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Impact of Multidimensional DSS Capability on CRM Efficiency: Evidence from CMWU Using a Formative-Formative HCM

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Abstract:

This study investigates the impact of multidimensional Decision Support System (DSS) capabilities on Customer Relationship Management (CRM) efficiency in the Coastal Municipalities Water Utility (CMWU). The study proposes a sequential mediation model in which CRM plans and CRM strategies act as organizational mechanisms linking DSS capability to CRM efficiency. Data were collected using a structured questionnaire distributed to administrative and technical employees at CMWU, yielding 79 valid responses. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS, employing a formative-formative Hierarchical Component Model (HCM) to capture the multidimensional nature of DSS capability.

The results reveal that DSS capability significantly enhances CRM plans ($\beta = 0.669$), which in turn strengthen CRM strategies ($\beta = 0.485$), ultimately improving CRM efficiency ($\beta = 0.523$). However, the direct relationship between DSS capability and CRM efficiency is not statistically significant, indicating that the value of DSS is realized through organizational planning and strategic processes rather than through direct technological effects. The structural model explains 66.5% of the variance in CRM efficiency.

The findings contribute to the information systems and CRM literature by conceptualizing DSS capability as a multidimensional organizational capability and by demonstrating the sequential process through which technological resources translate into CRM performance outcomes. The study also provides practical insights for public utility organizations seeking to leverage DSS capabilities to enhance CRM effectiveness and service efficiency.

Keywords: Decision Support Systems (DSS), DSS Capability, Customer Relationship Management (CRM), CRM Efficiency, CRM Planning, CRM Strategies, Hierarchical Component Model (HCM), PLS-SEM.

أثر قدرات نظم دعم القرار متعددة الأبعاد على كفاءة إدارة علاقات العملاء: دليل تطبيقي من مصلحة مياه بلديات الساحل باستخدام نموذج المكونات الهرمية التكويني-التكويني

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الملخص:

تستكشف هذه الدراسة أثر القدرات المتعددة الأبعاد لنظم دعم القرار (DSS) على كفاءة إدارة علاقات العملاء (CRM) لدى مصلحة مياه بلديات الساحل (CMWU). وتقترح الدراسة نموذج وساطة متسلسلة، تؤدي فيه خطط إدارة علاقات العملاء واستراتيجياتها دور آليات تنظيمية تربط بين قدرة نظم دعم القرار وكفاءة إدارة علاقات العملاء. جمعت البيانات باستخدام استبانة منظمة وزعت على الموظفين الإداريين والفنيين في مصلحة مياه بلديات الساحل، وأسفرت عن (79) استجابة صالحة للتحليل. وقد جرى تحليل البيانات باستخدام نمذجة المعادلات الهيكلية بالمربعات الصغرى الجزئية (PLS-SEM) عبر برنامج Smart PLS ، مع توظيف نموذج المكونات الهرمي (HCM) من نوع تكويني- تكويني، بما يمكن من تمثيل قدرة نظم دعم القرار بوصفها بنية متعددة الأبعاد.

وتظهر النتائج أن قدرة نظم دعم القرار تعزز خطط إدارة علاقات العملاء تعزيزاً ذا دلالة إحصائية ($\beta = 0.669$)، وهو ما يفضي بدوره إلى تقوية استراتيجيات إدارة علاقات العملاء ($\beta = 0.485$)، بما ينعكس في نهاية المطاف على رفع كفاءة إدارة علاقات العملاء ($\beta = 0.523$). غير أن العلاقة المباشرة بين قدرة نظم دعم القرار وكفاءة إدارة علاقات العملاء لم تكن ذات دلالة إحصائية، الأمر الذي يشير إلى أن القيمة المتحققة من نظم دعم القرار إنما تتجسد عبر عمليات التخطيط التنظيمي والمسارات الإستراتيجية، لا عبر آثار تكنولوجية مباشرة. وقد فسر النموذج البنائي نسبة 66.5 % من التباين في كفاءة إدارة علاقات العملاء.

تسهم هذه النتائج في أدبيات نظم المعلومات وإدارة علاقات العملاء من خلال تأطير قدرة نظم دعم القرار بوصفها قدرة تنظيمية متعددة الأبعاد، وإبراز العملية المتسلسلة التي تتحول عبرها الموارد التكنولوجية إلى مخرجات أداء في إدارة علاقات العملاء. كما تقدم الدراسة دلالات تطبيقية للمنظمات العمومية الخدمية الساعية إلى توظيف قدرات نظم دعم القرار لتعزيز فاعلية إدارة علاقات العملاء ورفع كفاءة الخدمة.

كلمات مفتاحية: نظم دعم القرار (DSS)، قدرة نظم دعم القرار، إدارة علاقات العملاء (CRM)، كفاءة إدارة علاقات العملاء، تخطيط إدارة علاقات العملاء، استراتيجيات إدارة علاقات العملاء، نموذج المكونات الهرمي (HCM)، نمذجة المعادلات الهيكلية بالمربعات الصغرى الجزئية (PLS-SEM).

1. Introduction

In today's dynamic business world, the capacity to analyze massive volumes of information and assist smart decisions is a leading factor of accomplishment. Decision Support Systems (DSS) are complex information systems developed to assist organizations in addressing decisions of different levels of clarity, including structured, semi-structured, and even unstructured issues. Unlike traditional information systems applied in data processing technology, DSS enable managers to explore massive volumes of information and analyze different alternatives and complex decision situations (Tripathi, 2011). Within this context, DSS improve organizational efficiency and reduce costs while supporting informed managerial decisions. The necessity for DSS is driven by the challenges of contemporary management, which involve making decisions in different timeframes. Managers are required to deal with daily decisions and long-term strategic decisions that will define the future of the organization (Goldmann & Zawadzki, 2025). In this context, organizations are increasingly relying on information systems that are flexible and able to generate different outputs based on different decision requirements (O'Brien & Marakas, 2010).

In the context of modern organizations, technological and digital capabilities are no longer regarded as merely technological and digital capabilities, as their strategic role in improving organizational performance and managerial decisions is recognized (Wielgos et al., 2021). Recent studies have highlighted the critical role of digital capabilities in improving organizational performance through supporting managerial processes and the quality of strategic decisions (Neiroukh et al., 2024). In the context of digital transformation, information technologies are used as a tool to support organizational learning and strategic processes (Barba-Sánchez et al., 2024). These developments underscore the strategic role of technological capabilities as a basic tool to support managerial processes and organizational performance.

Throughout history, the notion of decision support has witnessed a significant paradigm shift. The initial body of literature on decision support systems (DSS) perceived these systems as tools for evaluating alternative solutions and supporting problem-solving activities. Recent literature, however, has perceived decision support systems as environments that promote information processing in organizations and support complex managerial activities, such as decision-making (Gupta et al., 2006). In this context, DSS are perceived as information technology tools that help managers better understand complex organizational problems and develop appropriate solutions (Bresfelean et al., 2009). The structural architecture of DSS was first formalized by Sprague (1980), who emphasized the importance of database, application, and hardware infrastructure in managerial decision environments. Subsequent research has indicated that the effectiveness of DSS is contingent upon various interconnected components in organizations, such as technological, database, and application infrastructure, and top management support (Al-Alwan, 2019).

This technological capability has special importance in organizational contexts in which customer information and service interactions are key to organizational effectiveness. In the domain of Customer Relationship Management (CRM), advanced analytical technologies allow organizations to leverage their large amounts of customer information to create strategic knowledge that can be used to support customer-centered decision-making. Empirical studies have shown that the effectiveness of organizational performance and the achievement of competitive advantage can be enhanced by the capabilities of digital and analytical technologies in the context of CRM (Rahman et al., 2023; Yoo et al., 2024). Moreover, the capabilities of CRM can be used to enhance customer engagement and support the effectiveness of innovation outcomes by helping organizations better understand their customers and deliver more responsive service (Binsaeed et al., 2023).

Despite extensive research on the contribution of information systems and decision support systems to organizational performance, important gaps remain regarding how DSS capability contributes to CRM efficiency, particularly in public utility organizations. Much of the prior research has focused on private-sector settings and has frequently treated DSS as a primarily technical resource, providing limited insight into its multidimensional organizational capability. Specifically, existing studies have provided limited examination of how multiple DSS components such as technological infrastructure, databases, software systems, and managerial support jointly influence CRM outcomes. In addition, the mechanisms through which DSS capability translates into CRM efficiency remain insufficiently explored, as the mediating roles of CRM planning and CRM strategies have received limited empirical attention. Furthermore, only a limited number of studies have applied hierarchical component modeling approaches within PLS-SEM to examine such multidimensional capabilities (Saihi et al., 2023).

Addressing these gaps, the present study examines the impact of multidimensional DSS capability on CRM efficiency in the Coastal Municipalities Water Utility (CMWU). Specifically, the study conceptualizes DSS capability as a multidimensional organizational capability and investigates how it influences CRM efficiency through the mediating roles of CRM plans and CRM strategies within a formative-formative hierarchical component model.

1.1. Study Problem and Questions

In recent years, public utilities have shown increased reliance on DSS to improve the level of service delivery and achieve efficiency in their customer relationship management (CRM). Despite the fact that many utilities have made substantial investments in DSS, there are challenges in converting this to tangible improvements in the efficiency of their CRM processes. Although there is substantial literature on the relationship between DSS and its impact on organizational performance in general, there is very limited and inconclusive literature on whether DSS influences CRM performance directly or indirectly through organizational factors, including CRM planning. In addition, there is limited literature on the multidimensional nature of DSS, including DSS technology and equipment, data resources, software and top management support, particularly in the context of public utilities, as opposed to other organizations in the for-profit sector. Decision-making processes in the public sector differ significantly from those in the for-profit sector, and as such, there is a clear need to examine the contribution of the multidimensional nature of DSS to the efficiency of CRM processes using models that can capture higher-order capabilities.

On the basis of the research problem, this study proposes the following research questions:

1. What is the direct effect of multidimensional DSS capability on CRM efficiency for the Coastal Municipalities Water Utility?
2. How does multidimensional DSS capability influence CRM planning and CRM strategies?
3. Do CRM plans and CRM strategies act as a mediator for the relationship between DSS capability and CRM efficiency?
4. How well does the proposed formative-formative hierarchical component model explain and predict CRM efficiency for the Coastal Municipalities Water Utility?

1.2. Importance of the Study

The present study is deemed significant from both theoretical, methodological, and practical perspectives. Theoretically, this study extends the existing body of information systems and customer relationship management literature, as it provides empirical results concerning the influence of the capability of a multi-dimensional decision support system on the efficiency of CRM, instead of assuming a direct technology-outcome relationship, as is common in previous research. Methodologically, this study is deemed significant, as it demonstrates the application of a formative-formative hierarchical component model in the context of partial least squares structural equation modeling, thus capturing the complex nature of decision support system capabilities and showing that such a model can be employed to measure not just total but also indirect effects in the context of CRM research. Finally, from a practical perspective, this study is deemed significant, as it provides valuable insights concerning the way in which organizational performance can be enhanced in public sector organizations, particularly in the water industry.

1.3. Objectives of the Study

The objective of this study is to assess the role of the capability of a multidimensional decision support system in enhancing the efficiency of customer relationship management in the context of the Coastal Municipalities Water Utility. To attain this overarching objective, this study has the following specific objectives:

1. To assess the direct influence of the capability of a multidimensional decision support system on the efficiency of CRM.
2. To examine the influence of the capability of a multidimensional decision support system on CRM plans and CRM strategies.
3. To investigate the mediating role of CRM plans and CRM strategies in the relationship between the capability of a multidimensional decision support system and CRM efficiency.
4. To validate the appropriateness and suitability of using a formative-formative hierarchical component model in analyzing complex organizational capabilities and CRM outcomes using PLS SEM.

1.4. Study Model and Hypotheses

The theoretical basis for this study combines concepts from both the Resource-Based Theory and the Dynamic Capabilities perspective. According to the Resource-Based Theory, technological capabilities such as decision support systems (DSS) act as organizational resources that improve the decision-making processes of the management. On the other hand, the Dynamic Capabilities perspective reveals the mechanisms for achieving organizational outcomes from technological resources, which involve the activities of management, such as planning and execution of strategy. Therefore, the DSS capability will improve the planning and strategy of CRM efficiency.

In accordance with the study problem and objectives, the following hypotheses were tested as shown in Figure 1:

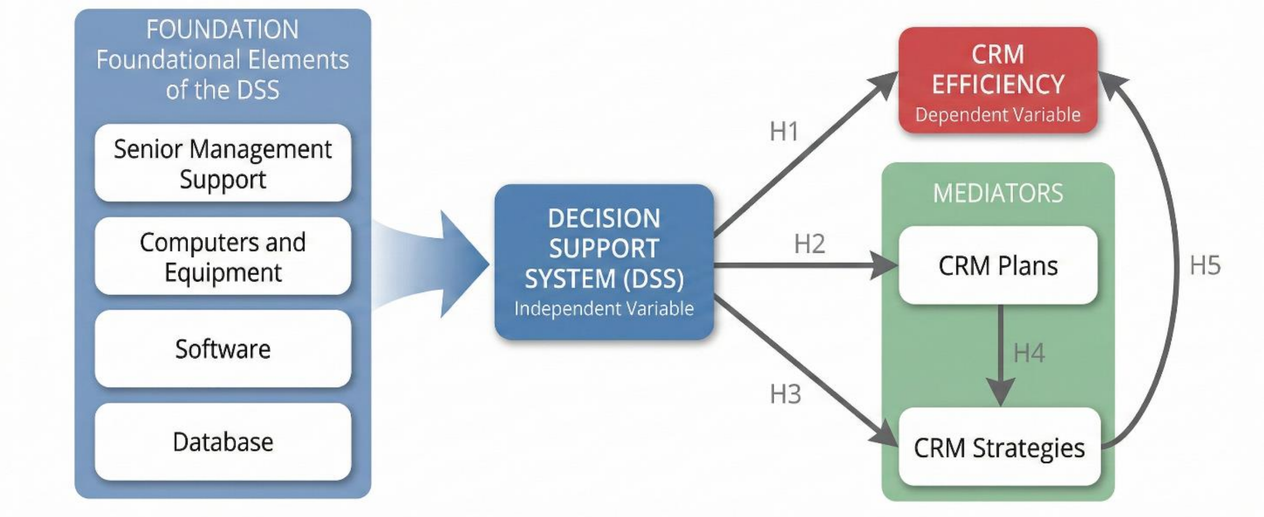

Figure (1): Study Framework and Hypotheses

H1: Multidimensional DSS capability has a direct and positive influence on CRM efficiency at the level ($\alpha \leq 0.05$).

H2: Multidimensional DSS capability has a direct and positive influence on CRM plans at the level ($\alpha \leq 0.05$).

H3: Multidimensional DSS capability has a direct and positive influence on CRM strategies at the level ($\alpha \leq 0.05$).

H4: CRM plans mediate the influence of Multidimensional DSS capability on CRM strategies at the level ($\alpha \leq 0.05$).

H5: CRM plans and CRM strategies sequentially mediate the influence of Multidimensional DSS capability on CRM efficiency at the level ($\alpha \leq 0.05$).

2. Literature Review

2.1. CMWU Profile

The Coastal Municipalities Water Utility (CMWU) is a financially autonomous body entrusted with the responsibilities of providing water services, managing wastewater, and stormwater in the Gaza Strip. The main aim behind the establishment of this utility is to consolidate water and wastewater services under a single framework, thus improving operational efficiency in the Gaza Strip (CMWU, 2011).

CMWU is committed to providing safe and drinkable water and environmentally sustainable wastewater services through the effective and efficient operation, maintenance and development of its infrastructure and utility services. The utility is operating in an environment characterized by raw materials constraints, financial constraints and limited access to developmental resources. Despite these adverse conditions, the utility is committed to the institutional and operational initiatives aimed at enhancing organizational capacity, improving water supply systems and enhancing the quality of services in the Gaza Strip (CMWU, 2011).

Considering the operational complexities involved in managing water utility services and the need to manage substantial volumes of operational and customer-related data, organizations such as the CMWU increasingly rely on decision support and information technology to improve managerial decisions. Thus, Decision Support System (DSS) can play a pivotal role in improving the efficiency of Customer Relationship Management (CRM).

2.2. Decision Support Systems Capability as a Multidimensional Organizational Resource

Decision Support Systems (DSS) are computer-based information systems that are specifically designed to support managerial decision-making processes through the integration of data, models, and interface systems. One of the most seminal conceptual models of DSS was proposed by Sprague (1980), who proposed a basic framework that defined DSS as interactive systems that support managerial decision processes through structured analytical tools and information resources. This conceptual model provided the basic framework that guided further research on the use of DSS in supporting managerial decision-making processes in complex organizational settings.

Early DSS research emphasized the role of analytical models and computational tools in supporting decision-making activities. According to Turban et al. (2005), managerial decision-making was historically perceived as an art based largely on managerial experience and intuition. However, the increasing complexity of organizational environments and the growing availability of digital information have shifted decision-making toward more systematic and data-driven approaches. In this context, DSS are defined as computer-based systems that assist managers in retrieving, analyzing, and summarizing organizational data in order to improve decision quality and organizational performance (Turban et al., 2010).

DSS integrates concepts from management science, operations research, behavioral science, and information technology to support structured decisions (Xie & Rui, 2010). DSS traditionally focused on analytical techniques that enable managers to evaluate different alternatives for structured or partially structured problems. These systems enable organizations to create analytical models for exploring different decision alternatives and determining possible outcomes (Hicks, 1990; Tripathi, 2011).

DSS excels in providing a framework for exploring decisions. With what-if questions, goal-seeking, and scenario models, decision-makers can look into the future and see how decisions can turn out (Hicks, 1990). These models can also be employed in carrying out cost-benefit and financial analyses, enabling organizations to develop tools for analyzing the financial implications of different decisions (Gupta et al., 2006). With these features, DSS can make managerial decisions more reliable and transparent.

Beyond simply calculating numbers, decision support systems also promote organizational learning and knowledge growth. When visualization and analysis are incorporated into DSS systems, managers are able to understand complex organizational information and improve knowledge acquisition processes (Cascante et al., 2002; Bresfelean et al., 2009). This is because DSS systems improve managers' comprehension of complex data structures and therefore improve the quality of strategic decisions.

However, our understanding of decision support systems has evolved from a technology-centered perspective to a more encompassing, capabilities-oriented perspective. Thus, DSS are not merely technologies or tools, but also capabilities that involve the integration of technology networks, data resources, analysis tools, and management support systems (Petter et al., 2007; Becker et al., 2012). With this understanding, a DSS capability is the organization's ability to access and use information in order to substantiate decisions and strategic planning.

In contemporary digital environments, technological capabilities play a critical role in enabling organizations to leverage digital transformation initiatives and improve organizational performance. Digital business capabilities allow firms to transform data resources into strategic insights that guide managerial decision-making and improve firm performance (Wielgos et al., 2021). Similarly, information technology capabilities enable organizations to implement digital transformation strategies that enhance organizational efficiency and innovation outcomes (Barba-Sánchez et al., 2024).

Current research indicates the influence of artificial intelligence on the decision-making processes of various organizations. For instance, AI technologies have the capacity to dig into massive data pools and unearth hidden patterns, which enable managers to make better decisions and improve organizational performance accordingly (Neiroukh et al., 2024).

From a structural point of view, decision support systems consist of a few essential elements that are technologically and organizationally interconnected and influence the effectiveness of the system. Traditionally, decision support systems have three essential components, as depicted in Figure 2, the database management system, the model management system, and the user interface that facilitates the interaction of decision-makers with the analytical models and the organizational data (Power & Sharda, 2007). The model management system contains the analytical models used for forecasting and decision analysis, while the database management system contains the organizational data from both internal and external sources.

The user interface plays an essential role in assisting managers in interacting with the decision support systems, where visualization tools are used to assist in decision analysis (Jung et al., 2020). Similarly, the knowledge base combines data from internal transaction systems and external databases, enabling organizations to utilize various information sources in decision-making processes (Aerts et al., 2022).

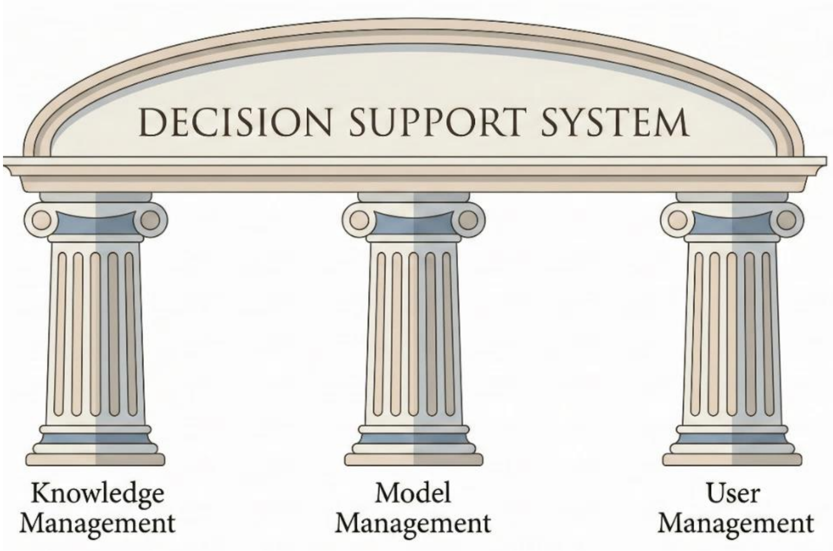

Figure (2): Structure of DSS

As depicted in Figure 3, the implementation of Decision Support Systems is not only dependent on technology but also on the organizational setup and support from management. The hardware component is fundamental in facilitating data processing activities, while the software component is vital in facilitating analytical modeling and information handling activities (Alter, 2002; Hazayma, 2011). Additionally, adequate support from top management is widely recognized as a major motivator for the adoption of DSS technologies in organizations (AL-Shawabkeh, 2018).

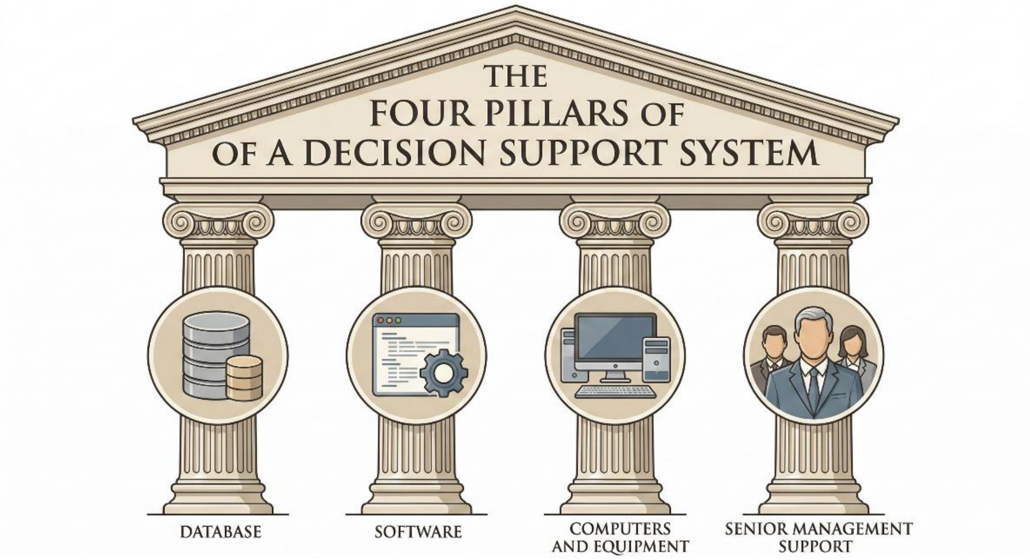

Figure (3): DSS components

The literature has identified different types of decision support systems (DSS) based on their functional characteristics, as shown in Figure 4. Model-driven DSS focus on the use of analytical models to assess decision alternatives and to measure performance outcomes (Felsberger et al., 2017). Data-driven DSS emphasize the use of a large amount of internal and external organizational data to support decision-making (Gandhi et al., 2018). Communication-driven DSS encourage decision-makers to work together using communication technologies (Al-Alawi & Coker, 2018). Document-driven DSS use unstructured information sources, including text and multimedia data (Schuh et al., 2018). Knowledge-driven DSS use artificial intelligence and data mining to generate recommendations and support decision-making (Prasad & Ratna, 2018).

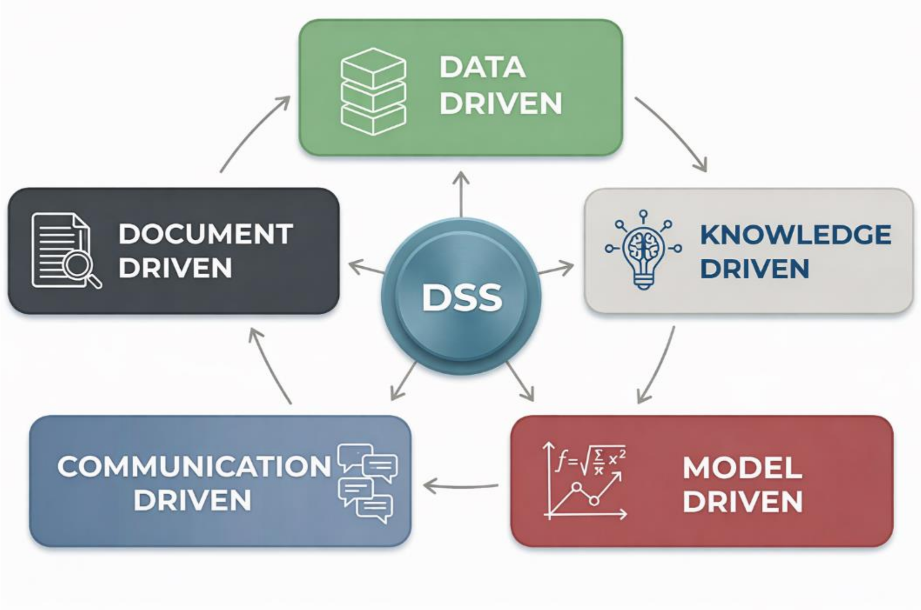

Figure (4): DSS clusters

In general, the body of literature suggests that the capabilities of decision support systems (DSS) improve the quality of decisions and organizational performance because they allow managers to transform complex information into useful insights. However, the empirical findings on the direct effects of DSS technologies on organizational performance vary significantly. A major reason for this inconsistency is that many studies conceptualize DSS as a technological system rather than as a multidimensional organizational capability that incorporates technological, information, analytical software, and managerial support aspects. Therefore, exploring the concept of DSS as a multidimensional concept can provide a more comprehensive understanding of the effects of decision support resources on organizational processes and performance outcomes.

The Resource-Based View (RBV), as a theoretical approach, provides a robust framework for explaining the role of technological capabilities in determining organizational performance. Under the RBV approach, for instance, organizational performance is said to result from the availability of resources that are considered valuable, scarce, difficult to imitate, and not substitutable (Barney, 1991). In light of these propositions, it is possible to view information systems capabilities, such as Decision Support Systems (DSS), as a set of resources for organizational competitiveness, where these resources play a role in improving the capabilities of an organization for information collection, processing, and utilization for managerial decision-making. DSS capabilities, rather than being viewed as mere technological tools for organizational competitiveness, can thus be considered as a set of organizational resources for improving infrastructure, databases, analytical software, and managerial support for information utilization and conversion for managerial planning and decision-making. Thus, from the RBV approach, it is possible for an organization with improved DSS capabilities to develop customer relationship management (CRM) planning and strategies for improving efficiency.

Although the Resource-Based View (RBV) places emphasis on the strategic importance of resources, the Dynamic Capabilities perspective extends this approach by emphasizing the organization's ability to integrate, create, and reconfigure resources in response to changing environments (Teece, 2007). Thus, in dynamic information environments, improvements in performance are seldom achieved through technological resources unless these are integrated into the organization's processes, which transform technological understanding into strategic action.

From this perspective, DSS capability can be conceptualized as an information-processing capability facilitating managerial sensing, planning, and strategic decision-making. Thus, CRM planning and CRM strategy are seen as organizational mechanisms through which understanding facilitated by DSS is transformed into coordinated customer management initiatives, hence improving the efficiency of CRM.

2.3. CRM Planning and Strategy as Organizational Process Mechanisms

Customer Relationship Management (CRM), as a paradigm, represents a strategic approach for managing customer interactions through the integration of technology and organizational management. A CRM system allows an organization to collect and use customer information for improving service delivery and reinforcing customer relationships (Gil-Gomez et al., 2020).

Modern customer relationship management involves different layers of technology and management, transforming customer information into a strategic approach for decision-making. The analytical-operational-directional (AOD) model represents a framework for understanding how customer relationship management systems facilitate decision-making at different levels of an organization. In this model, analytical components process customer information for generating insights, operational components manage customer interactions, and directional components facilitate decision-making for strategic processes (Naim & Alqahtani, 2024).

Significant advancements in digital technologies have led to improved analytical capabilities in customer relationship management (CRM) systems. Artificial intelligence and big data analysis have enabled organizations to derive useful insights from large volumes of customer information and develop more effective strategies to engage with customers (Rahman et al., 2023). These capabilities have helped organizations to identify important customers, make personalized services more effective, and improve the outcomes of customer relationships.

The use of AI in CRM systems has also led to improved organizational performance and strengthened competitive advantage due to the ability to derive more in-depth information about customers and improve the outcomes of customer engagement processes (Yoo et al., 2024). In addition, the use of CRM capabilities has improved customer engagement and innovation performance by enabling organizations to better understand their customers and make necessary strategic changes (Binsaeed et al., 2023).

Nevertheless, despite the growing importance of technological capabilities in customer relationship management (CRM) systems, research literature reveals that the direct impact of technological resources on organizational performance is rare. Instead, the effect of these resources is channeled through organizational processes, which transform these capabilities into effective strategies (Soltani et al., 2018).

In this context, the role of CRM planning appears critical in transforming the findings of analysis into effective strategies. Specifically, CRM planning involves the formulation of policies, processes, and systems through which customer-centric initiatives are executed. Thus, successful CRM planning ensures the alignment of findings from the analysis with overall business objectives, as well as the integration of these findings into managerial processes.

On this basis of planning, CRM strategies are formulated, which translate overall business strategies into action, thus influencing customer-centric processes. These processes can include customer segments, personalized services, and marketing automation, which are aimed at improving customer relationships (Almohaimmeed, 2021).

Operational CRM systems also improve the management of customers by automating the activities of the sales force and marketing processes. The technologies used for automation decrease the time required for the conversion process and enable the management of customers more efficiently (Er, 2020).

Overall, the findings of these studies indicate that the impact of organizational resources, such as technology, does not directly contribute to organizational outcomes. Instead, the contribution of these resources becomes evident when organizational processes enable the transformation of the insights gained from technology into strategic organizational actions. The same idea can be used to explain the findings of the current study, where the importance of planning and strategy can be used as a crucial element for the alignment of technology with customer-oriented strategies within the context of CRM systems. The idea suggests that the impact of DSS would be on the efficiency of the CRM system indirectly through the processes of planning and strategy.

2.4. CRM Efficiency and Technology-Enabled Performance

The concept of CRM efficiency refers to the ability of an organization to successfully execute its customer-related processes with the aim of optimizing the utilization of the organization's resources. The efficiency of the organization in the management of its customer relationships is critical in the coordination and processing of customer interactions, delivery of services, and processing of information in a timely and cost-efficient manner.

In the context of the digital environment, the efficiency of the CRM process has various dimensions, such as the speed, accuracy, integration, and cost efficiency of the organization in managing the different customer interaction processes (Martinho et al., 2025; Yoo et al., 2024). These dimensions represent the integration of the organization's technological and customer processes with the aim of improving its operational efficiency.

Empirical literature shows that the use of customer relationship management (CRM) systems significantly improves organizational productivity as it helps businesses to analyze their customers and provide personalized services that can strengthen their relationship with customers (Gilboa et al., 2019). Similarly, the use of CRM systems improves the coordination of different organizational activities, which in turn improves organizational efficiency and productivity (Hein et al., 2017).

The inclusion of big data analytics in the customer relationship management (CRM) system improves the efficiency of the organizational process of managing customers. It helps organizations to analyze their customers and predict their needs (Saha et al., 2021).

Efficient customer relationship management (CRM) systems help businesses to identify profitable customers and manage resources effectively, thus improving the return on investment in marketing activities (Khan et al., 2020). This strategic approach is in line with the relationship marketing concept, which suggests that businesses should develop long-term relationships with their customers to increase their loyalty and trust (Hayati et al., 2020).

The organizational implementation of the latest technologies associated with CRM often faces various impediments. Small and medium-sized businesses, for instance, face structural impediments such as financial constraints, limited technology expertise, and resistance to digital transformation initiatives (Faiz et al., 2024; Clemente-Almendros et al., 2024). The adoption of CRM technologies can be comprehended from the Technology-Organization-Environment (TOE) model, which suggests that the adoption of technologies by an organization is influenced by factors such as the organization’s technology readiness, organizational resources, and environmental factors including market rivalry and regulatory factors (Nguyen et al., 2022).

Organizational performance within digital environments is considerably influenced by factors such as the strategic support of the organization’s top management and the development of digital capabilities that enable the organization to utilize technology resources (Kim & Jin, 2024; Kallmuenzer et al., 2025).

Although the implementation of CRM technology would increase business costs at the onset due to the associated costs of training and implementation, it would improve the organization’s profit efficiency over time (Udeh et al., 2024).

2.5. Modeling Multidimensional Capabilities Using Hierarchical Component Models

Many organizational capabilities are multidimensional constructs that include several dimensions or aspects of the same concept. Using Hierarchical Component Models (HCM) in SEM, researchers can model multidimensional constructs as higher-order factors with several dimensions (Becker et al., 2012). In terms of the PLS-SEM approach, formative models are applicable in cases where the indicators of a particular construct represent different components that define the concept as a whole, as opposed to a single underlying latent variable (Petter et al., 2007). This approach has

gained widespread use in information systems research in modeling complex technological capabilities, including IT capabilities and digital capabilities (Hair et al., 2017).
Recent studies have used hierarchical component modeling as a framework in understanding the role of multidimensional organizational capabilities, including their impact on organizational performance outcomes (Saihi et al., 2023). From this perspective, the explanation of the role of DSS capability in influencing CRM outcomes requires an analytical framework that can capture the multidimensional nature of technological capabilities, as well as the processes through which these capabilities create value. Hierarchical component modeling can be used as an appropriate methodological framework in understanding the complex nature of these capabilities, including the modeling of higher-order constructs, which are formed through the presence of multiple dimensions. Using this perspective in understanding DSS capability can provide greater insights into the role of decision-support resources in influencing CRM planning, strategy, and ultimately, CRM efficiency.

2.6. Comparative Analysis of Previous Studies

Previous research has extensively examined the relationship between information systems capabilities and organizational performance, with special emphasis on the context of CRM applications. However, empirical findings vary in terms of the mechanisms that underpin the relationship between technological capabilities and organizational performance in the context of CRM applications. Previous research has revealed positive direct relationships between information systems capabilities and performance outcomes in the context of CRM applications. For instance, Rahman et al. (2023) revealed that analytical technologies in the context of CRM applications, with support from sophisticated digital infrastructure, significantly enhance organizational performance and customer engagement. Similarly, Yoo et al. (2024) revealed that AI-driven technologies in the context of CRM applications strengthen organizational competitive advantage by supporting data-driven processes in customer management.
On the other hand, various studies have found that technological capabilities do not have a direct impact on organizational performance outcomes; instead, the impact occurs indirectly via organizational processes. According to Soltani et al. (2018), the impact of customer relationship management (CRM) technologies on organizational performance outcomes occurs when these technologies are integrated with organizational processes such as planning and strategy development. Similarly, Hein et al. (2017) found that the impact of CRM systems on organizational profitability outcomes occurs via strategic mechanisms of implementation rather than the deployment of these technologies.
With respect to decision support systems (DSS) capabilities, the existing literature has conceptualized DSS as a technological tool for supporting managerial decision processes (Power & Sharda, 2007; Turban et al., 2010). Recently, the literature has started to conceptualize DSS as organizational capabilities that amalgamate infrastructure, databases, and analytical tools with managerial support (Petter et al., 2007; Becker et al., 2012). However, the process mechanisms for the impact of DSS capability on CRM performance outcomes have not been examined empirically. Furthermore, the major body of previous research has been centered around organizations in the private sector, especially in banking, retail, and manufacturing industries (Saha et al., 2021; Khan et al., 2020). As such, little is known in terms of empirical research concerning the influence of decision support capabilities on CRM efficiency in public utility organizations, considering the unique factors in such organizations.
A limitation in the extant literature is also observed in terms of the methodology for addressing the multidimensionality of technological capabilities. Most previous research has used reflective models in measuring technological capabilities, which may not capture the full essence of technological capabilities, considering their complex nature, which is comprised of multiple dimensions. The Hierarchical Component Models (HCM), which are components of the Partial Least Squares Structural Equation Modeling (PLS-SEM), are more appropriate in addressing this

limitation (Becker et al., 2012; Hair et al., 2017). However, empirical applications of this model in the context of formative-formative hierarchical modeling in CRM research are few.

2.7. Research Gap and Theoretical Contribution

In particular, despite the numerous research studies on information systems and different aspects of CRM technologies, there remain a number of conceptual gaps in the understanding of the role and effects of DSS capabilities on organizational performance in the context of CRM systems. Firstly, most research studies on the subject have conceptualized DSS as a technological artifact rather than as a multidimensional organizational capability that is embedded in different technological and managerial infrastructures (Becker et al., 2012; Petter et al., 2007). In particular, this technological perspective on DSS capabilities has often neglected the organizational processes that link decision support technologies with managerial decision-making and strategic planning processes. Secondly, most research studies on the subject have focused on direct relationships between technological capabilities and organizational performance outcomes, with limited attention to the process mechanisms that link technological resources with organizational performance in the context of CRM systems (Soltani et al., 2018). In particular, there has been limited attention to the role of planning and strategic processes in this context.

Third, empirical research into the role of decision support system (DSS) capabilities in public utility organizations is relatively limited, even as the relevance and importance of digital technologies in the pursuit of enhanced efficiency in public utility organizations and in managing public utility organizations' customer relationships become more prominent. To this end, this study employs a dynamic capabilities perspective, which suggests that firms generate value by leveraging and combining technological and organizational resources in adapting to a dynamically changing environment (Teece, 2007; Teece, 2025). Thus, technological resources, in and of themselves, are not a source of sustainable competitive advantage, especially in the absence of their integration and assimilation into organizational processes and activities, such as strategic decision-making. Thus, the concept of DSS capability may be viewed as an organizational information processing capability, which allows firms to sense opportunities, develop plans, and implement strategies in pursuit of enhanced CRM efficiency outcomes.

3. Methodology and Study Design

3.1. Study Design

In particular, the research utilized a quantitative, cross-sectional, explanatory research design in empirically examining the assumptions and the mediating role of CRM strategies through Partial Least Squares Structural Equation Modeling (PLS-SEM). Data collection was based on a systematic survey research methodology, which was consistent with the structured process of accumulating data to empirically examine the aforementioned assumptions. It utilized a cross-sectional research design, where data was gathered from a large sample at a single point in time, where quantitative data was analyzed based on two or more variables, where data sets are examined based on the concept of universality (Bryman & Bell, 2011). It utilized a 5-point Likert scale, where 1 represents "strongly disagree" and 5 represents "strongly agree". The dependent and independent variables are presented in Figure 5, where the conceptual framework was primarily depicted.

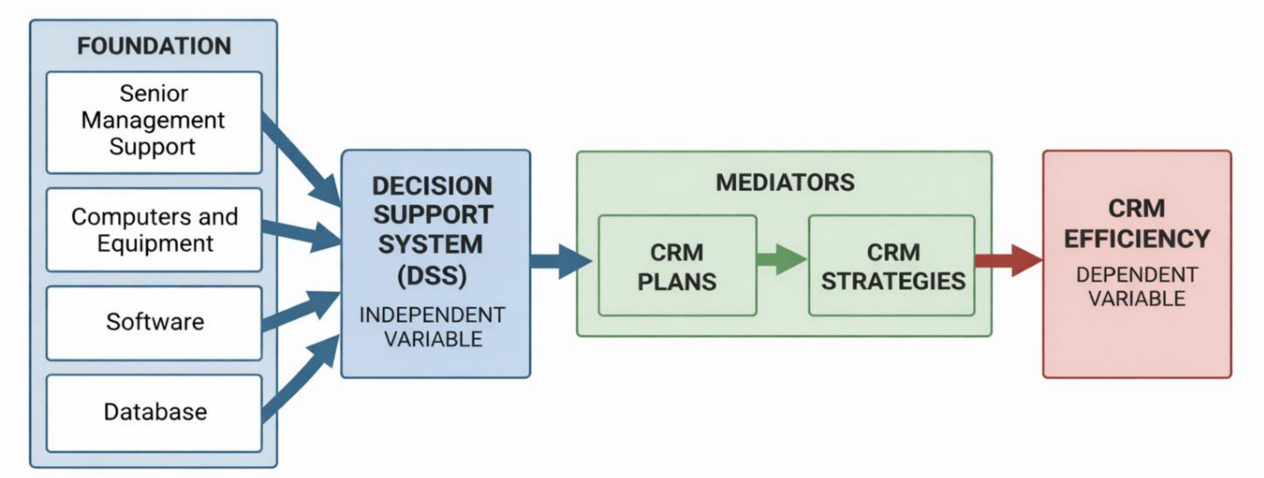

Figure (5): The main conceptual framework of the study

3.2. Population and Sampling Design

3.2.1. Population

The term population refers to the total number of people or entities that possess the characteristics of interest (Creswell, 2018). In this project, the population will be composed of staff working in different departments in the utility who work with a Decision Support System (DSS) and have experience working with customers within the organization. This population will be a vital source of feedback on the organization's Customer Relationship Management (CRM) strategy and organizational planning.

3.2.2. Sampling Design and Technique

In terms of time and resource constraints, it is not possible to obtain information from the entire population, and hence a representative sample of the population must be selected (Creswell, 2018). Creswell (2018) defined sampling as a statistical tool to collect individual observations to develop information about a particular population, mostly based on inferential purposes. In this study, a sampling technique was used, and it was based on people who had expertise in customer affairs and were aware of the decision support system (DSS).

3.2.3. Sample Size

The population was defined through a two-stage approach. First, a preliminary population of 327 employees was identified. Then, criteria for inclusion and exclusion were set, and only those employees who were actively interacting with customers and using DSS/CRM were considered for participation. This criterion identified 79 employees, who were all invited for participation. Thus, it can be stated that the study was based on a census of the defined population, as all targets were addressed. The alignment of the research methodology is supported by the significance of experience and qualification requirements for the phenomena under investigation (Creswell, 2018). The aggregated data collected had a 100% response rate, as there were 79 employees.

3.2.4. Data Collection Methods

The study applied different primary and secondary methods of information collection. Primary information is defined as information collected and developed for the current study, and it is often compared and differentiated with other information on the basis of its originality (Creswell, 2018). All primary information was collected through a structured questionnaire because it is easy to apply, economical, and efficient in information collection without directly involving the researcher (Bryman & Bell, 2011). The secondary information applied in this study was developed from a comprehensive review of different literature and relevant scholarly works concerning business journals on the subject of interest.

3.2.5. Study Procedures

Before administering the survey, it was subject to evaluation and review by a panel of experts composed of academic scholars in the field of interest. Based on the evaluation and review of the survey, minor modifications were made based on the information obtained from the evaluation and review process. This helped to ensure that it was more accurate and precise. Based on these modifications, the survey was administered using Google Forms over a two-week period. The survey was voluntary, and participants were made aware of its purpose. To encourage participants and address any challenges they might encounter, communication through phone calls and text messages was employed. Based on its self-reported nature, there is a possibility of common method bias (CMB), and it was addressed through procedural and statistical remedies. To address CMB procedurally, the survey was anonymous, and there was a psychological separation of measures. Additionally, it employed appropriate wording to reduce social desirability and evaluation apprehension bias. To address it statistically, the full collinearity VIF approach was employed, and all constructs had a VIF of less than 3.3, indicating that there is less likelihood of CMB, which would affect its validity.

An a priori statistical power analysis with G*Power 3.1.9.7 software was used to determine the minimum sample required for the analysis of the proposed structural model. In accordance with Cohen's (1988) recommendations for multiple regression analysis, a medium effect size ($f^2 = 0.16$) was used for the analysis. With a significance level of 0.05, desired statistical power of 0.80, and three predictors for the most complex structural equation in the model, the analysis indicated that a minimum sample of 73 cases would be required to evaluate the proposed structural model. The actual sample used in the study comprised 79 cases, thus indicating that the sample exceeds the recommended minimum. In addition to this, PLS-SEM is considered to be particularly appropriate for studies with relatively small to medium-sized sample sizes with complex research models, as in the present study.

A two-stage estimation of the hierarchical component model (HCM) with the two-stage approach in SmartPLS software used, as discussed in Section 3.2.7.

3.2.6. Data Analysis Methods

The questionnaires were thoroughly tested for errors and completeness before the coding process, where each question was considered a variable (Bryman & Bell, 2011). The coded data was then imported into the SPSS program to obtain the necessary statistics, such as the mean, variance, and standard deviation. After that, the data analysis continued with the use of the Structural Equation Modeling technique with the SmartPLS program. The proposed method represents a well-established scientific method that makes it possible to examine the existing dependency relations among the predefined theoretical constructs within the research.

3.2.7. Hierarchical Component Model Specification

This study conceptualized multidimensional decision support system capability as a formative-formative hierarchical component model (HCM). At the lower-order level, hardware capability, software capability, database capability, and senior management support were conceptualized as formative constructs. The four dimensions collectively conceptualize the higher-order decision support system capability construct, which corresponds with the theoretical underpinning that the removal of any one dimension would change the conceptual meaning of the capability construct. The HCM model was estimated with the two-stage procedure of the SmartPLS software package (Becker et al., 2012; Hair et al., 2017). At stage 1, all the lower-order constructs, which include the four DSS dimensions and the customer relationship management (CRM) constructs of CRM Plans, CRM Strategies, and CRM Efficiency, were estimated with their respective multi-item measures and generated latent variable scores. At stage 2, the latent variable scores for the four DSS dimensions were used as manifest indicators to estimate the higher-order decision support system capability construct. The CRM constructs were used as single-indicator latent composites by integrating their stage 1 latent variable scores into the structural model at stage

2. For the assessment of the formative measurement model, collinearity among the formative indicators was examined by assessing the variance inflation factor (VIF) values, and the significance and relevance of the outer weights were examined with the aid of bootstrapping with 5,000 resamples and bias-corrected 95% confidence intervals (Hair et al., 2017).

4. Results

The outcomes of the results are presented here in light of guidelines on PLS-SEM. First, it summarizes the demographic characteristics of the respondents for contextualization of the sample. Second, it assesses the measurement model, focusing on those formative constructs from the study. Consequently, analysis will be done on indicator collinearity-VIF, contributions by outer weights or loadings, and their respective significance with bootstrapping. Through this, the propriety of the formative specification is confirmed as a prelude to assessing the structural model and hypotheses.

4.1. Analysis of Demographic Variables

This section will highlight the demographic features of the participants as depicted in Figure 6. The features include gender, age, educational attainment, years of experience, and job position. Table 1 will be used to present frequencies and percentages to give a clear idea of the composition of the respondents. The gender composition of the participants shows a wide disparity, with males dominating at 86.1%, while the female population represents only 13.9% of the participants. The age composition shows that the majority of the participants have reached the mid-career stage. The largest percentage of the participants falls within the 30-40 age bracket at 41.8%, while the second largest falls within the 40-50 age bracket at 38%. The participants above the age of 50 make up only 13.9%, while the 25-30 age bracket makes up only 6.3% of the participants. The findings show that the participants have reached the prime of their career and have the necessary decision-making abilities to contribute to the research. The respondent pool is marked by a high level of education, with 49.4% holding undergraduate qualifications and 40.5% holding postgraduate qualifications, while 10.1% have college diplomas. This high level of education suggests a respondent pool that is capable of complex reasoning and logic, and is expected to comprise people in positions of high responsibility and understanding of policies. With regard to professional longevity, the data suggests a stable working environment with considerable experience. The majority, 60.8%, have organizational tenure in excess of 10 years, while a further 25.3% have worked in the organization between 5 and 10 years, and 13.9% have worked in the organization for less than 5 years. This high level of experience suggests that the respondents have a high level of understanding of procedures and practices in the utility. With regard to their positions, the largest proportion of respondents is in the middle to upper tiers of the organizational hierarchy. Thus, department heads make up 38.0%, administrative staff 32.9%, and department directors 24.1%. The executive leadership is represented at a much lower rate, with deputy executives at 3.8% and top executives at 1.3%.

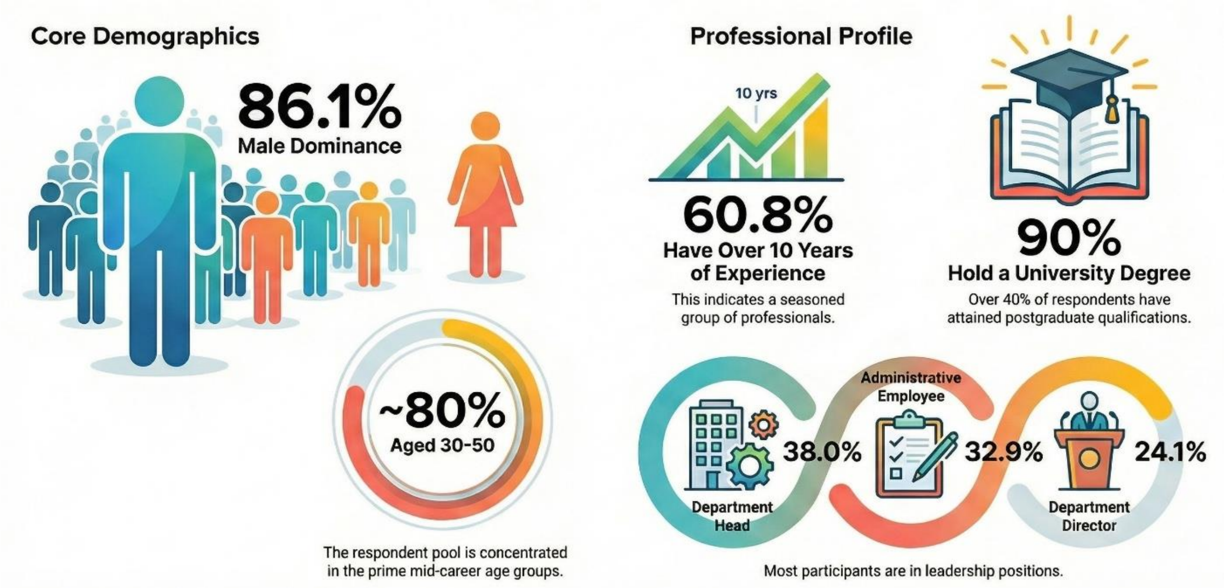

Figure (6): Demographic characteristics

Table (1): Demographic characteristics of respondents (N = 79)

Variable	Category	n	%
Gender	Male	68	86.1
	Female	11	13.9
Age	25–30 years	5	6.3
	30–40 years	33	41.8
	40–50 years	30	38.0
	50 years and over	11	13.9
Educational Qualification	College degree	8	10.1
	Undergraduate	39	49.4
	Postgraduate	32	40.5
Years of Experience	Less than 5 years	11	13.9
	5 to less than 10 years	20	25.3
	10 years and over	48	60.8
Job Position	Administrative employee	26	32.9
	Department head	30	38.0
	Department director	19	24.1
	Deputy executive manager	3	3.8
	Executive manager	1	1.3

Source: (Researcher prepared, based on results from SPSS, 2025)

Regarding the descriptive findings on the DSS capability dimensions, as depicted in Table 2, there are significant variations in the specific practices. Specifically, in the Computers and Equipment dimension, the highest mean is related to the aspect of having sufficient computers with advanced components to enable information exchange and decision-making processes (M = 3.94). Conversely, the lowest mean is related to having an integrated IT infrastructure, which allows the operation and implementation of DSS (M = 3.29). Thus, there is a stronger perception regarding the availability of equipment rather than the integration of the IT infrastructure. Regarding the database dimension, the highest agreement is related to the aspect of having data stored in the organization's databases (M = 3.86), while the lowest agreement is related to having an advanced database, which allows organizations to store data and enable operations and decision-making processes (M = 3.25).

For the Senior Management Support dimension, the highest level of agreement pertains to the provision of continuous funding for the maintenance and development of the Decision Support System DSS (M = 3.65), while the lowest pertains to the provision of sufficient resources for the development and use of the DSS (M = 3.52). The above findings indicate that the level of support for the development and use of the DSS by the senior management of the organization is moderate. For the Software dimension, the highest level of agreement pertains to the provision of software that can operate the DSS databases (M = 3.42), while the lowest pertains to the provision of advanced software for the analysis of data for decision making (M = 3.01), which indicates a potential deficiency. The same differentiated findings were also present for the CRM dimensions. As shown in Table 3, the CRM Efficiency dimension reached the highest level of agreement for the provision of customized programs and services for the organization's key customers (M = 4.03), while the lowest pertains to the provision of systems and channels for the maintenance of continuous customer contact (M = 3.54).

The highest agreement was found for having multiple channels for serving and interacting with customers in CRM Strategies, with (M = 3.84). The lowest means were found for aligning the CRM system with the diverse organizational operations in CRM Strategies, with (M = 3.51). This could imply that multichannel interaction is possibly more developed than alignment with organizational operations. For CRM Plans, it was found that having a perception of the availability of technical knowledge and skill on the part of employees regarding providing support for the CRM system was associated with the highest means, (M = 3.68). The lowest means were found for having a clearly defined training program during the implementation of CRM systems and for having a dedicated project for managing the implementation of the CRM systems, with (M = 3.14) each. These findings suggest that perceived levels of capability are generally medium to high but also point to areas of improvement, such as integrating infrastructures and advanced analytical tools, planning for CRM implementation, and training preparedness.

Table (2): Mean values of DSS dimensions

Construct	Variable	Mean	Std. Deviation	Variance
Senior Management Support	SM1	3.63	0.908	0.825
	SM2	3.52	0.945	0.894
	SM3	3.54	0.889	0.790
	SM4	3.65	0.863	0.745
	SM5	3.61	0.926	0.857
Computers and Equipment	CM1	3.94	0.896	0.804
	CM2	3.56	1.059	1.122
	CM3	3.76	0.977	0.954
	CM4	3.29	1.002	1.004
	CM5	3.70	0.806	0.650
Software	SF1	3.37	0.936	0.876
	SF2	3.42	0.969	0.939
	SF3	3.23	1.012	1.024
	SF4	3.08	0.844	0.712
	SF5	3.01	0.954	0.910
Database	DB1	3.86	0.944	0.891
	DB2	3.78	0.929	0.863
	DB3	3.58	0.886	0.785
	DB4	3.67	0.970	0.942

	DB5	3.25	0.954	0.909

Source: (Researcher prepared, based on results from SPSS, 2025)

Table (3): Mean values of CRM dimensions

Construct	Variable	Mean	Std. Deviation	Variance
CRM Efficiency	EF1	3.82	0.844	0.712
	EF2	4.03	0.832	0.692
	EF3	3.54	0.971	0.944
	EF4	3.75	0.884	0.781
	EF5	3.76	0.866	0.749
CRM Strategies	SR1	3.59	0.793	0.629
	SR2	3.51	0.799	0.638
	SR3	3.84	0.791	0.626
	SR4	3.68	0.743	0.552
	SR5	3.51	0.845	0.715
CRM Plans	PL1	3.52	0.814	0.663
	PL2	3.14	0.944	0.891
	PL3	3.27	0.930	0.864
	PL4	3.14	0.828	0.685
	PL5	3.68	0.899	0.809

Source: (Researcher prepared, based on results from SPSS, 2025)

4.2 Common Method Bias Assessment

Additionally, the results of Harman's single factor test were obtained as a secondary measure. In this regard, all the measurement items were included in an unrotated principal component analysis. From the results, it was clear that there was an emergence of multiple factors with eigenvalues higher than 1. Notably, however, the first factor explained only 42.25% of the total variance, thus remaining below the 50% threshold. From this evidence, it can be deduced that there exists no single factor that dominates the covariance between the different variables. In essence, there is no need to be concerned about common method bias in this study. This view is in agreement with the conventional interpretation of Harman's single factor test. Furthermore, it aligns with the recommended methodology for dealing with common method variance (Harman, 1976; Podsakoff et al., 2003).

4.3. Hierarchical Component Model (HCM) Specification

The formative-formative hierarchical component model (HCM) was evaluated following PLS-SEM guidelines. DSS capability was specified as a higher-order formative construct composed of four lower-order dimensions: Senior Management Support, Computers and Equipment, Database, and Software. The measurement and structural assessment results are presented below.

4.4. Measurement model: Confirmatory Composite Analysis

The measurement model was evaluated using Confirmatory Composite Analysis (CCA) in the context of Partial Least Squares (PLS) path modeling. As shown in Table 4, the model displays good composite model fit as indicated by the standardized root mean square residual SRMR at (0.023), which is significantly lower than the threshold of 0.08. Moreover, the squared discrepancy measures d_ULS (0.015) and d_G (0.028) show that there are minimal differences between the empirical and model-implied correlation matrices. In addition, the normed fit index NFI is (0.969), which is greater than the threshold of 0.90, suggesting good model fit. These findings support the use of the proposed composite measurement model in evaluating the proposed structural model (Hair et al., 2017).

Table (4): Model Fit Indices

Index	Saturated Model	Estimated Model
SRMR	0.023	0.023
d_ULS	0.015	0.015
d_G	0.028	0.028
Chi-Square	10.986	10.986
NFI	0.969	0.969

Source: (Researcher prepared, based on results from SMARTPLS, 2025)

For evaluating collinearity among the formative variables, variance inflation factor (VIF) values were used. As presented in Table 5, all VIF values are found to fall within the range of 1.000 to 2.569, thus remaining below the threshold. The results, therefore, indicate the absence of critical multicollinearity problems.

Table (5): VIF values

Construct	VIF
CRM Plans	1.000
CRM Strategies	1.000
CRM efficiency	1.000
Computers and Equipment	1.789
Database	2.569
Senior Management Support	1.770
Software	2.352

Source: (Researcher prepared, based on results from SMARTPLS, 2025)

4.5. Outer Weights and Outer Loadings (Formative Constructs)

The formative measurement model was assessed by examining outer weights and outer loadings. As shown in Table 6, the CRM constructs were incorporated as single-indicator latent scores; therefore, their weights and loadings equal 1.000 by design.

Table (6): Single-Item Formative Constructs Outer Weights

Construct	Indicator	Weight
CRM Plans	CRM Plans	1
CRM Strategies	CRM Strategies	1
CRM Efficiency	CRM Efficiency	1

Source: (Researcher prepared, based on results from SMARTPLS, 2025)

As reported in Table 7, the Database dimension demonstrates the strongest contribution to DSS capability (weight = 0.497, $p < 0.001$), followed by Computers and Equipment (0.311, $p = 0.033$). Senior Management Support and Software exhibit non-significant outer weights, indicating relatively lower unique contributions to the higher-order construct.

Table (7): DSS Multi-Item Formative Outer Weights

Construct	Indicator	Weight	t-value	p-value	Decision
DSS	Computers and Equipment	0.311	2.136	0.033	Significant
DSS	Database	0.497	3.69	< 0.001	Significant
DSS	Senior Management Support	0.271	1.558	0.120	Not Significant
DSS	Software	0.096	0.63	0.529	Not Significant

Source: (Researcher prepared, based on results from SMARTPLS, 2025)

Outer loadings provide complementary evidence of indicator relevance. As presented in Table 8, all DSS dimensions exhibit high and significant loadings (0.786-0.927), confirming their substantive contribution to DSS capability.

Table (8): DSS Multi-Item Formative Outer Loadings

Construct	Indicator	Weight	t-value	p-value

DSS	Computers and Equipment	0.806	8.500	< 0.001
DSS	Database	0.927	24.016	< 0.001
DSS	Senior Management Support	0.786	7.920	< 0.001
DSS	Software	0.797	9.072	< 0.001

Source: (Researcher prepared, based on results from SMARTPLS, 2025)

The CRM constructs, specified as single-indicator latent scores, exhibit loadings of 1.000 by design as shown in Table 9.

Table (9): Single-Item Formative Constructs Outer Loadings

Construct	Indicator	Loading
CRM Efficiency	CRM Efficiency	1
CRM Plans	CRM Plans	1
CRM Strategies	CRM Strategies	1

Source: (Researcher prepared, based on results from SMARTPLS, 2025)

4.6. Structural Model Evaluation

Bootstrapping with 5,000 subsamples and 95% confidence intervals was used to test the significance of the paths. As presented in Table 10, the direct effect of DSS capability on CRM Efficiency is found to be positive but not significant ($\beta = 0.186$, $p = 0.063$). On the other hand, DSS capability is found to have a significant influence on CRM Plans ($\beta = 0.669$, $p < 0.001$) and also on CRM Strategies ($\beta = 0.332$, $p = 0.019$). It is also found that CRM Strategies have a significant influence on CRM Efficiency ($\beta = 0.523$, $p < 0.001$), whereas the direct influence of CRM Plans on CRM Efficiency is not significant ($\beta = 0.194$, $p = 0.076$).

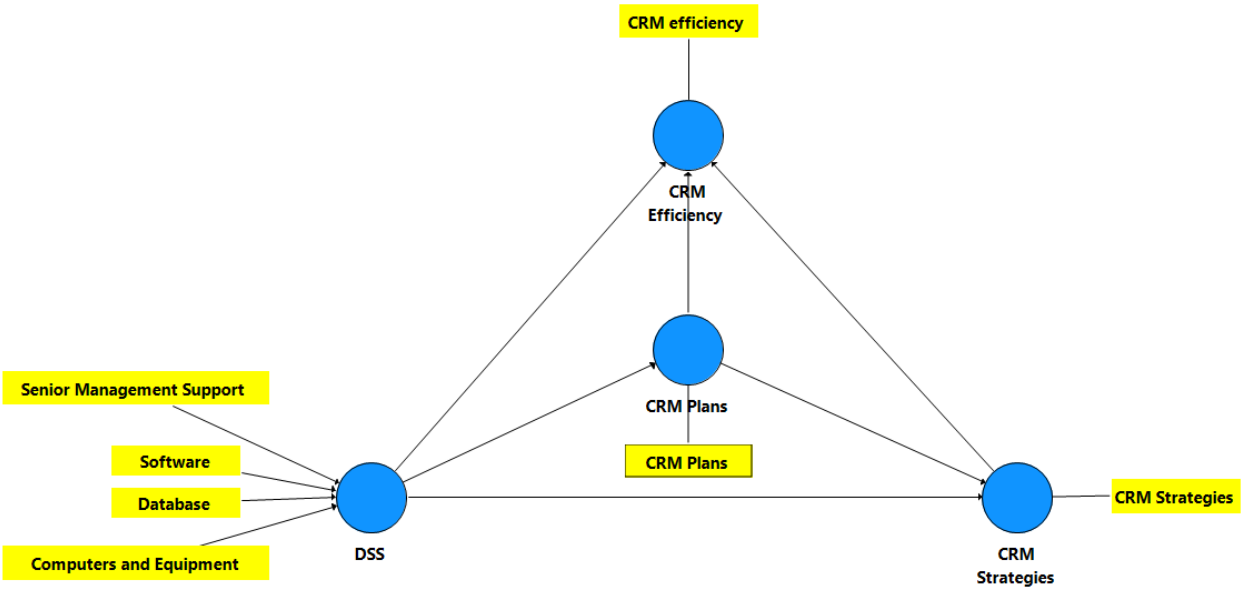

Figure (7): Structure Equation Model

Source: (Researcher prepared, based on SMARTPLS, 2025)

Table (10): Path Coefficient

Relation	β	T Statistics	P Values	95% CI Lower	95% CI Upper
CRM Plans → CRM Efficiency	0.194	1.779	0.076	-0.003	0.424
CRM Plans → CRM Strategies	0.485	3.071	0.002	0.169	0.745
CRM Strategies → CRM Efficiency	0.523	4.956	< 0.001	0.308	0.696
DSS → CRM Efficiency	0.186	1.862	0.063	-0.002	0.391
DSS → CRM Plans	0.669	9.126	< 0.001	0.485	0.788
DSS → CRM Strategies	0.332	2.348	0.019	0.063	0.611

Source: (Researcher prepared, based on results from SMARTPLS, 2025)

4.6.1. Mediation Analysis

Mediation was assessed using bootstrapped specific indirect effects. As shown in Table 11, the indirect effect of DSS capability on CRM efficiency is significant (β = 0.473, $p < 0.001$). But as shown in Table 12 The total effect is also significant (β = 0.659, $p < 0.001$), indicating indirect-only mediation. Table 11 reports the specific indirect effects, while the summary of the hypothesized mediation relationships is presented later in Table 16.

Table (11): Specific Indirect Effects (Bootstrapped 95% CI)

Relation	β	T Statistics	P Values	95% CI Lower	95% CI Upper
CRM Plans → CRM Efficiency	0.253	2.615	0.009	0.107	0.498
DSS → CRM Efficiency	0.473	5.181	< 0.001	0.305	0.662
DSS → CRM Strategies	0.324	2.941	0.003	0.122	0.521

Source: (Researcher prepared, based on results from SMARTPLS, 2025)

Table (12): Total Effects

Relation	β	T Statistics	P Values	95% CI Lower	95% CI Upper
CRM Plans → CRM Efficiency	0.448	3.299	0.001	0.183	0.697
CRM Plans → CRM Strategies	0.485	3.071	0.002	0.169	0.745
CRM Strategies → CRM Efficiency	0.523	4.956	< 0.001	0.308	0.696
DSS → CRM Efficiency	0.659	8.554	< 0.001	0.458	0.786
DSS → CRM Plans	0.669	9.126	< 0.001	0.485	0.788
DSS → CRM Strategies	0.656	7.448	< 0.001	0.432	0.803

Source: (Researcher prepared, based on results from SMARTPLS, 2025)

4.6.2. Explained Variance and Effect Sizes

The model explains substantial variance in CRM Efficiency ($R^2 = 0.665$), as well as in CRM Plans ($R^2 = 0.447$) and CRM Strategies ($R^2 = 0.560$) as shown in Table 13. Effect size analysis as illustrated in Table 14 shows a large effect of DSS capability on CRM Plans ($f^2 = 0.808$), a medium effect on CRM Strategies ($f^2 = 0.139$), and a small direct effect on CRM Efficiency ($f^2 = 0.050$). CRM Strategies exhibit a large effect on CRM Efficiency ($f^2 = 0.359$).

Table (13): R square

Construct	R Square	R Square Adjusted
CRM Efficiency	0.665	0.652
CRM Plans	0.447	0.440
CRM Strategies	0.560	0.549

Source: (Researcher prepared, based on results from SMARTPLS, 2025)

Table (14): F square

Independent Variable	Dependent Variable	f^2	Effect Size
CRM Plans	CRM Efficiency	0.048	Small

CRM Plans	CRM Strategies	0.295	Medium
CRM Strategies	CRM Efficiency	0.359	Large
DSS	CRM Efficiency	0.050	Small
DSS	CRM Plans	0.808	Large
DSS	CRM Strategies	0.139	Medium

Source: (Researcher prepared, based on results from SMARTPLS, 2025)

4.6.3. Predictive relevance

Predictive relevance was assessed using the Stone-Geisser Q^2 obtained through blindfolding. All endogenous constructs exhibit Q^2 values greater than zero (CRM Efficiency = 0.637; CRM Strategies = 0.529; CRM Plans = 0.415), indicating adequate predictive capability as shown in Table 15.

Table (15): Q square

Construct	Q^2 (=1-SSE/SSO)
CRM Efficiency	0.637
CRM Plans	0.415
CRM Strategies	0.529

Source: (Researcher prepared, based on results from SMARTPLS, 2025)

4.7. Findings Summary

In general, the findings support the adequacy of the formative HCM and the DSS capability's contribution to the efficiency of the CRM, mainly through the mediated processes of the CRM, not directly.

5. Discussion

5.1. Hypotheses Assessment and Interpretation

The results obtained from the structural model provide differentiated support for the proposed hypotheses. Specifically, the direct path from DSS capability to CRM efficiency is not statistically significant, as the bootstrapped confidence interval includes zero. Therefore, the proposed hypothesis regarding the direct positive effect of DSS capability on CRM efficiency is not supported, implying that technological capability does not inherently translate into efficiency benefits in CRM processes.

On the contrary, DSS capability does have a significant effect on CRM plans and CRM strategies. This finding supports the proposed hypotheses regarding the effect of DSS capability on the development of CRM planning activities and on the formation of CRM strategy. This result aligns with previous research, which emphasized the role of DSS systems in improving managerial processes and CRM strategy, rather than having a direct effect on performance metrics (Power & Sharda, 2007; Turban et al., 2010; Gupta et al., 2006).

Regarding internal relationships, CRM plans have a significant effect on CRM strategies, thus supporting the proposed hypothesis regarding the role of CRM planning in the development of CRM strategy. However, CRM plans do not directly enhance CRM efficiency, suggesting that planning activities are not sufficient on their own to enhance efficiency in customer management processes. Finally, CRM strategies have a significant positive effect on CRM efficiency, thus supporting the proposed hypothesis regarding the role of CRM strategy in the development of efficiency benefits in customer management processes.

The outcomes of the hypotheses tests show that there is a clear pattern in the results, with upstream capabilities (DSS) having a significant impact on the planning and strategic levels, whereas efficiency outcomes are obtained through strategic execution, not directly affected by technological or planning capabilities.

The obtained outcomes provide empirical support to both the Resource-Based View (RBV) theory and the Dynamic Capabilities approach. Consistent with the RBV theory, the DSS capability plays the role of a strategic organizational resource that improves the manager's process in the context of CRM planning and strategic actions. The absence of a significant direct effect of DSS capability on the efficiency of the CRM process supports the Dynamic Capabilities approach, which argues that technological resources create value only to the extent that they are integrated into the organizational process and strategic actions.

5.2. The Indirect and Sequential Nature of Value Realization

The mediation results offer a precise explanation of how DSS capability translates into CRM-related outcomes. As reflected in the structural model results as shown in Table 16, the direct effect of DSS on CRM efficiency H1 is not supported ($\beta = 0.186$, $p = 0.063$; 95% BC CI includes zero), confirming that DSS capability does not exert an immediate performance impact.

Regarding indirect relationships, the mediation hypothesis H4 (DSS → CRM Plans → CRM Strategies) is supported ($\beta = 0.324$, $p = 0.003$; 95% BC CI excludes zero). This indicates that DSS capability strengthens CRM plans, which subsequently enhance CRM strategies. Planning therefore operates as a transmission mechanism through which DSS capability influences strategic CRM orientation.

More importantly, the sequential mediation hypothesis H5 (DSS → CRM Plans → CRM Strategies → CRM Efficiency) is also supported ($\beta = 0.169$, $p = 0.008$; 95% BC CI excludes zero). This confirms a structured value-realization chain in which DSS capability first improves CRM planning, planning shapes CRM strategies, and strategic execution ultimately drives CRM efficiency. The absence of a significant direct effect H1 combined with a significant sequential indirect effect H5 indicates an indirect-only (full) mediation structure.

Thus, DSS capability influences CRM efficiency exclusively through intervening organizational mechanisms namely planning and strategic execution rather than through a direct technological-performance linkage. Conceptually, this finding extends the DSS literature by suggesting that organizational value from DSS emerges through managerial and strategic transformation processes rather than direct technological impact (Sprague, 1980; Power, 2006). In the CRM domain, the results reinforce the argument that performance improvements depend on converting analytical and informational capabilities into structured strategies that guide customer-facing operations (Gil-Gomez et al., 2020; Khan et al., 2020; Saha et al., 2021).

Table (16): Hypothesis

Hypothesis	Relationship	Effect Type	Path Coefficient (β)	t-value	p-value	Decision ($\alpha \leq 0.05$)
H1	DSS → CRM Efficiency	Direct	0.186	1.862	0.063	Not Supported
H2	DSS → CRM Plans	Direct	0.669	9.126	< 0.001	Supported
H3	DSS → CRM Strategies	Direct	0.332	2.348	0.019	Supported
H4	DSS → CRM Plans → CRM Strategies	Indirect (Mediation)	0.324	2.941	0.003	Supported
H5	DSS → CRM Plans → CRM Strategies → CRM Efficiency	Indirect (Sequential Mediation)	0.169	2.65	0.008	Supported

Source: (Researcher prepared, based on results from SMARTPLS, 2025)

5.3. Alignment of DSS Capability Priorities with Mediation Results

In order to determine the relative contribution of each of these DSS dimensions towards the higher-order DSS capability construct, the analysis evaluated both outer weights (which measure relative importance) and outer loadings (which measure absolute relevance) for the formative DSS

dimensions of Database, Computers and Equipment, Senior Management Support, and Software. For formative measurement models, outer weights are of greater interest, as they measure the unique contribution of each dimension while controlling for the presence of other dimensions.
As illustrated in Table 17, it is evident that the observed patterns of importance and relevance are similar to those of structural and mediation analyses. Although the outer weights for Senior Management Support and Software were not statistically significant, the outer loadings were strong (all greater than 0.70), indicating absolute relevance for DSS capability. For formative measurement models, where outer weights were not significant but outer loadings were strong, it is likely that there is shared variance with other dimensions and not necessarily a lack of relevance for DSS capability.
The Database dimension is found to be significant, and infrastructure and managerial support are found to make significant contributions. This result is in line with the proposition that the capability of decision support system (DSS) does not have a direct influence on the efficiency of customer relationship management (CRM), but this influence is mediated by planning and strategic mechanisms. It is found that data foundations and infrastructure enable more structured planning in CRM, which in turn positively impacts CRM strategies and thus CRM efficiency.
However, in the case of the Software dimension, lower importance and mean scores are observed, which may also explain the absence of a significant direct relationship between DSS and CRM efficiency. This may indicate that, in the absence of advanced analytical functionalities, the role of DSS is limited to strategic mechanisms and not to direct influence on efficiency outcomes.
The results of the importance-relevance analysis confirm the sequential mediation mechanism observed in the structural model, which in turn supports the argument that the organizational value of DSS is mediated by structured managerial processes and not technology deployment.
Table (17): Importance-Relevance of DSS Dimensions

DSS Dimension	**Outer Weight (Importance)**	**Outer Loading (Relevance)**	**Mean**	**Priority Level**
Database	0.497	0.927	3.63	Very High
Computers & Equipment	0.311	0.806	3.65	High
Senior Management Support	0.271	0.786	3.59	Moderate-High
Software	0.096	0.797	3.22	Moderate (Improvement Needed)

Source: (Researcher prepared, based on results from SMARTPLS, 2025)

5.4. Contextual Interpretation: Public Utility Setting

The non-direct impact of CRM plans on efficiency can be explained in terms of the nature of the institutional characteristics that define public utility organizations. In this sense, it can be argued that efficiency will be more evident in terms of the development of strategies that directly manage resource allocation and service delivery routines, as defined in the context of formal strategies that manage the relationship with customers, as highlighted in the context of CRM strategies that define the execution level of the relationship with customers and its direct relationship with efficiency outcomes, as supported in the context of research on CRM that differentiates between coordination-oriented planning and performance-oriented strategic implementation (Hein et al., 2017; Almohaimmeed, 2021; Soltani et al., 2018).

5.5. Theoretical Contributions

This study makes three primary theoretical contributions. First, it reconceptualizes DSS capability as a multidimensional organizational resource whose performance implications materialize through planning and strategic mechanisms rather than direct technological effects. Second, it clarifies the CRM performance pathway by empirically demonstrating that CRM strategies serve as the proximal driver of efficiency, while planning represents a necessary but insufficient condition. Third, it contributes methodologically by applying a formative-formative hierarchical component model within a PLS-SEM framework, consistent with established modeling guidelines for multidimensional capabilities (Becker et al., 2012; Hair et al., 2017; Petter et al., 2007).

5.6. Managerial Implications

From the managerial perspective, the research findings suggest that investments in DSS infrastructures, databases, and tools should be strategically integrated into the planning and execution of customer relationship management (CRM). It is suggested that managers should ensure that the outputs of DSS are integrated into structured CRM planning and are operationalized as strategies guiding service activities. From the perspective of public utilities, DSS should not be seen as a technical solution but rather as an integral component of strategic CRM governance.

5.7. Limitations and Future Research

Despite its contributions, this study has several limitations that open avenues for future research. First, the study is based on data collected from a single public utility organization, which may limit generalizability. Future studies could replicate the model in private-sector firms, cross-industry settings, or different national contexts to examine whether the indirect mediation pattern remains stable.

Second, the cross-sectional research design restricts strong causal inference. Longitudinal studies would allow researchers to examine how DSS capability, CRM planning, and CRM strategies evolve over time and how their interactions influence performance trajectories.

Third, while DSS capability is modeled as a multidimensional formative construct, future research may further decompose its components (e.g., analytical infrastructure, data quality, managerial support) to explore whether specific dimensions exert stronger indirect effects through CRM mechanisms. Multi-group or comparative analyses may also enrich understanding of contextual contingencies.

Addressing these limitations would strengthen the theoretical robustness of the DSS-CRM performance linkage and advance understanding of technology-enabled value realization mechanisms.

6. Conclusion

The present study aims to explore the impact of the multi-dimensional Capability of the Decision Support System on the efficiency of Customer Relationship Management in the context of the Coastal Municipalities Water Utility, with the proposed model being analyzed via the PLS-SEM tool in accordance with the formative-formative Hierarchical Component Model. The results show that the Capability of the Decision Support System does not have a direct impact on the efficiency of Customer Relationship Management. Its impact on efficiency is mediated by the plans for Customer Relationship Management and the execution of the plans. Although the Capability of the Decision Support System has a non-significant impact on the efficiency of Customer Relationship Management, it has a strong and significant impact on the plans for Customer Relationship Management and the strategies for Customer Relationship Management. The variables collectively form a mediation chain that links the Capability of the Decision Support System to the efficiency of Customer Relationship Management. In order to attain efficiency in Customer Relationship Management, the capability of the Decision Support System must be embedded in the strategizing process rather than in technology implementation. In terms of methodology, the present study confirms the applicability of the formative-formative Hierarchical Component Model with Confirmatory Composite Analysis. In that respect, the present study confirms the applicability of the formative-formative Hierarchical Component Model in relation to overall model significance. The results of the present study affirm the significance of overall database capability as well as infrastructure capability in relation to overall DSS capability. In that respect, the present study contributes to the body of knowledge by shedding light on the contribution that the capability of the Decision Support System can make to the outcome of Customer Relationship Management. The study shows that the functionality of the Decision Support System in the pursuit of enhanced performance depends on proper strategizing. The present study highlights that in the context of public utilities, the capability of the Decision Support System must be embedded in the strategic planning for Customer Relationship Management in order to attain enhanced efficiency in Customer Relationship Management.

7. Recommendations

- Embedding Decision Support System (DSS) in the CRM process: DSS should be incorporated in the planning and implementation of CRM strategies rather than considering it as a separate entity.
- Strengthening data foundations: Emphasize the importance of databases in terms of quality, integration, security, and accessibility for effective customer-centric decision-making.
- Enhancing implementation readiness: Provide DSS-based training for CRM implementation.
- Utilize DSS for customer-centric decision-making: DSS should be utilized for analyzing service delivery and customer requirements and resolving complaints.
- Improving systems alignment: DSS should be utilized for improving alignment between information technology and application systems and CRM systems.
- Sustaining management commitment: DSS should be resourced and implemented to ensure sustained commitment from top management.
- Prioritize database capability as the core DSS resource: DSS should be recognized as a vital component of CRM and its importance should be recognized by investing in its quality and integration.
- Upgrading software to advanced analytics: The relatively poor performance of the software dimension should be improved by introducing advanced analytical software and tools to enhance the downstream effect of DSS on CRM efficiency.

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