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SUPERCHARGING CRM WITH AI: THE POWER OF READINESS, SUPPORT, IDENTIFICATION, AND TRUST DYNAMICS

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ABSTRACT
This study examines the impact of Artificial Intelligence (AI) adoption, technological readiness, and organizational support on Customer Relationship Management (CRM), with Customer Identification as a mediating variable and Customer Trust as a moderator. Drawing on a sample of 300 respondents across technology, finance/banking, healthcare, and retail sectors in Pakistan, the study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to test eleven hypotheses. Findings reveal that AI adoption (β = .456), organizational support (β = .403), and technological readiness (β = .329) significantly predict Customer Identification, which in turn strongly predicts CRM (β = .699). Customer Identification fully mediates the relationships between the three antecedents and CRM. However, the moderating effect of Customer Trust on the Customer Identification–CRM relationship was not statistically significant (β = .136, p = .057). The study contributes to the literature by integrating resource-based and social identity theories in the context of AI-driven CRM. Practical implications for managers and directions for future research are discussed.

Keywords: artificial intelligence adoption, technological readiness, organizational support, customer relationship management, customer identification, customer trust

INTRODUCTION
The high rate of digitization of the business processes has essentially re-defined the way organizations can manage and maintain relationships with their customers. Artificial intelligence

(AI) has become a disruptive technology in contemporary business ecosystems that allows companies to gather, process, and take action on customer data in the most significant volume and speed (Davenport et al., 2020). In the Customer Relationship Management (CRM) field, AI can be used to provide the abilities of predictive analytics and individualized communication, as well as automated customer support and clever segmentation. Such developments have transformed CRM into a reactive practice that has a transactional nature to a proactive approach that has the ability to predict the customer needs in real-time (Huang & Rust, 2021).

However, the implemented AI in CRM is not always successful due to the technology. It is heavily reliant on the preparedness of the technological infrastructure in an organization (Sarwar et al., 2025) and the extent of organizational support offered to individuals and departments dealing with customers (Merkel et al., 2021). Technological readiness involves how individuals and firms are inclined towards the adoption and use of new technologies with effectiveness, whereas the organizational support is the policies, resources, and culture that makes employees use these technologies in the delivery of customer oriented objectives. Even though the overall effect of AI implementation, technological readiness, as well as organizational-level support on CRM outcomes, are intuitive, they are not studied within the context of a comprehensive theoretical framework.

One of the most significant yet neglected ways of how these factors could affect CRM is Customer Identification the level of how customers feel that they share values and identity with a company (Shehzadi et al., 2026). The more technologically advanced organizations are, the more sufficient support infrastructure available, and the more they implement AI in a manner that is both transparent and customer-centric, the higher chances they have of creating a sense of shared identity with the customers. This identification, in its turn, can increase the engagement, loyalty, and the overall quality of relationship of the customers which are the main goals of any decent CRM tool.

Moreover, Customer Trust is another element that should be looked at as a possible limit of such relationships. Trust has been traditionally viewed as one of the pillars of sustainable customer relationships. Trust, in the context of AI-based CRM, in which algorithmic decision-making and data privacy issues are relevant, might mediate the level on which Customer Identification is converted into valuable CRM results. Customers with trust in an organization will react positively when AI is used in communication, and less trustful customers will oppose even a well-planned CRM program (Choung et al., 2023).

Scope of the Study

The target market of this research is staff and professional people who work in the customer facing job sector in the technology, finance/banking, healthcare and retail/e-commerce industries in Pakistan. These industries have been chosen because they are well developed in terms of AI implementation and they are more dependent on CRM systems in order to maintain a competitive advantage. This paper uses an individual level unit of analysis which quantifies perceptions of AI adoption, organization support, technological preparedness, customer identification, CRM quality, and customer trust by using a standardized survey tool, which was given to 300 respondents.

Research Objectives

The following objectives are followed in the study:

- ✓ To investigate the direct impact of AI implementation, technological preparedness, and organizational assistance on Customer Identification.
- ✓ To explore the mediating between Customer Identification in the relationship among the three antecedents and CRM.
- ✓ To test the direct impact of Customer Identification on CRM.
- ✓ To determine the moderation of Customer Identification–CRM relationship by Customer Trust.

Research Questions

The following are the research questions that have been addressed in the study:

- ➢ Does the use of AI, technology preparedness, and organizational support play a major role in Customer Identification?
- ➢ Does Customer Identification moderate the AI adoption, technological readiness, organizational support and CRM relationship?
- ➢ Does Customer Trust mediate the Customer Identification on CRM?

LITERATURE REVIEW

Customer Relationship Management and AI Adoption.

Ai adoption in the organizational setting can be defined as the degree of the integration of intelligent, data-driven technologies in the operational and strategic activities of companies (Dwivedi et al., 2021). In the marketing and customer management field, AI can be used to customize interactions, streamline service delivery, and forecast customer behavior more accurately than ever (Davenport et al., 2020). According to the prior studies, the companies that make use of AI in their CRM systems attain greater customer satisfaction, retention, and revenue performance (Huang & Rust, 2021). It is therefore hypothesized that the implementation of AI will have a positive impact on the quality of CRM directly and indirectly.

Technological Readiness

The technological readiness which has been defined as the inclination of people to adopt and apply new technologies in achieving goals by (Parasuraman, 2000) has emerged as a very important construct in the field of organizational behavior and marketing research. According to the Technology Readiness Index, there are four dimensions, namely optimism, innovativeness, discomfort, and insecurity, that influence the way people relate to digital systems (Sarwar et al., 2025). When considering AI-enabled CRM, the collective technological preparedness of organizations plays in their favor as they will be in a better position to adopt advanced tools successfully, reduce resistance, and provide customers with better experiences. When employees feel their organization is technologically competent to do so, they are more likely to enable customer-facing digital innovations, which help to achieve better CRM results.

Organizational Support

The original organizational support theory, which was developed by (Merkel et al., 2021) suggests that employees develop beliefs regarding the extent to which their organization cares about them and the importance it attributes to their input. This perceived support increases commitment, motivation, and performance of the employees (Merkel et al., 2021). The organizational support offered in the AI-driven work environment goes beyond interpersonal concern to include provision of training, resources, and even policies that can help in effective use of technology. Employees tend to adopt relationship-oriented behaviors, which affect the quality of CRM positively, when they feel that their organization encourages the use of AI and offers the tools that are required in customer management.

Mediator Customer Identification

Social identity theory-based Customer Identification is an explanation of how much a customer cognitively connects his identity with a company (Shehzadi et al., 2026). When the customers feel that there is a fit between their values and the practices of the firm, such as the high-level of technology and its application in a morally sound manner, the customers become more attached to the firm in terms of the shared identity. This recognition develops loyalty, advocacy, and relationship depth, which are the main focus of successful CRM (Krishna & Kim, 2021). The current research assumes that Customer Identification is brought about by AI adoption, technological readiness, and organizational support, and it is through this that these antecedents affect CRM performance.

Customer Trust as a Moderator

Trust is readiness to be vulnerable due to positive intentions regarding the actions of another party. Customer trust has acquired an even greater importance in online and AI-mediated space where consumers consider the value of personalized service against the risk of data privacy breaches, algorithmic bias or organizational motives (Choung et al., 2023). The hypothesis is that trust could have a positive impact in strengthening the positive influence of Customer Identification on CRM since the likelihood of customers returning relational investment of organizations is higher when they trust them. Nevertheless, there is still limited empirical data regarding trust as a moderator in AI-CRM relationships, which justifies the exploration of the topic in the present study.

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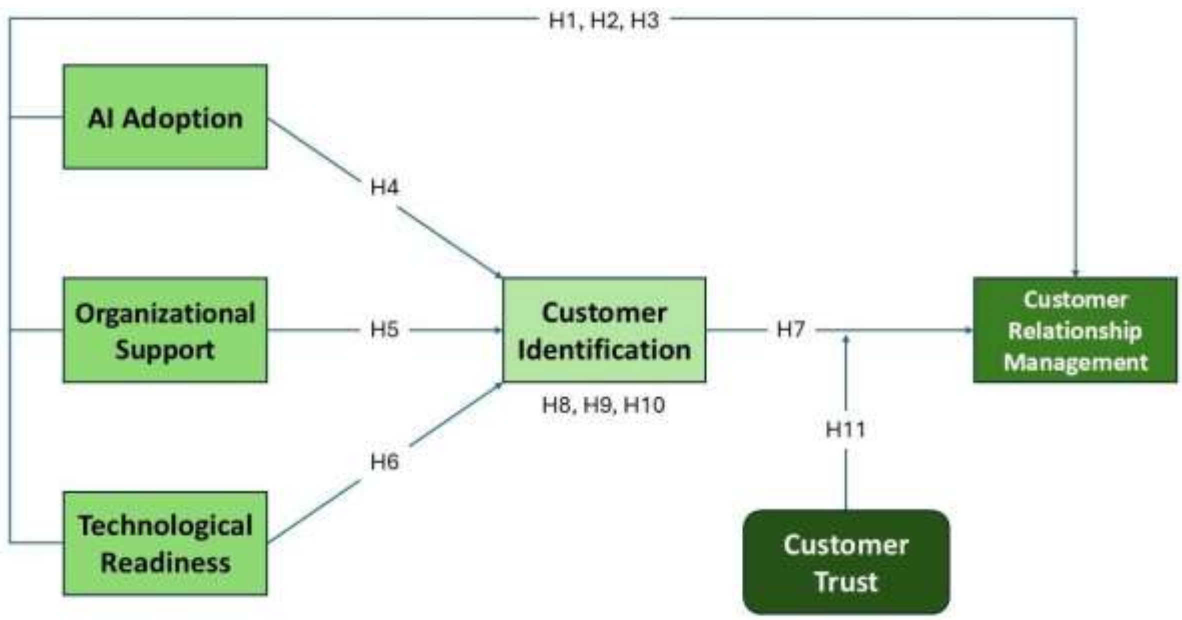

Hypotheses Development

Based on the theoretical background of the studies described above, the subsequent hypotheses are made:

H1: There is a positive effect on CRM due to AI adoption.
H2: Organizational support has a positive overall impact on CRM.
H3: Technological preparedness has a positive effect on CRM (combinative).
H4: AI adoption positively influences Customer Identification.
H5: Organizational support positively influences Customer Identification.
H6: Technological readiness positively influences Customer Identification.
H7: Customer Identification has positive effect on CRM.
H8: Customer Identification is an intermediate of AIA and CRM relationship.
H9: There is a mediating role of Customer Identification between the OS and CRM.
H10: Customer Identification Mediates TR CRM relationship.
H11: Customer Trust has a mediating effect on Customer Identification -CRM relationship.

RESEARCH METHODOLOGY

Research Design and Sample

The research design is a quantitative and cross-sectional survey research. Two hundred and thirty-two respondents in the field of technology, 253 in the field of finance/banking, 257 in the field of healthcare, 167 in the field of retail/e-commerce and 87 in the field of other sampled the questionnaires. The sample was gender balanced both males and females. Most of the respondents

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were 25-44 years old, had at least bachelor's degree, and had one-ten years of work experience. The use of purposive sampling was to make sure that the respondents had sufficient experience with AI-enabled tools in customer-facing positions.

Measuring of all constructs was done with validated multi-item scales based on previous literature. The scales of AI Adoption (AIA; 4 items), Organizational Support (OS; 4 items), and Technological Readiness (TR; 4 items) were administered in a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Customer Identification (CI; 5 items) and Customer Relationship Management (CRM; 5 items) were based on the works by (Bhattacharya & Sen, 2003) and Chatterjee et al. (2022), respectively. Customer Trust (CT; 4 items) was measured in dependence on the dimensions of trust as proposed by (Ahearne et al., 2005).

The analysis of data was conducted with the help of Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS 4.0. The method PLS-SEM was chosen because it is appropriate to the working with complicated structural models, and it is powerful when the data is non-normally distributed (Hair et al., 2019). To evaluate path significance, mediation and moderation effects, bootstrapping using 5,000 subsamples was used to determine the significance of a path. IBM SPSS statistics generated descriptive statistics and correlation matrices (George & Mallery, 2019). The level of effects was assessed based on the f^2 criteria of.

DATA ANALYSIS AND RESULTS

Descriptive Statistics

Table 1
Demographic Profile of Respondents (N = 300)

Characteristic	Category	*f*	%
Gender	Male	150	50.0
	Female	150	50.0
Age Group	Below 25	39	13.0
	25–34	90	30.0
	35–44	93	31.0
	45–54	50	16.7
	55 and above	28	9.3
Education Level	Matric / O-Level	38	12.7
	Intermediate / A-Level	104	34.7
	Bachelor's	113	37.7
	Master's & above	45	15.0
Work Experience	Less than 1 year	50	16.7
	1–5 years	88	29.3
	6–10 years	99	33.0
	More than 10 years	63	21.0
Industry	Technology	71	23.7

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	Finance / Banking	76	25.3
	Healthcare	77	25.7
	Retail / E-commerce	50	16.7
	Other	26	8.7

Note. f = frequency. The sample was also equally gender-distributed. Most of the respondents were aged between 25 and 44 years (61%), had a bachelor degree (52.7%), and had 1-10 years of work experience (62.3%).

The demographic profile of the respondents (N = 300) is shown in Table 1. Table 2 shows the descriptive statistics of all the six constructs. The standard deviations were 0.836 to 0.905 and the mean scores were 3.262 (Customer Trust) to 3.430 (Technological Readiness), which means that all items were agreed upon in a moderate to strong manner. The value of skew and kurtosis were within the acceptable range of ±2, which proves the approximate normality (George & Mallery, 2019).

Descriptive Statistics

Table 2
Descriptive Statistics

Construct	Items	N	M	Mdn	SD	Min	Skewness	Kurtosis
AI Adoption (AIA)	AIA1–AIA4	300	3.408	3.500	0.905	1.00–5.00	−0.378	−0.416
Organizational Support (OS)	OS1–OS4	300	3.367	3.500	0.892	1.25–5.00	−0.181	−0.578
Technological Readiness (TR)	TR1–TR4	300	3.430	3.500	0.876	1.25–5.00	−0.429	−0.338
Customer Identification (CI)	CI1–CI5	300	3.369	3.400	0.886	1.00–5.00	−0.400	−0.443
CRM	CRM1–CRM5	300	3.338	3.400	0.836	1.00–5.00	−0.133	−0.488
Customer Trust (CT)	CT1–CT4	300	3.262	3.250	0.890	1.00–5.00	−0.077	−0.714

Note. Everything was measured on a 5-point Likert scale (1 = strongly disagree, to 5 = strongly agree). The values of skewness and kurtosis are within a normal range (±2) which suggests a normal distribution (George & Mallery, 2019).

Constructs have moderate values of means (~3.263.43), which reflect neutral-positive responses. The standard deviations (~0.83 0.90) indicate that there is not high dispersion but rather reasonable variability. Skewness and kurtosis are within the range of the values of 2 which verify the approximate normal distribution. On the whole, data are clean, balanced and can be analyzed using parametric and SEM (Sarwar et al., 2025).

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Measurement Model Assessment

Table 3
Outer Loadings (Measurement Model)

Indicator	Construct	Loading (λ)	*SD*	*t*	*p*
AIA1	AI Adoption	.779	.027	28.380	.000
AIA2	AI Adoption	.715	.039	18.414	.000
AIA3	AI Adoption	.738	.034	21.383	.000
AIA4	AI Adoption	.788	.028	27.862	.000
OS1	Organizational Support	.791	.028	28.491	.000
OS2	Organizational Support	.776	.034	22.711	.000
OS3	Organizational Support	.680	.046	14.701	.000
OS4	Organizational Support	.769	.035	21.783	.000
TR1	Technological Readiness	.751	.047	15.856	.000
TR2	Technological Readiness	.820	.035	23.469	.000
TR3	Technological Readiness	.754	.045	16.894	.000
TR4	Technological Readiness	.689	.054	12.720	.000
CI1	Customer Identification	.686	.041	16.792	.000
CI2	Customer Identification	.770	.028	27.511	.000
CI3	Customer Identification	.711	.033	21.816	.000
CI4	Customer Identification	.696	.035	20.063	.000
CI5	Customer Identification	.659	.042	15.788	.000
CRM1	CRM	.722	.029	25.095	.000
CRM2	CRM	.680	.039	17.361	.000
CRM3	CRM	.732	.032	22.793	.000
CRM4	CRM	.681	.037	18.300	.000
CRM5	CRM	.719	.035	20.415	.000
CT1	Customer Trust	.789	.367	2.153	.031
CT2	Customer Trust	.116	.311	0.374	.708
CT3	Customer Trust	.102	.321	0.319	.750
CT4	Customer Trust	.692	.329	2.102	.036

Note. All the outer loadings of AIA, OS, TR, CI, and CRM are more than the recommended figure of.650 (Hair et al., 2019). *The threshold was not reached by CT2 and CT3.*

Table 4 shows the outer loading of all the indicators. The values in all the fields of AI Adoption, Organizational Support, Technological Readiness, Customer Identification, and CRM were greater than the suggested value of .650 (Hair et al., 2019). The Customer Trust scale (CT2 =.116; CT3 =.102) had two items that did not pass this criterion and were identified as weak measures. Construct reliability and validity are reported in Table 5. All constructs had the acceptable value of alpha of Cronbach of .70. The AVE was over.50 in all constructs except Customer Trust (AV=.281), which suggests that there may be some convergent validity issues with the trust construct.

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Construct Reliability

Table 5
Construct Reliability and Validity

Construct	Cronbach's α	AVE
AI Adoption (AIA)	.750	.571
Organizational Support (OS)	.749	.570
Technological Readiness (TR)	.749	.570
Customer Identification (CI)	.747	.498
Customer Relationship Management (CRM)	.750	.500
Customer Trust (CT)	.750	.281

Note. A 0.70 value of Cronbachs alpha shows that it is sufficiently reliable (Hair et al., 2019). AVE 0.50 means satisfactory convergent validity; CT is below threshold.

All the constructs reach the level of reliability (≥ .70), which means internal consistency. The values of AVE are acceptable (.50 or higher) except Customer Trust (CT =.281). Weak convergent validity Low AVE of CT indicates that items do not measure the construct adequately. This is a grave weakness- the results of CT ought to be viewed with reservations (Khalid et al., 2026).

Structural Model and Hypothesis Testing

Table 6
R-Square Values (Coefficient of Determination)

Endogenous Variable	R^2	R^2 Adjusted	*SD*	*t*	*p*
Customer Identification (CI)	.488	.482	.039	12.513	.000
Customer Relationship Management (CRM)	.508	.503	.041	12.335	.000

Note. R 2 of 0.25, 0.50, and 0.75 are weak, moderate, and substantial, respectively (Hair et al., 2019).

In Table 6, the values of R 2 are given. Customer Identification explained 48.8% of variance (R^2 = .488, adjusted R^2 = .482), and CRM explained 50.8% (R^2 = .508, adjusted R^2 = .503). They both belong to the moderate-to-substantial effects (Hair et al., 2019). Direct path coefficients are shown in table 7. AI Adoption (β = .456, t = 11.298, p < .001), Organizational Support (β = .403, t = 9.780, p < .001), and Technological Readiness (β = .329, t = 8.860, p < .001) all positively and significantly predicted Customer Identification, supporting H4, H5, and H6. Customer Identification strongly predicted CRM (β = .699, t = 23.050, p < .001), supporting H7 (Fahad et al., 2026; Naeem et al., 2026).

Direct Effects

Table 7
Structural Model — Path Coefficients (Direct Effects)

Path	*β*	*M*	*SD*	*t*	*p*	f^2
AIA → CI	.456	.456	.040	11.298	.000	.404

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OS → CI	.403	.405	.041	9.780	.000	.314
TR → CI	.329	.332	.037	8.860	.000	.210
CI → CRM	.699	.692	.030	23.050	.000	.979
CT → CRM	.002	−.017	.053	0.032	.975	.000
CT × CI → CRM	.136	.099	.071	1.907	.057	.045

Note. 2 = standardized path coefficient; f 2 effects of.02,.15 and.35 indicate small, medium, and large effect sizes (Khalid et al., 2026). The bootstrapping was done with 5,000 subsamples.

AIA, OS and TR have a large impact on Customer Identification (strong effects, $p < .001$). Customer Identification has a high predictive power on CRM (=.699, very large effect size). There is no direct impact of Customer Trust on CRM (p =.975 = entirely unimportant). Moderation (CT CI CRM) is marginal (p =. 057) 0 - statistically not significant (Kamran et al., 2026; Shehzadi et al., 2026).

Mediation Analysis

Table 8

Specific Indirect Effects (Mediation Analysis)

Indirect Path	*β*	*M*	*SD*	*t*	*p*
AIA → CI → CRM	.319	.316	.032	9.803	.000
OS → CI → CRM	.282	.280	.032	8.710	.000
TR → CI → CRM	.230	.230	.027	8.383	.000

Note. All the indirect effects are also significant at p <.001 which means that Customer Identification is a complete mediator between the three independent variables and CRM.

The indirect effects in detail are shown in table 8. All the three mediated paths were found to be significant. AIA → CI → CRM ($\beta = .319$, $t = 9.803$, $p < .001$), OS → CI → CRM ($\beta = .282$, $t = 8.710$, $p < .001$), and TR → CI → CRM ($\beta = .230$, $t = 8.383$, $p < .001$). Since direct effects of AIA, OS, or TR to CRM were not modeled, and all the indirect effects were important, Customer Identification is fully mediated (H8, H9, H10 supported).

Summary of Hypothesis Testing

Table 9

Summary of Hypothesis Testing Results

Hypothesis	Path / Relationship	*β*	*t*	*p*	Decision
H1	AI Adoption → CRM (Total Effect)	.319	9.803	.000	Supported
H2	Organizational Support → CRM (Total Effect)	.282	8.710	.000	Supported
H3	Technological Readiness → CRM (Total Effect)	.230	8.383	.000	Supported
H4	AI Adoption → Customer Identification	.456	11.298	.000	Supported

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H5	Organizational Support → Customer Identification	.403	9.780	.000	Supported
H6	Technological Readiness → Customer Identification	.329	8.860	.000	Supported
H7	Customer Identification → CRM	.699	23.050	.000	Supported
H8	AIA → CI → CRM (Mediation)	.319	9.803	.000	Supported
H9	OS → CI → CRM (Mediation)	.282	8.710	.000	Supported
H10	TR → CI → CRM (Mediation)	.230	8.383	.000	Supported
H11	CT × CI → CRM (Moderation)	.136	1.907	.057	Not Supported

Note. Significance threshold: $p < .05$. H1-H3 are total effects (indirect, completely mediated by CI). The H8-H10 are certain indirect effects. H11 is the Customer Trust moderating effect. Bootstrapping was used with 5000 subsamples.

Strong significant support is given to all of the direct and mediated relationships (H1 to H10). Customer Identification is a complete mediator between AIA, OS, TR to CRM. Customer Trust does not work as both direct predictor and moderator (H11 rejected). Model is good in general, but CT is a poor construct that is a detriment to theoretical strength.

DISCUSSION AND CONCLUSION

To test the hypothesis that adoption of AI, technological readiness, and support by the organization affect Customer Relationship Management and to explore the mediation of Customer Identification and the moderation of Customer Trust in the relationships, the research was conducted. These results provide a number of theoretical and practical conclusions.

To begin with, the adoption of AI became the most powerful predictor of Customer Identification (=.456) and then organizational support (=.403) and technological readiness (=.329). These findings are consistent with the previous studies that indicate that in case companies implement AI tools successfully and offer staff sufficient support and infrastructure, clients are more likely to think that the organization is innovative, customer-focused, and values-oriented, which contributes to the development of a sense of shared identity (Davenport et al., 2020; Huang & Rust, 2021). In the social identity theory perspective (Bhattacharya & Sen, 2003), customers identifying themselves with technologically progressive and supportive organizations are more likely to establish the relationship based on which good CRM is built.

Second, Customer Identification was found to be a very powerful predictor of CRM (699), with which more than one half of the variance in CRM results were explained (R 2 =.508). The mediation analysis also supported the fact that Customer Identification completely mediates the relationships between AI adoption and organizational support and technological readiness to CRM. This observation highlights the high significance of identity-driven customer engagement as an intervening variable in AI-based CRM. Instead of having direct impacts on CRM, technological and organizational capabilities have psychological channel of customer identification, which increases their downstream influence on relationship quality.

Third, the Customer Trust moderating effect on Customer Identification-CRM relationship was not supported (136 =.136, t =1.907, p =.057). This is a near-threshold finding that is worth paying close attention to. Absence of the meaningful moderation could be due to measurement issues of Customer Trust construct in that two of the four indicators (CT2 and CT3) produced subthreshold loadings and the AVE was below the.50 threshold. Perhaps in the present sample and situation, trust functions as an antecedent to identification as opposed to being a condition of the identification CRM relationship. Alternatively, trust can act as a direct predictor of CRM without identification, which is not directly modelled in the present paradigm. These possibilities should be captured in future researches by using refined measures of trust and other model specifications.

LIMITATIONS

A number of weaknesses must be recognized. To begin with, the cross-sectional design does not allow the researcher to make causal conclusions because the correlations measured are only at a point in time. Longitudinal data would support arguments of the directionality of effects. Second, the research was carried out in Pakistan, and one should take caution with the generalizability of the results to other cultural and organizational settings. Third, Customer Trust construct had psychometric weaknesses, two items did not pass the loading threshold, and the AVE was less than.50, which is why the scale might need additional development to be used in AI-CRM studies. Fourth, there is a possibility of common method bias due to the self-reported nature of the data which is single source. Even though this issue is partially addressed by PLS-SEM due to its structural disinter action of constructs, the use of objective performance data or multi-source design should be considered in the future research.

FUTURE RESEARCH DIRECTION

This framework can be taken in a number of directions in future research. To begin with, researchers are supposed to construct and test an improved Customer Trust measure that is specifically scaled to the service contexts which AI mediates, including such dimensions as the transparency of the algorithm, privacy of the data, and perceived AI impartiality. Second, longitudinal and experimental designs would reinforce the causal inference and enable the analysis of the dynamics of how AI adoption influences customer identification over time. Third, the cross-cultural studies would enlighten on the importance of the mediating role of Customer Identification as being universal or situational. Fourth, the further studies may examine other boundary conditions of the Customer Identification CRM relationship, including service type, the size of the firm, and the extent to which AI is customized. Lastly, the contribution of ethical AI governance including accountability, explainability, and fairness as a precursor of Customer Identification as well as Customer Trust within AI-driven CRM systems is a deep and understudied field.

CONCLUSION

The present research shows that AI implementation, organizational support and technological preparedness are meaningful organizational competency that facilitate Customer Relationship Management- although they do so by the psychological process of Customer Identification. Those organisations that use AI in transparent and customer-focused manners, offer well-developed internal support systems, and develop technological competence are in a better position to develop strong customer identities that subsequently lead to high CRM results. Although Customer Trust did not play a significant moderating role in this relationship, probably because of measurement issues and the fact that a more refined operationalization will be necessary in AI-based situations, its theoretical significance is not diminished. As AI keeps changing the nature of customer engagement, the knowledge of psychological processes of how technology affects customer-firm relationships will be critical to both academics and practitioners. This paper is a base upon which that question can be answered and it demands further empirical interest towards the intersection of artificial intelligence, organizational behavior, and customer relationship science.

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