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MSc Business Administration – Strategic Management

Master Thesis

“Adoption of AI-CRM systems in SMEs: A TAM and TOE Framework analysis”

by

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ABSTRACT

Adopting Artificial Intelligence in Customer Relationship Management (AI-CRM) poses both significant opportunities and challenges for small and medium-sized enterprises (SMEs). While AI-CRM can enhance personalization, efficiency, and marketing outcomes, its adoption remains limited across SMEs due to organizational constraints and environmental uncertainty. This study investigates the impact of technology acceptance (TAM) and contextual (TOE) factors on AI-CRM adoption in SMEs across European companies. Drawing on a sample of 112 respondents, a multiple linear regression analysis was conducted to investigate how different factors influence adoption behavior. Results indicate that management support and competitive pressure are significant drivers of AI-CRM adoption, while factors such as perceived usefulness and ease of use are not statistically significant. Findings suggest that adoption is less influenced by individual perceptions and more by strategic and organizational readiness. This study contributes to the growing body of hybrid adoption models, offering practical insights for SME managers, technology providers, and policymakers seeking to accelerate AI integration in marketing functions. It emphasizes the need for leadership involvement, tailored support by firm size, and strategic framing of AI as a value-generating tool.

Introduction

1.1 Background and context:

Artificial Intelligence (AI) has emerged as one of the most transformative technologies in the modern business landscape, reshaping operations, decision-making, and particularly marketing strategies (Toorajipour et al., 2021; Kumar et al., 2023; Dwivedi et al., 2021). While the ambition to replicate human intelligence can be traced back to early philosophical thought, such as Aristotle's[1] explorations of logic and reasoning (Loureiro et al., 2021), AI in its current form is data-driven, computational, and strategically embedded in business systems.

In the context of marketing, AI plays an increasingly central role. Huang and Rust (2020) describe AI's influence across three marketing dimensions: research, strategy, and action. Its capabilities – ranging from automation and predictive analytics to personalization and sentiment analysis – are already driving major shifts in how companies engage with customers. Vlačić et al. (2021) define Marketing AI as "the development of artificial agents that, given the information they have about consumers, competitors, and the focal company, suggest and/or take marketing actions to achieve the best marketing outcome". This definition underscores AI's role not merely as a technological tool, but as a strategic enabler and catalyst for reshaping customer engagement, driving value creation, and transforming the strategic direction of marketing practices (Kedi et al., 2024).

Among the most impactful applications of AI is its integration into Customer Relationship Management (CRM) systems. AI-powered CRM enables businesses to collect, interpret, and act on customer data in real-time, leading to more personalized, efficient, and scalable interactions (Campbell et al., 2020). From virtual assistants and chatbots to predictive lead scoring and customer segmentation, AI-CRM is revolutionizing how firms manage relationships and drive engagement (Davenport et al., 2019; Chatterjee et al., 2021).

Real-world evidence further supports these claims. According to a 2023 McKinsey report, AI-enhanced customer service significantly boosts engagement and reduces operational costs. In one case study, an Asian bank saw a 2-3x increase in self-service usage, a 40-50% drop in service interactions, and a 20% cost-to-serve savings – all through the implantation of AI

[1] Aristotle is one of the most influential ancient Greek philosophers and scientists, lived between 384 and 322 B.C. and significantly influenced not only the intellectual people of his time but also all the scientists across the globe throughout the years.

tools such as sentiment analysis and API-driven technologies (Das et al., 2023). Another McKinsey report by Harkness et al. (2023) highlights how generative AI accelerates marketing campaign development and execution. For example, Michael Stores[2] increased their use of personalized email campaigns from 20% to 95%, after implementing AI solutions.

These real-world examples underscore AI's transformative impact not just on marketing efficiency but also on strategic business outcomes. They highlight the growing necessity – especially for small and medium-sized enterprises (SMEs)[3]– to adopt AI-powered CRM systems as a means of staying competitive, optimizing resources, and delivering superior customer value.

1.2 Research objectives and Research question:

Although AI adoption in marketing has been widely examined, most existing research has concentrated on large enterprises, often overlooking the distinctive characteristics and constraints of smaller firms (Keskin et al., 2010), which will be further discussed in Section 2.2. Recent E.U. statistics highlight this disparity: only 11.21% of SMEs (from the examined sample) have integrated some form of AI in their operations, compared to 41.17% of larger corporations (European Commission, 2024). This difference reflects the additional complexity SMEs face in adopting advanced technologies. At the same time, while consultancy firms have primarily analyzed AI adoption among large corporations, there remains a noticeable gap in academic research concerning its drivers and barriers in smaller businesses.

However, as digital transformation accelerates, the adoption of AI-powered CRM systems becomes increasingly critical for these firms in order to remain competitive and responsive to evolving customer expectations (San-Martín, Jiménez, & López-Catalán, 2016). Parallelly, it's been proven that when implemented effectively, AI-driven solutions have shown promising results for SMEs. For instance, Salesforce (2024) reports that 91% of SMEs who have adopted AI technologies experienced revenue growth, and 80% believe that AI will become a game changer for their business operations. Consequently, with the right strategies and industry support, SMEs are able to compete with larger companies, leveraging AI for personalization and efficiency (Kedi et al., 2024).

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[2] Michael Stores is a privately held retail chain of American and Canadian arts and crafts stores.
[3] For the sake of simplicity, the term SMEs is used throughout this study to refer to small and medium-sized enterprises.

Although prior studies using the TAM and TOE frameworks have identified key determinants of technology adoption, several theoretical gaps remain (Haefner et al., 2023). For instance, studies such as Chatterjee et al. (2021) often treat leadership and management support as moderating variables. However, in SMEs – where leadership exerts a more direct and centralized influence – this study conceptualizes it as a direct predictor of AI-CRM adoption. Additionally, while data privacy concerns are frequently cited as adoption barriers, they are rarely tested empirically (Chatterjee et al., 2021). This study addresses that gap by incorporating data privacy as a moderating variable in the relationship between perceived usefulness and AI-CRM adoption.

Thus, by addressing these gaps, this research seeks to advance the understanding of the key factors that either drive or obstruct the adoption of AI-powered CRM[4] in SMEs.

Translating this problematic, the following research question arises: *"How do perceived usefulness, perceived ease of use, technological readiness, management support, financial costs, and rival competition influence the adoption of AI-powered CRM in SMEs, and how do data privacy concerns moderate the effect of perceived usefulness?"*

1.3 Theoretical and Practical Contributions

In response to the gaps identified in previous research, this study aims to contribute both theoretically and practically to the field of AI adoption in marketing, with a particular focus on small and medium enterprises (SMEs). By employing an integrated dual-framework approach that combines the Technology Acceptance Model (TAM) and the Technology – Organization – Environment framework, the study provides a holistic view of the adoption process (Gangwar et al., 2014; Awa et al., 2015). This integration enables a more holistic exploration of adoption behavior, accounting for both individual-level perceptions and organizational-environmental conditions.

Moreover, this study, as briefly mentioned before, introduces two key theoretical extensions. First, it repositions management support as a direct determinant of AI-CRM adoption, an adjustment particularly suited to SMEs (Chatterjee et al., 2021). Second, it incorporates data privacy concerns as a moderating variable, addressing a commonly cited limitation in earlier studies and responding to recent calls for a more structured examination of privacy-related adoption barriers (Chatterjee et al., 2021). Moreover, the findings reinforce the view that AI

[4] CRM stands for Customer Relationship Management.

adoption should be understood as a strategic and socio-technical undertaking, rather than merely a function of user-level attitudes. In doing so, the study offers a novel contribution to the literature by uncovering meaningful differences in adoption levels across SME size categories, highlighting the distinct challenges faced particularly by small enterprises.

On a practical level, this research provides insights that can help managers, technology providers, and policymakers understand the specific factors influencing AI adoption in marketing activities (Campbell et al., 2020). The results suggest that efforts should focus on strengthening leadership commitment, building organizational readiness, and addressing competitive pressures, rather than relying solely on improving system usability. The brief roadmap included outlines actionable recommendations based on observed adoption patterns, including the need for firm-size-sensitive interventions and the strategic framing of AI as a driver of business value. Lastly, while the ethical implications of AI remain beyond the study's core scope, the evaluation of data privacy concerns as a perceived barrier represents a step toward more responsible and trust-centered marketing innovation.

1.4 Thesis outline

This study consists of five chapters. The first chapter introduces the report, outlining the research objective and research question. The second chapter discusses the theoretical background. In this section, the explanation of the key concepts and theoretical frameworks (TOE and TAM frameworks) used to structure the research, are analyzed. The third chapter describes the methodology used in the research, including the research design, data collection techniques, sample characteristics, measuring instruments, quality of the research data, and ethical considerations. Chapter four includes the results of the analysis and concluding chapter five focuses on further discussion of the extracted results and forming specific conclusions, managerial recommendations, and suggestions for future research.

Theoretical framework:

2.1 Customer Relationship Management (CRM):

Customer Relationship Management, since the late 1990s, has evolved from a purely technological solution into a strategic, data-driven business tool aimed at fostering profitable customer relationships (Stone, Foss, & Ekinci, 2008). Central to CRM is the management of customer knowledge, which enables businesses to deliver personalized experiences and better understand customer behavior (Khodakarami & Chan, 2014). This knowledge can be categorized as:

1. Knowledge for customers - Information provided to customers, such as product details and personalized recommendations.
2. Knowledge about customers - Data on customer preferences, behavior, and interactions.
3. Knowledge from customers - Insights gathered from customer feedback, interactions, and engagement.

To manage customer knowledge effectively, CRM systems are structured around distinct but interrelated functions. Specifically, CRM processes operate across strategic, operational, and analytical levels (Rababah et al., 2011). Strategic focuses on fostering a customer-centric culture and long-term engagement. Operational CRM deals with the automation of marketing, sales, and service tasks. Analytical CRM, building on operational data, applies advanced analytics to generate actionable insights. A related sub-category, collaborative CRM, integrates communication across departments and external stakeholders to ensure a seamless customer experience. These levels work in tandem to help businesses manage customer journeys more effectively.

2.1.1 Transition to AI-CRM:

With data volumes growing rapidly, traditional CRM systems are no longer sufficient. AI-powered CRM (AI-CRM) systems address this challenge by integrating machine learning and predictive analytics to enhance personalization, automation, and decision-making (Ledro et al., 2023; Chatterjee et al., 2021).

AI optimizes CRM processes at all three levels (Rababah et al., 2011). In strategic CRM, AI-driven predictive analytics helps anticipate customer behavior, enabling businesses to develop proactive sales strategies. Moreover, operational CRM leverages AI to boost efficiency, automate customers' interactions, improve workflows, and handle customer questions instantly. This is particularly beneficial for small and medium sized enterprises, where automation can lower operational expenses and enhance marketing effectiveness. Finally, AI in analytical CRM, facilitates data mining, forecasts analytics, and classifies customers. All these are crucial roles for grasping how the use of AI affects marketing success in SMEs (Rababah, et al, 2011).

To function optimally, AI-CRM requires seamless integration, ensuring that customer data is well-organized, easily accessible, and AI-ready (Chatterjee et al., 2019). In addition to this AI-CRM's adoption also depends on organizational readiness. As Chatterjee et al. (2021)

note, cultivating a supportive organizational culture is critical to realizing the full potential of AI in CRM.

2.2 Small and Medium Enterprises (SMEs):

SMEs can be categorized into micro-enterprises with fewer than 10 employees, small enterprises with up to 50 employees, and medium enterprises with 50 to 200 employees (Keskin et al, 2010). EU sets a threshold of 250 employees for SMEs and subdivides them into medium-sized, small, and micro enterprises, while at the same time noting their turnover, which is less than 50 million euros (European Commission, n.d.).

SMEs' economic importance is vital, contributing significantly to employment and GDP. Yet they operate under tighter resource constraints compared to larger corporations. SMEs tend to have limited financial resources, less technical expertise, and lower organizational capacity to absorb the risks and complexity associated with digital transformation. These constraints make the adoption of AI-based systems – especially for marketing and customer engagement – particularly challenging (Kedi et al., 2024).

At the same time, external pressures such as intensifying market competition and rising customer expectations are pushing SMEs toward digital innovation. In this context, smaller companies must evaluate not only their internal technological capacity (Kedi et al., 2024; Abed, 2020) but also their ability to respond strategically to environmental demands.

Given the typically centralized decision-making structure of SMEs, managerial support plays a disproportionately influential role in shaping technology adoption outcomes (Chatterjee et al., 2021). Unlike in larger corporations, where decision-making may be distributed across multiple levels, SME leaders are often directly involved in both strategy and implementation. As such, variables like management support, technological readiness, financial constraints and competitive pressure become critical drivers – or barriers – to adoption.

Consequently, to capture these dynamics, this study draws on two complementary theoretical perspectives. The Technology Acceptance Model (TAM) provides insight into how individuals within SMEs assess new technologies based on perceived usefulness and ease of use. In parallel, the Technology – Organization – Environment (TOE) framework offers a broader lens to assess organizational readiness and environmental influences. Together, these frameworks present a robust foundation for analyzing the factors that shape AI-CRM adoption in the SME context.

2.3 Technology Acceptance Model (TAM)

The TAM model, developed by Fred Davis and Richard Bagozzi and first introduced in 1989, as the researchers report, has its roots in the Theory of Reasoned Action[5] and the Theory of Planned Behavior[6], and consists of the first model to be explored (Awa et al., 2010; Rahimi et al., 2018; Scherer & Teo, 2019). Its primary purpose is the exploration of how external factors influence decisions, shape internal beliefs, build attitudes, and steer behavioral intentions (Awa et al., 2010). Today, it consists of one of the most important and widely used theoretical models in the technological field assessing the acceptance and behaviors related to the ICT[7] introduction in businesses (Rahimi et al., 2018). Although there are different TAM versions, they all end up with the same central variables, these are the perceived ease of use, perceived usefulness, attitudes toward technology, and the intentions to use technology (Scherer & Teo, 2019). In this research, the two variables related to TAM model - perceived usefulness (PU) and perceived ease of use (PEU) – are being used for the hypotheses' formulation. Data privacy concerns - an aspect that influences the behavior and perception of many organizations towards implementing AI - is also being tested as a moderating variable influencing the AI-CRM adoption.

H1: Perceived usefulness (PU) of AI-CRM has a positive effect on AI-CRM adoption.
H1.a: Data privacy concerns moderate the effect of perceived usefulness on AI-CRM adoption, reducing its positive impact.

"Perceived usefulness": According to Awa et al. (2015), PU reflects user's subjective belief whether a specific application is able of enhancing an organization's operations. However, PU is not merely limited to enhancing the organization's effectiveness but has positive effects on the individual's perception of improving their performance as well (Na et al, 2022).

H2: Perceived ease of use (PEU) influences positively AI-CRM adoption.

"Perceived ease of use": Perceived ease of use relates to how much mental effort a user believes is required to navigate and utilize a given application. Applications easier to use,

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[5] The Theory of Reasoned action was created to explain how consumers make purchasing decisions (Ha, 1998)
[6]The Theory of Planned Behavior, which is an extension of TRA, is a psychological theory that considers behavioral performance as a joint function of intentions and perceived behavioral control (Ajzen, 1991).
[7] ICT stands for Information and Communications Technology.

requiring less physical effort and steep learning curve, tend to encourage more adoption compared to those perceived as more complex for users (Awa et al., 2015; Na et al. 2022).

Gangwar, Date, and Raoot (2014) state that the TAM model – like any other model - presents certain limitations, such as the generation of conflicting findings which results in confusion. This is why researchers propose to search for more variables and not be constrained merely on the ones proposed by the TAM model (Gangwar et al., 2014). Despite its limitations, the TAM model is frequently chosen by researchers because of its simplicity and universality as well as its applicability with other models (Singh & Srivastava, 2019). This research, taking into account the limitations of TAM and at the same time exploiting its robustness for combination with other frameworks, combines it with the TOE framework.

2.4 Technology – Organization – Environment (TOE) framework:

The TOE framework, developed by Tornatzky and Fleischer (1990), incorporates three elements to evaluate, predict, and explain technology adoption: technology development (technology), organizational conditions (organization), and industry environment (environment) (Awa et al., 2015; Ngah et al., 2017). As Abed (2020) states in his paper, the TOE model offers a well-structured theoretical basis and is valuable for analyzing technology adoption in SMEs. Contrary to other theoretical models that through the years have been used to explain technology adoption in marketing, such as the resource-based view (RBV) or Rogers innovation models, the TOE framework takes into consideration the distinctive characteristics of SMEs (Eze et al. 2019).

A deeper exploration of each of the model's aspects provides valuable insights. Beginning with the technological element, it refers to both the internal and external technological capabilities available to the organization (Eze et al. 2019). According to Na et al. (2022), the adoption of a new technology by an organization requires the consideration of its advantages and benefits, in comparison to the existing technology. In this study, the technological context is operationalized through the variable of technological readiness, reflecting the extent to which SMEs are equipped with the necessary infrastructure and expertise to integrate AI-powered CRM solutions.

H3: The level of technological readiness[8] *in SMEs positively influences AI-powered CRM adoption.*

Next one, the organization context, refers to the internal characteristics of a firm, including its structure, culture, and resource base – factors that play a crucial role in shaping the adoption of innovative technologies (Abed, 2020; Na et al.,2022). This dimension highlights the importance of organizational readiness, particularly in terms of managerial support and financial capacity, which are often limited in smaller firms. Moreover, firm size itself is an inherent factor influencing adoption behavior and is central to this study, as the research focuses specifically on SMEs (Eze et al. 2019). In this context, the research considers management support and financial costs as key organizational variables affecting AI-CRM adoption.

H4: Management support[9] *positively affects AI adoption.*
H5: Higher AI implementation financial costs[10] *negatively impact AI-CRM adoption.*

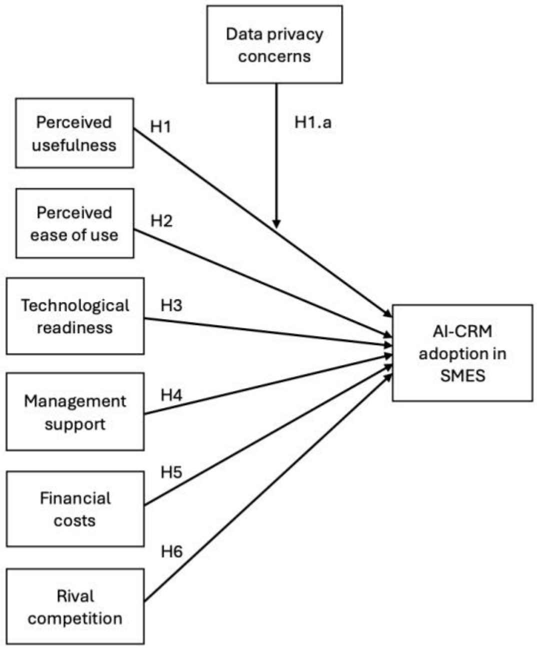
Lastly, the environmental context concerns aspects such as competition, trading partners' readiness, sociocultural issues, and government behavior (Awa et al., 2015). This context contributes to a better understanding of the powers outside the organization that influence the organization in a dynamic way and can hinder or foster the technological adoption decision. Examining what is happening solely internally in the organization is not enough, we need to take into account the transactional and contextual environment as well. This research focuses on *competitive pressure*[11] as a key aspect of environmental context.

H6: Rival competition positively affects AI-CRM adoption in SMEs.

2.5 Conceptual model:

Figure 1 represents the conceptual model that guides this research. Based on the hypotheses developed, the model depicts the factors influencing the adoption of AI-CRM in SMEs.

[8] Technological readiness refers to the extent to which SMEs already possess the necessary IT infrastructure, employee expertise, and capabilities required to successfully integrate AI into CRM systems.
[9] Management support is in this case directly related to the involvement, commitment, and facilitation provided by the organization's leadership regarding the implementation of AI systems.
[10] By "financial cost" in this case we refer to the various expenses associated with the adoption and implementation of systems powered by Artificial Intelligence.
[11] Competitive pressure refers to the external forces – such as rival activity, shifting customer demands, or industry changes – that drive SMEs to adopt Ai to stay competitive.



(Figure 1: Conceptual model)

Methodology:

3.1 Research design and data collection techniques

For this research, a quantitative approach has been adopted. Although a qualitative approach was considered a valuable alternative due to its strength in exploring in-depth perspectives through interviews and case studies (Mehrad & Zangeneh, 2019), it was not chosen. As it is less suitable for testing predefined hypotheses and establishing generalizable patterns, it was deemed less effective for analyzing the factors influencing the adoption of AI-CRM in SMEs. Consequently, a quantitative survey-based approach is considered the most appropriate, as it facilitates the identification of correlations between variables and data collection from multiple respondents.

The data collection tool that was used for the research is an online questionnaire. The questionnaire is a commonly used instrument for gathering survey information, that allows the researcher to not be present while participants fill it out (Cohen, Manion, & Morrison, 2007). Online questionnaires also give the opportunity for equal access among the respondents, while at the same time they allow for anonymity (Quick & Hall, 2015). In this case, the questionnaire was designed with close-ended questions, using a five-point Likert scale to capture varying degrees of opinion from respondents. (Quick & Hall, 2015). Moreover, a structured questionnaire was chosen as the method of data collection because it allows respondents to express their opinions systematically, reducing interviewer bias, while enhancing reliability and validity (Krosnick & Vannette, 2018).

In the survey, the questions are formulated based on the variables outlined by the two analyzed frameworks (TAM and TOE frameworks). The design of the instruments was informed by previously validated measures, particularly those used by Chatterjee et al. (2021) in their TAM-TOE based framework for studying AI adoption to enhance measurement accuracy (Ahmad, Drus, & Kasim, 2020). With consent from the original authors, this study adapted those items to fit the specific SME context of AI-CRM implementation. Additional items were drawn from Gangwar et al. (2015) and Na et al. (2022), and refined to reflect insights from current industry trends, including McKinsey & Company's (2025) report on the state of AI.

Finally, the purpose of the survey was clearly stated at the beginning of the questionnaire, along with ethical considerations such as participant anonymity, voluntary participation, and the estimated completion time (5-7 minutes). These safeguards align with best practices in ethical research design.

3.2 Sampling

Meng (2013) states that sampling is an essential technique when conducting a statistical analysis. Analyzing vast amounts of datasets is a challenging task. For this reason, researchers often decide to select specific parts of the population and emphasize their analysis and extraction of specific results on them. To ensure objectivity and generalizability, probability-based sampling methods such as simple random sampling are commonly used (Cohen, Manion, & Morrison, 2007).

According to Meng (2013), stratified sampling involves dividing the population into homogenous subgroups, also called strata, based on specific characteristics that are relevant to the research objectives. Adding to this, Imbens and Lancaster (1996) highlight that stratified sampling allows researchers to account for differences among subgroups explicitly, thereby providing more accurate results compared to when using simple random sampling, where subgroup representation might be uneven.

In this research, although proportional stratified sampling was initially considered – based on dividing SMEs into three distinct strata according to company size: micro (1 to 10 employees), small (11 to 50 employees), and medium (51 to 250 employees) – this was not fully implemented due to practical limitations in data access. Instead, the final sample was obtained through non-probability sampling methods.

The collected sample did not reflect the intended EU proportions (Eurostat, 2024), where micro-enterprises make up 93.2% of SMEs, small enterprises 5.6%, and medium 1.0%. Micro-enterprises were notably underrepresented, likely due to lower response rates and difficulty in reaching decision-makers in smaller firms (see 5.5 Limitations).

Nevertheless, stratified descriptive analysis was conducted post hoc to examine differences across firm sizes. While the sample may not be fully representative, it still enables meaningful comparisons and provides valuable insights across the SME landscape.

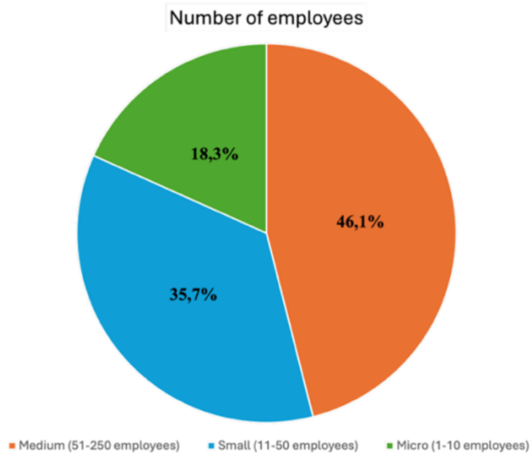
3.2.1 Sample size determination

The sample size determination is an essential step of every analysis technique, influencing the statistical power of the analysis and the generalizability of our results (Hair et al., 2019). A well-defined sample size ensures that the study can detect meaningful relationships. In this research, as will be mentioned later, multiple regression analysis was conducted. The general rule of thumb suggests that multiple regression analysis requires at least 15 to 20 observations per independent variable (Hair et al., 2019). Given that in this case, we have included six independent variables and one moderator, the minimum sample size to be selected was 100 respondents, while the optimal goal would be 150 respondents.

3.2.2 Sample characteristics

The final sample consisted of 112 respondents affiliated with SMEs operating within the European Union. The majority of participants (67.9%) indicated that their companies operate in EU countries other than the Netherlands, Belgium, Germany, and Luxembourg. The Netherlands represented the second-largest group (26.8%), with the remaining participants distributed across Belgium, Germany, and Luxembourg in smaller proportions.

Regarding company size, 46.1% of respondents worked in medium-sized enterprises (51-250 employees), 35.7% in small enterprises (11-50 employees), and 18.3% in micro-enterprises (1-10 employees) (see Figure 2). While micro-enterprises were underrepresented relative to their actual prevalence in the EU, this distribution nonetheless provides a basis for examining differences between SME tiers.



(Figure 2: Number of employees)

Last, participants represented a diverse range of industries. The largest groups were from Technology, IT & Software Services (22.6%) and Manufacturing, Construction & Logistics (22,6%). Other sectors included Marketing, Media & Creative Industries (18.3%), Consulting/ Business Services (14.8%), Retail & E-commerce (8.7%), Finance & Accounting (7%), and Other (6%). This industry spread enhances the breadth and applicability of the research findings.

3.3 Measurement instruments

3.3.1 Independent variables

Field (2018) defines an independent variable as “a variable thought to be the cause of some effect; a variable that the experimenter has manipulated”. In this research, the independent variables were selected based on the theoretical background of the paper, and more specifically they stemmed from the TOE and TAM models. Based on those models, several independent variables influence the adoption of AI-powered CRM systems. More particularly, the study assessed the impact of perceived usefulness (how valuable AI adoption is perceived by SMEs), perceived ease of use (how user-friendly the AI system is judged), technological readiness (the already developed infrastructure and expertise of SMEs), management support (leadership’s behavior and encouragement toward AI-CRM adoption), financial costs (financial barriers companies face in this venture), and rival competition (pressure from competitors that have integrated AI in their operations). Last, data privacy concerns were considered as moderator potentially influencing negatively the relationship between perceived usefulness and AI-CRM adoption.

3.3.2 Dependent variable

Field (2018) defines dependent variables as “variables thought to be affected by changes in the independent variable; and adds that someone can think of a dependent variable as an outcome”. The dependent variable in this research is AI-powered CRM adoption which is defined as the extent to which small and medium-sized enterprises (SMEs) decide to implement and use Customer Relationship Management (CRM) systems powered by artificial intelligence (AI). Adoption includes the readiness, intent, and actual actions of small and medium-sized businesses to integrate AI tools into their business practices. This integration aims to better manage customers, streamline processes, and enhance decision-making capabilities.

3.3.3 Operationalization of Constructs

Table 1 below outlines the constructs used in the questionnaire, outlining the variables measured along with the corresponding survey items and their sources.

Constructs	**Measurement Items**	**SPSS Code**	**Sources**
AI-CRM Adoption (DV)	Has your company adopted AI-powered CRM systems?	AI-CRM Adoption	Chatterjee et al. (2021) and McKinsey & Company (2025)
Perceived Ease of Use (TAM)	1. AI-CRM systems are easy to operate. 2. I believe my team can easily learn how to use AI-CRM. 3. AI-CRM solutions have a user-friendly interface. 4. Using AI tools in CRM would not require much training.	PEU1, PEU2, PEU3, PEU4	Chatterjee et al. (2021), Gangwar et al. (2015), Na et al. (2022)
Perceived Usefulness (TAM)	1. Using an AI-powered CRM system improves our customer service quality. 2. AI-CRM systems would help us deliver personalized customer experiences. 3. Using AI in CRM positively impacts customer satisfaction and loyalty. 4. Adopting AI-CRM would contribute to achieving our business goals more effectively. 5. AI-CRM is important for our future marketing strategy.	PU1, PU2, PU3, PU4, PU5	Chatterjee et al. (2021, Na et al. (2022), Gangwar et al. (2015), McKinsey & Company (2025)

Data Privacy Concerns	1. I'm concerned about how customer data is processed by AI tools. 2. Privacy regulations make it harder for us to implement AI-CRM. 3. Our organization is cautious about using AI systems due to potential data privacy risks.	DP1, DP2, DP3	Chatterjee et al. (2021), McKinsey & Company (2025), Na et al. (2022)
Technological Readiness (TOE, Technology)	1. Our company has the IT infrastructure to support AI-CRM systems. 2. Our employees have the necessary digital skills for AI-CRM. 3. We have previously adopted advanced digital tools successfully.	TR1, TR2, TR3	Chatterjee et al (2021), Gangwar et al. (2015), McKinsey & Company (2025)
Financial Costs (TOE, Organization)	1. Implementing AI-CRM is too costly for our organization. 2. Our budget does not allow for AI-related investments right now. 3. We are concerned about the financial risks of implementing AI.	FC1, FC2, FC3	Chatterjee et al. (2021), Gangwar et al. (2015)
Management Support (TOE, Organization)	1. Top management in our company supports the adoption of AI-based tools. 2. Management is committed to digital transformation. 3. Resources are allocated to support AI-CRM adoption (training, time, staff). 4. With management's team support, our organization is prepared to adopt (or continue adopting) AI-CRM systems in the near future. 5. The management team is promoting the use of AI-powered CRM systems among employees.	MS1, MS2, MS3, MS4, MS5	Chatterjee et al. (2021), McKinsey & Company (2025), Na et al. (2022)
Rival Competition (TOE, Environment)	1. The competitive environment pressures us to adopt AI-powered CRM systems. 2. There is pressure in our industry to adopt AI technologies. 3. AI adoption is necessary to remain competitive in our industry.	RC1, RC2, RC3	Chatterjee et al. (2021), Gangwar et al. (2015)

(Table 1: Operationalization of Constructs and Measurement Items)

3.4 Data analysis technique

The present study applies multiple linear regression analysis (MLR) as the method for examining the factors influencing AI-CRM adoption among SMEs. This choice is rooted in both the research objectives – which aim to understand how various organizational and perceptual factors jointly predict adoption – and the metric nature of the prepared dataset. MLR is especially suited to this research context because it enables the estimation of the independent effects of multiple predictors simultaneously (Hair et al., 2019; Thrane, 2020).

Originally, the dependent variable, AI-CRM adoption, was collected as a categorical variable with four levels: "No", "Not aware of", "Planning to", and "Yes". While multinomial logistic regression was also considered appropriate for such a structure (El-Habil, 2012; Kwak & Clayton-Matthews, 2002), this approach was ultimately set aside. The decision was driven by the low frequency of responses in the "Not aware of" category, which would compromise the stability and interpretability of multinomial models. Following academic guidance and common practice in applied regression (Thrane, 2020), the categories were numerically recoded into an ordinal scale reflecting increasing levels of adoption. The transformed variable, AI_CRM_new, was subsequently treated as a continuous dependent variable to allow for parametric analysis- this process is further detailed in Chapter 4.

Compared to alternative techniques such as logistic or ordinal regression, multiple regression offers advantages in statistical power and interpretability when its assumptions are met. These assumptions – including linearity, normality, homoscedasticity, absence of multicollinearity, and lack of influential outliers – were tested and confirmed using standard SPSS diagnostics (Field, 2018).

Lastly, the sample size of 112 respondents and seven predictors complies with common recommendations for regression analysis, which advise 10-20 cases per predictor to ensure sufficient statistical power and model reliability (Field, 2018). Given its theoretical alignment, robustness, and analytical flexibility, MLR was deemed the most appropriate analytical technique for this study.

3.5 Quality of the research

This section is focused on how the quality of the research was ensured, focusing mainly on the aspects of reliability, generalizability, and validity. Given the use of a quantitative research design and multiple regression analysis as the main analytical technique, particular attention was paid to ensuring methodological rigor.

Reliability concerns the reproducibility of the same results remaining consistent over time and under different conditions. The reliability of the specific research was assessed via the statistical program of SPSS by conducting a reliability test and assessing for Cronbach's alpha. Cronbach's alpha is a measure of internal consistency, with values above .70 indicating a reliably acceptable result (Hair et al., 2019; Field, 2018).

Moreover, validity is another important condition that needs to be assured and refers to the condition where the researcher measures exactly what he is supposed to measure. Construct validity was reinforced by basing the questionnaire items on established scales from previous literature (Bogdan & Biklen, 1992), including Chatterjee et al. (2021), Gangwar et al. (2015), and Na et al. (2022). This alignment with prior validated instruments helps ensure that the survey items effectively capture the theoretical constructs of interest. Internal validity, while less of a focus in non-experimental designs like this, was supported by careful operationalization. Finally, external validity – the extent to which findings can be generalized – was considered during the sampling process (Hair et al., 2019).

To support a more informative interpretation of the sample composition, SMEs were grouped descriptively into three size-based categories: micro, small, and medium enterprises. Although stratified sampling was not employed as a formal sampling method, this post hoc stratification enabled clearer subgroup insights related to AI-CRM adoption. This approach aligns with recommendations by Hair et al. (2019), who highlight the value of subgroup analysis for contextual understanding. While proportional representation based on the actual distribution of SMEs in the population was initially intended, micro-enterprises were underrepresented in the final dataset. This limitation, which may constrain the generalizability of the results – particularly to micro-enterprises – is acknowledged in section 5.4. Nonetheless, the presence of varied SME types enhances the interpretive richness and supports meaningful subgroup comparisons (Field, 2018).

Finally, MLR was selected not only for its analytical strength but also for its methodological suitability. Prior to analysis, all assumptions were systematically evaluated through diagnostic procedures in SPSS, including residual plots, histograms, P-P plots, variance inflation factors (VIFs), and Cook's distance. These tests confirmed that the regression assumption was met, lending credibility to the findings. Additionally, the sample size adhered to accepted guidelines, ensuring the stability of parameter estimates and the reliability of the regression model (Hair et al., 2019).

3.6 Research ethics

This study prioritizes ethical considerations, focusing on transparency, informed consent, privacy, and confidentiality. The questionnaire begins by mentioning its purpose and duration, making sure that people were motivated to participate voluntarily. All participants were informed about their right to withdraw at any time without any consequences (Cohen et al., 2007). In addition to that all data remain anonymous to protect data privacy and the access to them is restricted. At the same time, no personally identifiable information was asked in the questionnaire (Quick & Hall, 2015). Finally, the research provides fair and respectful treatment, ensuring that data collection, analysis, and reporting were done accurately and honestly, following ethical standards.

Results

This chapter presents the findings from the statistical analyses conducted to examine the factors influencing the adoption of AI-powered CRM systems (AI-CRM) among small and medium-sized enterprises (SMEs). Grounded in the TAM and TOE frameworks, the analysis explores the role of perceived usefulness, perceived ease of use, technological readiness, management support, financial constraints, rival competition, and data privacy concerns. Both descriptive and inferential statistics are presented, including measures of central tendency, reliability analysis, cross-tabulations, ANOVA, and multiple regression. Additionally, differences in adoption patterns across firm sizes and the potential moderating effect of data privacy are investigated. The results provide empirical insight into the relative importance of various organizational and technological factors in shaping AI-CRM adoption decisions in the SME context.

4.1 Data cleaning and missing values

Before conducting the main analyses, the dataset was carefully examined for missing responses using IBM SPSS. This process included visual inspection of both the Data View and Variable view, as well as the use of frequency tables and descriptive statistics to detect any patterns of non-response or irregularities.

Initial screening revealed a total of 11 missing values, with no single variable missing more than three responses. This corresponds to less than 3% missingness per variable – well below the commonly accepted threshold of 5%, as suggested by Field (2018) and Hair et al. (2019).

The missing values appeared to be randomly distributed, without evidence of systematic patterns.

Given the low volume and random distribution of missing data, the listwise deletion method was adopted. This approach excludes any case from a given analysis if it contains missing data on any variable involved in that analysis. In SPSS, listwise deletion is applied by default in most statistical procedures such as linear regression, ANOVA, correlation, and reliability analysis. To ensure consistency, this setting was explicitly confirmed and selected via the "Options" menu for each procedure, by choosing the "Exclude cases listwise" option (Field, 2018).

4.2 Treatment of the Dependent Variable

As explained earlier, the dependent variable in this study, "AI-CRM adoption", was originally measured as a categorical variable with four response options: "No", "Not aware of", "Planning to", and "Yes". However, due to the small number of responses in the "Not aware of" category, and following academic guidance, the variable was transformed into a continuous variable to enable parametric statistical analysis, particularly multiple linear regression.

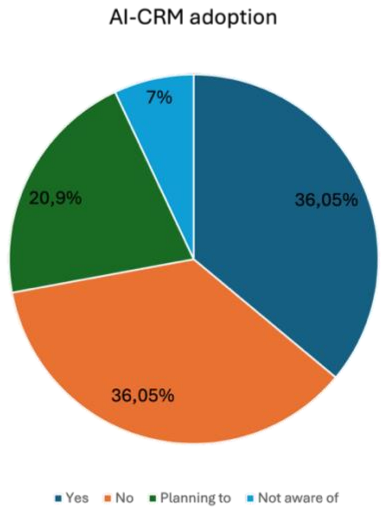
Each response category was assigned a numeric value to reflect increasing levels of adoption maturity: "No" =1, "Not aware of" =2, "Planning to" = 3, and "Yes" =4. This transformation assumes that the stages of the adoption represent a meaningful progression with approximately equal intervals (Field, 2018). The resulting variable, labeled "AI_CRM_new", was treated as a scale variable in SPSS and used in subsequent regression analysis.

4.3 Construction of Composite Variables

To prepare the data for analysis, composite variables were created by averaging the individual item scores for each construct. For example, PU_mean was computed as the average of PU1 to PU5, and similarly, PEU_mean, TR_mean, MS_mean, FC_mean, RC_mean, and DP_mean were calculated using their corresponding items. All items were measured on a five-point Likert scale (1= strongly disagree to 5= strongly agree). This aggregation approach was supported by reliability.

4.4 Descriptive statistics

Descriptive statistics were computed to provide an overview of the central tendencies and variability of the main variables included in the study. The dependent variable was measured on a 4-point scale ranging from 1 ("No adoption") to 4 ("Full adoption"). The average level of AI-powered CRM adoption was 2.54 (SD=1.30), indicating a wide spread of responses, with companies evenly distributed between full adoption and no adoption. Despite the average being slightly above the midpoint, the majority of firms are either at the extremes of full adoption or no adoption, rather than in the early or unaware stages (see Figure 3).



(Figure 3: Percentages of AI-powered CRM adoption)

To provide further contextual understanding, descriptive statistics were stratified by firm size. Results revealed that medium-sized enterprises (51-250 employees) reported the highest scores for perceived usefulness (M= 3.92), management support (M= 3.61), and technological readiness (M= 3.56). Interestingly, Perceived Ease of Use (PEU) scores were relatively stable across all firm sizes, highlighting that usability perceptions may be consistent regardless of organizational scale. These findings support the relevance of considering firm-level differences, particularly in resource-based constructs such as management support and technological readiness.

4.5 Reliability Analysis

To assess the internal consistency of the multi-item constructs used in the analysis, Cronbach's alpha (α) was calculated for each scale (see Appendix A). Following guidelines provided by Hair et al. (2019), alpha values above .70 are generally considered acceptable, while values between .60 and .70 can be deemed adequate in exploratory studies, particularly for scales with fewer than four items. This analysis ensured that each construct reliably measured the intended latent variable prior to inclusion in the regression models.

The Perceived Usefulness (PU) construct, consisting of five items, demonstrated strong internal consistency with a Cronbach's alpha of .848. All items showed corrected item-total

correlations above .58, and the removal of any item did not meaningfully improve the overall reliability. These results supported the retention of all five PU items in the analysis.
In contrast, the initial reliability of the Perceived Ease of Use (PEU) construct was lower than expected (a= .672). Item-total statistics revealed that the fourth item (PEU4), which assessed training requirements for AI tools, had a low item-total correlation and contributed negatively to the internal consistency of the scale. Moreover, this item showed conceptual overlap with other ease-of-use items. As a result, PEU4 was removed, and the revised three-item scale produced an improved Cronbach's alpha of .702, surpassing the acceptable threshold. This decision aligns with Field's (2018) recommendations for improving scale clarity and statistical robustness by excluding underperforming items.

The Technological Readiness (TR) construct, comprised of three items, showed an alpha of .694. Although slightly below the .70 benchmark, this value is considered acceptable in the context of short exploratory scales. All three items had correlated item-total correlations above .48, and removing any item would have reduced the scale's conceptual and statistical validity.

Moreover, the Data Privacy Concerns (DP) construct, used as a moderator in the analysis, was also composed of three items and demonstrated a Cronbach's alpha of .687. While also slightly below the ideal threshold, this value was retained given the exploratory nature of the study and the importance of maintaining conceptual coverage. In addition to that, no item significantly would improve reliability if removed, and item-total correlations ranged from .43 to .58.

Lastly, the constructs of Management Support (MS), Financial Costs (FC), and Rival Competition (RC) all demonstrated acceptable internal consistency. The MS scale (five items) yielded a Cronbach's alpha of .844, with corrected item-total correlations ranging from .62 to .70. The FC construct (three items) showed an alpha of .747, and all items had correlations above .55. Similarly, the RC scale (three items) achieved an alpha of .764, with item-total correlation between .57 and .63. No items in these constructs warranted removal, confirming the reliability of each scale.

4.6 Multiple Linear Regression Analysis

4.6.1 Assumptions Testing

Before estimating the regression model, key assumptions of multiple linear regression were assessed. These include linearity, homoscedasticity, independence of observations, normality of residuals, and the absence of multicollinearity, as outlined in Field (2018) and Hair et al. (2019).

Linearity was examined through scatterplots and preliminary descriptive statistics, which indicated consistent and proportional relationships between the independent variables and the dependent variable (AI_CRM_new). Homoscedasticity was assessed by examining residual plots (see Appendix B), which showed that the variance of the residuals remained roughly constant across predicted values. The assumption of independent residuals was considered reasonable based on the study's cross-sectional design and the sampling method used. Data were collected from individual SMEs operating across various sectors and countries, with no known clustering or sequential dependence.

The normality of residuals was tested through histograms (see Appendix C) and normal probability (P-P) plots of the standardized residuals (see Appendix D), which approximated a normal distribution. Finally, multicollinearity was evaluated using both the Variance Inflation Factor (VIF) and Tolerance values. All VIF values were below the commonly accepted threshold of 10, and Tolerance values exceeded 0.10 (see Table 2), suggesting no issues of multicollinearity among the predictors (Hair et al., 2019). These diagnostic steps confirmed that the data met the conditions required for valid linear regression analysis.

Collinearity Statistics		
	Tolerance	VIF
(Constant)		
PU_mean	.638	1.567
TR_mean	.547	1.828
MS_mean	.560	1.787
FC_mean	.790	1.265
DP_mean	.793	1.261
RC_meann	.646	1.549
PEU_mean_updated	.738	1.354

(Table 2: Collinearity Statistics)

4.6.2 Model Estimation and Fit

To assess the relationship between the identified predictors and AI-CRM adoption, a standard multiple linear regression analysis was conducted. The independent variables included PU, PEU, TR, MS, FC, RC, and DP, all of which were entered simultaneously into the model. The dependent variable was the transformed AI-CRM adoption score (AI_CRM_new), treated as a continuous variable to reflect increasing levels of implementation maturity.

The regression model was statistically significant, $F (7, 104) = 6.559$, $p < .001$ (see Appendix E), indicating that the combination of independent variables significantly predicted AI-CRM adoption (Table 3). The model yielded a coefficient of determination (R^2) of .306, suggesting that approximately 30.6% of the variance in AI-CRM adoption can be explained by the set of predictors. The adjusted R^2 value was .260, which accounts for model complexity and provides a more conservative estimate of explanatory power (Field, 2018; Hair et al., 2019). The standard error of the estimate was 1.119, which is considered acceptable given the range of the dependent variable.

An examination of the regression coefficients revealed that Rival Competition had a positive and statistically significant effect on AI-CRM adoption ($\beta= .349$, $t= 3.432$, $p <.001$). This finding suggests that competitive pressure is a major driver of AI-CRM implementation in SMEs. Management Support also exhibited a significant positive association with AI-CRM adoption ($\beta= .275$, $t= 2.300$, $p= .023$). This finding aligns with theoretical expectations and underscores the critical role that top management plays in facilitating technology implementation.

The remaining predictors did not reach statistical significance but still provided valuable directional insights (Table 3). Technological Readiness (TR) and Financial Costs (FC) had negative coefficients, suggesting that concerns around infrastructure or investment may hinder adoption, although these were not significant at the 5% level. Perceived Usefulness (PU) and Data Privacy Concerns (DP) both showed small, non-significant effects. Even though DP did not significantly influence adoption directly, it was retained for further analysis as a potential moderating variable due to its theoretical relevance. Perceived Ease of Use (PEU), captured via a refined composite variable, also exhibited a non-significant negative effect. While not statistically meaningful, these directional trends remain aligned with the theoretical assumptions of the TAM and TOE frameworks.

Coefficients					
	Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
(Constant)	.324	.896		.361	.718
PU_mean	.152	.176	.088	.863	.390

TR_mean	-.104	.159	-.072	-.654	.514
MS_mean	.398	.173	.251	2.300	.023
FC_mean	-.280	.146	-.176	-1.921	.058
DP_mean	.062	.131	.044	.475	.636
RC_mean	.487	.142	.349	3.432	<.001
PEU_mean_updated	-.156	.184	-.080	-.846	.400

(Table 3: Coefficients Table, AI-CRM predictors)

In addition, residual diagnostics were conducted to evaluate the assumptions of normality, linearity, and the absence of influential outliers. Standardized and studenized residuals fell within the acceptable range of ± 3. Cook's Distance values were all below .10, indicating no observations exerted undue influence on the model. The maximum Mahalanobis Distance was 22.07, which, while approaching conventional cutoffs, did not exceed thresholds suggesting multivariate outliers (Field, 2018). Visual inspection of the residual histogram and normal P-P Plot (Appendices B and C) further supported the assumption of normally distributed residuals.

Collectively, these findings confirm that the model met the core assumptions required for linear regression and that it offers a statistically meaningful explanation of AI-CRM adoption behavior in the sample.

4.6.3 Moderation Test: Data Privacy as a Moderator

To examine whether Data Privacy Concerns (DP) moderate the relationship between Perceived Usefulness (PU) and AI-CRM adoption, a moderated multiple regression analysis was conducted. The independent variables included PU_centered, DP_centered, and their interaction term (PUxDP), all of which were mean-centered prior to analysis to reduce potential multicollinearity, as recommended in regression modeling practices (Hair et al., 2019).

The model was statistically significant, $F(3, 108) = 4.894$, $p = .003$ (see Appendix F), indicating that the combination of main and interaction effects contributes meaningfully to the prediction of AI-CRM adoption. The model explained 12% of the variance in the dependent variable ($R^2 = .120$), with an adjusted R^2 of .095, and a standard error of the estimate of 1.237, suggesting weak explanatory power.

However, while the overall model was significant, the interaction term PUxDP was not statistically significant ($\beta = .037$, $t = .250$, $p = .803$), indicating that data privacy concerns do not significantly moderate the relationship between perceived usefulness and AI-CRM adoption. The main effect of PU_centered remained significant ($\beta= .583$, $p < .001$), reinforcing the central role of perceived usefulness in predicting adoption. DP_centered, as an independent predictor, was not significant ($\beta= .113$, $p= .382$), consistent with prior results from the primary regression analysis.

4.6.4 Firm size differences in AI-CRM adoption

To explore whether AI-CRM adoption levels vary significantly across firm size categories, a one-way Analysis of Variance (ANOVA) was conducted. Firm size (micro, small, and medium enterprises) served as the independent variable, with the AI_CRM_new score as the dependent variable. Descriptive statistics revealed that micro-enterprises ($M= 2.90$) and medium enterprises ($M= 2.73$) reported higher levels of AI-CRM adoption compared to small enterprises ($M= 2.13$).

Levene's Test of homogeneity of variance was non-significant ($p= .598$), indicating that the assumption of equal variances was met, thereby validating the ANOVA procedure (Field, 2018). The analysis revealed a statistically significant effect of firm size on adoption levels, $F(2, 109) = 3.534$, $p= .033$, with an effect size of $\eta^2= 0.061$ (see Appendix G), representing a moderate practical significance (Hair et al., 2019).

Although post hoc comparisons did not yield statistically significant results at the conventional threshold ($p < .05$), two comparisons approached significance: small vs micro firms and small vs medium firms. These results suggested that small enterprises may meaningfully differ in adoption behavior from both smaller and larger firms, despite the marginal difference.

Homogenous subset analysis confirmed this pattern by grouping firms into two distinct categories: small enterprises formed one cluster ($M= 2.13$), while micro and medium firms were grouped together, reflecting statistically similar adoption levels. This indicated that small enterprises may represent a structurally distinct group with lower adoption propensity.

Discussion and Conclusions

5.1 Conclusion

This study set out to answer the research question: "How do perceived usefulness, perceived ease of use, technological readiness, management support, financial costs, and rival competition influence the adoption of AI-powered CRM in SMEs, and how do data privacy concerns moderate the effect of perceived usefulness?"

The findings provide a clear response: AI-CRM adoption in SMEs is primarily driven by organizational and environmental factors – specifically, management support and competitive pressure. Both of these variables showed statistically significant and positive effects, highlighting that strategic leadership engagement and external market forces are central to driving adoption.

Conversely, technology-focused perceptions such as perceived usefulness and perceived ease of use, while conceptually relevant, did not show statistically significant effects within the full regression model. Perceived usefulness retained predictive power only when assessed in isolation, suggesting its role may be secondary or moderated by organizational dynamics. Similarly, technological readiness, financial costs, and data privacy concerns were not significant predictors, though financial constraints approached significance and remain a practical barrier, particularly for smaller firms.

In sum, these results indicate that successful AI-CRM adoption in SMEs depends less on how useful or easy the technology is perceived to be, and more on the strategic readiness of the organization and the pressures it faces in its competitive environment.

5.2 Key findings

The most critical finding of this study is the statistically significant impact of management support (H4) ($t= 2.300$, $p= .023$) and rival competition (H6) ($t= 3.432$, $p <.001$) on AI-CRM adoption. These results confirm that leadership commitment and external rivalry are central enablers of digital transformation in SMEs – consistent with prior research (Gangwar et al., 2015; Chatterjee et al., 2021).

Regarding technological readiness (H3), the regression analysis revealed a non-significant negative coefficient ($\beta= -.072$, $p= .514$), suggesting that SMEs' existing infrastructure and digital capability did not play a meaningful predictive role in determining adoption. This may reflect either a conceptual overlap with more dominant organizational factors like management support or a potential threshold effect – where a baseline level of readiness is necessary but not sufficient to drive adoption decisions (Abed, 2020).

Furthermore, although perceived usefulness (H1) and perceived ease of use (H2) were not statistically significant predictors in the regression model, they remain conceptually important. This outcome aligns with the argument by Awa et al. (2015) that traditional TAM constructs may be overly narrow when applied to complex organizational settings.

Similarly, the moderation hypothesis (H1.a) concerning data privacy was also not supported, indicating firms prioritize competitiveness and value creation over privacy risks, a fact that has been acknowledged in the past (Gangwar et al., 2015; Chatterjee et al. 2021). While the interaction term (PU x DP) was not statistically significant, proving that DP does not act as a moderator, the main effect of PU_centered remained highly significant ($\beta = .583$, $p < .001$). This suggests that perceived usefulness retains considerable predictive power when modeled independently – reinforcing its central theoretical role in adoption behavior, particularly in simplified or user-focused models. Its effect may have been diminished in the full regression model due to conceptual overlap with broader organizational factors (Baby and Kannammal, 2020).

Financial costs (H5) showed a near significant negative effect ($p = 0.58$), echoing findings from Ngah et al (2017) that cost remains a practical inhibitor – especially in smaller or less digitally mature firms.

Last but not least, the study explored firm size as a contextual factor, revealing that small enterprises – not micro-enterprises – exhibited the lowest levels of AI-CRM adoption. This suggests that while larger firms benefit from more established infrastructures and micro-enterprises from flexibility and rapid decision-making, small firms appear structurally disadvantaged – lacking both agility and sufficient support systems. This “structural squeeze” has been noted in prior research by Awa et al. (2010) and Chatterjee et al. (2021), both of whom stress the importance of firm-level readiness and targeted support in ensuring equitable technology adoption across SME categories.

5.3 Academic Contributions

This study contributes to the theoretical discourse on technology adoption by highlighting the limitations of traditional TAM constructs, particularly when applied to the complex, resource-constrained environment of SMEs. While perceived usefulness and perceived ease of use have demonstrated consistent predictive power in past research (Scherer et al., 2019; Scherer & Teo, 2019; Baby & Kannammal, 2020), this study’s findings align with more recent literature suggesting these variables may lose explanatory strength when organizational and environmental conditions are considered concurrently (Chatterjee et al., 2021; Gangwar et al., 2015). Importantly, the presence of non-significant results should not be hastily interpreted as a theoretical weakness. Instead, they may reflect deeper structural barriers or conceptual overlap with more dominant contextual variables.

The significant roles of management support and competitive pressure on AI-CRM adoption in this study support the assertion that strategic and leadership-related variables are more decisive in organizational contexts than individual-level cognitive perceptions (Awa et al., 2015; Chatterjee et al., 2021). Furthermore, this study highlights the relevance of firm size as a contextual moderator in AI-CRM adoption, supporting prior findings that small firms often occupy a structurally disadvantaged position between micro and medium enterprises (Awa et al., 2010; Chatterjee et al., 2021).

Thus, this research contributes to the growing stream of literature advocating for hybrid adoption models that integrate TAM with TOE to better capture the strategic, organizational, and environmental contingencies influencing technological uptake in SMEs.

5.4 Managerial and Practical Implications

This study offers a practical roadmap for SME managers, policymakers, and technology providers aiming to facilitate effective AI-CRM adoption. The following recommendations are derived from the empirical findings and grounded in theoretical frameworks:
For SME Managers:

- Prioritize leadership involvement: Active managerial support is a critical enabler of AI-CRM adoption. Leaders should demonstrate commitment, allocate resources, and visibly champion AI initiatives within the organization (Chatterjee et al., 2021; Wang et al., 2010).
- Shift the focus from usability to strategy: Rather than overemphasizing how easy a system is to use, decision-makers should focus on aligning AI-CRM with core business goals and competitive positioning (Chatterjee et al., 2021; McKinsey & Company, 2025).

For Policymakers:

- Support SME readiness beyond funding: While financial is helpful, capacity-building programs (e.g., digital skills training, mentoring) are equally essential for SMEs to be AI-ready. As suggested by Chatterjee et al. (2021), enhancing organizational readiness – including skills development, digital literacy, and infrastructural maturity – is essential for sustained adoption success.
- Tailored support by firm size is crucial: This study found that small enterprises (11-50 employees) are structurally disadvantaged compared to both micro and medium firms.

Policies and consultancy practices should offer size-specific programs to address this "structural squeeze" (Awa et al., 2010; Chatterjee et al., 2021).

For technology vendors and consultants:

- Frame AI as a strategic enabler, not just a tool: As McKinsey (2025) highlights, organizations that realize tangible value from AI treat its deployment as a transformation of workflows, decision-making, and long-term strategy – not just a technical tool. Therefore, technology vendors should present AI-CRM systems not just as user-friendly tools, but also as business-critical platforms that drive ROI, customer engagement, and operational excellence.

5.5 Reflections and Limitations

The following discussion considers how the study's design choices shaped the findings, while also acknowledging important limitations that may affect their generalizability and interpretation.

A key limitation of this study concerns sample representativeness across SME categories. Although the design aimed for proportional stratified sampling, micro-enterprises – who make up over 93% of all SMEs in the EU (Eurostat, 2024) – were underrepresented, accounting for only 18.3% of the dataset. This imbalance likely stemmed from lower response rates and restricted access to decision-makers in micro-firms. As a result, the generalizability of findings to micro-enterprises may be limited, and caution is warranted when extrapolating conclusions to this subsegment.

Another limitation lies in the prevalence of non-significant results across several tested hypotheses, particularly those grounded in the TAM model, such as perceived usefulness (H1) and perceived ease of use (H2). Although these constructs have consistently shown predictive power in previous research (Rigopoulos & Askounis, 2007), they did not retain statistical significance in the multiple regression model employed here. This divergence, as discussed previously, may be attributed to several context-specific factors. Furthermore, some constructs may conceptually overlap, reducing the distinct explanatory power of each despite acceptable multicollinearity levels (Hair et al., 2019; Thrane, 2020).

From a methodological standpoint, the use of a quantitative survey facilitated broad data collection across multiple EU countries, thereby enhancing the study's cross-national relevance and generalizability. However, this breadth came at the expense of depth constraining a deeper exploration of how individual SMEs experience adoption in practice. A mixed-methods approach could uncover additional explanatory factors – such as internal resistance, cultural readiness, or informal decision-making styles.

While cross-national sampling introduced valuable contextual diversity, it also limited the ability to control for national-level influences – such as regulatory frameworks or variations in digital infrastructure – which may have shaped firm-level readiness and adoption behavior.

Furthermore, the decision to treat SMEs as a single analytical group simplified the model but masked important intra-group differences. Although firm size was considered in post hoc analyses, future studies would benefit from segmenting firms further by digital maturity, industry sector, or organizational structure.

Lastly, the sample size (N= 112), though suitable for exploratory research may have limited the statistical power required to detect smaller effects (Hair et al., 2019). Studies like those by Awa et al. (2015) and Gangwar et al. (2015) have also highlighted that TAM variables may perform inconsistently in studies with limited respondent pools. The same applies to predictors from the TOE framework – such as financial costs (H5) – which approached significance and might have yielded stronger results with a larger or more evenly distributed sample, especially across firms' sizes (Hair et al., 2019).

Despite these limitations, one notable strength of this study lies in its integration of the TAM and TOE frameworks. This hybrid approach enabled a multi-layered examination of both individual and contextual determinants, offering a richer and more realistic account of AI adoption in resource-constrained SME environments.

In sum, while the study design offered important advantages in scope and theoretical integration, certain trade-offs in-depth, representativeness, and contextual control shaped the findings. These reflections not only contextualize the limitations but also inform potential directions for future research.

5.7 Recommendations for Future Research

Building on the findings and limitations of this study, the following recommendations offer directions for future research on AI-CRM adoption in SMEs:

- Explore sector-specific adoption patterns: Different industries may face unique technological, regulatory, and customer-related pressures that shape their approach to AI-CRM adoption. Sectoral analysis could help determine whether the predictors identified here hold consistently across domains such as retail, manufacturing, or services, or if distinct drivers emerge in each context.

- Utilize longitudinal research designs: Technology adoption is a dynamic process, not a single decision point. Longitudinal studies could provide a richer understanding of how organizational attitudes, capabilities, and environmental conditions evolve, revealing adoption trajectories and maturity stages.
- Assess the impact of AI adoption on organizational performance: Although this study focused on adoption intent, future research should examine performance outcomes as dependent variables. Specifically, AI's impact on marketing performance, customer engagement, and financial outcomes deserves attention. AI-enabled tools such as chatbots, predictive analytics, and personalization systems are designed to drive efficiency and enhance the customer experience, which can contribute to long-term competitive advantage (Davenport et al., 2019).
- Evaluate performance through concrete KPIs: Future studies should consider key performance indicators (KPIs) such as return on investment (ROI), return on assets (ROA), conversion rates, and sales growth to quantify the strategic benefits of AI implementation (Katsikeas et al., 2016; Kedi et al., 2024). These metrics will allow researchers to establish a clearer link between technology adoption and business value, providing practical insights for firms evaluating their AI investments.
- Incorporate mixed-methods approaches: Qualitative interviews or case studies could uncover contextual factors that quantitative models alone cannot fully detect – such as organizational culture, internal resistance, or informal decision-making dynamics. These approaches would enhance our understanding of the socio-technical complexity underlying AI implementation in SMEs (Quick & Hall, 2015).

Concluding, based on this study's results, future research should explore how TAM variables operate as mediators or moderators, particularly in the presence of strong organizational or strategic factors. Structural equation modeling may clarify these dynamics (Hair et al., 2019). Further work is also needed to examine the "structural squeeze" affecting small enterprises, including how sector, agility, or resource availability shape their adoption trajectories.

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Appendices

Appendix A

Reliability – PU

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.848	.855	5

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.542	.426	.655	.228	1.536	.005	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PU1	15.04	9.723	.702	.557	.807
PU2	14.92	9.617	.714	.530	.804
PU3	15.21	9.598	.647	.439	.820
PU4	14.84	9.569	.679	.483	.812
PU5	14.84	8.927	.587	.371	.845

Reliability – PEU

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.672	.686	4

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.353	.183	.480	.297	2.619	.014	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PEU1	10.02	3.798	.556	.315	.545
PEU2	9.75	3.453	.460	.275	.606
PEU3	9.78	3.970	.530	.319	.566
PEU4	10.65	4.084	.314	.131	.701

Reliability – TR

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.694	.696	3

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.433	.395	.466	.071	1.181	.001	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TR1	6.75	3.427	.539	.293	.564
TR2	6.87	3.693	.487	.237	.632
TR3	6.63	4.035	.509	.263	.607

<u>Reliability – MS</u>

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.844	.846	5

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.524	.436	.686	.250	1.574	.007	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
MS1	13.55	11.009	.627	.463	.820
MS2	13.40	11.724	.649	.476	.815
MS3	14.41	10.374	.673	.538	.808
MS4	13.96	11.128	.699	.574	.801
MS5	14.14	11.398	.620	.436	.821

<u>Reliability – FC</u>

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.747	.749	3

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.498	.483	.522	.039	1.081	.000	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
FC1	5.33	3.205	.582	.340	.657
FC2	5.63	2.846	.587	.346	.649
FC3	5.57	3.007	.557	.311	.683

<u>Reliability – RC</u>

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.764	.764	3

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.519	.471	.551	.080	1.169	.001	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
RC1	7.38	4.113	.572	.331	.711
RC2	7.25	3.649	.633	.401	.640
RC3	6.94	3.879	.585	.348	.696

<u>Reliability – DP</u>

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.687	.689	3

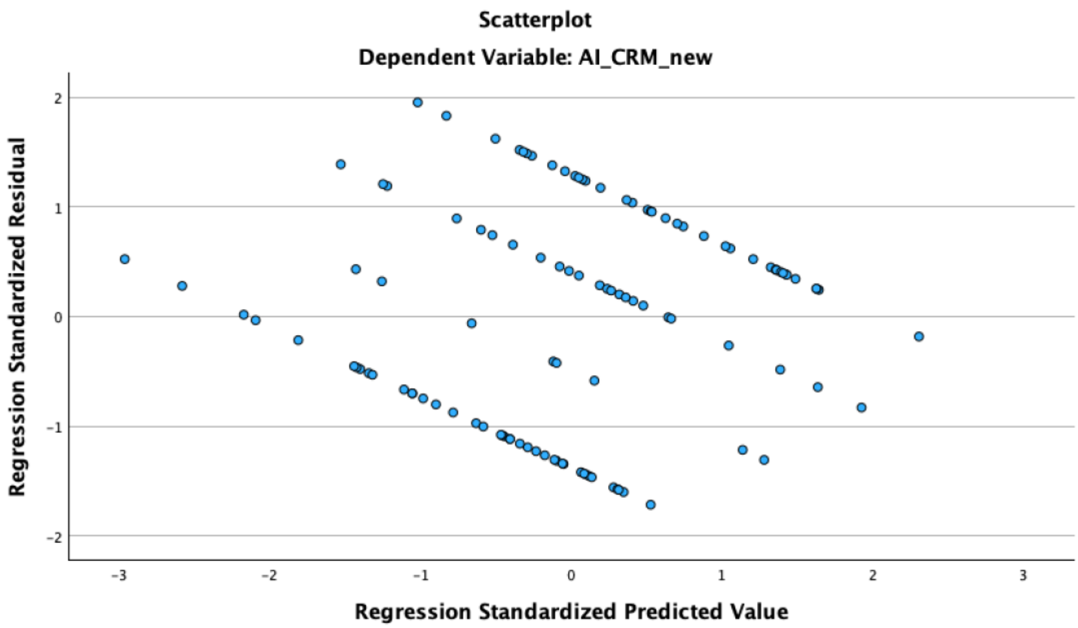
Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.425	.323	.524	.201	1.622	.008	3

Item-Total Statistics

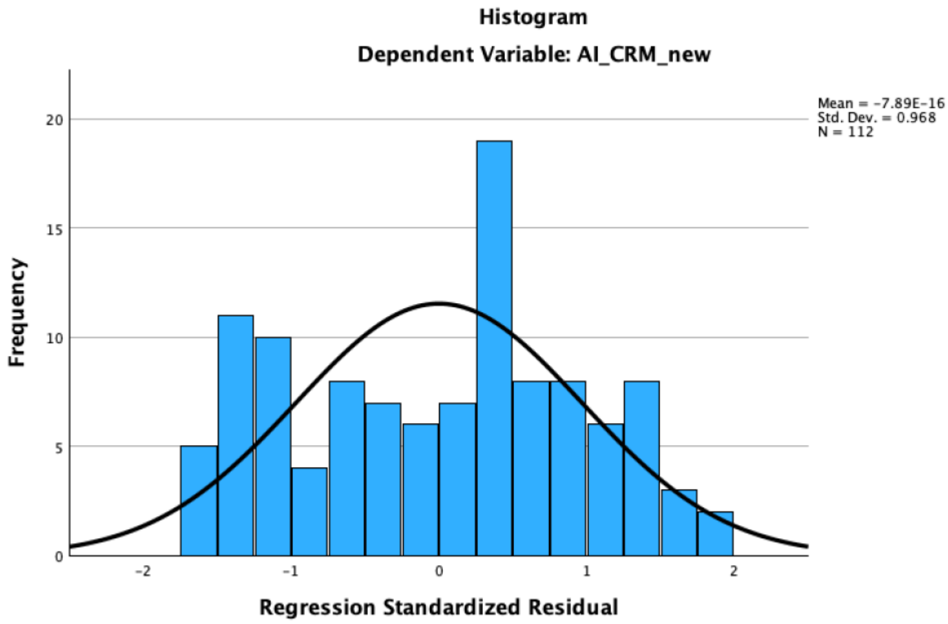
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
DP1	6.52	3.852	.434	.197	.684
DP2	6.63	4.144	.500	.286	.599
DP3	6.63	3.399	.580	.349	.485

Appendix B

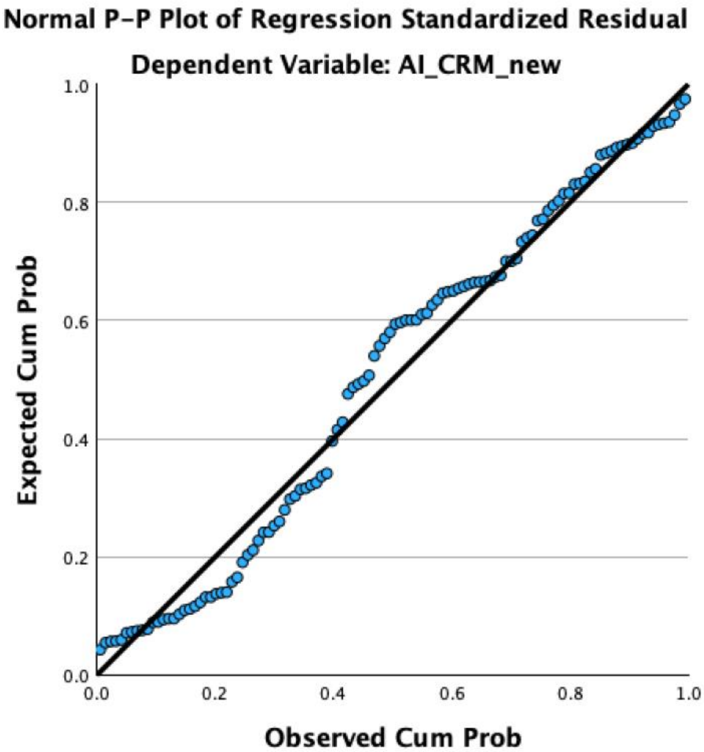


Appendix C

Charts



Appendix D



Appendix E

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.553[a]	.306	.260	1.119

a. Predictors: (Constant), PEU_mean_updated, DP_mean, PU_mean, FC_mean, MS_mean, RC_mean, TR_mean

b. Dependent Variable: AI_CRM_new

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	57.510	7	8.216	6.559	<.001[b]
	Residual	130.267	104	1.253		
	Total	187.777	111			

a. Dependent Variable: AI_CRM_new

b. Predictors: (Constant), PEU_mean_updated, DP_mean, PU_mean, FC_mean, MS_mean, RC_mean, TR_mean

Appendix F

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.346[a]	.120	.095	1.237

a. Predictors: (Constant), PUxDP, DP_centered, PU_centered

b. Dependent Variable: AI_CRM_new

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	22.470	3	7.490	4.894	.003[b]
	Residual	165.306	108	1.531		
	Total	187.777	111			

a. Dependent Variable: AI_CRM_new

b. Predictors: (Constant), PUxDP, DP_centered, PU_centered

Appendix G

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
AI_CRM_new	Based on Mean	.516	2	109	.598
	Based on Median	.133	2	109	.876
	Based on Median and with adjusted df	.133	2	81.486	.876
	Based on trimmed mean	.500	2	109	.608

ANOVA

AI_CRM_new

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	11.435	2	5.718	3.534	.033
Within Groups	176.341	109	1.618		
Total	187.777	111			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
AI_CRM_new	Eta-squared	.061	.000	.153
	Epsilon-squared	.044	-.018	.138
	Omega-squared Fixed-effect	.043	-.018	.137
	Omega-squared Random-effect	.022	-.009	.073

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.