suitability (Dwivedi et al., 2021; Thompson & Williams, 2023; Nguyen & Tran, 2023).

Although AI has gained increasing attention in management and digital transformation research, scholarly work on the relationship between AI and CRM remains relatively fragmented. AI research has developed across several fields, including computer science, operations research, service management, and organisational studies, while CRM research has continued to focus on customer interaction, customer value, service experience, and relationship management (Raisch & Krakowski, 2020; Loureiro et al., 2021; Kumar, Ramachandran, & Kumar, 2020). As a result, existing studies provide useful insights into AI or CRM separately, but limited empirical attention has been given to how specific AI-enabled CRM factors influence customer satisfaction in public-sector organisations, particularly within the Ministry of Interior UAE.

Furthermore, while the Ministry of Interior UAE has shown interest in AI-supported decision-making and service improvement, there remains limited systematic evaluation of how AI-enabled CRM practices affect customer satisfaction in this specific institutional context. Existing studies related to the Ministry of Interior UAE emphasize the importance of customer service improvement and the role of AI in decision-making, but further empirical investigation is needed to understand how AI-CRM tools contribute to customer satisfaction through customer engagement (Al-Mansoori, 2023; Almansoori & Al-Tahitah, 2021). Without such evidence, policymakers and managers may find it difficult to determine which AI-CRM tools are most effective, how they should be integrated, and how they can be used to improve service users' experiences.

Another important gap concerns the mediating role of customer engagement. Customer satisfaction may not always result directly from the use of AI tools. Instead, AI-enabled CRM may improve satisfaction by first enhancing customer engagement. Customer engagement reflects the active, cognitive, emotional, and behavioural connection between customers and service providers. Engaged customers are more likely to interact with services, provide feedback, trust the organisation, and perceive the service experience positively (Kumar & Reinartz, 2021; Lemon & Verhoef, 2022). For example, predictive analytics may help the Ministry anticipate needs, but satisfaction may increase more strongly when those insights are used to engage customers through timely communication. Similarly, chatbots may improve satisfaction not only because they provide automated responses, but because they make customers feel supported and connected. Personalization, sentiment analysis, and retention tools may also contribute to satisfaction by strengthening the quality, relevance, and responsiveness of customer engagement.

Therefore, this study focuses on the impact of AI in CRM on customer satisfaction in view of the mediating role of customer engagement, with the aim of proposing an AI-CRM framework for the Ministry of Interior UAE. The study examines how predictive analytics, churn prediction and retention tools, chatbots and virtual assistants, personalization, and sentiment analysis influence customer satisfaction directly and indirectly through customer engagement. By doing so, the study responds to the need for a more integrated understanding of AI-enabled CRM in the public sector and provides a framework that can guide the Ministry of Interior UAE in improving customer-centred service delivery.

2. Framework Development

The proposed AI-CRM framework for the Ministry of Interior UAE, as shown in Figure 1, was developed based on the empirical findings of this study and the supporting literature on artificial intelligence, customer relationship management, customer engagement, and customer satisfaction. The framework explains how AI-enabled CRM capabilities improve customer satisfaction directly and indirectly through customer engagement. In this study, AI in CRM is represented by five key technological factors: predictive analytics, churn prediction and retention tools, chatbots and virtual assistants, personalization, and sentiment analysis. These AI-CRM capabilities are expected to enhance customer engagement and, subsequently, customer satisfaction within the service environment of the Ministry of Interior UAE.

The development of the framework is justified by the increasing relevance of artificial intelligence in CRM systems. AI is increasingly being used to improve service delivery, automate customer interactions, support decision-making, predict customer needs, and personalize service experiences (Ahmad & Pande, 2024; Chatterjee et al., 2019; Dwivedi et al., 2021). In public sector institutions such as the Ministry of Interior UAE, the integration of AI into CRM is particularly important because customers expect efficient, responsive, accurate, and accessible public services. Al-Mansoori (2023) emphasized that customer service dynamics within the Ministry of Interior UAE require continuous improvement in daily operations, while Almansoori and Al-Tahitah (2021) highlighted the growing role of artificial intelligence in decision-making processes at the Ministry of Interior in the United Arab Emirates. Therefore, the framework is contextualized within the UAE public sector environment, where AI-enabled CRM can support both operational efficiency and customer-centred service delivery.

The first layer of the framework is the AI-CRM capability layer. This layer consists of five AI-driven CRM constructs: predictive analytics, churn prediction and retention tools, chatbots and virtual assistants, personalization, and sentiment analysis. Predictive analytics enables the Ministry to anticipate customer needs, forecast service demand, identify behavioural patterns, and support proactive service planning. This is consistent with the view that predictive analytics improves CRM effectiveness by helping organizations generate customer insights and make better decisions (Choudhury, Singh, & Sharma, 2023; Davenport et al., 2020; Kumar & Reinartz, 2022; Zhang, 2023). In the Ministry of Interior UAE context, predictive analytics can be applied to identify frequently requested services, forecast peak service periods, and improve the allocation of resources across digital and physical service channels.

Churn prediction and retention tools represent the second AI-CRM capability in the framework. Although churn is commonly discussed in private sector CRM, it is also relevant to public services because customers may disengage from official digital platforms, abandon online service processes, or become dissatisfied with service channels. Machine learning approaches can help organizations identify customers who are at risk of disengagement and allow timely interventions to retain them (Kumar, Singh, & Gupta, 2022; Ngai, 2022; Nguyen, Tran, & Hoang, 2023). In this framework, churn prediction and retention tools are positioned as mechanisms for identifying declining engagement, service dissatisfaction, incomplete transactions, and repeated complaints. Such tools may become more valuable when they are connected to active engagement strategies, such as follow-up communication, service reminders, complaint resolution, and personalized support.

The third AI-CRM capability in the framework is chatbots and virtual assistants. These tools are included because they improve service accessibility, response speed, and customer interaction. AI-driven chatbots can provide immediate responses, support routine inquiries, guide users through service processes, and reduce waiting time (Kumar, Singh, & Gupta, 2023; Patel, 2023; Khneyzer, Boustany, & Dagher, 2024). However, the framework also recognizes that chatbots may face limitations when dealing with complex queries, sensitive service issues, or emotionally charged interactions (Huang & Lee, 2023; Zhou, Xu, & Yang, 2023). Therefore, the proposed framework supports a hybrid service model in which chatbots handle routine inquiries while complex issues are escalated to human service officers. This is consistent with Khan, Ali and Patel (2023), who argued that hybrid customer service models combining chatbots with human support can improve service quality and customer experience.

The fourth AI-CRM capability is personalization. Personalization is central to the proposed framework because customers are more likely to engage with services that are relevant to their needs, preferences, history, and service context. Prior studies indicate that AI and big data can be used to deliver personalized customer experiences, improve satisfaction, and strengthen customer relationships (Choudhury, Gupta, & Singh, 2022; Kumar & Gupta, 2022; Lee & Kim, 2023; Zhang & Zhao, 2023). In the Ministry of Interior UAE context, personalization may include customized service reminders, tailored digital dashboards, language preferences, service recommendations, and notifications based on previous interactions. However, personalization must be balanced with data privacy and ethical considerations, as excessive or unclear use of customer data may reduce trust (Miller & Johnson, 2023; Nguyen & Tran, 2023; Thompson & Williams, 2023).

The fifth AI-CRM capability is sentiment analysis. Sentiment analysis is incorporated into the framework because it enables the Ministry to understand customer emotions, opinions, complaints, and satisfaction levels through the analysis of feedback, reviews, complaints, call centre records, and social media comments. Sentiment analysis has been identified as an important tool for measuring customer satisfaction and managing customer experience (Jiang, Xu, & Wang, 2022; Kumar, Singh, & Sharma, 2023; Liu & Zhang, 2023; Wang, Chen, & Zhang, 2023). In this framework, sentiment analysis functions as a feedback intelligence tool that allows the Ministry to identify negative service experiences, respond to complaints, and improve service design. It also supports continuous improvement by transforming customer feedback into actionable service insights.

The second layer of the framework is the customer engagement layer. Customer engagement serves as the mediating mechanism through which AI-CRM capabilities are expected to influence customer satisfaction. This layer is included because engaged customers are more likely to develop trust, loyalty, positive perceptions, and satisfaction with service providers (Kumar & Reinartz, 2021; Hassan, Shiu, & Parry, 2023; Lemon & Verhoef, 2022). In the Ministry of Interior UAE context, customer engagement may be reflected in active use of digital platforms, responsiveness to service notifications, participation in feedback channels, repeated use of online services, and positive interaction with AI-enabled service tools.

The third layer is the customer satisfaction outcome layer. Customer satisfaction is the final outcome of the proposed framework. The framework positions AI-CRM capabilities as important service mechanisms that can contribute to customer satisfaction by making services more responsive, accessible, personalized, predictive, and feedback-driven. The literature supports the relationship between AI-enabled CRM and customer satisfaction, particularly when AI tools improve service speed, accuracy, convenience, and perceived value (Patel & Verma, 2023; Sathyamoorthy & Pattabiraman, 2024; Ozay et al., 2024). Therefore, customer engagement is placed at the centre of the framework as the key pathway through which AI-CRM initiatives can become meaningful to customers and contribute to improved service experiences within the Ministry of Interior UAE.

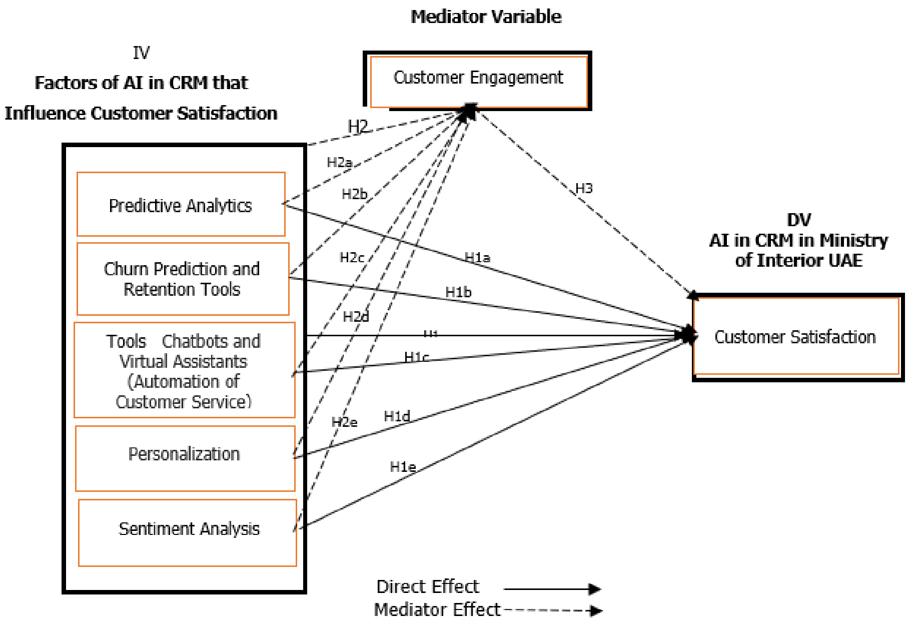

Figure 1. Proposed AI-CRM framework for enhancing customer satisfaction through customer engagement in the Ministry of Interior UAE

Note. PA = Predictive Analytics; CPR = Churn Prediction and Retention Tools; CVA = Chatbots and Virtual Assistants; PER = Personalization; SA = Sentiment Analysis; CE = Customer Engagement; CS = Customer Satisfaction. H1a–H1e represent the direct effects of AI-CRM capabilities on customer satisfaction. H2a–H2e represent the effects of AI-CRM capabilities on customer engagement. H3 represents the effect of customer engagement on customer satisfaction. H4–H8 represent the indirect effects of AI-CRM capabilities on customer satisfaction through customer engagement.

Based on the framework of Figure 1, the hypotheses that can be drawn are as in Table 1.

Table 1. Hypotheses of the framework

Code	Hypothesis Statement
H1a	Predictive Analytics significantly enhances Customer Satisfaction.
H1b	Churn Prediction and Retention Tools significantly enhance Customer Satisfaction.
H1c	Chatbots and Virtual Assistants significantly enhance Customer Satisfaction.
H1d	Personalization significantly enhances Customer Satisfaction.
H1e	Sentiment Analysis significantly enhances Customer Satisfaction.
H2a	Predictive Analytics significantly enhances Customer Engagement.
H2b	Churn Prediction and Retention Tools significantly enhance Customer Engagement.
H2c	Chatbots and Virtual Assistants significantly enhance Customer Engagement.
H2d	Personalization significantly enhances Customer Engagement.
H2e	Sentiment Analysis significantly enhances Customer Engagement.
H3	Customer Engagement significantly influences Customer Satisfaction.
H4	Customer Engagement mediates the relationship between Predictive Analytics and Customer Satisfaction.
H5	Customer Engagement mediates the relationship between Churn Prediction and Retention Tools and Customer Satisfaction.
H6	Customer Engagement mediates the relationship between Chatbots and Virtual Assistants and Customer Satisfaction.
H7	Customer Engagement mediates the relationship between Personalization and Customer Satisfaction.
H8	Customer Engagement mediates the relationship between Sentiment Analysis and Customer Satisfaction.

3. Data and Respondent Demographic Profile For Modelling

Data for this study were collected from service users of the Ministry of Interior, United Arab Emirates. A random sampling technique was employed, and an online questionnaire was administered to the selected respondents. Out of the 500 questionnaires distributed, 422 were returned, representing an initial response rate of 84.4%. After data screening, 33 incomplete responses were removed, leaving 389 complete responses, equivalent to 77.8% of the total questionnaires distributed. In addition, 38 cases were identified and removed as outliers. Therefore, the final valid sample consisted of 351 responses. This represents a usable response rate of 70.2% of the questionnaires distributed and 83.2% of the returned questionnaires.

The final sample was considered adequate for the planned SEM-based analysis because it exceeded the minimum sample size of 306 required for multivariate analysis, as recommended by Hair et al. (2019). Therefore, the retained sample was suitable for examining the relationships among AI-enabled CRM practices, customer engagement, and customer satisfaction in the context of the Ministry of Interior UAE.

The demographic profile of the 351 respondents indicates that the sample was sufficiently diverse for the purpose of the study. In terms of age, most respondents were within the active adult age groups, particularly those aged 25 to 34 years and 35 to 44 years. This suggests that many participants were likely to have experience with digital government services, online service platforms, and customer-facing digital systems. The gender distribution was relatively balanced, with males representing 51.6% and females representing 45.9% of the sample.

With respect to employment status, government employees formed the largest group, followed by private sector employees, students, and respondents in other employment categories. This profile is relevant to the study because employed respondents are more likely to interact with government service portals, digital identity systems, and administrative service platforms. Similarly, the income distribution shows that respondents came from different economic groups, with the largest proportion earning between AED 10,000 and AED 15,000 per month. This indicates that the sample included service users from different income levels.

The educational profile also shows that the respondents had an adequate level of education to understand the issues examined in the study. Degree holders formed the largest group, followed by master's degree holders and diploma holders. This suggests that the respondents were generally capable of evaluating issues related to AI-enabled CRM, digital services, customer engagement, and customer satisfaction.

Furthermore, most respondents, representing 69.5%, indicated that they were aware of or had used AI-enabled CRM services. However, 16.5% were not aware of such services, while 14.0% were unsure. This finding shows that although many respondents had some level of exposure to AI-enabled services, awareness was not uniform across the sample. This variation is useful because it allows the study to capture different levels of user experience, awareness, and perception.

Overall, the demographic results show that the sample was diverse in terms of age, gender, employment status, income, education, and awareness of AI-enabled CRM services. This diversity strengthens the descriptive value of the study and supports the relevance of examining how different service users perceive AI-enabled CRM, customer engagement, and customer satisfaction in the Ministry of Interior UAE.

4. Modelling of the Framework

This chapter presents the modelling and empirical assessment of the proposed AI-CRM framework developed for the Ministry of Interior, UAE. The model examines the impact of AI-enabled CRM capabilities on customer satisfaction, with customer engagement serving as a mediating variable. The AI-CRM dimensions assessed in the model include predictive analytics, churn prediction and retention tools, chatbots and virtual assistants, personalization, and sentiment analysis. The analysis follows the Partial Least Squares Structural Equation Modelling approach. First, the measurement model was assessed to establish construct reliability, convergent validity, and discriminant validity. Second, the structural model was evaluated using the coefficient of determination, effect size, model fit, and hypothesis testing. This approach ensures that the constructs were measured reliably before interpreting the relationships among the variables in the proposed AI-CRM framework. The construct abbreviations used in the analysis are as follows: Customer Engagement (CE), Churn Prediction and Retention Tools (CPR), Customer Satisfaction (CS), Chatbots and Virtual Assistants (CVA), Predictive Analytics (PA), Personalization (PER), and Sentiment Analysis (SA).

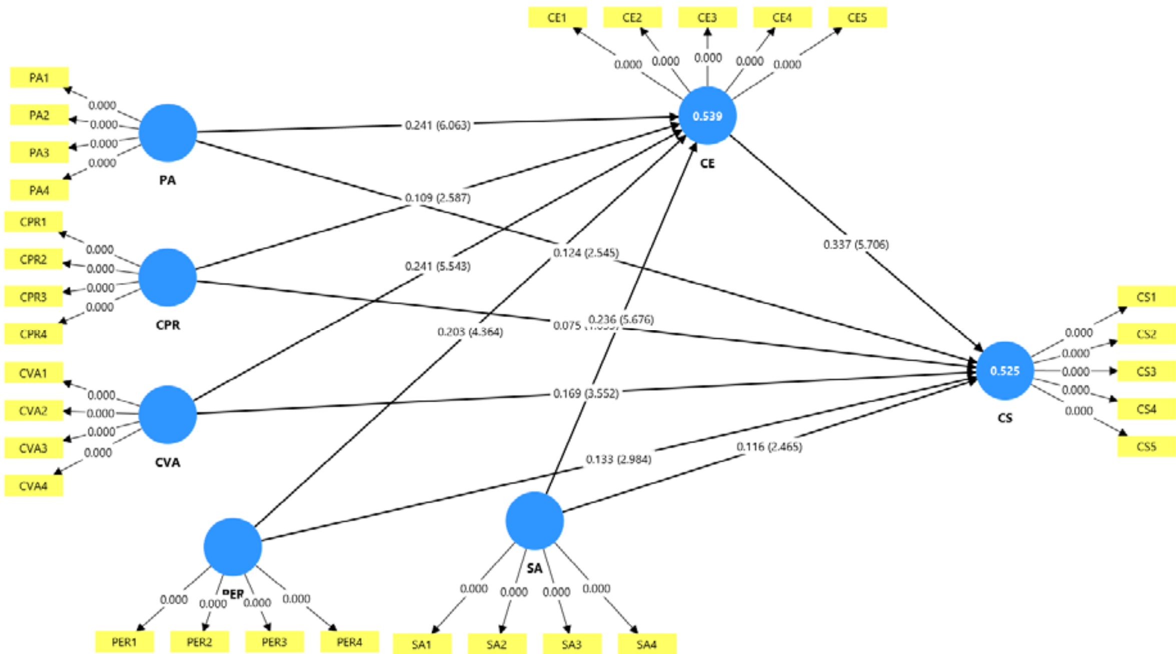

Figure 2. PLS-SEM model of the framework

4.1 Construct Reliability and Convergent Validity

Construct reliability and convergent validity were assessed to determine the adequacy of the measurement model. Internal consistency reliability was examined using Cronbach's alpha, composite reliability rho_A, and composite reliability rho_C. Cronbach's alpha is widely used as a traditional measure of reliability, while composite reliability is considered more appropriate in PLS-SEM because it does not assume equal indicator loadings across measurement items. According to Hair et al. (2019), reliability values of 0.70 and above are considered acceptable, while values above 0.95 may indicate possible item redundancy. In this study, none of the constructs exceeded the upper threshold of 0.95, suggesting that item redundancy was not a concern.

As presented in Table 2, the Cronbach's alpha values ranged from 0.876 to 0.889, indicating strong internal consistency among the measurement items. The composite reliability rho_A values ranged from 0.879 to 0.890, while the composite reliability rho_C values ranged from 0.915 to 0.919. All these values exceeded the recommended threshold of 0.70, confirming that the constructs demonstrated satisfactory internal consistency reliability.

Convergent validity was assessed using the Average Variance Extracted (AVE). AVE measures the extent to which a construct explains the variance of its indicators. An AVE value of 0.50 or above indicates that the construct explains more than half of the variance in its indicators and is therefore acceptable for convergent validity. As shown in Table 2, the AVE values ranged from 0.682 to 0.740, which were all above the recommended minimum threshold of 0.50. This confirms that convergent validity was established for all constructs in the measurement model.

Table 2. Construct reliability and convergent validity

Construct	Cronbach's Alpha	Composite Reliability rho_A	Composite Reliability rho_C	AVE
Customer Engagement	0.889	0.890	0.919	0.693
Churn Prediction and Retention Tools	0.882	0.887	0.918	0.738
Customer Satisfaction	0.884	0.885	0.915	0.682
Chatbots and Virtual Assistants	0.881	0.883	0.918	0.737
Predictive Analytics	0.876	0.879	0.915	0.729
Personalization	0.882	0.887	0.918	0.738
Sentiment Analysis	0.883	0.883	0.919	0.740

The results in Table 2 show that all constructs were measured reliably and consistently. Customer Engagement recorded the highest Cronbach's alpha value of 0.889, while Predictive Analytics recorded the lowest Cronbach's alpha value of 0.876. However, even the lowest value was substantially above the recommended threshold of 0.70. Similarly, the composite reliability values confirmed that all constructs had strong reliability. The AVE values further demonstrated that the indicators of each construct shared sufficient common variance, thereby confirming convergent validity. Therefore, the measurement model satisfied the requirements for both internal consistency reliability and convergent validity.

4.2 Discriminant Validity Using HTMT

Discriminant validity was assessed to determine whether each construct in the measurement model was empirically distinct from the other constructs. The first criterion used was the Heterotrait-Monotrait ratio of correlations (HTMT). Henseler et al. (2015) argued that HTMT provides a more reliable and rigorous assessment of discriminant validity than the traditional Fornell-Larcker criterion and cross-loadings. In this study, the conservative threshold value of 0.85 was adopted. Therefore, HTMT values below 0.85 indicate that discriminant validity has been established.

As shown in Table 3, all HTMT values were below the recommended threshold of 0.85. The highest HTMT value was 0.741, which occurred between Customer Engagement and Customer Satisfaction. Although this was the strongest association among the constructs, it remained below the conservative threshold. This indicates that Customer Engagement and Customer Satisfaction, despite being theoretically related, were empirically distinct.

Therefore, the HTMT results confirmed that discriminant validity was established among all constructs in the model.

Table 3. HTMT results for discriminant validity

Construct	CE	CPR	CS	CVA	PA	PER	SA
CE							
CPR	0.452						
CS	0.741	0.433					
CVA	0.625	0.315	0.600				
PA	0.599	0.376	0.548	0.461			
PER	0.610	0.405	0.582	0.531	0.433		
SA	0.590	0.349	0.534	0.423	0.376	0.456	

Note. CE = Customer Engagement; CPR = Churn Prediction and Retention Tools; CS = Customer Satisfaction; CVA = Chatbots and Virtual Assistants; PA = Predictive Analytics; PER = Personalization; SA = Sentiment Analysis.

The HTMT results indicate that the constructs were related but not overlapping or redundant. The strongest relationship was observed between Customer Engagement and Customer Satisfaction, which is theoretically expected because customers who are more engaged with AI-enabled CRM services are likely to report higher levels of satisfaction. However, the HTMT value of 0.741 was still below the threshold of 0.85, confirming that these two constructs measured different concepts. The remaining HTMT values were also within the acceptable range. Therefore, discriminant validity was established using the HTMT criterion.

4.3 Discriminant Validity Using the Fornell-Larcker Criterion

The second method used to assess discriminant validity was the Fornell-Larcker criterion. According to Fornell and Larcker (1981), discriminant validity is established when the square root of the AVE for each construct is greater than its correlations with other constructs. This means that a construct should share more variance with its own measurement indicators than with other constructs in the model.

As shown in Table 4, the diagonal values represent the square root of AVE for each construct. The diagonal values were 0.833 for Customer Engagement, 0.859 for Churn Prediction and Retention Tools, 0.826 for Customer Satisfaction, 0.858 for Chatbots and Virtual Assistants, 0.854 for Predictive Analytics, 0.859 for Personalization, and 0.860 for Sentiment Analysis. These values were higher than the corresponding inter-construct correlations in their respective rows and columns. Therefore, the Fornell-Larcker criterion was satisfied.

Table 4. Fornell-Larcker criterion

Construct	CE	CPR	CS	CVA	PA	PER	SA
CE	0.833						
CPR	0.404	0.859					
CS	0.660	0.384	0.826				
CVA	0.554	0.281	0.533	0.858			
PA	0.531	0.332	0.486	0.406	0.854		
PER	0.543	0.360	0.517	0.471	0.382	0.859	
SA	0.523	0.312	0.474	0.374	0.332	0.403	0.860

The results in Table 4 provide additional evidence of discriminant validity. The highest inter-construct correlation was 0.660 between Customer Engagement and Customer Satisfaction. However, this value was lower than the square root of AVE for Customer Engagement, which was 0.833, and lower than the square root of AVE for Customer Satisfaction, which was 0.826. This confirms that even the most strongly related constructs remained empirically distinct.

Overall, the findings from both the HTMT criterion and the Fornell-Larcker criterion confirmed that discriminant validity was achieved. This indicates that the constructs in the measurement model were sufficiently distinct from one another and suitable for further structural model assessment.

4.4 Coefficient of Determination

The coefficient of determination was assessed using the R^2 value. R^2 explains the proportion of variance in an endogenous construct that is accounted for by its predictor constructs. In PLS-SEM, R^2 is an important criterion for assessing the explanatory power of the structural model. According to Hair et al. (2022), R^2 values of 0.25, 0.50, and 0.75 may be interpreted as weak, moderate, and substantial, respectively, in many social science studies. However, the interpretation of R^2 should also consider the research context, the complexity of the model, and the nature of the constructs being examined.

The R^2 results are presented in Table 5. Customer Engagement recorded an R^2 value of 0.539. This indicates that Predictive Analytics, Churn Prediction and Retention Tools, Chatbots and Virtual Assistants, Personalization, and Sentiment Analysis collectively explained 53.9% of the variance in Customer Engagement. This result suggests that the AI-enabled CRM factors included in the model have moderate explanatory power in predicting customer engagement within the Ministry of Interior, UAE context.

Customer Satisfaction recorded an R^2 value of 0.525. This means that Customer Engagement and the AI-enabled CRM factors collectively explained 52.5% of the variance in Customer Satisfaction. This also represents moderate explanatory power and indicates that the proposed AI-CRM model is useful in explaining customer satisfaction.

Table 5. Coefficient of determination

Endogenous Construct	R^2	Interpretation
Customer Engagement	0.539	Moderate
Customer Satisfaction	0.525	Moderate

The results in Table 5 demonstrate that the structural model has moderate explanatory power. This is appropriate for a behavioural and service management study because customer engagement and customer satisfaction are complex outcomes influenced by various technological, organisational, service-related, and individual factors.

In the context of this study, the findings suggest that AI-enabled CRM capabilities play an important role in explaining customer engagement and customer satisfaction at the Ministry of Interior, UAE. However, the moderate R^2 values also indicate that other factors outside the scope of the present model may further explain these outcomes. Therefore, while the proposed model provides meaningful explanatory power, future studies may extend it by including additional variables such as service quality, trust in AI, digital literacy, perceived ease of use, data privacy concerns, and organisational support.

Overall, the R^2 results support the usefulness of the proposed AI-CRM framework. The findings indicate that the selected AI-CRM dimensions are relevant predictors of customer engagement and customer satisfaction, thereby providing empirical support for the proposed framework model.

4.5 Effect Size Assessment

Effect size was assessed using the f^2 value. The f^2 statistic measures the extent to which an exogenous construct contributes to the R^2 value of an endogenous construct when it is included in the structural model. While R^2 explains the overall predictive strength of the model, f^2 shows the unique contribution of each predictor construct. Cohen (1988) suggested that f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. In PLS-SEM, f^2 is particularly useful because a statistically significant path may still have a relatively small practical contribution to explaining the dependent construct.

The results in Table 6 show that most of the effects were small. The effect of Customer Engagement on Customer Satisfaction was 0.110, indicating a small effect that approached the medium effect level. This suggests that Customer Engagement made an important contribution to explaining Customer Satisfaction, although the effect was not large.

Among the predictors of Customer Engagement, Predictive Analytics had the strongest effect size, with an f^2 value of 0.094. This was followed by Sentiment Analysis with an f^2 value of 0.092, Chatbots and Virtual Assistants with an f^2 value of 0.087, Personalization with an f^2 value of 0.060, and Churn Prediction and Retention Tools with an f^2 value of 0.021. Although these values are classified as small effects, they indicate that each AI-enabled CRM factor contributed to explaining Customer Engagement.

Table 6. Effect size

Path	f^2	Interpretation
CE → CS	0.110	Small
CPR → CE	0.021	Small
CPR → CS	0.009	No meaningful effect
CVA → CE	0.087	Small
CVA → CS	0.038	Small
PA → CE	0.094	Small
PA → CS	0.022	Small
PER → CE	0.060	Small
PER → CS	0.023	Small
SA → CE	0.092	Small
SA → CS	0.020	Small

As shown in Table 6, the structural model did not contain any large effect sizes. However, this does not weaken the model, as small to moderate effects are common in social science, behavioural, and service management studies. Customer engagement and customer satisfaction are influenced by multiple factors, and no single AI-enabled CRM capability is expected to dominate the model entirely.

In practical terms, the Ministry of Interior, UAE should not rely on a single AI-CRM tool to improve customer engagement and satisfaction. Instead, the findings support an integrated AI-CRM framework that combines predictive analytics, churn prediction and retention tools, chatbots and virtual assistants, personalization, and sentiment analysis. When implemented together, these AI-enabled CRM capabilities can strengthen customer engagement and subsequently improve customer satisfaction.

Overall, the effect size results provide additional support for the proposed model. Although the individual effects were mostly small, the combined explanatory power of the model was moderate. This confirms that AI-enabled CRM capabilities are relevant and meaningful in explaining customer engagement and customer satisfaction in the Ministry of Interior, UAE context.

4.6 Model Fit Assessment

Although PLS-SEM is primarily prediction-oriented and focuses mainly on explained variance and predictive relevance, model fit may still be reported as supplementary evidence of model adequacy. In this study, model fit was assessed using the Standardised Root Mean Square Residual (SRMR). SRMR measures the difference between the observed correlation matrix and the model-implied correlation matrix. According to Henseler et al. (2016) and Hair et al. (2022), SRMR values below 0.08 generally indicate acceptable model fit.

As shown in Table 7, the SRMR value for both the saturated model and the estimated model was 0.042. This value was below the recommended threshold of 0.08, indicating that the discrepancy between the observed and model-implied correlations was low. Therefore, the model demonstrated an acceptable level of fit.

Table 7. SRMR model fit

Model	SRMR	Decision
Saturated Model	0.042	Acceptable fit
Estimated Model	0.042	Acceptable fit

The SRMR results in Table 7 provide additional support for the adequacy of the proposed AI-CRM model. The low SRMR value suggests that the model-implied correlation matrix was reasonably close to the observed correlation matrix, indicating that the model fits the data satisfactorily.

However, the SRMR result was interpreted as supplementary evidence rather than the primary basis for evaluating the model. This is because PLS-SEM is mainly used for prediction, theory development, and explaining variance rather than for covariance-based model fit assessment. Therefore, the model fit result should be considered together with the R^2 values, effect sizes, predictive relevance, and hypothesis testing results.

4.7 Results of Hypothesis Testing on the Model

The AI-CRM factors examined in the model were Predictive Analytics, Churn Prediction and Retention Tools, Chatbots and Virtual Assistants, Personalization, and Sentiment Analysis. Customer Engagement was examined as the mediating variable, while Customer Satisfaction was the final outcome variable. The results were assessed using path strength, t-statistics, and p-values. A hypothesis was considered supported when the t-statistic was greater than 1.96 and the p-value was less than 0.05.

4.7.1 Results of Direct Effects

Table 8. Results of direct effects

Hypotheses Code	Direct Path	Path Strength	t Statistics	p Values	Decision
H3	CE → CS	0.337	5.706	0.000	Supported
H2b	CPR → CE	0.109	2.587	0.010	Supported
H1b	CPR → CS	0.075	1.633	0.102	Not supported
H2c	CVA → CE	0.241	5.543	0.000	Supported
H1c	CVA → CS	0.169	3.552	0.000	Supported
H2a	PA → CE	0.241	6.063	0.000	Supported
H1a	PA → CS	0.124	2.545	0.011	Supported
H2d	PER → CE	0.203	4.364	0.000	Supported
H1d	PER → CS	0.133	2.984	0.003	Supported
H2e	SA → CE	0.236	5.676	0.000	Supported
H1e	SA → CS	0.116	2.465	0.014	Supported

Table 8 indicates that most of the direct relationships in the AI-CRM model were statistically supported. The strongest direct effect was found between Customer Engagement and Customer Satisfaction. Customer Engagement had a positive and significant effect on Customer Satisfaction, with a path strength of 0.337, t-statistic of 5.706, and p-value of 0.000. This supports H3 and confirms that customer engagement is a major determinant of customer satisfaction in the context of AI-enabled CRM services at the Ministry of Interior, UAE.

The findings also show that AI-CRM factors significantly enhance customer engagement. Predictive Analytics had a significant positive effect on Customer Engagement, with a path strength of 0.241, t-statistic of 6.063, and p-value of 0.000, supporting H2a. This implies that when the Ministry of Interior, UAE applies predictive analytics to anticipate customer needs, service demands, and behavioural patterns, customer engagement is likely to improve.

Churn Prediction and Retention Tools also had a significant positive effect on Customer Engagement, with a path strength of 0.109, t-statistic of 2.587, and p-value of 0.010, supporting H2b. This suggests that tools used to identify dissatisfied or disengaged customers can help the Ministry improve interaction, follow-up, and retention efforts.

Chatbots and Virtual Assistants significantly influenced Customer Engagement, with a path strength of 0.241, t-statistic of 5.543, and p-value of 0.000, supporting H2c. This result suggests that automated and intelligent service tools can improve customer interaction by providing quick responses, continuous availability, and easier access to public services.

Personalization also had a significant positive effect on Customer Engagement, with a path strength of 0.203, t-statistic of 4.364, and p-value of 0.000, supporting H2d. This means that when services are tailored to the specific needs, preferences, and profiles of customers, engagement with Ministry of Interior, UAE services is enhanced.

Similarly, Sentiment Analysis had a significant positive effect on Customer Engagement, with a path strength of 0.236, t-statistic of 5.676, and p-value of 0.000, supporting H2e. This indicates that analysing customer opinions, complaints, feedback, and emotions can help the Ministry better understand customer expectations and respond in ways that improve engagement.

With respect to direct effects on Customer Satisfaction, Predictive Analytics had a significant positive effect on Customer Satisfaction, with a path strength of 0.124, t-statistic of 2.545, and p-value of 0.011, supporting H1a. Chatbots and Virtual Assistants also had a significant positive effect on Customer Satisfaction, with a path strength of 0.169, t-statistic of 3.552, and p-value of 0.000, supporting H1c. Personalization significantly influenced Customer Satisfaction, with a path strength of 0.133, t-statistic of 2.984, and p-value of 0.003, supporting H1d. Sentiment Analysis also had a significant positive effect on Customer Satisfaction, with a path strength of 0.116, t-statistic of 2.465, and p-value of 0.014, supporting H1e.

However, the direct relationship between Churn Prediction and Retention Tools and Customer Satisfaction was not statistically significant. The path strength was 0.075, the t-statistic was 1.633, and the p-value was 0.102. Since the p-value was greater than 0.05, H1b was not supported. This means that Churn Prediction and Retention Tools may not directly improve customer satisfaction in the Ministry of Interior, UAE context. Instead, their value may be realised through improving customer engagement first.

4.7.2 Results of Indirect Effects

Table 9. Results of indirect effects

Hypotheses Code	Indirect Path	Path Strength	t Statistics	p Values	Decision
H5	CPR → CE → CS	0.037	2.307	0.021	Significant
H6	CVA → CE → CS	0.081	3.957	0.000	Significant
H4	PA → CE → CS	0.081	4.266	0.000	Significant
H7	PER → CE → CS	0.069	3.548	0.000	Significant
H8	SA → CE → CS	0.080	3.774	0.000	Significant

Table 9 indicates that all indirect effects were statistically significant. This confirms that Customer Engagement plays a significant mediating role in the relationship between AI-CRM factors and Customer Satisfaction at the Ministry of Interior, UAE.

The indirect effect of Predictive Analytics on Customer Satisfaction through Customer Engagement was significant, with a path strength of 0.081, t-statistic of 4.266, and p-value of 0.000. Therefore, H4 was supported. This suggests that Predictive Analytics improves customer satisfaction not only directly but also indirectly by strengthening customer engagement.

The indirect effect of Churn Prediction and Retention Tools on Customer Satisfaction through Customer Engagement was also significant, with a path strength of 0.037, t-statistic of 2.307, and p-value of 0.021, supporting H5. This result is particularly important because the direct effect of Churn Prediction and Retention Tools on Customer Satisfaction was not significant. Therefore, the findings suggest that Customer Engagement fully mediates this relationship. In practical terms, Churn Prediction and Retention Tools contribute to customer satisfaction when they are used to engage customers more effectively.

The indirect effect of Chatbots and Virtual Assistants on Customer Satisfaction through Customer Engagement was significant, with a path strength of 0.081, t-statistic of 3.957, and p-value of 0.000, supporting H6. This implies that Chatbots and Virtual Assistants enhance satisfaction by improving customer interaction, accessibility, response speed, and engagement with Ministry services.

Personalization also had a significant indirect effect on Customer Satisfaction through Customer Engagement, with a path strength of 0.069, t-statistic of 3.548, and p-value of 0.000, supporting H7. This means that personalized AI-CRM services improve satisfaction by making customers feel more recognized, understood, and effectively served.

Finally, Sentiment Analysis had a significant indirect effect on Customer Satisfaction through Customer Engagement, with a path strength of 0.080, t-statistic of 3.774, and p-value of 0.000, supporting H8. This shows that when the Ministry of Interior, UAE uses sentiment analysis to understand customer emotions, opinions, and feedback, it can improve engagement and, consequently, customer satisfaction.

Overall, the results demonstrate that AI-enabled CRM has a meaningful impact on Customer Satisfaction in the Ministry of Interior, UAE. The findings also confirm that Customer Engagement is a critical mechanism through which AI-CRM tools influence customer satisfaction. Therefore, the proposed AI-CRM framework for the Ministry of Interior, UAE should place Customer Engagement at the centre of AI-enabled CRM implementation. Predictive Analytics, Chatbots and Virtual Assistants, Personalization, Sentiment Analysis, and Churn Prediction and Retention Tools should not only be adopted as technological solutions but also integrated strategically to strengthen engagement, improve service responsiveness, and enhance customer satisfaction.

5. Discussion of the Findings

This section discusses the findings of the study in relation to the proposed AI-CRM framework for the Ministry of Interior, UAE. The discussion is based on the results of the structural model, which examined the effects of predictive analytics, churn prediction and retention tools, chatbots and virtual assistants, personalization, and sentiment analysis on customer satisfaction, with customer engagement serving as a mediating variable.

Overall, the findings indicate that AI-enabled CRM capabilities play an important role in improving customer engagement and customer satisfaction. The results also show that customer engagement is a central mechanism through which AI-CRM capabilities influence customer satisfaction. This supports the view that AI in CRM should not be understood only as a technological tool, but also as a strategic service capability that improves interaction, responsiveness, personalization, and customer value creation (Chatterjee et al., 2019; Dwivedi et al., 2021; Kumar, Sharma, & Dutot, 2023; Ozay et al., 2024).

5.1 Discussion of Predictive Analytics

The findings showed that predictive analytics had a significant positive effect on customer engagement and customer satisfaction. Predictive analytics significantly influenced customer engagement, with a path strength of 0.241, t-statistic of 6.063, and p-value of 0.000. It also had a significant positive effect on customer satisfaction, with a path strength of 0.124, t-statistic of 2.545, and p-value of 0.011. In addition, the indirect effect of predictive analytics on customer satisfaction through customer engagement was significant, with a path strength of 0.081, t-statistic of 4.266, and p-value of 0.000.

These findings suggest that predictive analytics is a key AI-CRM capability in the Ministry of Interior, UAE context. By using predictive analytics, the Ministry can anticipate customer needs, identify service demand patterns, predict potential service issues, and provide proactive support. This is consistent with Choudhury, Singh and Sharma (2023), who argued that predictive analytics enables organisations to use customer data to anticipate behaviour and improve CRM decision-making. Similarly, Davenport et al. (2020) highlighted the growing importance of AI and predictive analytics in strengthening business intelligence and improving decision quality.

The finding also agrees with Kumar and Reinartz (2022), who emphasized that advanced analytics in CRM can improve customer understanding and support more effective customer relationship strategies. In the context of public service delivery, predictive analytics can help the Ministry of Interior, UAE move from reactive service provision to proactive service management. This is particularly important because customers increasingly expect fast, accurate, and personalized digital services.

The significant indirect effect through customer engagement shows that predictive analytics improves satisfaction partly by increasing customers' interaction and involvement with services. This supports the argument that data-driven CRM capabilities are most effective when they are translated into meaningful customer engagement strategies (Kumar and Reinartz, 2021; Lemon and Verhoef, 2022). Therefore, predictive analytics should be positioned as a core component of the proposed AI-CRM framework.

5.2 Discussion of Churn Prediction and Retention Tools

The findings showed that churn prediction and retention tools had a significant positive effect on customer engagement, with a path strength of 0.109, t-statistic of 2.587, and p-value of 0.010. However, the direct effect of churn prediction and retention tools on customer satisfaction was not significant, with a path strength of 0.075, t-statistic of 1.633, and p-value of 0.102. The indirect effect through customer engagement was significant, with a path strength of 0.037, t-statistic of 2.307, and p-value of 0.021.

This result suggests that churn prediction and retention tools do not directly improve customer satisfaction in the Ministry of Interior, UAE context. Instead, their influence appears to operate through customer engagement. In other words, churn prediction tools are useful when they help the Ministry identify customers who may be dissatisfied, inactive, or disengaged, and then support targeted follow-up actions that improve engagement.

This finding is consistent with Kumar, Singh and Gupta (2022), who argued that machine learning approaches for churn prediction are useful for identifying customers at risk of leaving or disengaging. Similarly, Nguyen and Brown (2023) emphasized that AI-based retention strategies can help organisations respond more effectively to customer needs. However, the non-significant direct effect suggests that prediction alone is not enough to create satisfaction. The Ministry must act on the insights produced by churn prediction systems.

The result also aligns with Lee and Chen (2023), who noted that churn prediction models become more effective when customer feedback is integrated into the process. This means that churn tools should not only identify risk but should also guide service improvement, communication, and customer recovery strategies. In this study, customer engagement fully mediates the relationship between churn prediction and customer satisfaction. Therefore, churn prediction and retention tools should be treated as engagement-support tools rather than direct satisfaction-enhancing tools.

5.3 Discussion of Chatbots and Virtual Assistants

The findings revealed that chatbots and virtual assistants had a significant positive effect on both customer engagement and customer satisfaction. The effect on customer engagement was significant, with a path strength of 0.241, t-statistic of 5.543, and p-value of 0.000. The direct effect on customer satisfaction was also significant, with a path strength of 0.169, t-statistic of 3.552, and p-value of 0.000. In addition, the indirect effect through customer engagement was significant, with a path strength of 0.081, t-statistic of 3.957, and p-value of 0.000.

These findings indicate that chatbots and virtual assistants are important AI-CRM tools for improving service interaction at the Ministry of Interior, UAE. Chatbots can provide immediate responses, reduce waiting times, support customers outside normal working hours, and guide users through digital service processes. This finding supports Lee and Kim (2023), who argued that AI-powered chatbots are transforming customer service by improving response speed and accessibility. Similarly, Khneyzer, Boustany and Dagher (2024) highlighted that AI-driven chatbots provide economic and managerial benefits by improving CRM efficiency across industries.

The results are also consistent with Kumar, Singh and Gupta (2023), who found that chatbots can strengthen customer engagement by making customer interactions faster and more convenient. In the Ministry of Interior, UAE context, this is especially relevant because customers may require assistance with sensitive, urgent, or procedural public services. Chatbots and virtual assistants can support customers by providing clear information and reducing service complexity.

However, the Ministry should also be aware of chatbot limitations. Huang and Lee (2023) noted that chatbots may struggle with complex queries, while Khan, Ali and Patel (2023) suggested that hybrid models combining chatbots with human support may be more effective. Therefore, the proposed AI-CRM framework should integrate chatbots with human service agents, especially for complex or sensitive customer issues. This supports the idea of human-AI collaboration in customer service (Gnewuch, Morana, & Maedche, 2023).

5.4 Discussion of Personalization

The findings showed that personalization had a significant positive effect on customer engagement and customer satisfaction. The effect on customer engagement was significant, with a path strength of 0.203, t-statistic of 4.364, and p-value of 0.000. The direct effect on customer satisfaction was also significant, with a path strength of 0.133, t-statistic of 2.984, and p-value of 0.003. The indirect effect through customer engagement was also significant, with a path strength of 0.069, t-statistic of 3.548, and p-value of 0.000.

These findings suggest that personalization is an important factor in improving customer experience within the Ministry of Interior, UAE. Personalized services can include tailored notifications, relevant service recommendations, customized digital journeys, and targeted support based on customer profiles and previous interactions. This supports Choudhury and Kaur (2023), who argued that personalization plays an important role in driving customer engagement. Similarly, Kumar and Gupta (2022) found that data-driven personalization enhances customer satisfaction by creating more relevant and tailored customer experiences.

The findings also align with Lee and Kim (2023), who emphasized that AI and big data are increasingly shaping the future of personalization in customer experience management. In the public sector, personalization can help make services more citizen-centred by ensuring that customers receive information and support that are relevant to their needs. For the Ministry of Interior, UAE, personalization can improve satisfaction by reducing unnecessary effort and making services easier to access and complete.

However, personalization must be managed carefully because it depends heavily on customer data. Miller and Johnson (2023) and Nguyen and Tran (2023) highlighted the importance of balancing personalization with privacy and ethical considerations. Therefore, while personalization should be included in the proposed AI-CRM framework, it should be supported by strong data governance, transparency, and privacy protection.

5.5 Discussion of Sentiment Analysis

The findings indicated that sentiment analysis had a significant positive effect on customer engagement and customer satisfaction. The effect on customer engagement was significant, with a path strength of 0.236, t-statistic of 5.676, and p-value of 0.000. The direct effect on customer satisfaction was also significant, with a path strength of 0.116, t-statistic of 2.465, and p-value of 0.014. The indirect effect through customer engagement was significant, with a path strength of 0.080, t-statistic of 3.774, and p-value of 0.000.

These findings show that sentiment analysis is an important AI-CRM tool for understanding customer emotions, opinions, complaints, and feedback. Sentiment analysis can help the Ministry of Interior, UAE identify dissatisfaction, monitor customer perceptions, detect service problems, and respond more effectively to customer concerns. This finding is consistent with Jiang, Xu and Wang (2022), who described sentiment analysis as a useful tool for measuring customer satisfaction. Similarly, Kumar, Singh and Sharma (2023) highlighted the importance of sentiment analysis in customer experience management.

The significant relationship between sentiment analysis and customer engagement suggests that customers are more likely to engage when they feel that their feedback is heard and acted upon. This supports Wang, Chen and Zhang (2023), who argued that sentiment analysis can support customer engagement strategies by helping organisations understand customer attitudes and emotions. In the Ministry context, this means that sentiment analysis should be used not only for monitoring public feedback but also for improving service responses and strengthening trust.

However, the effective use of sentiment analysis depends on data quality, language accuracy, and ethical data use. Liu and Zhang (2023) noted that sentiment analysis continues to develop through advanced techniques and applications, but its accuracy may vary depending on context and data characteristics. Therefore, the Ministry should combine sentiment analysis with human review, especially when dealing with complex complaints or sensitive public service issues.

5.6 Discussion of the Mediating Role of Customer Engagement

One of the most important findings of this study is the mediating role of customer engagement. Customer engagement had the strongest direct effect on customer satisfaction, with a path strength of 0.337, t-statistic of 5.706, and p-value of 0.000. This confirms that customer engagement is a major determinant of customer satisfaction in the Ministry of Interior, UAE context.

This finding is consistent with Kumar and Reinartz (2021), who emphasized that engagement plays an important role in creating enduring customer value. It also supports Lemon and Verhoef (2022), who explained that customer experience should be understood across the customer journey rather than through isolated service interactions. In this study, customer engagement acted as the pathway through which AI-CRM tools improved customer satisfaction.

The mediation results showed that all AI-CRM factors had significant indirect effects on customer satisfaction through customer engagement. This means that predictive analytics, churn prediction and retention tools, chatbots and virtual assistants, personalization, and sentiment analysis are more effective when they enhance customer engagement. This is important because AI tools alone do not automatically create satisfaction. Their value depends on how they improve customer interaction, responsiveness, personalization, service accessibility, and trust.

The mediation result is especially important for churn prediction and retention tools. Since the direct effect of churn prediction and retention tools on customer satisfaction was not significant, but the indirect effect through engagement was significant, customer engagement appears to fully mediate this relationship. This means that churn prediction tools improve satisfaction only when they are used to engage customers more effectively.

5.7 Overall Discussion in the Ministry of Interior UAE Context

The findings are particularly relevant to the Ministry of Interior, UAE because public service organisations are increasingly expected to provide fast, reliable, personalized, and digitally enabled services. Al-Mansoori (2023) highlighted the importance of customer service dynamics in the Ministry of Interior's daily operations, while Almansoori and Al-Tahitah (2021) showed that artificial intelligence has a growing role in decision-making processes at the Ministry of Interior in the UAE.

The findings of this study extend this discussion by showing how AI-enabled CRM capabilities can improve customer engagement and customer satisfaction. The results suggest that AI should not be implemented only for automation or operational efficiency. Instead, AI-CRM tools should be designed to strengthen customer relationships, improve service responsiveness, and support more personalized customer experiences.

The findings also support the broader literature on AI-enabled CRM. Chatterjee et al. (2019) argued that organisations need readiness for effective AI-CRM integration, while Ahmad and Pande (2024) emphasized the importance of examining how AI can be integrated into CRM systems. Similarly, Sathyamoorthy and Pattabiraman (2024) noted that AI-driven CRM can improve customer relationship practices when implemented strategically.

Therefore, the proposed AI-CRM framework for the Ministry of Interior, UAE should place customer engagement at the centre of AI implementation. Predictive analytics, chatbots and virtual assistants, personalization, sentiment analysis, and churn prediction tools should be integrated as complementary capabilities. When these tools are used together, they can help the Ministry improve service quality, strengthen customer engagement, and enhance customer satisfaction.

5.8 Summary of the Discussion

In summary, the findings show that AI-enabled CRM capabilities have a meaningful influence on customer satisfaction at the Ministry of Interior, UAE. Predictive analytics, chatbots and virtual assistants, personalization, and sentiment analysis had significant direct effects on customer satisfaction. Churn prediction and retention tools did not directly influence customer satisfaction, but they had a significant indirect effect through customer engagement.

The results also confirm that customer engagement is a critical mediating variable in the AI-CRM framework. AI-CRM tools are most effective when they increase customer involvement, improve communication, support proactive service delivery, and create more personalized service experiences. Therefore, the Ministry of Interior, UAE should adopt an integrated AI-CRM framework that combines technology, customer engagement, service responsiveness, and ethical data management.

6. Conclusion

This study examined the impact of artificial intelligence in customer relationship management on customer satisfaction, with customer engagement serving as a mediating variable. The study was conducted within the context of the Ministry of Interior, UAE, with the aim of proposing an AI-CRM framework that can enhance customer satisfaction through improved engagement, responsiveness, and service delivery. The AI-enabled CRM factors investigated in the study were predictive analytics, churn prediction and retention tools, chatbots and virtual assistants, personalization, and sentiment analysis.

The findings confirmed that AI-enabled CRM capabilities play an important role in improving customer satisfaction at the Ministry of Interior, UAE. Specifically, predictive analytics, chatbots and virtual assistants, personalization, and sentiment analysis were found to have significant direct effects on customer satisfaction. This indicates that the adoption of AI technologies in CRM can improve service responsiveness, strengthen customer interaction, support personalized service delivery, and enhance the overall customer experience.

The study also found that customer engagement has a significant positive effect on customer satisfaction. This demonstrates that customer engagement is a key factor in improving satisfaction among customers of the Ministry of Interior, UAE. When customers are actively engaged, supported, and provided with timely, relevant, and accessible services, their satisfaction with the organisation is likely to increase.

Furthermore, the findings showed that customer engagement mediates the relationship between AI-enabled CRM factors and customer satisfaction. All indirect effects were statistically significant, confirming that AI-CRM tools are more effective when they strengthen customer engagement. This suggests that AI should not be implemented only for automation or operational efficiency, but also as a strategic tool for improving communication, interaction, responsiveness, and relationship management.

The result for churn prediction and retention tools was particularly important. Although churn prediction and retention tools did not have a significant direct effect on customer satisfaction, they had a significant indirect effect through customer engagement. This means that churn prediction and retention tools can enhance customer satisfaction when they are used to identify disengaged, dissatisfied, or at-risk customers and support them through effective engagement strategies. Therefore, customer engagement fully explains how churn prediction and retention tools contribute to customer satisfaction in this study.

Overall, the study concludes that AI in CRM has a meaningful impact on customer satisfaction at the Ministry of Interior, UAE. The findings provide empirical support for the proposed AI-CRM framework and show that customer engagement should be placed at the centre of AI implementation. Predictive analytics, churn prediction and retention tools, chatbots and virtual assistants, personalization, and sentiment analysis should be integrated into a unified AI-CRM framework that promotes customer engagement and improves customer satisfaction.

The successful implementation of this framework can support the Ministry of Interior, UAE, in delivering more responsive, customer-centred, data-driven, and technology-enabled public services. By using AI-CRM strategically, the Ministry can better understand customer needs, improve service quality, strengthen relationships with customers, and enhance satisfaction with public service delivery.

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