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ROLE OF AI-DRIVEN CUSTOMER RELATIONSHIP MANAGEMENT: AN EVALUATION OF CUSTOMER SATISFACTION, LOYALTY, AND INTERACTION RISKS

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ABSTRACT

Customer Relationship Management (CRM) is an AI-based innovation that combines effective technologies with the approaches and strategies of the company and customer-centered procedures in order to increase engagement, satisfaction, and loyalty, and introduce sustainable business operations. In the competitive digital market, customer retention is more cost-effective than customer acquisition, and it is vital to comprehend the aspects with direct effect on the performance of AI-powered CRM systems. The research considers how Employee Behavior (EB) and Employee Knowledge (EK), Customer Satisfaction (CS), and Customer Loyalty (CL) affect AI-based CRM effectiveness (CRME) in the context of online shopping. The research involved 293 Saudi Arabian participants who used AI-enabled platforms through structured questionnaires. Sentiment analysis was used to measure emotional reactions to customer reviews, identifying potential risks or dissatisfaction sources. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to estimate direct and indirect relationships. The results indicated that CS (β=0.34) and CL (β=0.29) had a significant influence on CRME. Other significant positive effects were EK (β=0.27) and EB (β=0.22), and, surprisingly, IR was found to have a negative effect (β=-0.18). The results confirmed the critical role of the combination of powerful information systems, the creation of informed and active workers, and the cautious use of AI-mediated customer relations to prevent possible threats. Lastly, companies can use such results to implement successful AI-based CRM initiatives that improve interaction, build loyalty, and facilitate sustainable long-term customer interactions with online businesses.

KEYWORDS: Artificial Intelligence (AI), Customer Relationship Management (CRM), Customer Loyalty (CL), Customer Satisfaction (CS), Sentiment Analysis.

1. INTRODUCTION

CRM represents a combination of corporate strategy, customer-focused processes, and computer technology. CRM, which stands for technology-centered relationship marketing, provides advantages through standard tactics and the technology used by e-business marketplaces to preserve client relationships. By bringing in and keeping customers and utilizing customer data, it is a crucial tool for creating long-term relationships and building connections with customers [1]. Digital transformation is accelerating the convergence of CRM as well as Artificial Intelligence (AI), along with technological breakthroughs, posing both potential and problems for strategic, operational, and analytical forms of CRM. To improve predictive analytics, chatbots, sentiment analysis, personalized recommendations, and voice recognition for more effective CRM, AI leverages Deep Learning (DL) with Machine Learning (ML) to gather information, identify patterns, decide, assess risks, and others [2].

1.1. AI Integration in CRM Systems

In today's competitive business world, client turnover has a huge influence on firms by cutting revenue and harming reputation. CRM is a combination of client contact information, interaction history, and previous purchases to offer a comprehensive understanding of client needs, real-time trend availability, churn forecasting, and targeted retention strategies that enhance CL and encourage the development of businesses in the long term [3]. A client-centric service strategy and customer retention are crucial for competitive advantage, given the financial sector's and the Internet's explosive growth. Banks can anticipate customer attrition, spot possible lost clients, improve goods and services, and create retention plans that prolong client life cycles and lower losses via data mining and analytics [4].

1.2. Customer Retention Strategies and Predictive Analytics

The development of technologies and AI-driven chatbots is transforming the travel experience and the communication of the destination. Chatbots enhance user satisfaction through personalization, interaction, and quick service by imitating the human dialogue, 24/7 serviceability, and successfully addressing consumer questions. The more extensively applied in the travel industry, the more consumer loyalty, purchase intention, communication, and service effectiveness are achieved through digital platforms [5]. Social networking sites are growing in popularity and changing the way customers are interacted with in marketing. Artificial intelligence-based solutions that control customer experience across touchpoints and enhance the quality of interaction. The increasing use of AI addresses privacy and skill level issues and enhances the performance of the operation and personalized experience, which further empowers CL [6].

1.3. AI Personalization Effect on Satisfaction and Loyalty

The AI-driven solutions, like individualized recommendation systems, transform consumer performance in the e-commerce industry by enhancing trust, satisfaction, and loyalty. The use of personalized suggestions that influence decision-making and control the relationship of trust and loyalty may help businesses to create end-lasting relationships, engage consumers intentionally, and build loyalty in online markets [7]. Due to algorithmic bias, inadequate training datasets, insufficient models, or historical and social circumstances, AI-driven marketing analytics in CRM raises Interaction Risks (IR) and ethical issues. The negative effects of unfair deployment include, but are not limited to, decreased customer equity, reduced access to marketing offerings, and equal access to marketing activities. The algorithms can be well controlled to minimize bias and protect the interests of the stakeholders [8].

1.4. Ethical Issues and Interaction Risks In AI-CRM

AI has become more widely used in a variety of industries, including CRM, via recent developments. AI-CRM provides automation, tailored offerings, and increased client engagement. Research is still scarce despite the adoption's sharp rise; new trends rely on early adoption goals, practical implications, and bridging the gap between organizational performance and individual user perception [9]. As attrition rates are high, customer expectations are changing, and old reaction methods are inadequate, it might be difficult to retain customers. Full integration of predictive analytics and machine learning with CRM systems, ensuring responsiveness in real time, and translating insights into consistent long-term loyalty and streamlined customer experiences are still problematic, although these technologies are becoming timelier in intervening and engaging with customers on a personalized level [10].

1.5. Sentiment Analysis and Consumer Insights

E-commerce AI sentiment analysis was a hybrid of classical ML and DL models used to analyze customer feedback and provide decisions [11]. There were challenges in maintaining the model transparency in the face of complexity but the results included more customer engagement, efficiency and accurate insights into consumer behaviors. To gain consumer confidence in AI-driven interaction, an emphasis on transparency and responsibility has also enhanced it, and explainable AI models are suggested to remove bias and enhance understanding [12]. Standard apprehensions of opacities, misinformation, and fairness were present, yet the information revealed that the policies of holistic transparency made people more confident and accepting of ethical AI usage and acceptance of AI-driven consumer interactions.

1.6. Accountable AI And Trust in Customer Interaction

The CRM system was also involved in AI integration to drive engagement and satisfaction through interpreting customer behavior, personalization of the service, and chatbots and predictive analytics [13]. While integrating management methods with client-centric strategies in competitive marketplaces presented challenges, the results showed improved decision-making, enhanced customer experience, bolstered business relationships, and improved long-term performance. The hyper- personalization provided by CRM relied on AI and ML to evaluate client's behaviors and preferences and adjusted interactions in real time, as well as recommend them individually [14]. The processing of the different data and orchestration of the omnichannel strategies was challenging but the outcomes showed that there were more contextually appropriate experiences that were provided in the touchpoints, greater emotional engagement, and higher CL and satisfaction.

1.7. AI-Driven Personalization and Hyper-Personalized Customer Relationship Management

Through data-driven automation, CRM with AI integration increased CS, service effectiveness, and tailored marketing for e-commerce businesses in Texas [15]. Although results showed overall improved CRM performance and competitive advantage due to the successful AI adoption, concerns were raised about data privacy and implementation costs. The Service Robot Acceptance Model, UTAUT2, trust-commitment theory, and parasocial relationship theory were employed to analyze the post-adoption behavior of AI-enabled services [16]. The outcomes showed that the performance anticipation, hedonic incentive, social impact, perceived correctness, and innovativeness played a positive role in enhancing engagement and continuance intentions, and the privacy concerns and the considerations of further usage were a challenge.

1.8. Artificial Intelligence (AI) Chatbots, Customer Loyalty, Service Efficiency.

The adoption of AI-based technology systems resulted in the efficiency of operational processes in customer service and the increase in customer satisfaction rates leading to the enhancement of CL [17]. Although the results indicated that the properly designed and responsive AI systems fostered trust, enhanced perceived service quality, and produced an urge to provide an ongoing interaction with the business, issues like the inability to meet diverse user expectations and ensure a perfect interaction arose. Multilevel data analysis was applied to the interaction between relationship investment and perceived innovativeness in an online poll of managers and the members of the private clubs [18]. The results indicated that relationship investment increased perceived innovativeness, resulted in positive word-of-mouth, a high degree of commitment level, and propensity to recommend, but there were challenges in aligning the managerial risk-taking with the expectations of the members.

1.9. CRM Performance, Innovation, And Data-Driven Automation

CRM acts as a key driver in reinforcing and prolonging client allegiance in commercial banking, which was examined while using quantitative methods, including descriptive and explanatory designs, and surveys [19]. Relationships and influence were assessed using regression and correlation analysis. Despite the difficulties in managing many CRM elements, the results showed that loyalty was positively impacted by competence, trust, commitment, communication, technology, and dispute resolution, with communication having a significant effect. AI's role in shaping modern e-commerce on CRM performance was investigated, considering the mediating function of CRM capabilities [20]. The model was tested using data from 193 firms. The challenges included comprehending effective AI deployment, whereas the outcomes revealed that AI increased CRM capabilities, which in turn enhanced CRM effectiveness, delivering significant both theoretical and empirical evidence for the implementation of AI.

The research explores how customer and employee factors affect CRME in e-commerce, specifically CS, CL, EK, EB, and IR. A quantitative, cross-sectional survey using a validated five-point Likert questionnaire was used, while PLS-SEM and CFA evaluated the structural associations, fit indices, and reliability metrics, offering guidance on optimizing customer interaction, retention, and the performance of AI-supported CRM systems.

1.10. Hypothesis Development

The research model analyzes the relationships between independent constructs such as CS, CL, EK, EB, and IR, with dependent constructs, including CRME in online shopping contexts. Existing literature shows that both human and technical elements influence customer experiences and retention outcomes.

Hypothesis (H1): Customer satisfaction is positively connected to AI-driven CRM effectiveness. **(CS) → (CRME)**

Hypothesis (H2): Customer loyalty is positively connected to AI-driven CRM effectiveness. **(CL) → (CRME)**

Hypothesis (H3): Employee knowledge is positively connected to AI-driven CRM effectiveness. **(EK) → (CRME)**

Hypothesis (H4): Employee behavior is positively connected to AI-driven CRM effectiveness. **(EB) → (CRME)**

Hypothesis (H5): Interaction risks are negatively connected to AI-driven CRM effectiveness. **(IR) → (CRME)**

The hypotheses together guide the empirical inquiry of the relationship between employee competency, customer perceptions, and CRME, providing insights into optimizing AI-mediated customer interaction techniques.

The remaining sections are organized as follows: Section 1 presents the research, evaluates the existing literature on AI-driven CRM, defines the key objectives, and develops the hypotheses. Section 2 describes the technique, which includes research design, data gathering, questionnaire construction, and statistical analysis. Section 3 summarizes the findings, encompassing CFA, reliability, discriminant validity, and structural model findings. Section 4 involves a discussion, conclusions, practical consequences, limitations, and suggestions for future research.

2. RESEARCH METHODOLOGY

Quantitative and analytical research design investigates the impact of variables of customers and employees on CRME in online shopping business. A total of 293 Saudi Arabian users that used AI-based platforms were surveyed using a designed questionnaire that collected CS, CL, EK, EB, and IR. To allow equal measurement of constructs, a five-point Likert scale was used in the questionnaire. Statistical analysis employs PLS-SEM, comprising CFA for validating reliability and validity constructs with structural model assessment to examine path significance, effect sizes, and explanatory power (R^2) to create strong insights about CRM effectiveness. Figure 1 depicts a schematic representation of the conceptual framework.

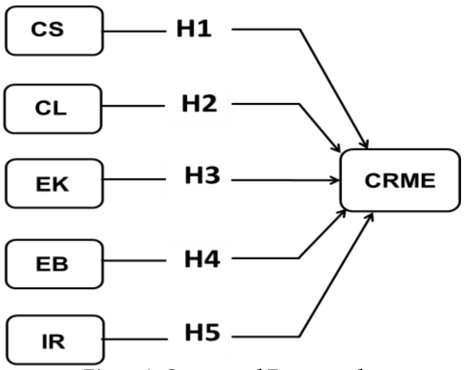

Figure 1: Conceptual Framework.

2.1. Research Design

Various factors using quantitative approaches were examined in the research that impact CRME in online retail environments. Data was collected using structured online surveys with 293 participants in

Saudi Arabia for attendance that assessed variables of CS, CL, EB, and EB. Furthermore, customer sentiment analysis of reviews on AI-enabled platforms was performed to measure emotional reactions and determine the risk of interaction. By combining the feedback and reviews of the survey and sentiment data, there is a large amount of data that can be examined in terms of performance effectiveness.

2.2. Data Collection and Sample

The sample of 293 online Saudi Arabian shoppers who engaged with AI-enabled systems was used to obtain data. CS, CL, EK, and EB, and perceived CRME were gathered through structured online questionnaires to gather information on CS. Sentiment analysis was also used to investigate customer feedback of these platforms to reveal emotion and possible IR. A summary of the demographic breakdown of the participants is provided in Table 1, and the pie chart in Figure 2 illustrates details of the participants by (a) age, (b) online shopping frequency, (c) platform of choice, and (d) satisfaction with the AI-assisted experience of shopping.

Table 1: Demographic Characteristics of Participants.

Demographic Factor	Group	Count (N=293)	Percentage (%)
Gender	Female	148	50.5
	Male	145	49.5
Age	18-25	72	24.6
	26-35	130	44.4
	36-45	61	20.8
	46+	30	10.2
Frequency of Online Purchases	Less than once a month	45	15.4
	1-3 times a month	128	43.7
	1-2 times a week	90	30.7
	More than twice a week	30	10.2
Type of Online Platforms Used	E-commerce marketplaces	175	59.7
	Brand-specific websites	88	30.0
	Mobile shopping apps	30	10.2
Shopping Experience with AI Tools	Less than 1 year	28	9.6
	1-3 years	102	34.8
	3-5 years	85	29.0
	More than 5 years	78	26.6

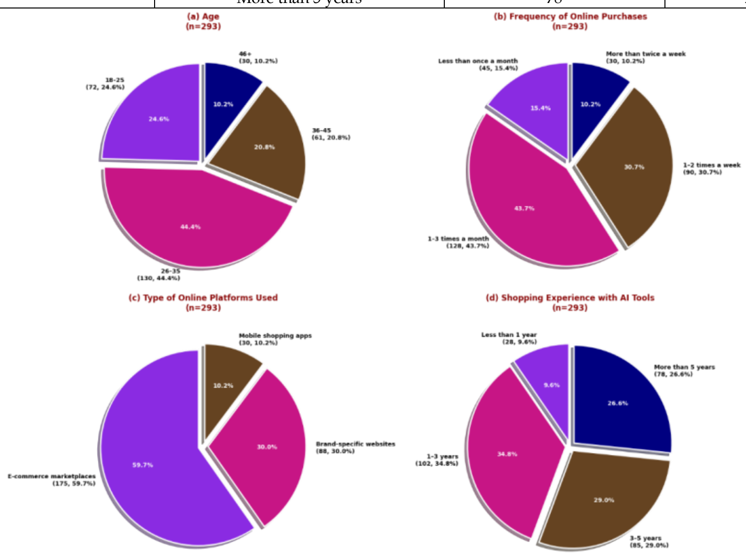

Figure 2: Demographic And Behavioral Breakdown of Participants.

2.3. *Questionnaire Design*

The survey was carried out on a sample of 293 online shoppers in Saudi Arabia who had interacted with AI-interfaces. The questionnaire was prepared based on five key concepts which were in line with the research hypotheses. Moreover, the stage obtained demographic and shopping-related information about the respondents including age, gender, online purchasing frequency, platform type, and experience with AI tools.

Demographics: The collected data included age, gender, preference for internet platforms, the number of times they buy products online, and their experience with artificial intelligence methods.

CS: Evaluated customer satisfaction with the use of AI-driven interactions, speed, personalization, and level of service. **CL:** Based on the preference of a specific brand, the frequency of use, and the inclination to recommend AI-enabled solutions. **EK:** The skill of the employees with goods, services and AI systems. **EB:** documented proactive, receptive, and sympathetic employee actions when interacting with AI, during consumer interactions. **IR:** Measured perceived inconveniences or inconveniences with AI, including trust problems, errors, and privacy. Questionnaire items are presented in Table 2 according to the variables.

Table 2: Questionnaire Structure and Variables.

Variables	Questionnaire Items
Customer Satisfaction (CS)	To what extent are you satisfied with the speed of responses you get using AI-enabled platforms? How much do you believe that AI suggestions suit your tastes? To what degree are you satisfied with the way your problems are resolved with the help of AI?
Customer Loyalty (CL)	What is the probability of using AI-enabled platforms to make future purchases? How would you rate your preference to some of the platforms based on AI-enhanced services? To what extent do you recommend AI-enabled platforms to other people?
Employee Knowledge (EK)	To what extent are employees knowledgeable on products/services in the context of assisting via AI platforms? How well do employees show proficiency in utilizing AI tools to facilitate your interactions? What is your confidence in the accuracy of the information that employees will give you in an interaction that is supported by AI?
Employee Behavior (EB)	To what extent are your employees proactive in responding to your concerns when they are interacting with AI? How do employees demonstrate compassion and empathy in helping with AI tools? What is the responsiveness of the employees in dealing with problems on AI-enabled platforms?
Interaction Risks (IR)	What is your level of concern regarding privacy concerns during your engagement with AI-enabled platforms? How much do mistakes or misadvise of AI make you less confident with the platform? Do you think you are likely to view AI interactions as either dangerous or annoying?

Each item was scored on a 5-point Likert scale (with 1 strongly disagree and 5 strongly agree). A pretest in the form of a questionnaire was conducted to ascertain that the questionnaire is clear and relevant, and reliable, and the questionnaire was refined to achieve a better quality of data collection.

2.4. *Statistical Analysis*

Analysis operations were done on the SPSS platform, which is comprises with PLS-SEM and CFA to generate adequate statistical estimation and model validation. The software aided hypothesis testing based on path analysis and significance assessment, which allowed one to extensively investigate the validity, reliability, and inter-construct interactions.

3. RESULTS

The PLS-SEM was applied to test the hypothesized relationships between customer and employee variables and CRME, with provisions that online consumers form more than one construct as the sample size. The CFA test was used to test the measurement model in which reliability and construct validity of CS, CL, EK, EB, and IR were ensured. The analysis also combined both measurement and structural models to give a strong result by assessing the explanatory power (R^2), the level of significance, t-values, and path coefficients, which gave a comprehensive understanding of what affects the success of CRM.

3.1. *CFA Test*

CFA was used to test the measurement model that was designed to measure the latent constructs of CRME and its determinants such as IR, EK, EB, CS, and CL. CFA calculated the relationship between the indicators observed and the latent variables between the observed and the latent variables, such that the items to be measured are sufficient for the theoretical dimensions. The basic aim was to determine convergent and discriminant validity, internal consistency, before the assessment of the structural model. Computation of the CFA test was done using Equations (1-2).

1) $X = \Lambda_x$

2) $Y = \Lambda_y \eta + \epsilon$

In this notation, X and Y denoted observed indicators (independent and dependent constructs), Λ_x and Λ_y indicated observed indicator factor loading matrices and latent constructs (ξ and η), and 8 (δ and ϵ) denoted measurement error. Table 3 illustrates results of CFA and Figure 3 illustrates the path diagram with a factor loading.

Table 3: Reliability And Validity of Constructs.

Latent Construct	Items	Loading Value	M	SD	Alpha (α)	Composite Reliability (CR)	AVE	DG rho	VIF
CS	CS1 CS2 CS3	0.86 0.83 0.79	3.9	0.74	0.87	0.90	0.68	0.84	2.1
CL	CL1 CL2 CL3	0.88 0.84 0.80	3.8	0.72	0.88	0.91	0.70	0.86	2.2
EK	EK1 EK2 EK3	0.84 0.81 0.77	3.7	0.70	0.86	0.89	0.67	0.83	2.0
EB	EB1 EB2 EB3	0.82 0.80 0.75	3.8	0.73	0.85	0.88	0.64	0.81	2.1
IR	IR1 IR2 IR3	0.79 0.76 0.73	3.6	0.71	0.80	0.86	0.61	0.79	1.9
CRME	CRME1 CRME2 CRME3	0.89 0.86 0.82	4.0	0.77	0.89	0.92	0.71	0.85	2.3

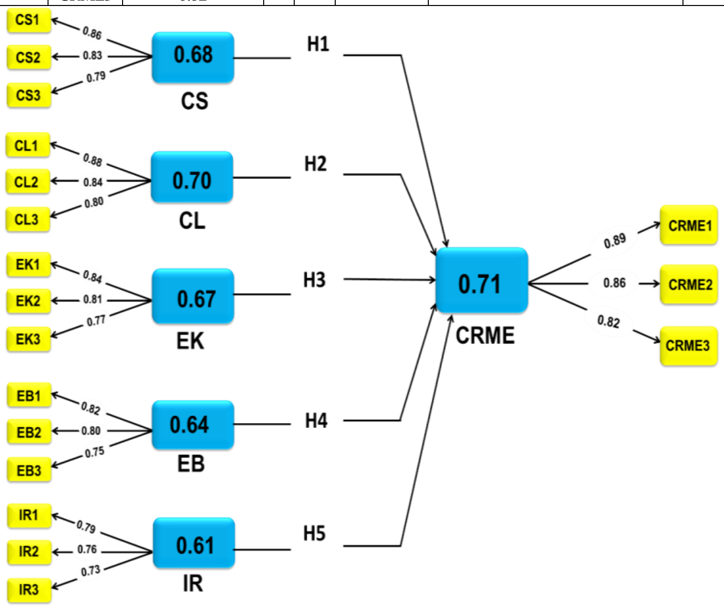

Figure 3: Visual Representation of Construct Relationships.

The outcome of CFA showed that the constructs demonstrated high internal consistency and high convergent validity of all constructs. Precisely, at CR and factor loading of more than 0.70 and AVE of more than 0.50, the model was found to meet the stipulated conditions of measurement robustness. VIFs less than 5 showed that multicollinearity is not a problem, and appropriate DG rho levels validated that discriminant validity is acceptable. The reliability of each of the constructs quantifies the desired latent variables, providing a solid foundation to further structural model studies of the effectiveness of AI-driven CRM.

3.2. Pls-Sem

PLS-SEM was applied to test the hypothesized relationships in which CRME was the dependent variable and CS, CL, EK, EB, and IR were independent variables. SEM can calculate the exact explanatory power R 2, path coefficients, and level of significance, and can test many connections simultaneously, with consideration of measurement errors. Direct and indirect impacts were considered in the analysis, which made it possible to create a complete portrait of how customer and employee factors affect the success of CRM in online purchases using AI.

3.2.1. Discriminant Validity Test

Every latent variable must be substantially different from the other constructs, corresponding to the principle of discriminant validity. As measured by Average Variance Extracted (AVE), which is derived in Equation (3), a construct is said to exhibit discriminant validity according to the Fornell-Larcker Criterion when it explained more variance in its indicators than it shared with other constructs.

3) $AVE_i > r_{i,j}$

Where AVE_i represents the AVE for construct i, and r_{ij} refers to the correlation between constructs i and j. The test demonstrates that the constructs of CS, CL, EK, EB, IR, and CRME present independent concepts in AI-driven CRM evaluation. Determining discriminant validity promotes accurate interpretation of structural connections and increases reliability in the measuring model. Table 4 reveals discriminant validity outcomes among the constructs.

Table 4: Assessment Of Discriminant Validity.

Constructs	CS	CL	EK	EB	IR	CRME
CS	**0.825**					
CL	0.612	**0.837**				
EK	0.548	0.584	**0.819**			
EB	0.523	0.558	0.601	**0.800**		
IR	−0.416	−0.432	−0.389	−0.364	**0.782**	
CRME	0.688	0.721	0.641	0.603	−0.471	**0.849**

The outcomes demonstrated strong discriminant validity, as all the diagonal values are greater than the off-diagonal correlation values in its corresponding columns and rows. The result supported a precise estimate of linkages in the structural model by confirming that each construct captured distinct variance.

3.2.2. Structure Model

An evaluation of the structural model was conducted to examine how the variables relate to each other and the reliability of these relationships among independent variables such as CS, CL, EK, EB, and IR with the dependent variable, CRME. The model was determined using Equation (4).

$$CRM\_E = \beta_1 CS + \beta_2 CL + \beta_3 EK + \beta_4 EB + \beta_5 IR + \zeta 1 \qquad (4)$$

Where CRM_E denotes CRME, $\beta_1, \beta_2, \beta_3, \beta_4$,and β_5 represents standardized path coefficients, and ζ_1 refers to the residual error term. Standardized path coefficients (β) represent the magnitude of influence, whereas R^2 values measure the proportion of explained variance. Significance levels (p-values) and t-values verify the strength of hypothesized relationships. All paths were highly significant at $p < 0.01$, proving that the model in question is effective in capturing the role played by customer and employee elements on CRM effectiveness. Table 5 and Figure 4 demonstrate hypothesized structural relationships.

Table 5: Structural Paths and Hypotheses.

Hypothesis	Path Relationship	β	p-value	t-value	Decision
H1	CS → CRME	0.34	0.000	5.86	Supported
H2	CL → CRME	0.29	0.000	5.21	Supported
H3	EK → CRME	0.27	0.001	4.57	Supported
H4	EB → CRME	0.22	0.002	3.94	Supported
H5	IR → CRME	-0.18	0.005	3.16	Supported (Negative)

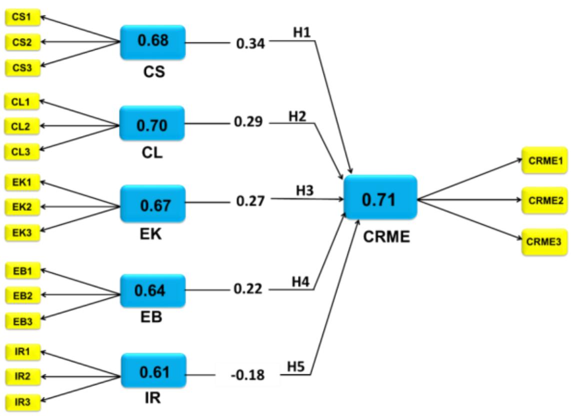

Figure 4: Structural Model.

H1 (CS → CRME): CS demonstrated a statistically significant positive relationship with CRME (β = 0.340). The path strongly supports H1 and is very significant (t = 5.86, p < 0.001).

H2 (CL → CRME): CL significantly, positively affects CRME, with β = 0.290. The statistical relationship is significant (t = 5.21, p < 0.001), which verifies H2.

H3 (EK → CRME): EK has a significant impact on CRM effectiveness, as indicated by a standardized coefficient of β = 0.270. The path coefficient is statistically significant (t = 4.57, p = 0.001), supporting H3.

H4 (EB → CRME): EB has a positive impact on CRME with β = 0.220. The relationship is significant (t = 3.94, p = 0.002), affirming H4.

H5 (IR → CRME): IR reduces CRM effectiveness (β = -0.180). The path is significant (t = 3.16, p = 0.005), which supports H5.

The structural model explains 68% of CRME variance (R^2 = 0.68), supporting the predicted linkages and displaying significant explanatory power.

In summary, CS and CL have the biggest positive impacts on CRME, followed by EK and EB. In contrast, IR has a significant negative impact. The model demonstrates significant variance (R^2 = 0.68), supporting the expected structural links.

4. DISCUSSION

The effects of EK, EB, CS, CL, and IR on CRME in online purchasing environments were examined in the research. The study by Akter et al. showed that algorithmic bias in AI-driven CRM created and presented significant interaction risks via data, model, and deployment inadequacies that might reduce customer equity and limit fair access to marketing offerings [8]. Algorithmic management across three key capability domes and nine subdomes protected stakeholder interest (by reducing bias) and ensured that human caregivers are at the core.

On other hand, the study by Randhawa denoted that the relationship investment directly increased innovativeness, which was perceived, and positively affected customer commitment, recommendation willingness, and word-of-mouth generation [18]. However, the alignment of managerial propensity to take risk and expectations of members was not an easy task because it was a moderator of the investment-innovativeness relationship and tended to directly affect the customer's perceptions of innovation.

In contrast, for the present study, the PLS-SEM analysis showed that, except for the moderating influence between CS and EK, all hypothesized relations were statistically significant. CS (β = 0.34, t = 5.86) and CL (β = 0.29, t = 5.21) significantly impact CRM effectiveness, demonstrating that satisfied and loyal customers evaluated AI-enabled platforms as more reliable and valuable. Both EK ($\beta = 0.27$) and EB ($\beta = 0.22$) had significant positive impacts, which further indicates the need to employ trained and active individuals to facilitate AI features. CRME was hurt by IR ($\beta = -0.18, \mathrm{t} = 3.16, \mathrm{p} = 0.005$), which claims that customer confidence had already been damaged by such issues as data privacy issues, algorithm bias, and the lack of transparency. The structural model is very explanatory ($R^2 = 0.68$), which means that these variables accounted 68 percent of the variance in CRME. The findings outline that CRME should be improved with the blend of the personnel competency, the customer-focused tactics, and the technology reliability.

Overall, the findings demonstrated that, even though the reduction of IR remained a key to maintaining the credibility of the system, integrated application of human intuition and AI potential enhanced the customer satisfaction and loyalty to the overall outcomes of CRM.

5. CONCLUSION

The importance of the customer and employee variables in the determination of CRME was evaluated in the context of internet shopping. There were five hypotheses that were tested to assess the effects of CS, CL, EK, EB and IR on CRM performance. It was quantitatively and analytically designed to collect data of 293 online consumers in Saudi Arabia based on a structured five-point Likert scale. The SPSS and PLS-SEM were used to model the statistics and CFA was used to test reliability and validity, and structural modeling was used to test the path significance, effect size and explanatory power. The findings showed that IR impacted CRME (β = -0.18, t = 3.16, p = 0.005), CS (β = 0.34, t = 5.86, p < 0.001), CL (β = 0.29, t = 5.21), EK (β = 0.27, t = 4.57), and EB (β = 0.22, t = 3.94) had a negative effect. With an R^2 of 0.68, the model described 68% of the variance, supporting every hypothesis. It was found that better customer experience and employee competence, along with the prevention of IR, had a significant impact on the performance of AI-based CRM and the involvement in digital commerce. The constraints were not taking into account the ethical and privacy considerations of the AI interactions that could lower consumer trust and CRM effectiveness and the inability to address the latest technologies, such as chatbots, recommendation engines, and customization algorithms. To enhance the creation of more efficient and trustworthy CRM systems, the future research can examine how the integration of AI-based CRM with these technologies can enhance online shopping experience and loyalty as well as consider ethical considerations, data security, reduction of bias, and transparency.

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