DEMOCRATIC AND POPULAR REPUBLIC OF ALGERIA

MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH

ECOLE SUPÉRIEURE DE COMMERCE

A Dissertation Submitted in Partial Fulfillment of the Requirements for Master's Degree in Commercial Sciences,
Specialty: Marketing

The Impact of Predictive CRM Capabilities on Customer Retention in B2B Industrial Sector: Case of Atlas Copco

Submitted by:
BOUHADJA
Aya

Supervised by:
Dr. GUENOUCHE
Nesrine

Address: ZERALDA, Algiers

Training period: From 4th March to 19th May 2026

2025-2026

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بسم الله الرحمن الرحيم

Dedication

This dissertation is more than an academic achievement; it is the reflection of a journey that transformed me in ways I never imagined.

It all started with a 17 years old girl, shaped by the uncertainty of the COVID era, who obtained her Baccalaureate with high grades and decided to leave everything familiar behind to move to an unknown place. At first, that place felt distant and intimidating, but little by little, it became home. It became her comfort zone, the place where she discovered who She truly is. That girl is ***Aya****, me!*

Before dedicating this work to anyone else, I want to thank myself for being hardworking, ambitious, mentally strong, and resilient throughout this journey. There were moments of doubt, pressure, exhaustion, and fear, yet I kept going. I grew, evolved, and became a version of myself I never thought I could become.

But none of this would have been possible without my parents ***Khouou*** *&* ***Moumou*** *, my greatest blessing and my strongest foundation. Thank you for believing in me endlessly, for supporting every dream I had, and for always pushing me forward even when I doubted myself. Everything I am today is because of your sacrifices, your love, and your prayers. May God grant you happiness, health, and a long beautiful life. If I reached this stage today, it is because of you and for you.*

To my brother and sisters, thank you for your unconditional encouragement, your gifts, your comforting words, and for always making difficult moments feel lighter. Having you by my side made this journey far less lonely.

To my best friends, from Koléa to Skikda, thank you for every laugh, every late-night conversation, every comforting word, and every memory we created together. I could not have asked for healthier or more genuine friendships. You brought balance, joy, and warmth into some of the most stressful years of my life.

And finally, to my classmates, especially ***Adlene*** *and* ***Fatene****, I want your names to remain written here because your kindness, constant help, and support throughout this journey deserve to be remembered not only in my memories, but also on these pages forever.*

This dissertation is dedicated to every person who walked beside me during this journey and helped shape the person I became along the way.

And although this may be the end of a beautiful five-year chapter, I truly believe that what is coming next will be even more beautiful.

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Aya. B

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Abstract

This study investigates the impact of perceived predictive CRM capabilities on customer retention among B2B industrial clients of Atlas Copco Algeria. Using an exploratory sequential mixed methods design, a qualitative phase confirmed three core dimensions; need anticipation, commercial proactivity, and hyper-personalization, which were subsequently tested quantitatively on a sample of 100 respondents using exploratory factor analysis and multiple regression in SPSS. The factor analysis refined commercial proactivity into proactive relational engagement, which primarily predicts switching resistance, while hyper-personalization emerges as the dominant retention driver. A Net Promoter Score of +1reflects a polarized client base requiring targeted CRM improvement.

Keywords: Predictive CRM, Customer retention, B2B industrial marketing, Hyper personalization, Need anticipation, Commercial proactivity, Exploratory sequential design, AI driven CRM

تبحث هذه الدراسة في تأثير القدرات المُدركة لإدارة علاقات العملاء التنبؤية على الاحتفاظ بالعملاء لدى عملاء أطلس كوبكو الجزائر في القطاع الصناعي .(B2B) واعتمدت الدراسة على تصميم بحثي مختلط استكشافي تسلسلي، حيث أكدت المرحلة النوعية ثلاثة أبعاد رئيسية، هي: استباق الاحتياجات، والمبادرة التجارية، والتخصيص الفائق، والتي تم اختبارها لاحقًا كمّيًا على عينة مكونة من (100) مشارك باستخدام التحليل العاملي الاستكشافي والانحدار المتعدد عبر برنامج .(SPSS) وأعاد التحليل العاملي صياغة بُعد المبادرة التجارية في صورة الانخراط العلائقي الاستباقي، الذي تبيّن أنه المتنبئ الأساسي بمقاومة تغيير المورّد، في حين برز التخصيص الفائق باعتباره المحرك الرئيسي للاحتفاظ بالعملاء. كما أظهر مؤشر صافي المروجين (NPS) البالغ (+1) وجود قاعدة عملاء منقسمة، مما يستدعي إجراء تحسينات مستهدفة في ممارسات إدارة علاقات العملاء.

الكلمات المفتاحية :إدارة علاقات العملاء التنبؤية، الاحتفاظ بالعملاء، التسويق الصناعي(B2B) ، التخصيص الفائق، استباق الاحتياجات، المبادرة التجارية، التصميم الاستكشافي التسلسلي، إدارة علاقات العملاء المعتمدة على الذكاء الاصطناعي.

Cette étude examine l'impact des capacités CRM prédictives perçues sur la rétention des clients B2B industriels d'Atlas Copco Algérie. Suivant un design séquentiel exploratoire, une phase qualitative a confirmé trois dimensions clés; l'anticipation des besoins, la proactivité commerciale et l'hyper-personnalisation, Testées ensuite quantitativement auprès de 100 répondants par analyse factorielle exploratoire et régression multiple sous SPSS. L'analyse factorielle a affiné la proactivité commerciale en engagement relationnel proactif, principal prédicteur de la résistance au changement de fournisseur, tandis que l'hyper-personnalisation s'impose comme le principal moteur de la rétention. Un NPS de +1 reflète une base clientèle polarisée nécessitant des actions CRM ciblées.

Mots-clés : CRM prédictif, Rétention client, Marketing B2B industriel, Hyper personnalisation, Anticipation des besoins, Proactivité commerciale, Design séquentiel exploratoire, CRM piloté par l'IA

List of Abbreviations

Abbreviation	Full Term
AI	Artificial Intelligence
B2B	Business-to-Business
CI	Continuance Intention
CLV	Customer Lifetime Value
CP	Commercial Proactivity
CRM	Customer Relationship Management
CT	Compressor Technique
CTS	Compressor Technical Service
DV	Dependent Variable
DW	Durbin-Watson Statistic
EFA	Exploratory Factor Analysis
ERP	Enterprise Resource Planning
HP	Hyper-Personalization
IV	Independent Variable
KMO	Kaiser-Meyer-Olkin Measure
ML	Machine Learning
MSA	Measure of Sampling Adequacy
NA	Need Anticipation
NPS	Net Promoter Score
PAF	Principal Axis Factoring
PRE	Proactive Relational Engagement
RB	Repurchase Behavior
RC	Relationship Commitment
RELPERS	Relational Persistence (SPSS label)

REPBEH	Repurchase Behavior (SPSS label)
RFM	Recency, Frequency, Monetary Value
RP	Relational Persistence
SA	Service Automation
SFA	Sales Force Automation
SPSS	Statistical Package for the Social Sciences
SR	Switching Resistance
SWITRES	Switching Resistance (SPSS label)
TOL	Tolerance
TVE	Total Variance Explained
VIF	Variance Inflation Factor

Chapter 1: Introduction

CRM has undergone a profound transformation over the past two decades alongside the rapid evolution of digital technologies, artificial intelligence, and data-driven business practices. Initially developed as a transactional data management tool, CRM has progressively evolved into an intelligent and predictive commercial system capable of anticipating customer needs, personalizing interactions, and supporting proactive decision-making (Payne & Frow, 2005; Buttle & Maklan, 2019).

This transformation carries particular strategic importance in B2B industrial markets, where relationships are characterized by long-term contracts, operational interdependence, high switching costs, and complex decision-making processes (Morgan & Hunt, 1994). In such environments, the ability to anticipate client needs, maintain proactive engagement, and deliver personalized commercial interactions increasingly represents a critical source of competitive advantage.

Customer retention therefore becomes a strategic priority rather than a simple commercial objective. Previous research demonstrates that retaining existing customers is significantly more cost-effective than acquiring new ones and contributes directly to long-term profitability and relationship stability (Reichheld & Sasser, 1990).

Despite the growing adoption of predictive CRM technologies in industrial organizations, an important gap remains in the literature. Existing studies have largely focused on the technological and organizational aspects of CRM systems, while limited attention has been devoted to understanding how clients themselves perceive predictive CRM capabilities and how these perceptions influence retention behaviors (Ngai, Xiu, & Chau, 2009).

More importantly, the literature does not provide a validated construct of "Perceived Predictive CRM Capabilities." While previous studies discuss dimensions such as need anticipation, commercial proactivity, and Hyper-personalization separately, these dimensions have never been empirically combined and validated as a unified client-perceived construct.

This dissertation addresses this gap by investigating how B2B industrial clients perceive predictive CRM capabilities within the context of Atlas Copco Algeria and how these perceptions influence customer retention behaviors. Unlike purely deductive studies, this research adopts an exploratory sequential mixed-methods approach in which the conceptual structure emerges progressively through both qualitative exploration and quantitative validation.

This study is important for both academics and practitioners. From an academic perspective, it contributes to the emerging literature on predictive CRM by proposing and empirically validating a new client-oriented conceptualization of predictive CRM capabilities grounded in industrial practice and customer perception. From a managerial perspective, the findings can help industrial organizations better understand how proactive and personalized CRM practices impact customer retention. In an increasingly competitive and digitalized B2B environment, identifying the relational capabilities that strengthen client retention is essential for building sustainable and long-term industrial partnerships.

1.1 Main Research Question

The main research question guiding this dissertation is:

- 'Does the perceived predictive CRM capabilities impact customer retention among B2B clients of Atlas Copco?'

1.2. Sub-questions

At the initial stage of the research, the following questions were considered as preliminary exploratory orientations rather than definitive sub-questions:

- How do B2B industrial clients perceive predictive CRM capabilities within supplier-client relationships?
- Which experiential dimensions emerge from clients' perceptions of predictive CRM capabilities?
- Do the dimensions identified through the exploratory phase influence customer retention behaviors?
- Which perceived predictive CRM dimensions appear to exert the strongest influence on customer retention?
- How does the conceptual structure of perceived predictive CRM capabilities evolve throughout the exploratory sequential research process?

However, since this study adopts an exploratory sequential approach, the final conceptual structure and research orientations will progressively be refined through empirical investigation, particularly during the qualitative exploratory phase and the subsequent exploratory factor analysis.

1.3 Reasons for Choosing the Research Topic

1.3.1 Objective Reasons

- ✓ **The growing strategic importance of predictive CRM**

CRM systems are undergoing a major transformation through the integration of artificial intelligence, machine learning, automation, and predictive analytics. Predictive CRM capabilities are increasingly becoming strategic tools allowing organizations to anticipate customer needs, optimize commercial engagement, and strengthen long-term customer relationships.

- ✓ **A significant conceptual gap in the literature**

Although predictive CRM has received growing academic attention, existing research remains heavily technology oriented and organizationally focused. Very limited research examines predictive CRM from the client perspective, particularly within industrial B2B environments. Furthermore, no validated multidimensional construct specifically conceptualizing *Perceived Predictive CRM Capabilities* currently exists in the literature.

- ✓**The underexplored nature of industrial B2B contexts**

Most CRM and customer retention studies focus primarily on B2C sectors such as retail, banking, and telecommunications. Industrial B2B environments characterized by long-term contracts, technical complexity, and relational interdependence remain comparatively underexplored.

1.3.2 Subjective Reasons

- ✓**Professional immersion within Atlas Copco Algeria**

This dissertation was conducted during a professional internship within the Compressor Technique Service department of Atlas Copco Algeria. Direct exposure to the company's CRM ecosystem, including SAP, C4C, Power BI, and predictive lead management systems, provided privileged access to observe predictive CRM practices in a real industrial environment.

- ✓ **Personal interest in the intersection between technology and relationship marketing**

This research reflects a strong academic and professional interest in understanding how emerging technologies transform customer relationships, commercial management, and

retention strategies. Predictive CRM represents a particularly relevant intersection between technological intelligence and relational marketing practices.

- ✓ **Practical managerial relevance**

Beyond its academic contribution, the research seeks to generate practical recommendations capable of improving proactive customer management, customer retention strategies, and CRM operational efficiency within industrial organizations.

1.4 Importance of the Research

This dissertation holds both theoretical and managerial importance. From a theoretical perspective, the study contributes to the emerging literature on predictive CRM by proposing a client-centered conceptualization of predictive CRM capabilities and examining how these capabilities influence customer retention within industrial B2B relationships.

The study is particularly important because it does not assume the existence of a pre validated predictive CRM construct. Instead, it adopts an exploratory sequential approach allowing the dimensions of predictive CRM capabilities to emerge progressively through qualitative exploration and empirical refinement before quantitative operationalization.

The research additionally contributes to expanding academic understanding of customer retention beyond purely behavioral perspectives by integrating relational and psychological retention dimensions such as relationship commitment and switching resistance.

Within the Algerian industrial context specifically, where academic research on predictive CRM remains scarce, this dissertation provides empirically grounded managerial insights relevant to organizations undergoing digital and relational transformation.

1.5 Research Objectives

The study seeks to explore how predictive CRM capabilities are perceived by B2B industrial clients, to identify and empirically structure the dimensions characterizing these capabilities, and to examine their influence on the dimensions of customer retention. Ultimately, the study aspires to develop a valid, robust, and empirically grounded model that captures the relationship between perceived predictive CRM capabilities and customer retention in B2B industrial contexts.

1.6 Research Design

This dissertation adopts an exploratory sequential design combining qualitative and quantitative approaches.

The research began with an exploratory qualitative phase based on semi-structured interviews conducted with industrial decision-makers and professionals associated with Atlas Copco Algeria. The qualitative phase aimed to explore how predictive CRM capabilities are experienced and perceived in practice and to identify the dimensions emerging from participant discourse through thematic analysis.

Building on the qualitative findings, the study then proceeded to a quantitative conclusive phase involving a structured questionnaire administered to B2B industrial clients of Atlas Copco Algeria.

The quantitative analysis employed descriptive statistics, exploratory factor analysis, multiple regression analysis, and cross-validation procedures using SPSS in order to validate and refine the emergent conceptual structure statistically.

Importantly, the exploratory sequential design allowed the study not only to test relationships between variables, but also to progressively refine and reorganize the conceptual framework based on empirical evidence.

1.7 Research Structure

This dissertation is organized into six chapters:

Chapter 1: Introduction presents the research background, research problem, sub-questions, objectives, research importance, methodological design, and overall dissertation structure.

Chapter 2: Literature Review develops the theoretical and conceptual foundations of the study, covering CRM evolution, predictive CRM, customer retention, B2B relationship marketing, and the theoretical frameworks supporting the research.

Chapter 3: Research Methodology presents the exploratory sequential mixed-methods design, including sampling procedures, qualitative thematic analysis, questionnaire development, and quantitative analytical methods.

Chapter 4: Research Findings and Discussion presents and discusses the empirical findings generated from both the qualitative and quantitative phases, including exploratory factor analysis, regression analysis, and conceptual model refinement.

Chapter 5: Conclusion and Recommendations summarizes the major findings of the dissertation, discusses theoretical and managerial implications, identifies research limitations, proposes future research directions, and presents practical recommendations for predictive CRM implementation in industrial B2B environments.

Chapter 6: It contains a list of references in which all the resources used to collect secondary data are listed.

Chapter 2: Literature Review

Introduction

This chapter presents a literature review that offers a clear and structured examination of previous studies related to Customer Relationship Management, predictive analytics, B2B industrial marketing, and customer retention. It explores the key concepts of CRM evolution, artificial intelligence and machine learning in CRM systems, and how these shapes the quality of supplier-client relationships and long-term retention outcomes in B2B industrial contexts. This review aims to meet the following objectives:

- Clarify the nature and evolution of CRM, from its operational origins to its current predictive paradigm driven by artificial intelligence and machine learning.
- Investigate the client perceptible manifestations of predictive CRM capabilities and their relevance in B2B industrial markets.
- Analyze the theoretical foundations of customer loyalty and customer retention, and their commercial importance in long term B2B relationships.

To meet these objectives, the chapter begins by diving into the foundations and evolution of CRM, exploring what makes a CRM system predictive, and how the integration of artificial intelligence, machine learning, and automated systems transforms a passive data repository into an anticipatory commercial intelligence platform. Rather than examining technology in isolation, this section focuses on how these systems are perceived by clients through their interactions with the firm, specifically through three client perceptible capabilities: need anticipation, commercial proactivity, and hyper personalization. The specificities of B2B industrial markets are subsequently examined to contextualize the strategic relevance of these capabilities in complex, long term supplier client relationships.

The chapter then follows a deliberate logic; moving from the macro to the micro, beginning with customer loyalty, reviewing its definitions, dimensions, levels, and strategic importance, before narrowing progressively to customer retention as its most commercially observable and measurable expression. This section examines the customer lifecycle, customer lifetime value, customer churn, and the multidimensional structure of retention in B2B industrial contexts.

Finally, the chapter presents four theoretical frameworks; Relationship Marketing Theory, Proactive Market Orientation Theory, Commitment-Trust Theory, and Relational Benefits Theory, which together provide the conceptual foundation for understanding the dynamics between predictive CRM capabilities and customer retention. The literature reviewed in this

chapter forms the theoretical basis for the research model and hypotheses developed in the subsequent chapters.

2.1 Basics of CRM

2.1.1 Evolution of CRM

Customer Relationship Management (CRM) has undergone significant evolution since its emergence in the late 1980s. In its early stages, CRM was primarily conceived as a technological tool designed to store, organize, and retrieve customer information, mainly supporting sales teams in managing contacts and tracking transactions. These initial systems were largely reactive in nature, focusing on recording past interactions without offering any capability to anticipate future customer behavior (Buttle & Maklan, Customer relationship management : Concepts and technologies, 2009).

During the 1990s, CRM experienced a fundamental transformation, shifting from a purely operational tool to a strategic, customer centric approach. It became recognized as an integrated business strategy aimed at building and sustaining valuable customer relationships, involving the alignment of marketing, sales, service, and information systems (Payne & Frow, 2005). Empirical research further demonstrated that organizations with well-developed CRM processes and strategies achieved superior financial and commercial performance (Reinartz, Krafft, & Hoyer, The customer relationship management process : Its measurement and impact on performance, 2004)

In its current phase, CRM is characterized by a decisive transition toward a proactive and predictive paradigm, driven by the widespread integration of Artificial Intelligence (AI) and Machine Learning (ML). Organizations now leverage advanced algorithms to analyze large volumes of transactional and behavioral data, enabling them to anticipate customer needs, predict churn, and optimize decision making with unprecedented accuracy. This evolution marks a shift from reactive relationship management to data-driven, forward looking customer engagement.

2.1.2 Definition of CRM

Customer Relationship Management (CRM) is an abbreviation for "customer relationship management." It has several definitions, including the following key perspectives:

CRM originated in the mid-1990s within the information technology (IT) vendor and practitioner communities. It refers to technologies, methodologies, and e commerce capabilities

that organizations use to organize and manage their relationships with customers. (payne & frow, P, 2006) (Stone, 2002)

From a marketing perspective, CRM is a philosophy aimed at meeting customer needs to achieve effective marketing and sales. This approach involves identifying customers, gaining their loyalty, collecting customer related information, integrating and processing that information, and distributing it across all organizational units through efficient information channels (Idzikowsk, Kuryło, P, Cyganiuk, & Ryczko, 2019)

CRM is also a method or system focused on building sustainable relationships between customers and organizations. It helps organizations understand customer needs and expectations, starting from sales and marketing through after (payne & frow, P, 2006)sales services. This strategy enhances customer satisfaction and loyalty by facilitating detailed information collection about customers and their preferences, while also enabling customers to quickly access accurate information about products or services (Sadani, M, Lumbanraja, P, & Sembiring, M. T, 2023)

In summary, CRM encompasses organizational activities designed to attract, satisfy, retain customers, and transform them into partners of the organization.

2.1.3 Components of CRM

Organizations tend to focus on three components in order to bolster customer relationships, these common components are explained as following:

2.1.3.1. Process: This component emphasizes focusing on individual customers by shifting organizational processes from being product centric to customer centric. The key business processes addressed during CRM implementation include: Marketing, Sales, and Services.

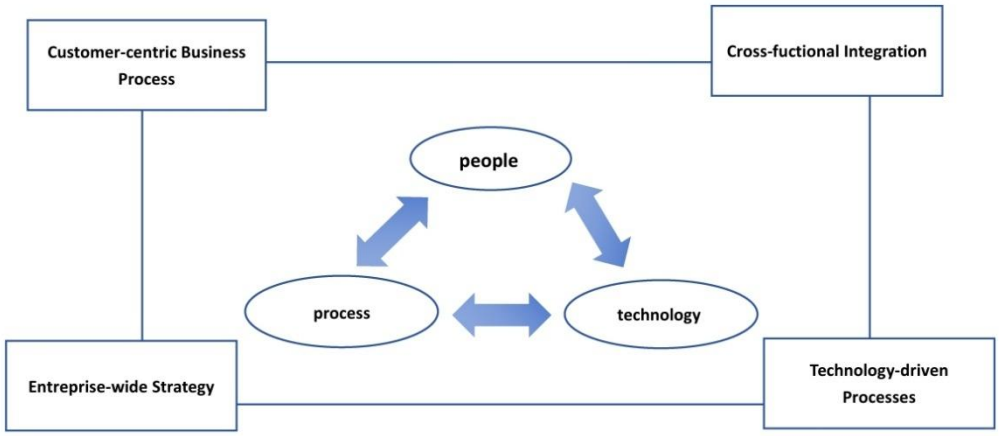
A customer centered marketing approach is required, prioritizing customers' needs. Relationships between clients and sales personnel should be more personal and face to face, with a strong emphasis on delivering high quality, long-term customer service. (MENDOZA & L,E, 2006)

2.1.3.2. Technology: Technology plays a crucial role by collecting and analyzing customer data to understand behavior and develop predictive models. It supports timely responses, effective and customized communication, and the delivery of personalized products and services to individual customers. (CHEN & POPOVITCH, 2003)

2.1.3.3. People: This involves organizational readiness and active collaboration among staff. Successful CRM implementation depends on the entire organization understanding and valuing new processes. Employees must be engaged with the CRM strategy and motivated to achieve its objectives. (RAHIMI, 2015)

some experts recognize **Knowledge** as an important CRM component. Knowledge management involves capturing customer and prospect information and tracking their interactions with the company. It requires careful consideration since not all data is valuable; some can even be harmful. Studies show that around 20% of organizational data becomes obsolete each year, underscoring the need for effective data management.

Figure 2. 1The components of CRM implementation model



Source: CHEN, (I) and POPOVITCH, (K): "Understanding customer relationship management (CRM) People, process and technology", Business process management journal, Vol.9 No.5, 2003, p. 676.

2.1.4. Types of CRM

CRM (Customer Relationship Management) can be defined as a business strategy and a cohesive process focused on selecting and managing customers to optimize long term value for organizations. It is utilized by organizations to identify, attract, satisfy, and maintain strong relationships with partners, potential customers, and existing customers.

Various researchers have categorized CRM in different ways. Some classify it into two main categories, others into three groups, and some into four types. One comprehensive approach lists two main categories and four primary types, noting that one category is implicitly included

as part of the main four types, which are strategic CRM, operational CRM, and collaborative CRM. Another classification divides CRM into three distinct groups:

- Interactive or collaborative CRM
- Transactional or operational CRM
- Analytical CRM

Notably, (Iriana & Buttle, F, 2006)) classify CRM into three types: strategic, operational, and analytic CRM. Later, (Buttle, 2009) expanded this classification into four levels: strategic, analytic, collaborative, and operational CRM. Overall, the types of CRM can be broadly understood by monitoring two different approaches or perspectives.

2.4.4.1 Strategic CRM

Strategic CRM focuses on using resources long term to build and maintain valuable customer relationships for sustained profit. It involves investing in customers based on their value to the company (Grant & M, 1998).

The goal is to create a customer focused organization that consistently delivers superior value and gains competitive advantage. This means embedding a customer first mindset across the business to make better decisions and optimize resource use (Iriana & Buttle, F, 2006).

2.1.4.2. Operational CRM

Operational CRM automates customer related processes through integrated tools that support sales, marketing, and customer service. It streamlines workflows and routine tasks, helping organizations manage customer interactions efficiently across departments.

Operational CRM improves both customer facing and support activities by unifying them into one system. This centralizes customer data, boosts efficiency, and ensures consistent experiences (Boulding, Staelin, Ehret, & Johnston, 2005) (payne & frow, P, 2006). Core features include contact management, call center functions, and customer support, which help manage interactions throughout the customer lifecycle (M & Walton , J, 2005).

Overall, operational CRM enhances efficiency, cuts costs, speeds up issue resolution, and strengthens customer relationship management.

2.1.4.3. Analytical CRM

Analytical CRM enhances organizational and customer value by mining data from operational CRM for strategic and tactical decisions. It involves collecting, processing, and analyzing

customer data to improve business performance (Buttle & Maklan, Customer relationship management : Concepts and technologies, 2009). Integration of operational and analytical CRM is essential for effective CRM systems (Appendix A, Table 1).

This approach enables firms to segment customers, tailor sales strategies, and customize communications, increasing offer acceptance and customer satisfaction. Organizations benefit through improved up selling and cross-selling, retaining existing customers and attracting new ones.

Analytical CRM relies on detailed historical customer data to inform marketing and relationship processes (Limayem, 2006). It reduces customer churn, boosts sales through targeted approaches, optimizes supply chain management, controls costs, and uncovers system weaknesses to convert them into strengths.

2.1.4.4. Collaborative CRM

Collaborative CRM, as defined by (Dyche, 2002), enables two-way communication between a company and its customers across multiple channels to enhance the quality of interactions. It facilitates engagement among customers, the enterprise, and employees, focusing on maintaining partner relationships to improve customer identification, attraction, retention, and development.

This CRM type supports information sharing along the supply chain and often includes Partner Relationship Management (PRM) applications. PRM helps companies manage complex partner networks, control promotions, allocate funds, and measure outcomes, sometimes extending to internal communications across sales, marketing, and service functions (Buttle & Maklan, Customer relationship management : Concepts and technologies, 2009). Collaborative CRM handles various data types structured, unstructured, conversational, and transactional, providing a unified customer view during real time interactions.

- After reviewing the many forms of CRM, **The Showroom CRM** can be introduced as a comprehensive CRM approach that addresses the need for a more integrated model. It brings together the four traditional CRM types: strategic, operational, analytical, and collaborative CRM, into a unified system, providing a full 360° customer view of the entire customer journey. Its main components are:

- **Sales force automation**: Sales Force Automation (SFA) is technology that helps sales teams meet their goals by streamlining tasks and improving CRM efficiency (Buttle, 2009). It

integrates sales, marketing, and service processes and operates across channels like web, email, and phone (Speier & Venkatash, V, 2002)

SFA comes as specialized tools, CRM modules, or part of larger enterprise systems (payne & frow, P, 2006). Key features include lead management, contact tracking, order processing, and sales forecasting. When easy to use and well supported, SFA enhances sales skills and performance (Ahearne & Schillewaert, N, 2001)

- **Marketing automation:** Marketing automation is a technology that helps marketing teams achieve their goals. It provides information about products, campaigns, and customer profiles (Cho et al., 2002). This technology improves marketing productivity, intelligence, responsiveness, and enhances the customer experience. It also helps the sales team quickly access marketing information to target the right customers at the right time (Tamošiūniene & Jasilioniene, R, 2007).

Marketing automation software offers various features such as managing assets, documents, campaigns, emails, loyalty programs, marketing performance, customer segmentation, online marketing, lead generation, analytics, search engine optimization, partner marketing, trigger marketing, telemarketing, workflow, and web analytics.

- **Service automation** : Service Automation (SA) is technology that helps service teams and management achieve their goals. It is mainly used in call centers, contact centers, field service, help desks, and web self-service. Service quality has two main views: meeting specifications or fitness for purpose (Crosby, 1979) (Juran, 1964) and includes technical, functional, and reputational aspects (Buttle & Maklan, Customer relationship management : Concepts and technologies, 2009). Value propositions are promises organizations make to customers about delivering value, which is key in strategic CRM. SA improves customer experience, service productivity, and efficiency (Buttle & Maklan, Customer relationship management : Concepts and technologies, 2009).

Service automation software includes functions like managing agents, cases, contracts, communications, scheduling, invoicing, self service, analytics, and workflow (Buttle & Maklan, Customer relationship management : Concepts and technologies, 2009)Along with sales and marketing automation, service automation plays a vital role in reaching organizational goals.which are interconnected across marketing, sales, logistics, customer service, and support functions to ensure organizational alignment and performance efficiency.

2.2. The switch from Traditional CRM to Predictive CRM

In large companies, customer data is massive and complex. Traditional CRM systems can store and track this information, but they struggle to turn it into meaningful insights. Predictive CRM, powered by artificial intelligence and machine learning, provides the strong technology needed to manage big data effectively. It helps businesses forecast customer behavior, anticipate needs, and make proactive decisions. This shift from traditional to predictive CRM is essential for organizations that want to build deeper, more personalized relationships with their customers.

2.2.1. Understanding Predictive Analytics in CRM

2.2.1.1. Definition and purpose (Reddy & R, 2021)

Predictive analytics stands out among advanced analytics by leveraging historical data, statistical models, AI and machine learning to anticipate future events. Within Customer Relationship Management (CRM), it is invaluable for forecasting customer behaviors, trends, and needs.

CRM systems collect extensive data, which can be analyzed to generate actionable insights about customers' likely future actions. This empowers businesses to make well informed decisions and develop targeted strategies.

The key purpose of predictive analytics in CRM is to enhance customer relationships and optimize business processes by predicting sales, scoring leads, and improve customer retention rates. Such insights enable organizations to proactively address potential challenges, capitalize on new opportunities, and strengthen customer engagement.

Overall, predictive analytics converts raw data into a strategic asset, allowing companies to move from reactive responses to proactive customer management.

2.2.1.2. Key components

Predictive analytics in CRM relies on three main components:

- **Data Collection and Processing**: Data is gathered from various customer touchpoints, such as social media, emails, purchase history, and web activity and stored in the CRM. This raw data is then cleaned and structured to ensure accuracy and readiness for analysis. (Potla, 2024)

- **Algorithms and Models:** Statistical and machine learning algorithms analyze processed data to identify patterns and predict outcomes like purchase likelihood or churn risk. These models are continuously updated with new data to improve accuracy. (Potla, 2024)
- **AI and Machine learning Integration**: AI and ML form the core of predictive analytics in predictive CRM systems. AI enables fast and accurate analysis of complex datasets, while ML allows the system to learn from data and improve predictions over time. Machine learning models adapt automatically to changes in customer behavior, making predictions more dynamic and relevant. For example, ML can detect changes in a customer's buying frequency and update forecasts accordingly, providing timely insights for businesses to act on. (Potla, 2024)

Combined, these components enable predictive analytics to generate deep insights into customer behavior and preferences, facilitating the development of more personalized and effective CRM strategies. Understanding these elements helps businesses grasp how predictive analytics functions and how it can be leveraged to enhance customer relationships and drive growth.

2.2.1.3. AI and Machine Learning in CRM Systems

The integration of Machine Learning (ML) in predictive CRM marks a shift from reactive data handling to a proactive approach that anticipates customer needs and automates retention efforts. By harnessing large datasets, ML evolves CRM systems from basic data stores into intelligent engines for business growth, uncovering patterns that are often invisible to human analysts.

2.2.1.3.1. definition of A I and Machine Learning

- **Machine Learning** (ML): is a subdiscipline of AI, a data driven analytical approach that enables systems to automatically learn from data, identify patterns, and improve their predictive performance over time without explicit programming or continuous human intervention. (Marsland, 2015) (Alpaydin, 2014).

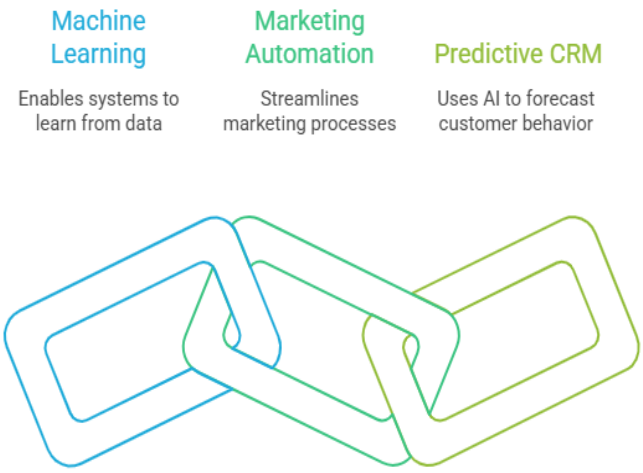
In CRM, ML trains on historical customer data, such as purchase behavior and service interactions, to generate more accurate forecasts of future customer needs and risks. ML is a specialized subfield of artificial intelligence, which broadly covers human like cognitive functions, whereas ML specifically enables learning from data without task specific programming (Russell & Norvig, P, 2020)

- **Artificial Intelligence**: Is defined as "a wide-ranging set of technologies that enable machines to sense, comprehend, act, and learn with human like levels of intelligence".

Within CRM, three key AI capabilities stand out: automating structured tasks to replace repetitive human work, augmenting human decision making to improve analytical quality, and generating autonomous insights that operate without human intervention during decision making. (Davenport, Guha, A, Grewal, D, & Bressgott, 2020)

AI in CRM involves integrating intelligent technologies: such as machine learning, predictive analytics, and marketing automation, into CRM systems. This allows organizations to automatically analyze vast customer data, forecast future behaviors and needs, and execute targeted actions without manual input.

Figure 2. 2: The Technological Foundations of Predictive CRM



Source: Personal Efforts

2.2.1.3.1.1. Types of Machine Learning Relevant to Predictive CRM

- **Supervised Learning :** It is the most widely applied approach in predictive CRM, as it leverages labeled datasets to train models for classification or regression tasks. Algorithms such as K-Nearest Neighbor, Support Vector Machine, Random Forest, and Neural Networks are particularly effective for predicting customer churn, estimating customer lifetime value, and detecting fraudulent activities. These methods excel in scenarios where historical customer data with known outcomes is available. (Boateng, Otoo, J, & Abaye, D. A, 2020)

- **Unsupervised learning :** It is crucial for discovering hidden structures in customer data without predefined labels. Techniques such as K means clustering and hierarchical clustering enable firms to segment customers into meaningful groups based on purchasing behavior, demographics, or engagement patterns. This segmentation supports targeted marketing strategies and personalization efforts, enhancing customer satisfaction and retention. (Jiang, et al., 2018; Reddy, K, Vinzamuri, & B, 2018)

- **Reinforcement learning (RL):** introduces adaptive decision-making by allowing systems to learn optimal strategies through trial and error interactions with the environment. In CRM, RL is increasingly applied to dynamic personalization, where customer journeys and offers are continuously optimized based on feedback signals. RL also powers intelligent chatbots and recommendation systems that improve over time through user interaction. (Liang, Wang, T, Yang, L, & Xing, E, 2018; Nian, Liu, & Huang, 2020)

- **Deep learning:** extends supervised and unsupervised paradigms by employing multi-layered neural networks capable of processing unstructured data such as text, images, and voice. In predictive CRM, deep learning is particularly valuable for sentiment analysis, enabling firms to capture customer emotions from social media or support interactions. (Nash, Drummond, T, & Birbilis, N., 2018; Singh K. B., 2019)

2.2.1.3.2. The Integration of AI and Machine Learning

In Customer Relationship Management, Artificial Intelligence (AI) and Machine Learning (ML) mark a significant evolution in how companies engage with customers, analyze data, and streamline business operations. These technologies elevate CRM systems from simple data storage tools to intelligent engines driving business growth. This section explores the integration of AI and ML in CRM by focusing on generating insights, personalizing data and customer segmentation, and automating CRM processes.

- **Data Driven Insights:** AI and ML significantly enhance CRM systems by enabling deeper and broader data analysis than traditional CRM tools. They can process vast amounts of data from sources like social media, emails, purchase history, and customer feedback to identify patterns and predict behaviors.

For instance, AI can analyze a customer's past purchases and browsing habits to forecast products they are likely to buy next. This predictive capability allows businesses to target the right customers with the right offers at the right time, improving marketing and sales effectiveness. (Alexander, 2024)

- **Personalization and Customer Segmentation:** Customer segmentation is a key element of effective engagement strategies. Machine Learning (ML) helps businesses categorize customers into distinct groups based on behavioral, demographic, and transactional data. This enables companies to customize retention strategies that meet the specific needs and preferences of each segment. ML analyzes customer interactions such as website visits, purchase frequency, and product preferences, to develop meaningful behavioral segments. (Ebrahimi, Basirat, M, & Yousefi, A, 2022)
- **Automation of CRM Processes:** The automation of Customer Relationship Management (CRM) processes has been significantly enhanced through the integration of Machine Learning (ML) technologies. ML enables systems to learn from historical data, identify patterns, and generate predictions with minimal human intervention, thereby transforming traditional CRM automation into a more intelligent and adaptive. Unlike rule based automation, which relies on predefined instructions, ML driven automation can process complex datasets and optimize decision making dynamically in real time.

Integrating ML into CRM automation marks a shift toward data driven customer management. By combining predictive insights, process automation, and real-time responsiveness, ML enhanced CRM systems boost operational efficiency, deliver more relevant interactions, and strengthen long term customer relationships. As these technologies advance, they play an increasingly vital role in proactive, performance driven CRM strategies helping sales teams prioritize high potential leads, enhancing efficiency and resource use. (Kalusivalingam, K., Sharma, Patel, N, & Singh, V, 2020)

2.2.1.4. From Technology to Client Perception: Key Capabilities of Predictive CRM

While predictive CRM is fundamentally rooted in advanced data analytics and machine learning technologies, its true strategic value does not lie in the technology itself, but in how it is perceived by clients through their interactions with the firm. In other words, predictive CRM only creates value when its underlying capabilities are translated into tangible, meaningful experiences for customers.

From a client perspective, predictive CRM is not experienced as algorithms or data models, but rather through the quality of interactions, the relevance of communications, and the timing of commercial engagement. This shift from a technology centered view to a customer centered perception is essential, particularly in B2B contexts where relationships are long-term and interaction quality is critical.

Based on the literature, three core and complementary capabilities emerge as the most relevant manifestations of predictive CRM: need anticipation, commercial proactivity, and Hyper personalization. Together, these dimensions capture how predictive CRM enhances the perceived quality of customer followup and interaction.

2.2.1.4.1. Need Anticipation

Need anticipation refers to a firm's ability to identify and address customer needs before they are explicitly expressed. This capability signifies a shift from reactive customer management responding only after customer initiated interactions to a predictive, data driven approach that infers future needs from patterns in historical and real time data ((Ajah & Nweke, H. F, 2019) & (Singh, Sharma, D, Patel, D, & Bose, N, 2020)

Predictive analytics strengthens need anticipation by using advanced methods to detect trends, forecast events, and anticipate customer behavior and market shifts. Firms leverage large datasets, including transactional histories and contextual factors, to generate reliable predictions of future requirements.

In industrial and service contexts, this extends beyond buying behavior to operational needs such as equipment maintenance and failure prevention. Predictive models analyze data streams to detect early warning signs, enabling preemptive actions that improve efficiency and reduce risks (Adewale, Olorunyomi, T. D, & Odonkor, T. N, 2021).

Compared to traditional CRM, which focuses on past interactions, predictive CRM leverages machine learning to provide forward looking insights, enhancing decision making accuracy and relevance (Kalusivalingam et al., 2020; Bates et al., 2020).

From the customer's perspective, need anticipation manifests as a firm's ability to understand current and future expectations, reducing uncertainty and reinforcing trust. This capability enhances the perceived value of the relationship and fosters long term loyalty.

In summary, need anticipation is a fundamental dimension of predictive CRM, enabling proactive customer management that improves operational outcomes and strengthens sustainable customer relationships.

While need anticipation captures the predictive intelligence of the CRM system, its capacity to forecast what the client will need, it does not by itself produce a client-perceptible outcome. The predictive insight must be translated into a concrete commercial action for the client to

experience its value. This action dimension of predictive CRM constitutes the second capability, commercial proactivity

2.2.1.4.2. Commercial Proactivity

Commercial proactivity is a firm's capability to initiate timely and relevant actions toward customers based on predictive insights, rather than waiting for customer requests. Unlike traditional CRM's reactive approach, predictive CRM leverages data and machine learning to anticipate customer needs and trigger appropriate responses (Hussain, et al., 2021)

Predictive models detect patterns such as purchase cycles, service needs, and churn risk, enabling firms to act early with retention strategies that improve customer loyalty and reduce response times. Integration with operational systems allows automated, real time follow ups and alerts, ensuring continuous and coordinated engagement (Okonkwo, Akinyemi, M. O, & Ogunnowo, F. A, 2021).

This proactive approach also optimizes resource allocation by prioritizing high potential customers and opportunities, leading to increased efficiency and lower operational costs. Additionally, by anticipating issues like service failures or dissatisfaction, firms can intervene before problems damage relationships, maintaining service continuity and trust ((Basiru, Ejiofor, C. L, Onukwulu, E. C, & Attah, R. U, 2023) (Ewim, Okeke, N. I, Alabi, O. A, Igwe, A. N, & Ofodile, O. C, 2024). In summary, commercial proactivity transforms predictive insights into timely, actionable engagements that enhance both customer satisfaction and business performance.

Commercial proactivity determines that the client is contacted, but it does not determine the quality and relevance of what they receive when contacted. A proactive contact that delivers a generic, poorly calibrated proposal produces little relational value. The third capability — hyper personalization, addresses this dimension, capturing the degree to which the content of each commercial interaction is individually calibrated to the client's specific profile, situation, and needs.

2.2.1.4.3. Hyper Personalization

Hyper personalization is the advanced CRM capability to deliver highly tailored interactions, offers, and communications to individual customers by leveraging both real-time and historical data. Unlike traditional personalization, which relies on basic segmentation, hyper-

personalization dynamically adapts content, timing, and value propositions based on behavioral data, context, and predictive analytics.

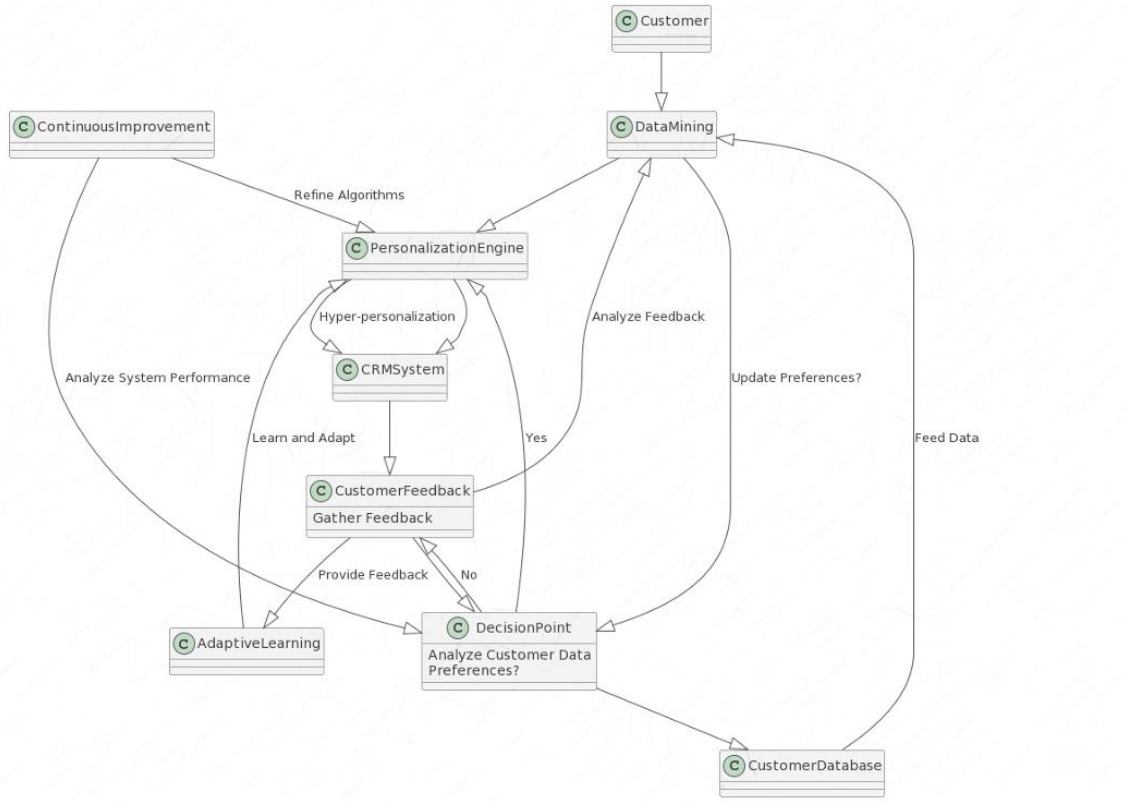
Machine learning algorithms continuously analyze customer behavior, interaction history, and preferences to predict needs and optimize engagement. This enables firms to move beyond generic marketing, offering individualized experiences that boost customer satisfaction and relationship quality.

Integration with sales automation further enhances hyper-personalization by providing actionable insights that allow sales teams to customize approaches, increasing conversion rates and commercial effectiveness. CRM personalization engines adjust recommendations and offers in real time, responding to evolving customer behavior. (Kumar, Ashoka Rajan, R, Swaminathan, A, & Johnson, E, 2022)

In B2B settings, hyper personalization means proposing solutions aligned with current and future operational needs, enhancing perceived value and fostering long term partnerships.

Academically, hyper personalization builds on the concept of personalized service encounters, adapting offerings to individual needs ((Surprenant & Solomon, M. R, 1987)), and is recognized as a strategic capability enabled by data-driven marketing and automation. making it a key pillar of modern CRM.

Figure 2. 3: Hyper personalization to enhance customer loyalty & satisfaction in CRM



Source: Rane, N., Choudhary, S., & Rane, J. (2023). Hyper-personalization for enhancing customer loyalty and satisfaction in Customer Relationship Management (CRM) systems. *SSRN Electronic Journal.*

2.3. Predictive CRM in B2B Industrial Contexts

2.3.1. Definition of B2B marketing

B2B marketing in industrial contexts refers to the processes through which firms deliver value to other organizations operating in sectors such as manufacturing and engineering. It is characterized by complex purchasing decisions involving multiple stakeholders, long sales cycles, and highly technical, high value offerings.

Unlike consumer markets, industrial buyers prioritize functional criteria such as reliability, performance, and cost efficiency, making decision making largely rational and information driven ((Hutt & Speh, T. W, 2013); (Philip Kotler & Keller, K. L, 2016). Moreover, relationships in industrial markets are typically long term and interdependent, with strong emphasis on trust, commitment, and after-sales support (Morgan & Hunt, S. D, 1994)

2.3.2. Specificities of B2B Commercial Relationships

The effectiveness of predictive CRM capabilities is strongly conditioned by the structural characteristics of B2B markets, which fundamentally differ from B2C environments.

These specificities not only increase relational complexity but also create favorable conditions for the strategic deployment of predictive CRM. Understanding these specificities is essential to contextualizing the independent variable of this study:

- **Multi stakeholder purchasing complexity:** Unlike B2C transactions, B2B purchasing decisions involve multiple stakeholders with distinct roles, objectives, and evaluation criteria. This structure is conceptualized in the *buying center theory*, where decision making authority is distributed across technical, financial, and managerial actors ((Webster & Wind, Y, 1972) (Johnston & Lewin, J. E, 1996). As emphasized by Philip Kotler, B2B exchanges are inherently organizational and require coordinated engagement across multiple contact-points.

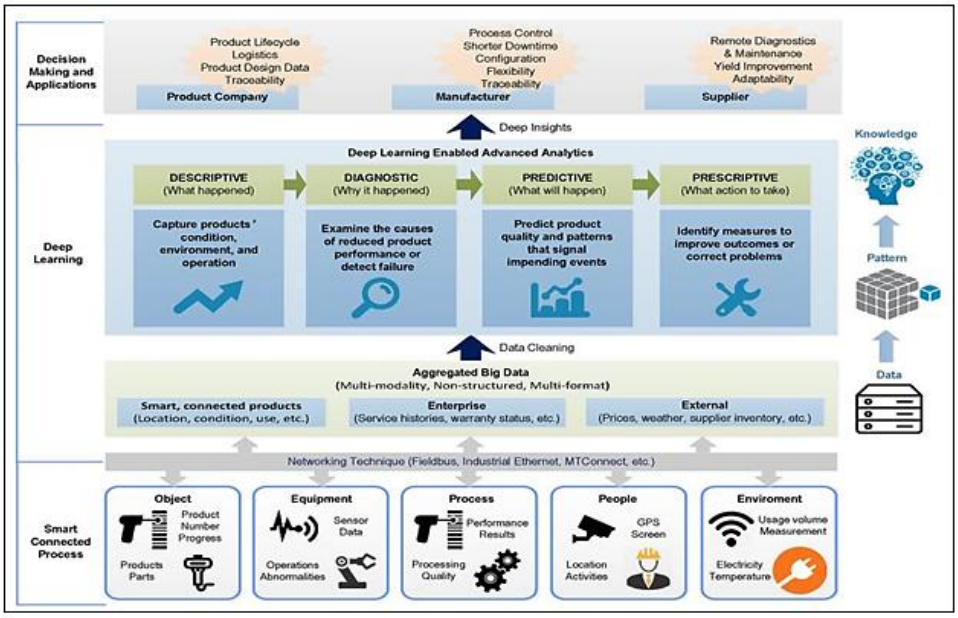
In such environments, managing customer relationships at a purely account level is insufficient. Predictive CRM systems address this limitation by integrating both firm level and contact level data, enabling more accurate identification of stakeholder specific needs and improving the relevance and timing of interactions (Elebe & Imediegwu, C. C, 2023).

- **Dynamic and data intensive customer behavior :** B2B relationships are characterized by continuous evolution in client needs, usage patterns, and engagement signals. Customers interact across multiple channels and generate large volumes of data through operational, transactional, and digital touchpoints (Lilien, 2016).

Traditional CRM approaches, based on static segmentation like industry or firm size are not sufficient to capture this behavioral complexity.

As a result, they often fail to detect emerging opportunities or risks in a timely manner. In contrast, predictive CRM relies on continuously updated data to identify patterns, anticipate changes in customer behavior, and support more adaptive relationship management (Elebe & Imediegwu, C. C, 2023).

Figure 2. 4: Deep learning–enabled advanced analytics for smart manufacturing



Source Wang J, Ma Y, Zhang L, Gao RX, Wu D. Deep learning for smart manufacturing: Methods and applications. Journal of manufacturing systems. 2018

- **Limitations of traditional CRM in B2B contexts**: The inadequacy of traditional CRM systems in B2B environments can be explained by several structural limitations. First, firmographic segmentation assumes homogeneous needs within client groups, which is rarely the case in industrial markets characterized by heterogeneous operational contexts ((Shah, Rust, R. T, Parasuraman, A, Staelin, R, & Day, G. S, 2006)). Second, reliance on historical data limits responsiveness to real time changes in customer behavior. Third, the absence of predictive capabilities restricts the ability to anticipate churn, identify upsell opportunities, or detect lifecycle transitions.

Finally, fragmented data systems often prevent the effective translation of insights into actionable commercial decisions (Elebe & Imediegwu, C. C, 2023). These limitations highlight the need for more advanced CRM approaches capable of managing complexity, uncertainty, and data integration.

Table 2. 1 Limitations of traditional segmentation models in B2B CRM environments

Segmentation Basis	Description	Limitations	Implications
Firmographic attributes	Segmentation by industry, company size geography and revenue.	Assumes uniform needs across firms, ignores behavioral nuance.	Broad, imprecise targeting reduces conversion efficiency
Static Data Dependance	Reliance on historical data snapshots that may be outdated.	Fails to reflect real-time behavior or sudden strategic shifts.	Slow response in High velocity sales environments.
Lack of predictive intelligence	No ability to anticipate churn, upsell Intelligence opportunities, or Lifecycle shifts.	Limits forecasting accuracy and strategic planning agility	Missed opportunities and reactive rather than proactive strategy.
Fragmented Data Architecture	Segmentation outputs not integrated with CRM or analytics systems	Creates silos: hampers execution and model improvement.	Disconnection from workflows impairs campaign effectiveness.

Source : Kalusivalingam, A., Bates, J., & Co-authors. (2020). *Automating B2B Market Segmentation Using Dynamic CRM Pipeline.*

- **CRM as a lifecycle management system :** In response to these challenges, CRM has evolved into an integrated lifecycle management system. Rather than serving as a passive data repository, modern CRM platforms support continuous monitoring and coordination of customer relationships across all interaction stages (payne & frow, P, 2006). In B2B contexts, this lifecycle perspective is particularly critical due to the long-term nature of relationships and the need for alignment across sales, service, and support functions. By integrating real-time data and predictive analytics, CRM systems enable organizations to adapt interactions to evolving customer needs and to manage relationships more proactively and strategically (Elebe & Imediegwu, C. C, 2023).

In conclusion, The theoretical analysis developed in these sections has established a comprehensive and structured foundation for the independent variable of this study, perceived predictive CRM capabilities. By tracing the evolution of CRM from a purely operational data

management tool to an analytically advanced and ultimately predictive system, this part has demonstrated that predictive CRM represents a qualitatively distinct commercial paradigm. Enabled by the integration of machine learning and marketing automation, predictive CRM transforms the supplier client relationship from a reactive and transactional process into a continuous, anticipatory, and data driven engagement.

Three client-perceived capabilities were identified as the core manifestations of predictive CRM at the experiential level: need anticipation, commercial proactivity, and hyper personalization.

Each capability was theoretically grounded in the literature, clearly distinguished from traditional CRM functionalities, and positioned within the specific context of B2B industrial markets. In such environments, characterized by multi stakeholder decision making, dynamic customer behavior, and high client heterogeneity, these capabilities are expected to generate significant commercial value.

The next sections therefore examine these constructs in depth, clarifying its definitions, dimensional structure, and the theoretical mechanism through which predictive CRM capabilities are expected to influence it.

2.4. Customer Loyalty

2.4.1. definition of customer loyalty

Oliver defines customer loyalty as “a deeply held commitment to repurchase a preferred product or service in the future, despite situational influences and marketing efforts that may encourage switching” (Khadha & Maharjan, S, 2017).

Jean Marc Lehu emphasizes that loyalty fundamentally involves the retention and development of existing customers (Lehu, 2003).

Humburg and Bruhn describe loyalty as encompassing “all company actions aimed at positively influencing a customer’s current and future purchasing behavior to stabilize and expand the customer relationship” (Meyer & Waarden, L, 2012)

These definitions collectively highlight key themes of relationship, retention, stability, and long term engagement. Loyalty is widely recognized as beneficial to companies, enabling them to increase profitability and gain competitive advantage.

2.4.2. Dimensions and Measurement of Customer Loyalty:

Customer loyalty has been extensively studied, with two primary approaches to its definition and measurement: behavioral loyalty and attitudinal loyalty.

- **Behavioral Loyalty:** Behavioral loyalty is assessed based on customer purchasing patterns, reflected in continued patronage and buying consistency. It considers whether customers remain active and whether the firm maintains its share of their spending. Many direct marketing firms use RFM metrics to measure behavioral loyalty, focusing on:

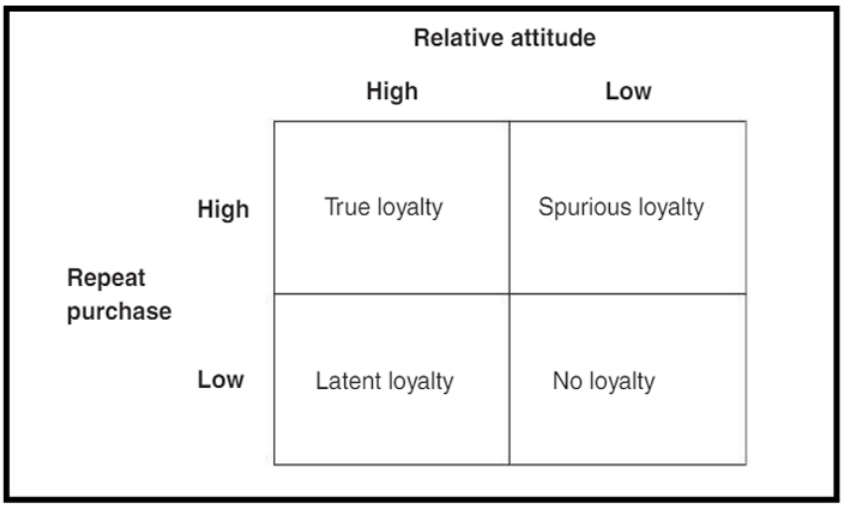
  - Recency (R): Time elapsed since the last purchase
  - Frequency (F): Number of purchases within a specified period
  - Monetary Value (M): Total spending within that period

- **Attitudinal Loyalty** : Attitudinal loyalty relates to customers' psychological commitment, including beliefs, feelings, and purchase intentions. Customers with stronger preferences or emotional involvement exhibit higher attitudinal loyalty.

Recent research has integrated both behavioral and attitudinal perspectives into comprehensive models of customer loyalty, with Dick and Basu's model being the most widely recognized.

The table above shows that :

Figure 2. 5: The two-dimensional models of customer loyalty



Source: Dick, A. S., & Basu, K. (1994). Customer loyalty: Toward an integrated conceptual framework. Journal of the Academy of Marketing Science, 22(2), 99–113.

Dick and Basu identify four types of loyalty based on the combination of attitudinal strength and repeat purchase behavior.

- "True Loyalty" exhibits both high repeats buying and strong positive attitudes toward the brand.
- "Spurious loyalty" shows frequent repeat purchases but have weak brand attachment, often due to inertia, high switching costs, or indifference.
- "Latent loyalty" occurs when customers have a strong positive attitude but do not frequently purchase, possibly due to issues like poor distribution or product availability.
- "No loyalty" when customers perceive competing offers as undifferentiated.

From a practical perspective, behavioral loyalty is often favored because sales and profits result from customer actions rather than attitudes.

2.4.3. Levels of customer loyalty (QMINDER, s.d.)

Based on customer loyalty theories, four primary levels of loyalty can be identified:

- **Cognitive Loyalty:** This is the weakest form of loyalty, primarily driven by price considerations. Customers remain loyal as long as the cost benefit ratio is favorable; they switch

brands when competitors offer better value. Some businesses may accept initial losses to secure this price-based loyalty.

- **Affective Loyalty:** At this stage, customers develop strong brand awareness and a slight preference due to positive past experiences, leading to satisfaction. Affective loyalty arises when brand attributes and services meet consumer expectations. Marketing efforts focus on reinforcing these positive feelings and memories associated with the brand.
- **Conative Loyalty:** Conative loyalty builds on affective loyalty, reflecting a deliberate intention to repurchase and stronger commitment. Key features include willingness to recommend, cross-buying intentions, and repeat purchases. However, customers remain open to competitors' offers. Loyalty programs, rewards, and exclusive access help retain conative customers. Losses often occur due to competitor disruption or poor service.
- **Action Loyalty:** The highest level, action loyalty, involves consumer-brand identification, where the brand aligns with the customer's personal or social identity. This results in habitual purchasing and positive word-of-mouth promotion. Unlike previous stages focused on intention, action loyalty reflects routine behavior and deep brand association. Companies must monitor loyal customers closely and refresh offerings carefully to maintain this loyalty without drastic changes.

2.4.4. Importance of Customer Loyalty

Customer loyalty has become increasingly vital for companies, offering several key benefits:

- **Cost Effectiveness of Retention:** The strategic importance of customer loyalty is grounded in the financial advantages of retention over acquisition. (Reichheld & Sasser, 1990) found that a 5% increase in customer retention can boost profits by 25% to 95%, depending on the industry.

This effect arises from four reinforcing factors: loyal customers buy more frequently, tolerate higher prices with less sensitivity, cost less to serve over time, and generate new customers through referrals.

(Zeithaml V. , 2000) highlights that a customer's economic value grows significantly with the length of the relationship, driven by the cumulative impact of repeated loyal purchases rather than isolated transactions.

- **Competitive differentiation through loyalty :** Beyond financial benefits, customer loyalty provides a competitive advantage that is both valuable and hard for rivals to imitate.

(Dick & Basu, 1994) show that truly loyal customers, characterized by strong positive attitudes and consistent repeat purchases—resist switching even when faced with economically better alternatives, creating a durable barrier that safeguards the firm's revenue.

In B2B industrial markets, where switching costs are already high due to technical integration, specialized staff, and tailored services, genuine loyalty adds a relational layer to these barriers, making it even more difficult for competitors to displace existing suppliers.

- **Word of mouth and organic referral generation :** (Reichheld F. , The one number you need to grow., 2003) identifies the propensity to recommend as the behavioral outcome most strongly predictive of sustainable revenue growth and demonstrates empirically that loyal clients who actively recommend a supplier generate an acquisition flow that is both less costly and more qualified than any paid marketing channel.

(Zeithaml, Berry, & Parasuraman, 1996) confirm this in their Behavioral Intentions Battery, establishing that high loyalty clients express significantly stronger word of mouth and referral intentions than moderately satisfied clients and that this referral behavior is directly conditioned by the perceived quality and consistency of the supplier's commercial engagement.

- **Feedback, forgiveness, and marketing receptivity:** Three additional dimensions of loyal client behavior are commercially significant for relationship management :

First, (Morgan & Hunt, 1994) demonstrate that highly committed clients engage in functional conflict — constructive, improvement-oriented feedback at rates significantly higher than weakly committed clients, because their relational investment motivates them to contribute to the improvement of a relationship they genuinely value.

Second, (Tax, Brown, & Chandrashekaran, 1998) establish that loyal clients evaluate service failures with significantly greater indulgence than non loyal ones and that clients whose complaints are effectively resolved demonstrate post incident loyalty intentions that exceed their pre incident levels.

Third, (Gwinner, Gremler, & Bitner, 1998) confirm that loyal clients perceive proactive commercial communications as a valued relational benefit rather than an intrusion making them structurally more receptive to marketing outreach and more likely to respond positively to commercial propositions.

- **Organizational and employee level benefits** (Heskett, Jones, Loveman, Sasser, & Schlesinger, 1994) establish through their Service Profit Chain framework that customer loyalty

generates organizational benefits that extend beyond revenue, specifically, that loyal client relationships reduce commercial and service team stress, simplify account management processes, and generate a more predictable and stable revenue environment that improves employee satisfaction and retention.

The relational nature of loyalty-oriented customer management contrasts structurally with the transactional and price sensitive dynamics of acquisition focused approaches, creating organizational conditions that are both commercially more productive and operationally more sustainable.

Overall, investing in customer loyalty supports sustainable growth, competitive strength, and organizational resilience.

2.5. Customer retention:

Customer retention refers to an organization's ability to maintain its existing clients over time by keeping them engaged, purchasing, and committed across successive commercial cycles, rather than allowing them to defect to competitors. It represents one of the most commercially significant outcomes in relationship marketing, directly associated with revenue stability, profitability, and long-term organizational sustainability.

(Reichheld & Sasser, W. E, 1990) define retention in its most fundamental commercial terms as the proportion of clients maintained from one period to the next. Their research demonstrates that a 5% increase in retention rates can generate profit increases ranging from 25% to 95%, depending on the industry context. Their foundational argument is both simple and empirically robust: retained clients cost less to serve, spend more over time, exhibit lower price sensitivity, and generate positive word of mouth referrals, thereby progressively increasing their financial value throughout the duration of the relationship.

(Zeithaml, Berry, L. L, & Parasuraman, A, 1996) extend this perspective by conceptualizing retention as a behavioral intention construct, namely, the client's forward-looking commitment to continue purchasing from the same supplier. Their study empirically demonstrates that such intentions constitute one of the strongest predictors of actual repurchase behavior, contract renewal, and long-term relationship continuity. Within their "Behavioral Intentions Battery," retention related behaviors include speaking positively about the supplier, considering the supplier as the first choice, increasing purchase volume, and maintaining the relationship despite potential price increases.

In B2B industrial contexts specifically, (Reinartz, Krafft, & Hoyer, The CRM process: A conceptual framework and its empirical application., 2004) define retention as the broader spectrum of relationship maintenance behaviors, encompassing contract renewal, share of wallet growth, resistance to competitive alternatives, and active commitment to the supplier partnership. Their findings demonstrate that CRM process quality constitutes the primary organizational determinant of retention outcomes within industrial markets.

More recently, (Adekunle , Chukwuma-Eke, Balogun, & Ogunsola, 2023) position customer retention within the contemporary data driven management landscape, describing it as "a fundamental aspect of business sustainability, directly impacting profitability and long term growth." Their research further confirms that machine learning enabled CRM systems represent one of the most commercially effective mechanisms for sustaining and improving retention rates in increasingly competitive markets.

2.5.1. Customer Life Cycle (Gadant, 2024)

The customer life cycle represents the different stages of the relationship between a company and its customers, from the first interaction to loyalty or customer loss. It is a strategic tool that helps companies understand and manage customer relationships effectively.

➤ **Acquisition**: Acquisition is the first stage of the customer life cycle. It refers to all the actions implemented by a company to attract potential customers and encourage them to discover its products or services through channels such as social media, email marketing, advertising, and sales activities.

➤ **Development**: The development stage begins when a customer makes a first purchase or engages commercially with the company. The objective is to strengthen the relationship, encourage repeat purchases, and increase customer engagement through personalized strategies and communication.

➤ **Loyalty**: Loyalty occurs when customers become attached to the brand and continue purchasing over time. Loyal customers are more likely to recommend the company to others, making customer retention and satisfaction essential for long term success.

➤ **Attrition**: Attrition is the final stage of the customer life cycle, where customers gradually disengage from the brand and may eventually stop purchasing. Companies can reduce attrition by identifying the causes of dissatisfaction and implementing corrective actions to re-engage customers.

Figure 2. 6: Phases of customer lifecycle



Source: Gadant, M. (2024, April 9). What is the customer lifecycle? Definition and stages. HubSpot Blog Service. https://blog.hubspot.fr/service/cycle-de-vie-client

2.5.1.1. Objectives of the Customer Life Cycle

The customer life cycle serves several important objectives for companies (Durand & Van Laethem, 2022):

- Measuring customer churn rates in order to define appropriate objectives and budgets for customer renewal.
- Evaluating the profitability of actions implemented to improve customer loyalty and retention.
- Determining the budget allocated to customer acquisition according to the average customer life cycle.
- Developing appropriate strategies based on the stage where the customer is positioned within the life cycle.

After analyzing the customer life cycle, which highlights the different stages a customer goes through, from acquisition to loyalty, including engagement and potential attrition, it becomes

essential to evaluate the actual value each customer brings to the company throughout this relationship.

This is where the concept of Customer Lifetime Value (CLV) becomes important. Understanding the customer life cycle alone is not sufficient; companies must also measure the long term financial contribution of each customer.

2.5.1.2. Customer Lifetime Value in B2B Industrial Contexts

Customer Lifetime Value (CLV) refers to the total long-term profit generated by a client throughout its relationship with a supplier (Berger & Nasr, 1998) In B2B industrial markets, CLV is particularly important because client relationships are usually long term, high value, and based on strong operational and technical interdependence.

(Reinartz & Kumar, 2000) demonstrate that long term industrial clients generate higher profitability through repeat purchases, lower service costs, and stronger cross selling opportunities. (Jackson, 1985) identifies two main approaches to understanding CLV in industrial markets:

- **Lost for Good Approach:** once a client leaves the supplier, the relationship is considered permanently lost due to high switching costs and long-term contractual commitments. In this context, retention becomes strategically critical.
- **Always a Share Approach:** clients may work with multiple suppliers and return after periods of inactivity. Here, the objective is to maximize share of wallet and maintain long term relevance.

These approaches highlight the strategic importance of CRM and predictive relationship management in improving retention, strengthening engagement, and maximizing long-term customer value in B2B industrial environments.

2.5.2. Customer Churn

2.5.2.1. Definition

Customer churn refers to the phenomenon whereby clients cease engaging with a supplier, whether through explicit contract termination, service cancellation, or gradual disengagement over time (Adekunle , Chukwuma-Eke, Balogun, & Ogunsola, 2023). Others are more difficult to detect, particularly when clients progressively stop purchasing or reduce their engagement with the company.

In such cases, transactional and behavioral data analysis helps identify relevant inactivity thresholds (for example, several months without purchases). Predictive analytics and purchase

history analysis allow companies to refine these thresholds, reduce false alerts, and improve the identification of clients genuinely at risk of churn.

2.5.2.2. Managing Churn Through Retention Strategies (Artun & Levin, 2015)

Customer retention programs may be either non targeted or targeted, and can adopt reactive or proactive approaches:

- **Non targeted retention**: focuses on general improvements in product quality, customer service, or mass communication campaigns.
- **Targeted retention:** focuses specifically on a risk clients.

- Advantages and Disadvantages of Retention Approaches:
  - **Reactive** : implemented after a customer decides to leave.
  - **Proactive :** based on predictive models identifying customers likely to churn before the final decision is made.

Reactive approaches reduce costs by targeting only departing clients but often intervene too late. In contrast, proactive retention helps preserve more customers by acting early through predictive CRM and behavioral analysis.

Proactive retention strategies rely on detecting early warning signs such as lower interaction frequency, or changes in purchasing behavior. Once identified, companies can implement personalized actions such as tailored offers, re engagement campaigns, or direct communication to strengthen the relationship and prevent customer loss.

2.5.3. The Dimensions of Customer Retention

Customer retention is a multidimensional construct encompassing several behavioral, attitudinal, and relational components that explain why clients maintain long-term relationships with a supplier. The literature commonly identifies four major dimensions of retention: continuance intention, repurchase behavior, switching resistance, and relationship commitment. Together, these dimensions provide a comprehensive understanding of customer retention in B2B relationships.

2.5.3.1. Continuance intention

It refers to a client's forward-looking commitment to maintain their relationship with a supplier in the future. It is the attitudinal precursor of actual retention behavior, what the client intends to do before they act. (Zeithaml, Berry, L. L, & Parasuraman, A, 1996) establish this as

the most sensitive early signal of future retention, detectable before any behavioral change occurs. A client with strong continuance intention plans to renew contracts, expand the relationship, and considers the supplier their first choice for future needs.

2.5.3.2. Repurchase Behavior

Repurchase behavior is the observable, past oriented dimension of retention — the concrete evidence that a client has actually stayed. It is reflected in consistent contract renewal, stable or growing purchase volume, expanded product adoption, and systematic preference for the same supplier when new needs arise. (Reichheld & Sasser, W. E, 1990) identify this as the primary financial driver of retention value, demonstrating that the profit contribution of a retained client compounds progressively across successive purchasing cycles.

2.5.3.3. Switching resistance

It captures the depth of retention, the degree to which a client actively chooses to remain with a supplier even when confronted with competitive alternatives or price pressure. It distinguishes genuine, loyalty driven retention from passive inertia-based staying. (Jones , Mothersbaugh, & Beatty, 2000) identify its three key drivers: the quality of the interpersonal relationship, the procedural and financial cost of changing supplier, and the perceived attractiveness of available alternatives.

2.5.3.4. Relationship Commitment

Relationship commitment is the deepest dimension of retention — the client's genuine psychological investment in and dedication to the long term partnership. (Morgan & Hunt, S. D, 1994) define it as the belief that "an ongoing relationship is so important as to warrant maximum efforts at maintaining it." It is the dimension most resistant to competitive threats and most predictive of sustained retention across extended time horizons.

2.6. Theoretical Framework

The following section presents the theoretical frameworks that collectively underpin this study. Each theory provides a distinct and complementary contribution to understanding the relationship between perceived predictive CRM capabilities and customer retention in B2B industrial contexts. Together, they form the conceptual foundation upon which the research model and hypotheses of this study are built.

2.6.1. Relationship Marketing Theory

Relationship Marketing Theory provides the overarching conceptual foundation for this study. Originally introduced by (Berry, 1983) who defined it as "attracting, maintaining and enhancing customer relationships," it represents a fundamental paradigm shift in marketing — from a transactional focus on individual exchanges to a relational focus on long term, mutually beneficial partnerships. (Grönroos, 1994) extended this paradigm, arguing that the core objective of marketing is not the management of the marketing mix but the establishment, maintenance, and enhancement of customer relationships in a way that meets the objectives of all parties involved.

In B2B industrial contexts, Relationship Marketing Theory is particularly relevant because commercial relationships are inherently long term, multi stakeholder, and strategically interdependent. (Sheth & Parvatiyar, 1995) confirm that relationship marketing is most commercially consequential in markets characterized by high product complexity, long purchasing cycles, and significant mutual investment — precisely the conditions of the industrial markets examined in this study. Predictive CRM, in this theoretical context, is not merely a technological tool but the contemporary operationalization of relationship marketing in data intensive B2B environments.

2.6.2. Proactive Market Orientation Theory

Proactive Market Orientation Theory provides the theoretical foundation for the independent variable of this study. (Narver, Slater, & MacLachlan, Responsive and proactive market orientation and new-product success., 2004) draw a fundamental distinction between two organizational orientations toward customer needs. A responsive market orientation addresses needs that customers have already expressed, it is reactive, demand driven, and limited to what clients consciously articulate.

A proactive market orientation, by contrast, seeks to identify and address customers' latent needs, those that clients have not yet recognized or expressed, through systematic anticipation, forward looking intelligence, and commercially proactive engagement. (Narver, Slater, & MacLachlan, Responsive and proactive market orientation and new-product success., 2004) demonstrate empirically that organizations exhibiting a proactive market orientation generate superior value for their customers and achieve stronger relational outcomes than those operating exclusively in a responsive mode.

(Blocker C. , Flint, Myers, & Slater , 2011) extend this framework to B2B international contexts, confirming that proactive customer orientation — operationalized as the supplier's demonstrated ability to anticipate future needs, initiate relevant commercial contact, and deliver individually calibrated solutions — is a primary driver of customer value creation and long term relationship strength in industrial markets.

This theory directly grounds the three constructs of the independent variable in this study. Need Anticipation is the perceptual manifestation of proactive intelligence, the client's experience of having their future needs identified before they express them. Commercial Proactivity is the behavioral manifestation, the client's experience of being contacted without initiating. Hyper Personalization is the calibration manifestation, the client's experience of receiving individually tailored interactions. Predictive CRM, powered by machine learning and automation, is the technological infrastructure that enables organizations to achieve and sustain a proactive market orientation at the scale of a large B2B industrial client portfolio.

2.6.3. Commitment Trust Theory

The Commitment Trust Theory, developed by Morgan and Hunt (1994), provides the theoretical foundation for the dependent variable of this study. The theory proposes that in B2B relational contexts, two core variables — trust and commitment — are the central mediating constructs through which relationship quality translates into behavioral retention outcomes. Trust is defined as "confidence in an exchange partner's reliability and integrity" (Morgan & Hunt, 1994), while commitment is defined as the belief that "an ongoing relationship with another is so important as to warrant maximum efforts at maintaining it."

(Morgan & Hunt, S. D, 1994) demonstrate empirically that trust and commitment jointly produce five key retention related behaviors: acquiescence, propensity to stay, cooperation, functional conflict management, and uncertainty reduction. Critically, they establish that these behaviors are not produced by satisfaction alone, it is the combination of genuine trust and active commitment that generates durable, competitive resistant retention.

This theory directly grounds the four constructs of the Customer Retention dependent variable in this study. Relationship Commitment is its most direct operationalization. Switching Resistance is its behavioral expression, a committed client actively resists competitive alternatives. Continuance Intention reflects the forward-looking dimension of commitment. Repurchase Behavior is its observable commercial outcome.

The link to the independent variable is equally direct. A predictive CRM system that consistently anticipates client needs, initiates proactive commercial contact, and delivers individually calibrated interactions systematically demonstrates to the client that the supplier is reliable, attentive, and genuinely oriented toward their interests; building trust. Over successive interactions, this trust deepens into relational commitment, the psychological investment that produces durable, resistance strong retention.

2.3.4. Relational Benefits Theory

Relational Benefits Theory, developed by (Gwinner, Gremler, & BitnerM . J, 1998), explains the mechanism through which the independent variable of this study produces its effects on the dependent variable. The theory identifies three categories of benefits that clients in service relationships perceive beyond the core product or service offering.

Confidence benefits refer to the reduction of anxiety and perceived risk that clients experience when they trust their supplier to manage their account reliably and proactively, without requiring constant follow up or verification. Social benefits refer to the sense of personal recognition and individual attention that clients derive from interactions that reflect genuine familiarity with their specific situation. Special treatment benefits refer to the preferential, individually calibrated, and proactively initiated commercial engagement that distinguishes a client's experience from the standard treatment received by other accounts.

(Gwinner, Gremler, & BitnerM . J, 1998) demonstrate empirically that special treatment benefits are the most directly and strongly associated with client loyalty and retention in B2B service contexts, confirming that clients who perceive themselves as receiving proactive, individually relevant commercial attention are significantly more likely to exhibit retention behaviors than those receiving standard, reactive service.

This theory provides the explanatory link between the independent and dependent variables of this study. Need Anticipation generates confidence benefits; the client feels that the supplier understands and manages their future situation, reducing operational uncertainty. Commercial Proactivity generates special treatment benefits; the client perceives that they receive a level of commercial attention that reflects the importance of their account. Hyper Personalization generates social benefits, the client feels recognized as a unique individual rather than a generic account. Together, these perceived benefits build the trust and commitment that produce the retention behaviors measured by the dependent variable.

To conclude, the theoretical frameworks discussed above; Relationship Marketing Theory, Proactive Market Orientation Theory, Commitment Trust Theory, and Relational Benefits Theory, collectively form a holistic foundation for understanding the dynamics of predictive CRM and its relationship with customer retention in B2B industrial contexts. Each theory provides a distinct contribution : Relationship Marketing Theory establishes the relational paradigm within which the study is situated, Proactive Market Orientation Theory explains the organizational capacity to anticipate and address customer needs before they are expressed, Commitment Trust Theory identifies the mechanisms through which relationship quality translates into durable retention behaviors, and Relational Benefits Theory explains how commercially proactive and individually calibrated interactions generate the perceived benefits that reinforce client loyalty over time. Together, these theories form the conceptual model of this study and guide the empirical investigation of the impact of perceived predictive CRM capabilities on customer retention in B2B industrial contexts.

Conclusion

The literature review has shown that customer retention in B2B industrial markets is a complex and strategically significant outcome shaped by both technological and relational factors. CRM has been traced in its evolution from a simple data storage tool to an intelligent, predictive system capable of anticipating customer needs, initiating proactive commercial engagement, and delivering individually tailored interactions. The shift from traditional to predictive CRM, enabled by artificial intelligence, machine learning, and automation, represents a fundamental transformation in how organizations manage and develop their client relationships.

Additionally, the study of customer loyalty and retention highlights the long term commercial value of maintaining strong, durable relationships with B2B industrial clients. Loyal customers are more profitable, more forgiving, more receptive to commercial communication, and more resistant to competitive alternatives — making retention not only a financial priority but a strategic one.

In conclusion, understanding the relationship between the quality of predictive CRM engagement and long-term customer retention is essential for organizations operating in B2B industrial environments seeking to build lasting and commercially resilient client partnerships.

Chapter 3: Research Methodology

Introduction

This chapter presents an overview of the research methods employed to examine how perceived predictive CRM capabilities impact customer retention among B2B industrial clients of Atlas Copco. The purpose is to explain the systematic approach used in designing the study, developing the data collection tools, selecting the sample, and planning the analytical process.

Firstly, the chapter describes the research design, which follows an exploratory mixed research approach, combining qualitative and quantitative methods applied sequentially. The exploratory phase employs semi structured interviews with decision makers, analyzed through thematic analysis, to investigate the manifestations of perceived predictive CRM capabilities in practice and to inform the construction of the measurement instrument. The conclusive phase applies a quantitative descriptive design to empirically test the study's hypotheses.

Secondly, the chapter explains the design and construction of the research instruments, elaborating on the measurement scales used, the constructs assessed, and the rationale behind the selection and wording of items across both the interview guide and the structured questionnaire.

Thirdly, the sampling design is presented, including the method used to select participants for each phase, the characteristics of the target populations, and the justification for the final sample sizes based on established methodological standards.

Lastly, the chapter introduces the data analysis strategy, outlining the statistical approach used in SPSS, including factor analysis, multiple regression, and Net Promoter Score analysis, to test the study's hypotheses and address the research sub questions.

In summary, this chapter provides a detailed and structured presentation of the research methods adopted, offering a comprehensive foundation for the empirical investigation presented in the following chapter.

3.1 Research Stimulus

To situate this research in a professional and pertinent setting, this study is grounded in an internship at Atlas Copco, a multinational, world leading provider of industrial compressors, vacuum solutions, and compressed air systems, and one of the oldest industrial equipment companies operating in Algeria. The internship was conducted within the CTS department — Compressor Technical Service — which represents the core of the company's commercial and client relationship operations.

While this internship provided valuable hands-on experience in the commercial, operational, and technical aspects of the CTS department, this section offers only a general overview of the company. Atlas Copco's business model, organizational structure, CRM modern tools, automation system, and internal operations are highly relevant from a professional learning perspective.

Nonetheless, Atlas Copco's professional environment was instrumental in shaping this dissertation. The company provided access to valuable insights into its commercial approach, operational processes, and technology adoption practices. This proximity to real B2B industrial client management played a key role in ensuring the research maintained a solid foundation, balancing both theoretical exploration and practical application — which was crucial in addressing the central question of this study on perceived predictive CRM capabilities and customer retention in B2B industrial contexts.

3.1.1 General Overview of ATLAS COPCO Group

Atlas Copco, a Swedish industrial group founded in 1873 and headquartered in Stockholm, is a world leader in innovative industrial solutions, particularly in compressed air technologies, industrial compressors, vacuum solutions, and productivity enhancing equipment. The Group employs approximately 49,000 people and serves customers in more than 180 countries worldwide. Recognized as a pioneer in technology and engineering, Atlas Copco develops products, solutions, and services that support industrial operations across a wide range of sectors and applications.

Present in Algeria since 1947, the company has played a significant role in supporting the development of the country’s industrial sector by providing high-quality equipment, technical expertise, and advanced industrial services. Atlas Copco Algeria was re-established in 2006 as a Public Limited Company (S.P.A.) under Algerian law. The subsidiary continued its expansion with the opening of branches in Oran and Sétif in 2009, strengthening its proximity to industrial

clients across the country. In 2010, Atlas Copco Algeria extended its operational scope to Tunisia, followed by Libya in 2016, in collaboration with local partners.

As a strategic partner for Algerian industries and infrastructure projects, Atlas Copco contributes to improving operational reliability, optimizing productivity, reducing operational costs, and supporting sustainable industrial development. The company serves key sectors including manufacturing, food processing, pharmaceuticals, construction, oil and gas, and mining, while responding to increasing industrial demands for energy efficiency, productivity optimization, and carbon footprint reduction.

Beyond the provision of technological solutions, Atlas Copco Algeria places strong emphasis on long-term customer support through maintenance services, technical assistance, and operational follow up. By ensuring the reliability and performance of industrial installations, the company contributes to strengthening the competitiveness of its partners and facilitating the transition toward more efficient and sustainable industrial practices.

Driven by innovation and engineering excellence, Atlas Copco's industrial ideas aim not only to help customers grow and improve operational performance, but also to contribute positively to societal and sustainable development.

3.1.2 Company Vision, Mission and values

- **Vision:** Atlas Copco's vision is to become and remain *First in Mind—First in Choice* for its customers and stakeholders by continuously delivering innovative, reliable, and high-performance industrial solutions.
- **Mission:** The company's mission is centered around achieving sustainable and profitable growth while generating a positive impact on both society and the environment. In line with this mission, Atlas Copco continuously invests in innovation, operational excellence, and customer-oriented solutions that improve productivity, reduce operational costs, and support sustainability objectives. The company also promotes a culture of continuous learning and development for its employees while integrating the expectations of customers and broader societal needs into its value-creation approach.
- **Values:** Atlas Copco's corporate culture is strongly built around three core values: interaction, innovation, and commitment, which collectively shape the company's approach toward customers, partners, employees, and broader stakeholders.

Figure 3. 1: ATLAS COPCO CORE VALUES



Source: Company's Data

3.1.3 Compressor Technical Service

The Compressor Technical Service department, referred to as CTS, constitutes the largest and most strategically significant operational unit within Atlas Copco Algeria. As a world leading provider of industrial compressors, Atlas Copco's core commercial activity is inherently centered on compressor equipment, making the CTS department the primary interface between the company and its B2B industrial client base.

CTS is a uniquely integrated department that combines three complementary dimensions under a single organizational structure. The technical dimension encompasses the maintenance, repair, overhaul, and diagnostic services associated with the company's full range of compressor equipment. The operational dimension manages the coordination of service interventions, scheduling of technician visits, spare parts logistics, and contract management. The commercial dimension drives client relationship management, contract renewal, upselling, and proactive lead generation, positioning CTS not merely as an after-sales service unit but as a fully integrated commercial and technical partnership center.

This triple integration makes CTS the department most directly involved in the client retention lifecycle, from initial equipment installation through successive service cycles, contract renewals, and long-term account development. It is within this department that the

dynamics of perceived predictive CRM capabilities and their impact on customer retention are most directly observable and commercially consequential.

3.1.3.1. CTS' CRM System

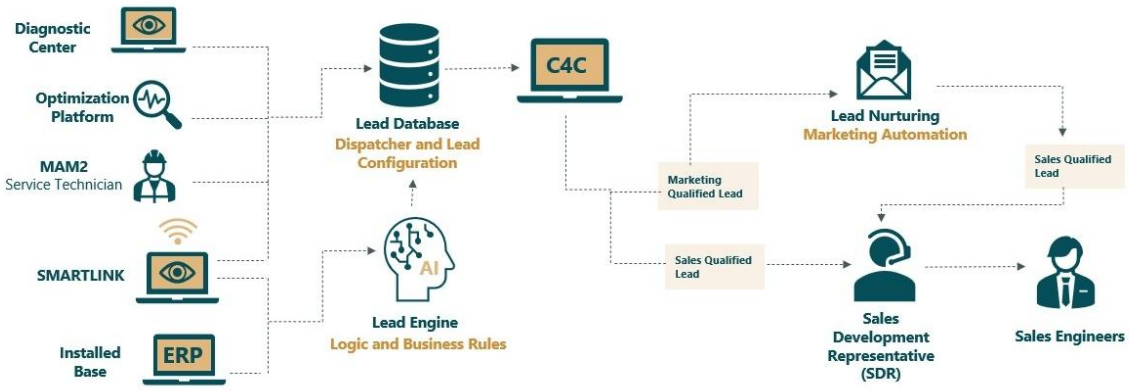
The CRM system deployed within the CTS department is C4C — Cloud for Customer — an enterprise grade customer relationship management platform that serves as the central operational hub for all commercial and client management activities. C4C centralizes client account data, installed base information, contract statuses, interaction histories, and commercial opportunity pipelines, providing the CTS commercial team with a unified 360-degree view of each client account.

What distinguishes Atlas Copco's CRM deployment from conventional systems is its integration with a suite of modern digital tools that continuously feed real time operational and behavioral data into C4C, transforming it from a passive data repository into an active, predictive commercial intelligence platform. The primary data sources feeding the system include:

- **SMARTLINK:** a remote monitoring technology embedded in Atlas Copco compressors that continuously tracks machine performance, operating hours, and anomaly signals in real time, transmitting live equipment data directly into the CRM ecosystem.
- **Installed Base**: a structured ERP connected database that maintains comprehensive records of every piece of equipment installed at each client site, including equipment age, model specifications, service history, and contractual status, that provides potential opportunities.
- **Diagnostic Center and Optimization Platform:** analytical tools that process equipment telemetry and performance data to generate predictive maintenance recommendations and identify service intervention opportunities before clients are aware of them.
- **MAM2** (Service Technician inputs): field service data contributed by CTS technicians during on site interventions, enriching the client profile with qualitative operational observations that complement the quantitative machine data.

Together, these interconnected data sources feed a **Lead Engine** an AI powered logic and business rules system that processes incoming data streams, applies predictive algorithms, and automatically generates commercially actionable leads within C4C. This architecture transforms raw operational data into structured commercial opportunities, without requiring manual intervention from the commercial team.

Figure 3. 2: CT AUTOMATED LEADS



Source: Company's Data

The automated lead ecosystem within the CTS department operates through three interconnected components that together form the backbone of Atlas Copco's predictive commercial intelligence infrastructure:

- **Lead Generation:** refers to the process of leveraging existing client data, customer interaction histories, and marketing intelligence to automatically trigger leads and create new business opportunities, eliminating the need for manual prospecting by the commercial team.
- **Lead Engine:** constitutes the digital brain of the system, processing all incoming data by applying business rules, machine learning algorithms, and artificial intelligence to deliver best in class leads to both sales and marketing teams. It is the analytical layer that transforms raw operational signals into commercially actionable outputs.
- **Lead Database:** serves as the integration API that connects all internal applications including Installed Base, Smart-link, the Diagnostic Center, and MAM2, with the Lead Engine and C4C. It operates as a web application platform that allows users to configure lead types and manage their dispatching directly into C4C, ensuring seamless data flow across the entire commercial ecosystem.

Together, these three components form a fully automated and intelligent lead generation architecture, one that continuously monitors client accounts, identifies commercial opportunities, and delivers structured, data driven leads to the CTS commercial team in real time.

3.1.3.2. The CT Automated Lead System:

The most direct expression of predictive CRM within the CTS department is the CT Automated Lead System, a proprietary lead generation mechanism built on the principle that commercial opportunity can be systematically predicted from equipment and behavioral data. The guiding philosophy of this system is explicitly stated in Atlas Copco's internal documentation: *"If we can predict, we can generate a lead."*

The strategic objective of this system is to generate 10% of total CT Opportunity Won Value from Automated Leads, a commercially ambitious target that reflects the company's commitment to transitioning from reactive to proactive commercial engagement at scale.

The automated lead strategy is structured around three strategic pillars:

- **Quality First**: ensuring that automatically generated leads are commercially relevant and qualified, improving conversion rates and reducing wasted commercial effort.
- **Sales Efficiency:** streamlining and automating the lead generation process to free commercial teams from manual prospecting and allow them to focus on high value client interactions.
- **Adoption Accelerator**: providing continuous training, communication, and support to engage lead champions within each customer center as key drivers of the system's commercial adoption.

The lead generation process follows a structured pipeline. Data from SMARTLINK, the Installed Base, the Diagnostic Center, the Optimization Platform, and MAM2 field inputs flows into the Lead Database, where a dedicated Lead Engine applies business logic and predictive rules to determine which accounts qualify for automated lead generation. Qualified leads are then pushed into C4C, where they are classified as either Marketing Qualified Leads, routed through Lead Nurturing and Marketing Automation or Sales Qualified Leads assigned directly to Sales Development Representatives and subsequently to Sales Engineers for commercial follow up.

3.1.3.3. Lead Typology and Business Rules

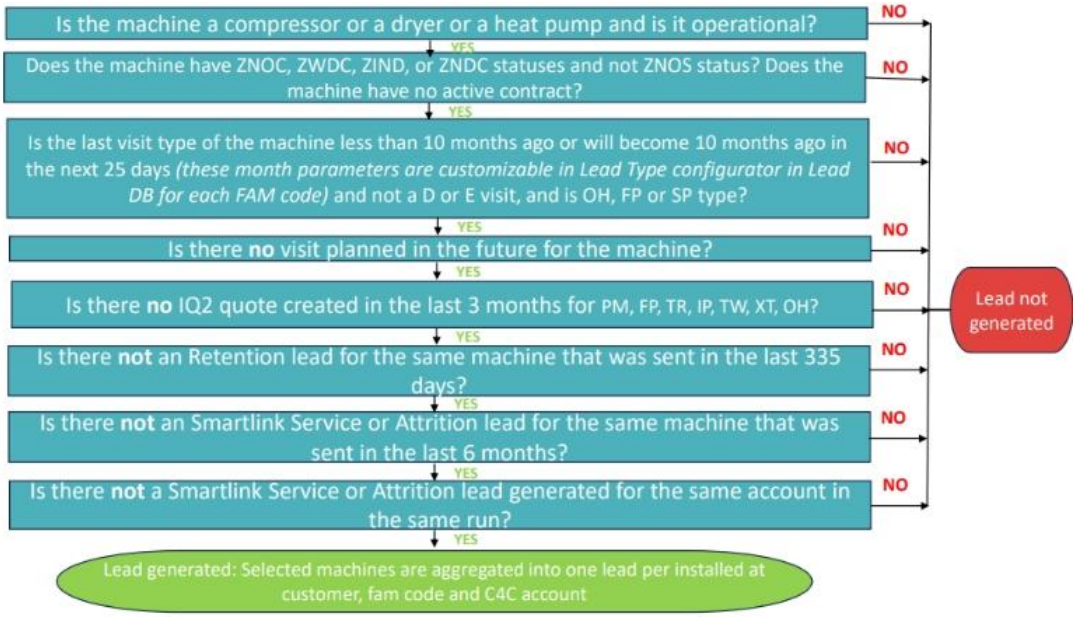
The automated lead system generates several distinct types of leads, each governed by a specific set of business rules designed to identify commercially relevant client situations with precision. What makes this system particularly advanced is its capacity to apply granular, account level segmentation at scale — automatically classifying each client account based on equipment status, operational data, contract situation, and interaction history, without requiring manual

analysis from the commercial team. This level of automated segmentation allows CTS to move beyond broad client categories and treat each account as a unique commercial profile, triggering the right intervention at the right moment for the right client.

The following are examples of leads automated workflow according to different type, illustrating how the business rules are applied in practice and how the system translates raw operational data into actionable commercial opportunities within C4 :

- Retention Lead: The goal from this lead is identification of machines, which are not under contract, before they drop from 1-to-1.

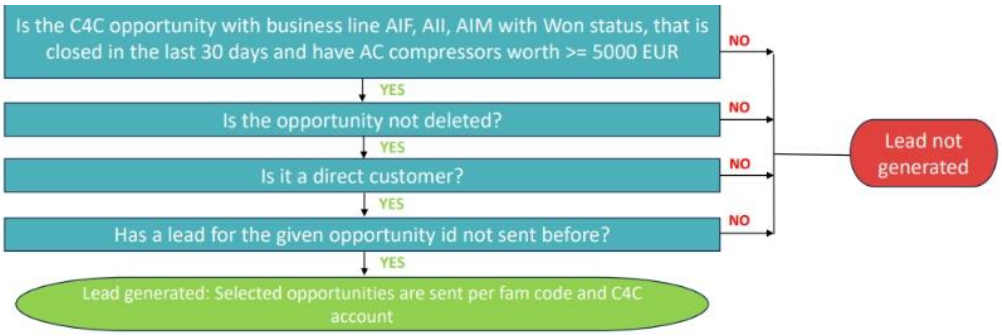
Figure 3. 3: EXAMPLE OF RETENTION AUTOMATED LEAD



Source: Company's Data

- New Machine Proactive Lead: The goal is identification of New Machines that have been sold as an equipment, but not yet have CTS sales, New machine proactive is based on new equipment opportunities won in the last 30 days for AIF/AII/AIM.

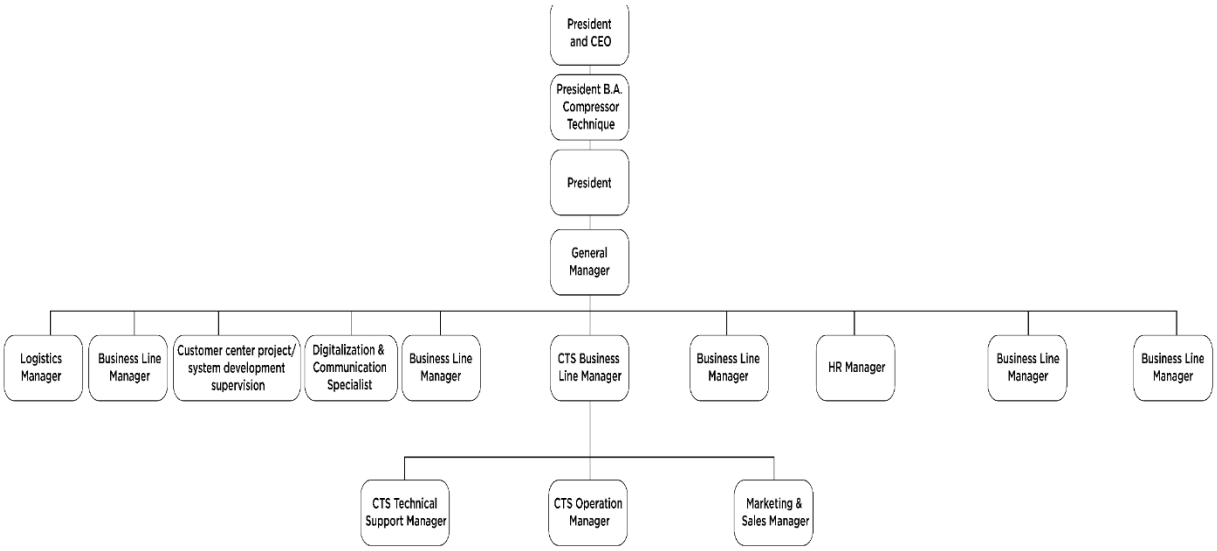
Figure 3. 4: EXAMPLE OF NEW MACHINE PROACTIVE LEAD



Source: Company's Data

3.2 Company Organigram

Figure 3. 5: COMPANY ORGANIGRAM



Source: Company DATA

3.3 Research Design:

In keeping with the aims of this dissertation, the research employs an Exploratory Sequential Design, combining both qualitative and quantitative methodologies applied in two successive phases. The study begins with a qualitative phase consisting of semi structured interviews with decision makers from Atlas Copco's CTS department, followed by a quantitative phase in which a structured questionnaire is administered to B2B industrial clients. This mixed methods

approach ensures both rich contextual understanding of the phenomenon and statistical validation of the findings.

3.3.1 Exploratory Research

Exploratory research is utilized when one is trying to elucidate a research problem, familiarize themselves with a phenomenon, or generate constructs and hypotheses for subsequent testing. It is especially valuable during the early stages of research to understand what is occurring and to identify the relevant variables (Saunders, Lewis, & Thornhill, 2019).

Exploratory research is particularly vital in this study, as the the constructs of perceived predictive CRM capabilities, require contextual exploration and validation within the specific B2B industrial environment of Atlas Copco before they can be meaningfully operationalized and measured. The qualitative findings either confirm and inform the quantitative measurement instrument, or reveal divergences that require further interpretation (Creswell & Plano Clark, Designing and conducting mixed methods research, 2017). The main methods used in this exploratory phase are qualitative research through semi structured interviews and secondary data analysis through the existing CRM and literature review.

3.3.2 Secondary Research

Secondary data refers to data that has already been collected by others for different purposes and made accessible to researchers (Malhotra, 2010). It consists of data collected from books, journal articles, government reports, websites, and industry reports. One of the biggest benefits of secondary data is its availability and the reduced time and resources required for collection.

Secondary data analysis was a primary instrument used at the exploratory stage of this research. The literature review presented in Chapter 2 reports the findings of the review of external secondary sources. These sources aided in the construction of the theoretical framework underpinning this study, specifically in establishing the conceptual foundations of customer retention in B2B industrial contexts, however for the independent variable, the constructs were defined during the qualitative research.

3.3.3 Qualitative Research

Qualitative research is applied to explore perceptions, experiences, and practices at a deeper level, offering rich insights through non numerical data (Creswell, Research design : Qualitative, quantitative, and mixed methods approaches, 2009).

In this dissertation, four semi structured interviews were conducted prior to the quantitative phase. The purpose was to explore how perceived predictive CRM capabilities manifest in practice within the B2B industrial context, generate the constructs of the independent variable, and formulate the hypotheses subsequently tested in the quantitative phase. These interviews also aimed to explain specific findings which emerged as critical themes in the survey results.

3.3.4 Conclusive Research

Conclusive research is used to validate findings and test formal hypotheses through formal procedures and quantitative analysis (Malhotra, 2010). It yields findings that can be utilized for decision making. There are two general types of conclusive research : descriptive and causal.

3.3.5 Descriptive Research

Descriptive research seeks to describe the attributes of a phenomenon or population and determine how variables relate to one another (Malhotra, 2010).

In this study, descriptive research was used to measure and quantify the impact of perceived predictive CRM capabilities on customer retention among B2B industrial clients of Atlas Copco. The structured questionnaire was the primary data collection tool for this phase.

3.3.6 Causal Research

Causal research identifies cause and effect relationships by analyzing the effect of changes in independent variables on dependent variables (Malhotra, 2010). In this dissertation, causal research was not applied, as the purpose was not to manipulate variables in a controlled setting but to describe and quantify existing perceptions and behaviors in a natural B2B environment.

Accordingly, this study adopts a descriptive single cross-sectional design, collecting data from B2B industrial clients at a single point in time, providing a snapshot of client perceptions of predictive CRM capabilities and their impact on retention behaviors.

3.4 Mixed Methods Research: Exploratory Sequential Design

This study adopts a mixed methods approach, integrating both qualitative and quantitative data to achieve a more comprehensive understanding of the research problem. An exploratory sequential design is employed, where the research begins with a qualitative phase that informs and shapes the subsequent quantitative phase. This sequence is particularly appropriate when

the constructs under investigation are not yet fully established in the literature and require contextual exploration before they can be formally measured and tested.

This approach is especially valuable when the researcher seeks to generate constructs from a specific context and then verify whether those constructs hold across a larger population.

Figure 3. 6: EXPLORATORY SEQUENTIAL DESIGN



Source: (Creswell, 2014, p. 74)

In this study, the qualitative phase, consisting of semi structured interviews with CTS decision makers at Atlas Copco, was conducted first with the explicit purpose of generating the constructs of perceived predictive CRM capabilities and formulating the hypotheses to be tested. The quantitative phase then served to measure and validate these constructs among B2B industrial clients, determining whether the qualitative findings could be confirmed and generalized to a broader population ((Creswell & Plano Clark, Designing and conducting mixed methods research, 2017).

3.4.1 Qualitative Phase of the Exploratory Sequential Design

Prior to the quantitative phase of this study, a qualitative investigation was conducted to confirm the practical relevance of the three constructs identified in the literature as the most prominent client perceptible manifestations of predictive CRM capabilities — need anticipation, commercial proactivity, and hyper personalization. Before operationalizing these constructs into survey items and administering them to B2B industrial clients of Atlas Copco, it was necessary to first validate their resonance with the actual commercial practices and client management realities of the CTS department.

To address this, four semi structured interviews were conducted face-to-face with decision makers from Atlas Copco's CTS department. Each interview lasted between 25 and 35 minutes. The participants were selected for their direct involvement in client relationship management

and their cross functional coverage of the department; commercial, operational, technical, and overall business line management.

Individual interviews were chosen over focus groups for two main reasons. First, the professional and hierarchical nature of the respondent profiles made it more appropriate to engage each decision-maker individually, allowing them to speak freely about internal practices without the influence of colleagues. Second, the individual format allowed for greater depth and flexibility in exploring each respondent's professional perspective, observations, and interpretations regarding client follow up and CRM practices.

The interview guide was structured around three thematic axes corresponding implicitly to the three constructs of the independent variable, without naming them explicitly at any point. It was reviewed and validated by the dissertation supervisor prior to use. The interviews were conducted in a mix of French, Darija, and English depending on the profile of each respondent, and were audio recorded with oral consent. All recordings were subsequently transcribed in full using a combination of personal knowledge and AI assisted tools, and the transcripts served as the primary dataset for thematic analysis.

3.4.1.1 Sampling Design

Participants were selected using purposive sampling, a non-probability strategy in which individuals are chosen deliberately based on their relevance to the research questions (Creswell, Research design : Qualitative, quantitative, and mixed methods approaches , 2014). Four decision makers from Atlas Copco's CTS department were selected, covering the commercial, operational, and technical areas, as well as the Business Line Manager overseeing the department. This multi-functional composition ensured that the themes emerging from the data reflected a comprehensive and cross functional understanding of how predictive CRM capabilities are deployed in practice.

Table 3. 1: An overview of the participant profiles

INTERVIEWEE	POSITION	DEPARTMENT	INTERVIEW DURATION	MODE
Interviewee 1	Business line Manager	Compressor technical Service	25 min	Face to face
Interviewee 2	Marketing and Sales Manager	Compressor technical Service	25 min	Face to Face
Interviewee 3	Master Data Steward and Inside Sales & Marketing	Compressor technical Service	30 min	Face to Face
Interviewee 4	Operation Manager	Compressor technical Service	35 min	Face to Face

Source: Author's Efforts

3.4.1.2 Ethical Considerations

All four participants were informed of the academic purpose of the research and gave their oral consent before participation. The study ensured voluntary participation, with all interview content used exclusively for academic analysis purposes. Participants also authorized audio recording of the interviews for the sole purpose of accurate transcription. Although the topic was not sensitive in nature, all interviews were conducted with full respect for participant comfort, privacy, and professional confidentiality.

3.4.1.3 Data Analysis Method

The data was analyzed using Braun and Clarke's (2006) six phase thematic analysis, as follows:

- **Phase 1 - Familiarization with the Data**

The first phase involved familiarization with the data. All interviews were transcribed in full using a combination of personal knowledge and AI assisted tools, while the transcription and verification process remained manual throughout. Each transcript was read multiple times to develop a deep understanding of participants' perspectives. Initial memos were taken to capture early impressions and recurrent patterns across the four interviews.

- **Phase 2 - Generating Initial Codes**

Initial codes were generated manually using an inductive approach, allowing meaningful units to emerge freely from the data. Codes were assigned based on content relevance and recurrence, without reference to the theoretical constructs, ensuring themes reflected respondents' authentic professional experience.

- **Phases 3 & 4 - Developing and Reviewing Themes**

Codes were grouped into broader thematic patterns capturing significant dimensions across respondents. All code assignments were reviewed iteratively for consistency and thematic coherence, with theme boundaries refined where necessary.

- **Phase 5 - Defining and Naming Themes**

Each theme was clearly defined and labeled to reflect the central idea it captured. Codes were reviewed for clarity and grouped under their most relevant theme, and their alignment with the three constructs of the independent variable was examined.

- **Phase 6 - Producing the Report**

The final phase involved organizing the findings into a structured narrative supported by illustrative participant quotes. A detailed analysis of these themes is provided in the following chapter.

3.4.2 Quantitative Phase of the Exploratory Sequential Design

Following the qualitative phase, which confirmed the constructs of the independent variable. The quantitative phase was designed to empirically measure their impact on customer retention. The four constructs of the dependent variable;; ontinuance intention, repurchase behavior, switching resistance, and relationship commitment — were theoretically grounded and defined in the literature review. Data were collected from a sample of 100 respondents, representing B2B industrial client companies of Atlas Copco across different sectors, using a structured self-administered online questionnaire

3.4.2.1 Questionnaire Design

The questionnaire was developed in two languages — English and French — to ensure accessibility to Atlas Copco's B2B client base. It was structured around all constructs of both the independent and dependent variables, with each construct measured through multiple Likert scale items.

Adoption of measurement items: To operationalize the constructs of the research model, measurement items were primarily adapted from previously validated scales in the existing literature. These items were carefully selected to ensure their relevance and reliability, and

subsequently modified to align with the specific context of perceived predictive CRM capabilities and customer retention in B2B industrial markets.

Table 3. 2 Measurement scale used in this study

Constructs	Measurement Items	References
Need Anticipation	1. Atlas Copco identifies my business needs before I am aware of them myself. 2. Atlas Copco identifies business opportunities relevant to my company before I consider them myself. 3. Atlas Copco seems to know when my equipment will need servicing or replacement, even before I notice any issue. 4. Atlas Copco demonstrates a thorough understanding of my future business needs, not just my immediate ones.	(Blocker et al., 2011 ; Narver et al., 2004) (Blocker et al., 2011 ; Saleh & Majali, 2023)
Commercial Proactivity	1. Atlas Copco's commercial team contacts me without me having to initiate the conversation. 2. I regularly receive relevant follow-up from Atlas Copco without needing to request it. 3. When Atlas Copco contacts me, their team is always well informed about my account and current operational situation. 4. I feel that Atlas Copco manages my account actively, rather than waiting for me to come to them 5. Atlas Copco proposes solutions and opportunities that I had not yet thought of requesting.	(Gwinner et al., 1998 ; Saleh & Majali, 2023) (Reinartz et al., 2004 ; Saleh & Majali, 2023)
Hyper Personalization	1. The proposals I receive from Atlas Copco are tailored to my specific equipment, usage history, and operational context, not generic offers. 2. Atlas Copco treats me as a truly unique client, every interaction reflects specific knowledge of my individual situation. 3. Atlas Copco's recommendations always reflect a precise understanding of my current equipment status and business priorities.	(Vesanen, 2007; Potla & Pottla, 2024) (Vesanen, 2007; Reddy, 2021)

	4. I never feel that the proposals and communications I receive from Atlas Copco are generic or mass produced.	
Continuance Intention	1. I intend to continue doing business with Atlas Copco for my future purchases and contracts. 2. I plan to maintain my current level of engagement with Atlas Copco in the coming years. 3. Renewing my contracts and agreements with Atlas Copco is a natural and expected next step for my company. 4. My company considers Atlas Copco a long-term strategic partner rather than a short-term supplier.	(Zeithaml et al., 1996; Allen & Meyer, 1990) (Allen & Meyer, 1990 ; Morgan & Hunt, 1994)
Repurchase Behavior	1. I have consistently renewed my contracts or continued purchasing from Atlas Copco over the past years. 2. I regularly return to Atlas Copco for new equipment, services, or maintenance needs without considering alternatives. 3. My business volume with Atlas Copco has remained stable or grown over time. 4. Over time, I have expanded the range of products and services I purchase from Atlas Copco.	(Reichheld & Sasser, 1990 ; Dick & Basu, 1994)
Switching Resistance	1. Even if a competitor offered a lower price, I would choose to remain a client of Atlas Copco. 2. Switching to another supplier would represent a significant risk and disruption for my business operations. 3. The quality of Atlas Copco's service and follow-up makes switching to a competitor unattractive to me. 4. I would not switch to another supplier even if they approached me with an attractive commercial offer.	(Jones et al., 2000 ; Patterson & Smith, 2003)

Relationship Commitment	1. I consider my relationship with Atlas Copco to be a genuinely important and valued business partnership. 2. I feel a strong sense of loyalty toward Atlas Copco as a business partner. 3. My company is deeply committed to maintaining a long term relationship with Atlas Copco. 4. I believe that the relationship between my company and Atlas Copco is built on mutual trust and shared value.	(Morgan & Hunt, 1994 ; Wetzels et al., 1998)
NPS	On a scale of 0 to 10, how likely are you to recommend Atlas Copco to a business partner or colleague in your industry ?	(Reichheld, 2003)

Source : Personal Efforts

3.4.2.2 Measurement Scaling

The questionnaire used in this study consisted of four distinct sections, each designed to serve a specific function with respect to the research objectives.

The first section allowed respondents to select their preferred language; English or French, ensuring accessibility across Atlas Copco's B2B client base.

The second section contained 13 items measuring the three constructs of the independent variable; Perceived Predictive CRM Capabilities, grouped as follows:

- Need Anticipation: 4 items (Q1 to Q4)
- Commercial Proactivity: 4 items (Q5 to Q9)
- Hyper Personalization: 4 items (Q10 to Q13)

The third section contained 16 items measuring the four constructs of the dependent variable Customer Retention, complemented by one independent NPS item, grouped as follows :

- Continuance Intention : 4 items (Q14 to Q17)
- Repurchase Behavior: 4 items (Q18 to Q21)
- Switching Resistance: 4 items (Q22 to Q25)
- Relationship Commitment: 4 items (Q26 to Q29)
- Net Promoter Score : 1 item (Q30)

All items were rated on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), a scale widely recognized for its consistency and capacity to capture fine differences in respondent opinions. All measurement items were adapted from established and validated scales in the existing literature.

The fourth section contained four profiling questions capturing respondent characteristics, including the sector of the company (Nominal Scale), the duration of the company's relationship with Atlas Copco (Ordinal Scale), the role of the respondent within their organization (Nominal Scale), and the frequency of commercial interaction with Atlas Copco (Nominal).

The questionnaire was administered online using Google Forms and distributed to Atlas Copco's B2B industrial clients, who were contacted through phone calls and followed up via email and WhatsApp messages.

3.4.2.3 Types of Questions

The questionnaire employed a variety of question types, each chosen for the particular kind of information being gathered and the logical flow of the instrument.

3.4.2.3.1 Single Choice Question

Used in the first section to allow respondents to select their preferred language — English or French — before proceeding with the questionnaire. This ensured accessibility and comfort for Atlas Copco's diverse B2B client base.

3.4.2.3.2 Likert-Scale Questions

Constituting the core of the second and third sections, 29 items employed a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) to measure the constructs of both the independent variable; need anticipation, commercial proactivity, and hyper-personalization, and the dependent variable; continuance intention, repurchase behavior, switching resistance, and relationship commitment. This format provides interval level measurement of agreement levels, as required for hypothesis testing and statistical analysis in social science research.

3.4.2.3.3 NPS Question

A single 0-to-10 scale question was included at the end of the third section to measure the Net Promoter Score, capturing the respondent's likelihood to recommend Atlas Copco to a business partner or colleague as a global retention indicator.

3.4.2.3.4 Single Choice Questions

Used in the fourth section to gather profiling information, including the respondent's sector, role within their organization, duration of relationship with Atlas Copco, and frequency of commercial interaction. These questions allowed respondents to select one answer from a pre-provided list, ensuring clarity and ease of response.

In order to promote accessibility and convenience for the respondents, the questionnaire was provided in two languages — English and French — selected through a single-choice question at the beginning of the instrument. The provision of two languages served to optimize participation and enabled Atlas Copco's B2B industrial clients to respond in the language in which they felt most at ease.

3.4.2.4 Sampling Design

3.4.2.4.1 Sampling Method

This study adopts a non-probability sampling method, specifically purposive sampling. Respondents were selected based on their direct relevance to the research objectives, namely, their status as active B2B industrial clients of Atlas Copco with sufficient commercial relationship history to meaningfully evaluate the constructs under investigation. This approach is appropriate given the specific and professional nature of the target population, as it allows the researcher to deliberately target individuals most likely to contribute relevant and informed data about the phenomenon under study.

3.4.2.4.2 Target Population

The target population of this study consists of B2B industrial companies that are active clients of Atlas Copco across different sectors in Algeria. The identification of the target respondents was based on Atlas Copco's Installed Base and Smartlink data; the company's internal equipment registry and remote monitoring system, which provided a structured and reliable pool of clients with an established and traceable commercial relationship with Atlas Copco, and who had therefore been directly exposed to the company's predictive CRM practices.

Respondents were required to hold a decision making or managerially relevant role within their organization. This population was considered the most appropriate for examining how B2B industrial clients perceive predictive CRM capabilities and the extent to which these perceptions influence their retention behaviors.

3.4.2.4.3 Simple Size

A total of 100 valid responses were retained for analysis, collected through an online questionnaire distributed in two languages; English and French. The questionnaire was administered via Google Forms and distributed to Atlas Copco's B2B industrial clients through phone calls, emails, and WhatsApp follow ups.

3.4.2.5 Data Analysis

- Following the qualitative phase, in which thematic analysis of the four semi-structured interviews allowed the identification of recurring themes reflecting and confirming the three constructs, the quantitative data were analyzed using inferential statistics with the support of SPSS software. The analysis includes the following steps:
- **Descriptive Statistics**: to summarize respondent characteristics and variable distributions, providing an overview of the sample profile and the central tendencies of each construct.
- **Exploratory Factor Analysis**: to assess the structure and reliability of the measurement instrument, and to verify that the items of the independent variable constructs load onto their expected factors, confirming the validity of the constructs extracted from the qualitative phase and extract the new model.
- **Multiple Regression Analysis** : to test the study's hypotheses and evaluate the impact of perceived predictive CRM capabilities on customer retention and its four dimensions.
- **Net Promoter Score Analysis**: to analyze the global retention indicator.

Together, these methods allow for a rigorous and comprehensive examination of the relationships between perceived predictive CRM capabilities and customer retention in B2B industrial contexts.

3.5 Conclusion

This chapter has presented the methodological framework of this dissertation. The study adopts an exploratory sequential mixed methods design, combining a qualitative interview phase and a quantitative survey phase applied successively. The main research question examines the impact of perceived predictive CRM capabilities on customer retention, measured through four dimensions : continuance intention, repurchase behavior, switching resistance, and relationship commitment, complemented by the Net Promoter Score as a global retention indicator.

The qualitative phase employed semi structured interviews with four CTS decision makers at Atlas Copco, analyzed through thematic analysis following (Braun & Clarke, 2006), with the purpose of confirming the constructs of the independent variable before their quantitative operationalization. The quantitative phase employs a 5-point Likert scale questionnaire adapted from validated academic scales, administered to 100 B2B industrial clients of Atlas Copco and analyzed using descriptive statistics, exploratory factor analysis, multiple regression, and Net Promoter Score analysis in SPSS.

Together, the two phases produce a comprehensive, methodologically rigorous, and theoretically grounded investigation of the impact of perceived predictive CRM capabilities on customer retention in B2B industrial contexts.

Chapter 4: Research Findings

Introduction

This chapter presents the empirical findings of the study, organized according to the exploratory sequential mixed methods design adopted. The analytical process follows a progressive and iterative logic, in which the findings of each phase inform and shape the subsequent one, ultimately leading to a refined and empirically grounded research model.

The chapter proceeds as follows. First, the findings of the qualitative phase are presented, revealing the themes that emerged from the four semi structured interviews with CTS decision makers at Atlas Copco. These themes serve as the empirical foundation for identifying the constructs of the independent variable — Perceived Predictive CRM Capabilities.

Second, an exploratory factor analysis is conducted on the items of both the independent and dependent variables. This step examines whether the items group into statistically coherent factors, and whether the factor structure confirmed by the data aligns with, or departs from qualitative analysis or the theoretical structure proposed in the literature. The factor analysis may result in a restructured set of constructs for both variables, fewer or differently configured than initially anticipated.

Third, based on the adjusted factor structures emerging from the data, a revised conceptual model is proposed, along with the final research hypotheses that will be empirically tested.

Fourth, multiple regression analysis is conducted to test the final hypotheses and measure the impact of perceived predictive CRM capabilities on customer retention.

Finally, the Net Promoter Score findings are presented as a complementary global retention indicator, before the chapter concludes with an overall discussion of the results in relation to the revised conceptual framework.

4.1 Qualitative Analysis - Thematic Analysis

This section presents the findings of four semi-structured interviews conducted with senior decision makers from Atlas Copco Algeria's Compressor Technical Service department, spanning the commercial, operational, technical, and business line management functions of the department.

In keeping with the exploratory sequential mixed zmethods design adopted in this study, the qualitative phase was conducted prior to the quantitative phase and serves a specific methodological purpose. While the literature review identified three dimensions as theoretically

relevant manifestations of predictive CRM capabilities from the client's perspective, these dimensions have not been formally validated as constructs of a unified independent variable in the existing literature. The qualitative phase was therefore designed to determine whether these dimensions are empirically real, operationally meaningful, and sufficiently distinct within the specific B2B industrial environment of Atlas Copco, before they could be legitimately proposed as the constructs of the independent variable and operationalized into a quantitative measurement instrument.

The interviews were conducted without naming the theoretical dimensions explicitly, allowing themes to emerge inductively from respondents' own language and professional experience. Each theme is presented with a statement of purpose, a cross participant analytical summary, illustrative direct quotes, initial codes, polarity ratings, and an analyst note. The four interviewees are referenced throughout as I1 through I4, corresponding to the Marketing and Sales Manager, the Business Line Manager, the Master Data Steward and Inside Sales Manager, and the Operation Manager respectively.

4.1.1. Theme 01: Need Anticipation

Purpose of This Theme:

This theme explores how the CTS decision makers at Atlas Copco identify, anticipate, and act upon client needs before those needs are explicitly expressed. Need Anticipation; is the client's perception that their future needs are identified before they are consciously aware of them. It is the first construct of the Perceived Predictive CRM Capabilities independent variable. This theme surfaces the technological infrastructure, data practices, and professional mindsets that make this capability operationally possible.

Summary

All four respondents unanimously confirmed that need anticipation is a central and systematic practice within the CTS department, grounded in a three-tool predictive architecture:

- Smartlink: Atlas Copco's remote equipment monitoring technology, continuously tracks machine performance, operating hours, temperature signals, and anomaly indicators, transmitting real time alerts to the CTS team before clients are aware of any issue.
- The Installed Base: a comprehensive equipment registry connected to C4C, provides the CTS team with a full view of each client's machine park, enabling contract lifecycle monitoring and proactive commercial lead generation.

- CT Automated Leads: the AI powered lead generation system, automatically identifies commercial opportunities (maintenance due, contract expiry, new solution potential…) and pushes qualified leads directly into C4C.

A cross-cutting finding is that anticipation is not experienced merely as a technological output but as a professional responsibility: respondents explicitly frame the CTS team's role as anticipating client needs as experts, before clients, who are often unfamiliar with compressed air technology can identify those needs themselves (I3: "we are the specialists, clients count on us to discover their need before it arises").

Notably, Interviewee 4 provides the strongest empirical illustration: the system detected an imminent machine breakdown based on remaining operating hours; a detail the client was entirely unaware of, enabling preemptive intervention through the AI powered predictive system. This case exemplifies the most advanced form of need anticipation: fully automated, client unaware, and commercially actionable.

Illustrative Quotes

- "Before making an offer we always check the client's history, behavior, and the history of interventions. Our predictive CRM helps us anticipate needs, to schedule visits before the need arises and verify stock availability, giving clients the feeling that we pay attention to their needs." (Interviewee 1 – Marketing & Sales Manager)
- "Smartlink monitors machines 24/7. It sends us an alert signal — for example, a machine that has not stopped but anticipates an issue by sending an elevated temperature signal. Also, the installed base sends us leads according to contracts that are reaching expiration." (Interviewee 2 – Business Line Manager)
- "Smartlink is truly the number one anticipation solution for the client, without the client even contacting us, it is a 100% anticipation tool. We discover the need well in advance." (Interviewee 3 – Master Data Steward)
- "We discovered that a client's machine would experience a breakdown soon based on the remaining operating hours, a detail the client did not know. With our powerful system and AI, we anticipated this problem and the need for an intervention, without the client realizing it." (Interviewee 4 – Operation Manager)

Coding Notes:

- **Initial Codes:** behavioral history tracking, AI driven breakdown prediction, 24/7 machine monitoring, operating hour-based prediction, client unaware anticipation, pre intervention data check, sentiment analysis, automated leads generation,
- **Polarity:** Uniformly positive (+) across all 4 respondents.
- **Analyst Note:** The convergence of all four respondents around the same three tool architecture (Smart-link, Installed Base, CT Automated Leads) is analytically significant: it suggests that need anticipation at Atlas Copco is not idiosyncratic but institutionalized and systematically operationalized. The expert responsibility framing (I3) adds a relational and professional dimension beyond the purely technological.

4.1.2. Theme 02: Commercial Proactivity

Purpose of This Theme

This theme examines how the CTS department initiates commercial contact without being solicited by the client, the timing, triggers, and quality criteria of proactive engagement. Commercial Proactivity; is the client's perception that the supplier contacts them at the right moment without requiring them to initiate; is the second construct of the Perceived Predictive CRM Capabilities independent variable.

Summary

All four respondents confirmed commercial proactivity as a core and systematic practice within CTS, grounded in two complementary mechanisms: automation driven triggers (contract renewal leads, Smartlink alerts, breakdown notifications) and human driven judgment calibrated by client profile knowledge and urgency assessment.

Three sub themes emerged consistently across the dataset. First, automation as the primary proactivity driver: the CT Automated Leads system, Smartlink, and the CRM reminder architecture collectively ensure that commercial contact is triggered at the moment of maximum commercial relevance, not based on calendar scheduling or client initiation.

Second, client profile as timing calibrator: respondents consistently articulate that the right moment to engage differs by client, sector, production rhythm, company size, and urgency level all determine the appropriate frequency and form of proactive contact (I3: "some clients need visiting once a month; others once or twice a year"). Third, the loyalty impact of proactive contact: all four respondents confirm that proactive contact, particularly when it pre-empts a

need the client was not yet aware of, generates strong positive loyalty responses (I1: "all our clients have been with us for more than decades"; I3: "they become loyal").

A notable cross cutting insight is that the B2B client's expectation has fundamentally shifted from product quality to partnership quality: clients now expect a supplier who tells them what they need before they realize it (I2: "they need a partner, not just a product; someone who tells them what they need before they realize it themselves"). This expectation precisely defines the commercial value of proactivity in the B2B industrial context.

Illustrative Quotes

- "Clients need a partner, not just a product. They are looking for solutions, someone who will tell them what they need before they realize it themselves. They want someone who can execute, not just make promises." (Interviewee 2 – Business Line Manager)
- "When Smartlink managed by AI, indicates the client will have a breakdown, we receive a notification or alert to remedy the cause. Leads coming from technicians are 90% qualified and won." (Interviewee 1 – Marketing & Sales Manager)
- "Contacting the client before they contact us makes them appreciate the gesture, they see that you care about their equipment. When you call them proactively, they become loyal." (Interviewee 3 – Master Data Steward)
- "A client will be happy when you call them before they have expressed their need or even know about it." (Interviewee 4 – Operation Manager)

Coding Notes:

- **Initial Codes:** contract renewal lead, Machine proactive lead, Smartlink alert, urgency-based intervention, CRM reminder system, client specific visit frequency, proactive advisory role, care perception, loyalty through proactive gesture
- **Polarity:** Uniformly positive (+) across all 4 respondents.
- **Analyst Note:** The shift from product expectation to partnership expectation (I2) is the most strategically significant finding in this theme. It positions commercial proactivity not as a sales technique but as the defining characteristic of the supplier-client relationship in B2B industrial markets.

4.1.3. Theme 03: Hyper Personalization

Purpose of This Theme

This theme examines the degree to which commercial interactions, recommendations, and proposed solutions are individually calibrated to the specific profile, history, and situation of each client account, as opposed to being designed for a general category or segment. Hyper Personalization, is the client's perception that every interaction is individually tailored to their unique profile, is the third construct of the Perceived Predictive CRM Capabilities independent variable.

Summary

All four respondents unanimously describe a commercial practice grounded in individual level calibration rather than segment level targeting. The dominant term across all four interviews is 'tailored' or 'tailor made' — not 'segmented' or 'categorized' — signaling that personalization is experienced and articulated at the individual account level, not the group level.

Three mechanisms of hyper personalization emerged across the dataset:

First, machine level data as the personalization foundation: each client's specific equipment, identified by serial number through the installed base, defines the individualization of every commercial proposal. The offer is built not from the client's industry profile but from the operational state of their specific machines (I3: "we always ask for the serial number, we give something specific and not global, tailored to the need of the client and their machine").

Second, relationship tenure as a personalization driver: the longer the client relationship, the richer the data available, and the more precisely customized the offer becomes (I4: "the longer a client stays with us, the better we know them and the more customized the offer is"). This temporal dimension of personalization; deepening over time, is a distinctively B2B industrial phenomenon absent from B2C personalization frameworks.

Third, system enabled personalization: tools such as the CT Automated Leads engine linked to C4C, enables the CTS team to generate offers that are not merely client specific but machine state specific, ensuring that what is proposed is, in the words of I4, "exactly what the client needs."

The most commercially significant finding in this theme is the explicit link between hyper personalization and retention: I4 states that a client, even if loyal to the brand, will leave if their

need is not met in a sufficiently tailored way, and that treating every client as a unique account is the primary condition for retention. This finding directly supports the theoretical hypothesis that hyper personalization is a significant predictor of customer retention in B2B industrial markets.

Illustrative Quotes

- "Each client has their precise offer according to their case. We always ask for the serial number and check if their machine is listed in the installed base. We give something specific and not global, tailored to the need of the client and their machine. We do not sell just to sell." (Interviewee 3 – Master Data Steward)
- "All our offers are made according to the client, their rhythm, sector, and activity. Our automation tools predict the potential of each client, allowing us to build targeted strategies." (Interviewee 1 – Marketing & Sales Manager)
- "It is like building a bridge, our offer is tailored to the client's need. Sometimes we push ourselves and ask them if they need something additional. They feel the offer is designed for them, not generic." (Interviewee 3 – Master Data Steward)
- "A client, even if loyal to the brand, will leave if not satisfied. To retain them, we have to treat them as our unique client, handling their case subtly and doing tailor made work." (Interviewee 4 – Operation Manager)
- "We know our clients by heart, both personally and with the help of the system, which allows us to be effective and retain them." (Interviewee 3 – Master Data Steward)

Coding Notes

- **Initial codes:** Sector specific offer, behavior-based segmentation, audit-based personalization, serial number-based tailoring, deep need understanding, tailor made offer, bridge building metaphor, technology enabled personalization, unique client treatment.
- **Polarity:** Positive (+) for 3/4 respondents. Neutral for Interviewee 1 and Interviewee 2 on Question 11.
- **Analyst Note:** The temporal dimension of personalization (I4: 'the longer a client stays, the more customized the offer') is the most analytically distinctive finding in this theme. It suggests that hyper personalization in B2B industrial markets is not a point-in-time capability but a longitudinally deepening one, becoming more precise and commercially effective as the relationship matures and enriching the CRM. This finding has direct

implications for CLV (Customer Lifetime Value) research, as it suggests that the commercial value of long tenure B2B clients extends beyond purchase volume to the personalization advantage they enable. The 'do not sell just to sell' principle (I3) introduces an ethical dimension of personalization, aligning with the Relational Benefits Theory framework mobilized in this study.

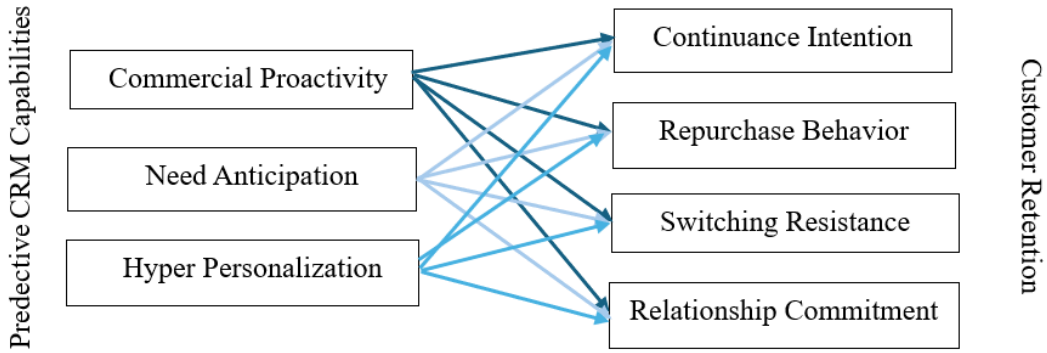
Conclusion

This thematic analysis conducted during the exploratory qualitative phase allowed the identification and refinement of the principal dimensions associated with perceived predictive CRM capabilities within the B2B industrial context. Through the analysis of recurring patterns, managerial perceptions, and relationship management practices discussed by decision makers, three dominant and recurrent themes emerged consistently across the interviews: need anticipation, commercial proactivity, and hyper personalization.

The findings suggest that predictive CRM is perceived not merely as a technological infrastructure, but rather as a set of relational and commercial capabilities enabled by the use of customer data, behavioral signals, operational histories, and predictive insights. These capabilities allow organizations to move beyond reactive relationship management toward a more anticipatory, timely, and individually adapted customer engagement approach.

Based on these exploratory findings and supported by the theoretical literature reviewed previously, a preliminary conceptual framework is proposed. In this framework, perceived predictive CRM capabilities are conceptualized as a multidimensional construct composed of the three emerging dimensions identified during the qualitative phase.

Figure 4.1: The component of CRM implementation CRM Model



Source: Self Elaborated

This preliminary framework will subsequently be subjected to empirical validation during the quantitative phase of the research. More specifically, an Exploratory Factor Analysis (EFA) will be conducted in order to examine the dimensional structure of the construct, assess the coherence and validity of the proposed dimensions, and determine whether the initial conceptualization should be confirmed, refined, merged, or adjusted based on the empirical data collected from clients.

4.2 Descriptive Analysis

To analyze the characteristics of the respondents, this research uses a descriptive analysis covering the four profiling variables collected in the fourth section of the questionnaire: the role of the respondent within their organization, the sector in which their company operates, the duration of the company's relationship with Atlas Copco, and the frequency of interaction with Atlas Copco.

The objective of this descriptive analysis is to create a comprehensive profile of the respondent sample and summarize the characteristics of the B2B industrial clients surveyed, thereby providing meaningful context before proceeding to more advanced statistical procedures.

4.2.1. Sector of Activity

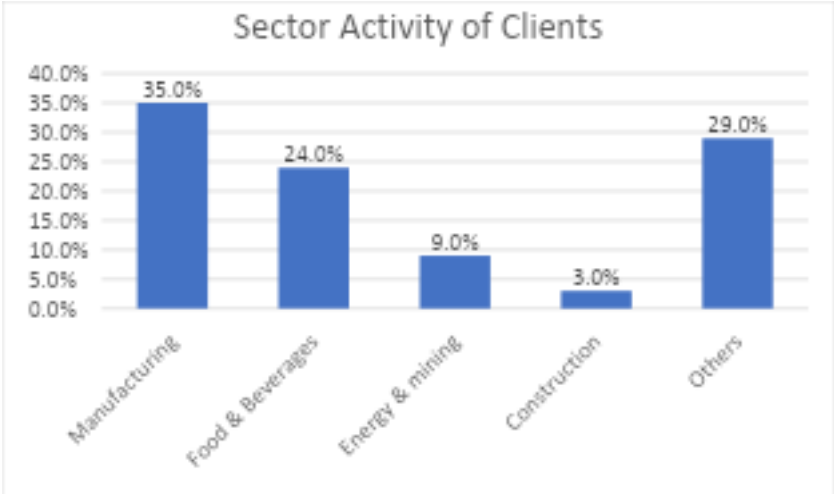
The sample is dominated by manufacturing (35%), reflecting Atlas Copco's core market. Food & Beverages (24%) ranks second due to heavy compressed air consumption. Manufacturing and Food & Beverages combined account for 59% of the sample, indicating a relatively homogeneous client base in terms of technical requirements.

Table 4.1: Activity sector of the respondents' statistics

Sector of Activity		
Label	**Effective (n)**	**Frequency (%)**
Manufacturing	35	35,0%
Food & Beverages	24	24,0%
Energy & mining	9	9,0%
Construction	3	3,0%
Others	29	29,0%
Total	100	100,0%

Source: SPSS Results

Figure 4.2: Clients sector of activity diagram



Source: Personal efforts using Excel

4.2.2. Relationship Longevity

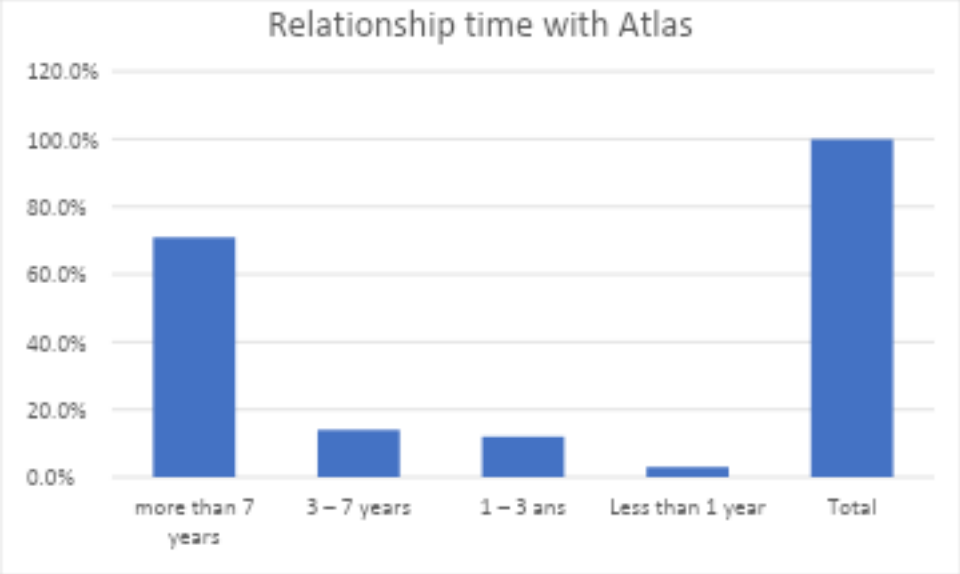
71% of respondents have been clients for more than 7 years, the most striking finding in the profile. This reflects exceptionally high loyalty and deeply embedded commercial relationships built on trust. Recent clients (less than 3 years) represent only 15%, confirming that the study primarily captures an established client base.

Table 4. 1: Client relationship longevity statistics

Client relationship longevity		
Label	**Effective (n)**	**Frequency (%)**
More than 7 years	71	71,0%
3 – 7 years	14	14,0%
1 – 3 years	12	12,0%
Less than one year	3	3,0%
Total	100	100,0%

Source: SPSS Results

Figure 4.3: Client Relationship longevity diagram



Source: Personal efforts using MS Excel

4.2.3. Role of respondents

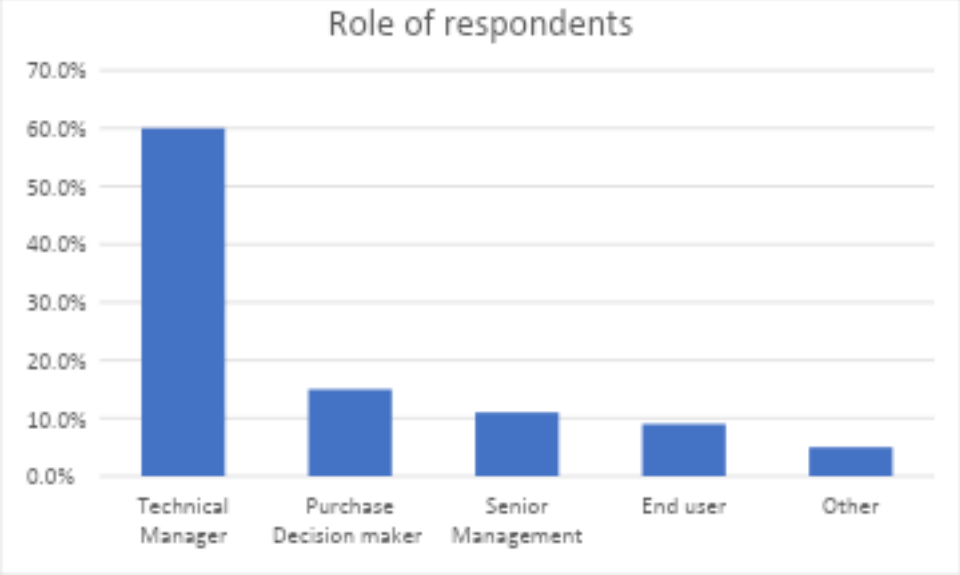
Technical Managers (60%) dominate the sample, consistent with the nature of Atlas Copco's industrial equipment, whose evaluation requires technical expertise. Purchasing decision makers and general management together represent 26%, capturing the strategic and financial dimension of the relationship. End users (9%) add an operational ground level perspective.

Table 4. 2: Role of respondent's statistics

Role of respondents		
Label	**Effective (n)**	**Frequency (%)**
Technical Manager	60	60,0%
Purchasing Decision maker	15	15,0%
General Management	11	11,0%
End user	9	9,0%
Other	5	5,0%
Total	100	100,0%

Source: SPSS Results

Figure 4.4: Role of respondent's diagram



Source: Personal efforts using MS Excel

4.2.4. Interaction frequency

Quarterly contact (38%) is the most common pattern, consistent with standard B2B follow-up. However, 29% of respondents interact rarely, a significant warning signal, as these clients are more vulnerable to competitor approaches. The "when needed" group (13%) reflects a reactive

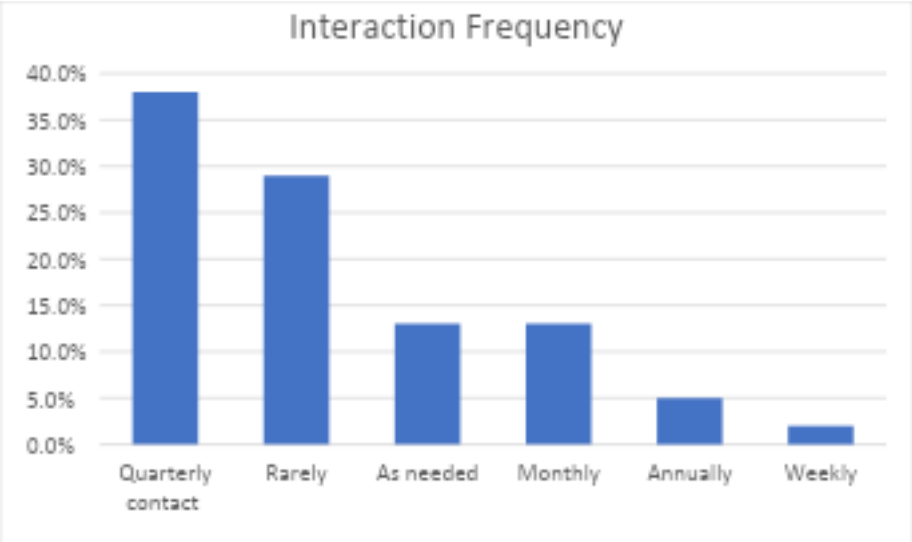
rather than proactive relationship dynamic, directly echoing the low Commercial Proactivity construct score.

Table 4. 3: Interaction frequency statistics

Interaction Frequency		
Modality	**Effectif (n)**	**Frequence (%)**
Quarterly contact	38	38,0%
Rarely	29	29,0%
when needed	13	13,0%
Monthly	13	13,0%
Annually	5	5,0%
Weekly	2	2,0%
Total	100	100,0%

Source: SPSS Results

Figure 4.5: Interaction Frequency diagram



Source: Personal efforts using MS Excel

4.3 Exploratory Factor Analysis

4.3.1 Exploratory Factor Analysis of Independent Variable:

The present section reports the results of an Exploratory Factor Analysis (EFA) conducted on the 13 items comprising the independent variable of this study, perceived Predictive CRM capabilities; operationalized through three proposed dimensions: Need Anticipation (NA1–NA4), Commercial Proactivity (CP1–CP5), and Hyper Personalization (HP1–HP4).

The EFA was performed using Principal Axis Factoring (PAF) with direct Varimax oblique rotation, implemented in IBM SPSS Statistics. Oblique rotation was selected a priori given the theoretical expectation that the three dimensions of Predictive CRM are related constructs sharing a common higher order variance, rendering orthogonal rotation methods theoretically inappropriate.

The analysis proceeded sequentially through five stages:

1. assessment of sample size adequacy;
2. evaluation of factorability through the KMO measure and Bartlett's Test of Sphericity;
3. examination of the inter item correlation structure via the anti image matrices;
4. determination of the number of factors to retain and the total variance explained;
5. interpretation of the rotated factor solution and labelling of the retained factors.4.3.1.1 Assessment of Sample Size Adequacy

A preliminary requirement for the valid application of EFA is that the sample size be sufficient to yield stable and replicable factor solutions. The most widely applied rule of thumb in the methodological literature stipulates a minimum ratio of five respondents per item (5:1), with some authors recommending a more stringent 10:1 ratio for greater solution stability (Hair, Black, Babin, & Anderso, 2019). With N = 100 respondents and k = 13 items.

The present study achieves a subject to variable ratio of 7.69:1 (100 ÷ 13), which comfortably satisfies the minimum 5:1 criterion (minimum required N = 65). While the ideal 10:1 ratio would necessitate N = 130, the achieved ratio falls within the acceptable range for EFA in applied social science research.

Hair et al. (2019) note that when communalities are consistently high (≥ 0.50) and factor loadings are strong (≥ 0.50), sample sizes of 100–150 are generally sufficient to yield interpretable and stable solutions. As will be demonstrated in subsequent sections, both conditions are met in the present data. The sample size is therefore deemed acceptable, and all results are interpreted with appropriate methodological caution given the moderate N.

4.3.1.1 Factorability of the Correlation Matrix: KMO and Bartlett's Test

Before extracting factors, it is necessary to confirm that the inter item correlation matrix contains sufficient shared variance to justify the application of EFA. Two complementary diagnostic statistics were examined for this purpose.

4.3.1.2 Kaiser Meyer Olkin (KMO) Measure of Sampling Adequacy

The Kaiser Meyer Olkin (KMO) measure of sampling adequacy assesses the proportion of variance in the items that is attributable to common factors rather than unique variance. KMO values range from 0 to 1, with values approaching 1.0 indicating that the patterns of partial correlations are compact and that factor analysis will yield distinct and reliable factors. (Kaiser, 1974) classified KMO values as: marvellous (≥ 0.90), meritorious (0.80–0.89), middling (0.70–0.79), mediocre (0.60–0.69), miserable (0.50–0.59), and unacceptable (< 0.50). The present analysis yields **KMO = .912**, which Kaiser (1974) classifies as **'marvellous'**. This exceptionally high value confirms that the 13 Predictive CRM items share substantial common variance and that the correlation matrix is highly suitable for factor analysis. No item was identified as problematic at the overall KMO level.

4.3.1.3. Bartlett's Test of Sphericity

Bartlett's Test of Sphericity (Bartlett, 1954) tests the null hypothesis (H_0) that the population correlation matrix is an identity matrix — meaning all inter item correlations are zero and no common factors exist. A statistically significant result is required to proceed with EFA, as a non-significant result would indicate that the items are entirely unrelated and that factor extraction is meaningless.

The present analysis yields $\chi^2(78) = 903.593$, $p < .001$, which decisively rejects H_0. This result confirms that significant and systematic inter item correlations exist among the 13 Predictive CRM items, validating the application of EFA to these data.

4.3.1.4 Individual Item Level MSA: Anti Image Correlation Matrix

Beyond the overall KMO statistic, the individual Measure of Sampling Adequacy (MSA) for each item is reported on the diagonal of the Anti-Image Correlation Matrix. Items with MSA values below .50 are considered unsuitable for factor analysis and should be excluded prior to extraction.

The present analysis yields individual MSA values ranging from .868 (HP4 'communications never feel generic') to .946 (CP5 'proposes unrequested solutions'). All 13 items exceed the .50 threshold by a substantial margin, confirming that no item requires removal on sampling adequacy grounds. The full set of items is therefore retained for factor extraction.

Table 4. 4 : Individual Measures of Sampling Adequacy (MSA)

Item	Description	MSA	Assessment
NA1	Identifies needs before client	.895	Excellent
NA2	Identifies business opportunities proactively	.877	Excellent
NA3	Anticipates equipment maintenance needs	.911	Excellent
NA4	Understands future not just immediate needs	.935	Excellent
CP1	Initiates contact proactively	.915	Excellent
CP2	Provides follow up without request	.892	Excellent
CP3	Team is well informed about account	.924	Excellent
CP4	Manages account actively	.903	Excellent
CP5	Proposes unrequested solutions	.946	Excellent
HP1	Tailored to equipment / history	.914	Excellent
HP2	Treats client as unique individual	.943	Excellent
HP3	Reflects understanding of equipment status	.919	Excellent
HP4	Communications never feel generic	868	Excellent

Source: Personal efforts Using IBM SPSS

4.3.1.5. Communalities

Communalities indicate the proportion of each item's total variance that is explained by the retained factors. Initial communalities reflect the squared multiple correlations of each item with all other items, providing an upper bound estimate of shared variance prior to extraction. Extraction communalities indicate the proportion of variance actually accounted for by the retained two factor solution. Items with extraction communalities below .40 are considered poorly represented by the factor solution and may warrant removal (Hair et al., 2019). As shown in Table 3, all 13 extraction communalities range from .509 (NA2) to .751 (CP2), all substantially exceeding the .40 threshold. CP2 (provides follow up without request) exhibits the highest communality (.751), indicating that this item is the most completely explained by the factor structure. NA2 (identifies business opportunities proactively) exhibits the lowest communality (.509), yet this value remains well above the acceptable minimum. No item is removed on communality grounds, and the overall communality-profile indicates strong item factor representation across the entire scale.

Table 4. 5: Initial and extraction communalities for all 13 Predictive CRM items

Item	Description	Initial h^2	Extraction h^2	Quality
NA1	Identifies needs before client	.723	.635	Strong
NA2	Identifies business opportunities proactively	.689	.509	Adequate
NA3	Anticipates equipment maintenance needs	.606	.593	Strong
NA4	Understands future not just immediate needs	.636	.577	Strong
CP1	Initiates contact proactively	.681	.629	Strong
CP2	Provides follow up without request	.737	.751	Excellent
CP3	Team well informed about account	.639	.541	Adequate
CP4	Manages account actively	.663	.544	Adequate
CP5	Proposes unrequested solutions	.582	.570	Strong
HP1	Tailored to equipment / history	.640	.678	Strong
HP2	Treats client as unique individual	.660	.684	Strong
HP3	Reflects understanding of equipment status	.602	.628	Strong
HP4	Communications never feel generic	.567	.538	Adequate

Source: Personal Efforts

4.3.1.6 Total Variance Explained and Factor Retention

The determination of the number of factors to retain was based on the convergence of three complementary criteria: Kaiser's eigenvalue greater than one rule, visual inspection of the scree plot, and theoretical parsimony.

4.3.1.6.1 Eigenvalue Criterion (Kaiser's Rule)

Kaiser's eigenvalue criterion (Kaiser, 1960) retains all factors with eigenvalues ≥ 1.0, on the logic that a retained factor should account for at least as much variance as any single standardized item.

The initial eigenvalue decomposition of the 13-item correlation matrix yields two factors with eigenvalues exceeding 1.0:

- Factor 1 (eigenvalue = 7.406, accounting for 56.97% of total initial variance) and

- Factor 2 (eigenvalue = 1.230, accounting for 9.47% of total initial variance).
- Factor 3 (eigenvalue = .998) narrowly falls below the 1.0 threshold and is not retained.

This criterion unambiguously supports a two-factor solution for the Predictive CRM capability construct.

Table 4. 6: Initial Eigenvalues decomposition

Factor 1	Eigenvalue = 7.406 : 53.97% variance (extraction)	Well above 1.0 : Dominant factor
Factor 2	Eigenvalue = 1.230: 6.62% variance (extraction)	Above 1.0: Retained
Factor 3	Eigenvalue = 0.998: Below 1.0	Below threshold : not retained

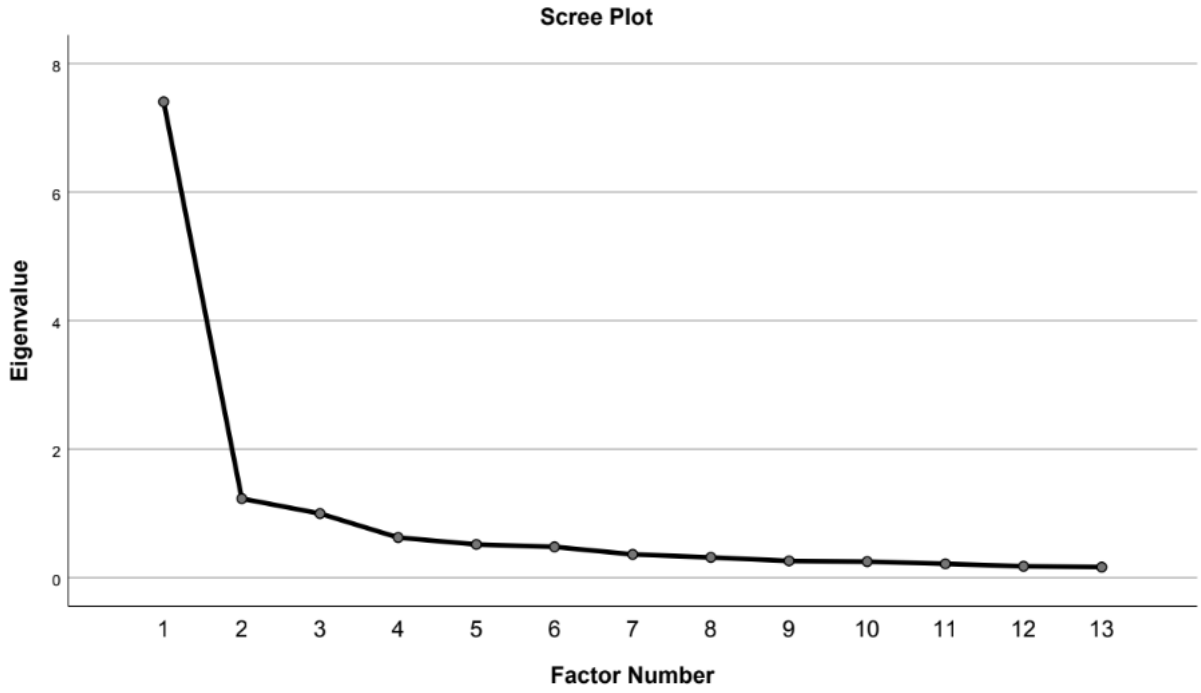
Source: Data gotten from SPSS

4.3.1.6.2 Scree Plot

Visual inspection of the scree plot corroborates the two-factor solution. The plot displays a sharp, dramatic decline in eigenvalues between Factor 1 (7.406) and Factor 2 (1.230), with a clear elbow, the inflection point-below which the curve flattens into a near horizontal plateau, visible at Factor 2. From Factor 3 onward, eigenvalues decline gradually and uniformly (from .998 to .164), forming the characteristic scree.

Consistent with Cattell's (1966) scree test, the factors positioned above the elbow Factors 1 and 2, are retained. The scree plot thus independently corroborates the Kaiser criterion decision.

Figure 4.6: Scree Plot Of Factor Analysis 1



Source: IBM SPSS Results

4.3.1.6.3. Total Variance Explained

Following extraction using PAF, the two retained factors account for a **cumulative total of 60.59% of the variance** in the 13 items (Factor 1: 53.97%; Factor 2: 6.62%). This exceeds the commonly accepted minimum threshold of 50–60% for acceptable factorial representation in social science research (Hair et al., 2019). The rotation sums of squared loadings under Varimax are reported as 6.398 (Factor 1) and 5.629 (Factor 2).

Because the factors are correlated under oblique rotation, these values cannot be summed to obtain a total, as SPSS correctly flags. The pre-rotation cumulative explained variance of 60.59% is therefore the appropriate overall summary statistic for reporting purposes.

Table 4. 7: Total variance explained. Two factors retained

Factor	Initial eigenvalue	% Variance (initial)	Extraction SS loading	% Variance (extraction)	Cumulative %
1	7.406	56.97%	7.016	53.97%	53.97%
2	1.230	9.47%	0.861	6.62%	60.59%
3 (not retained)	0.998	7.67%	—	—	—

Source: Personal Efforts Using IBM SPSS

4.3.1.7 Rotated Factor Solution: Pattern Matrix Interpretation

Following factor extraction, the solution was rotated using the direct Varimax method with Kaiser Normalization, converging in 7 iterations. For oblique rotation solutions, the Pattern Matrix is the primary interpretive output, reporting the unique contribution of each item to each factor after controlling for the inter factor correlation. Items are assigned to the factor on which they exhibit the highest pattern coefficient (primary loading), provided that loading exceeds the conventional threshold of 0.40, and that cross loadings on other factors remain substantially lower (Hair et al, 2019).

The Structure Matrix, which reports total correlations between items and factors including shared variance due to factor intercorrelation, is retained as supplementary evidence. Loadings below .30 were suppressed in the SPSS output. The full Pattern Matrix is presented in Table 4.6 below.

T

Table 4. 8: Pattern Matrix; Principal Axis Factoring

Item	Description	Factor 1 (PRE)	Factor 2 (HP)
CP2	Provides follow-up without request	(0.961)	—
NA3	Anticipates equipment maintenance needs	(0.82)	—
NA1	Identifies needs before client	(0.788)	—
CP1	Initiates contact proactively	(0.781)	—
NA4	Understands future / not just immediate needs	(0.609)	—
CP4	Manages account actively	(0.588)	—
NA2	Identifies business opportunities proactively	(0.53)	—
CP3	Team well-informed about account (cross-loader) ⚠	(0.481)	(0.317)
HP1	Tailored to equipment / history	—	(0.801)
HP4	Communications never feel generic	—	(0.787)
HP3	Reflects understanding of equipment status	—	(0.771)
HP2	Treats client as unique individual	—	(0.658)
CP5	Proposes unrequested solutions (cross-loader) ⚠	(0.339)	(0.481)

Source: Personal Efforts Using IBM SPSS

4.3.1.8 Factor Labelling and Theoretical Interpretation

4.3.1.8.1 Factor 1 — Proactive Relational Engagement (PRE)

Factor 1 is defined by **eight items** drawn from both the Need Anticipation (NA1–NA4) and Commercial Proactivity (CP1–CP4) constructs, with primary pattern loadings ranging from .481 (CP3) to .961 (CP2). The four defining items are: ‘provides follow up without request’

(CP2, λ = .961), 'anticipates equipment maintenance needs' (NA3, λ = .820), 'identifies needs before client' (NA1, λ = .788), and 'initiates contact proactively' (CP1, λ = .781).

The empirical convergence of Need Anticipation and Commercial Proactivity items onto a single factor is a substantively meaningful finding: it indicates that B2B industrial clients do not perceptually differentiate between a supplier's capacity to understand their future needs and its capacity to act on those needs without being solicited.

Both dimensions are experienced as a single, unified relational posture of forward looking, client attentive engagement; the supplier 'knows what I need before I do, and acts on it accordingly.' This finding is consistent with (Narver, Slater, & MacLachlan, Responsive and proactive market orientation and new-product success. Journal of Product Innovation Management, 21(5), 2004) who treat anticipation and proactive action as jointly constituting the proactive market orientation construct, and with (Blocker C. , Flint, Myers, & Slat, 2011), who operationalize proactive customer orientation as a holistic, integrated capability in B2B industrial contexts. This factor is accordingly labelled 'Proactive Relational Engagement' (PRE).

4.3.1.8.2 Factor 2 — Hyper Personalization (HP)

Factor 2 is defined by **four items** drawn exclusively from the Hyper Personalization construct (HP1–HP4), with primary pattern loadings ranging from .658 (HP2) to .801 (HP1). The defining items are: 'tailored to equipment / history' (HP1, λ = .801), 'communications never feel generic' (HP4, λ = .787), 'reflects understanding of equipment status' (HP3, λ = .771), and 'treats client as unique individual' (HP2, λ = .658).

All four HP items load cleanly on Factor 2 with no meaningful cross Loading onto Factor 1 — all HP cross loadings on Factor 1 are suppressed below the 0.30 reporting threshold, confirming full discriminant separation. This finding provides strong empirical support for the conceptual distinction between the content calibration dimension of Predictive CRM — what is communicated and how individually tailored it is — and the behavioral temporal dimension captured by Factor 1. From the client's perceptual standpoint, receiving interactions that are deeply individualized to their specific equipment history, operational situation, and identity as a unique account is experienced as qualitatively distinct from merely receiving proactive and timely contact. Factor 2 is accordingly labelled ***'Hyper Personalization' (HP)***, consistent with the original construct definition established in the theoretical framework.

4.3.1.8.3. Cross Loading Items: CP3 and CP5

Two items exhibit secondary cross loadings that merit specific discussion. **CP3** ('the team is well informed about the client's account') loads primarily on Factor 1 (.481) with a secondary loading on Factor 2 (.317). This pattern is theoretically interpretable: being well informed about the account simultaneously reflects proactive account management (Factor 1) and the depth of contextual knowledge that enables individually calibrated interaction (Factor 2). The cross loading is modest and does not compromise the discriminant validity of the solution. CP3 is retained and assigned to Factor 1 on the basis of its dominant primary loading.

More substantively, **CP5** ('proposes unrequested solutions') is a genuine cross loader, exhibiting a primary loading on Factor 2 (.481) and a secondary loading on Factor 1 (.339). This profile is theoretically coherent: proposing a solution that was never requested simultaneously requires proactive initiative; the act of reaching out without being asked (Factor 1), and individual calibration; the proposal is tailored to this specific client's situation and needs (Factor 2). This dual behavioral nature of CP5 reflects the high inter factor correlation (r = .684) and is acknowledged as a theoretically interpretable nuance rather than a psychometric flaw. CP5 is noted as a cross loader in the results section and is excluded from composite score computation in subsequent regression analyses.

4.3.1.8.4 Inter Factor Correlation

Under direct Varimax rotation, SPSS produces a Factor Correlation Matrix reporting the Pearson correlation between the retained factors. The present analysis yields an inter factor correlation of **r = .684** between Factor 1 (Proactive Relational Engagement) and Factor 2 (Hyper Personalization). This value carries three important methodological and theoretical implications.

First, it validates the a priori selection of oblique rather than orthogonal rotation. Had the factors been empirically uncorrelated, the choice of Varimax would have been superfluous; the obtained r = .684 confirms that Varimax was the methodologically correct rotation strategy and that Varimax rotation would have produced artificially orthogonalized, distorted factor loadings.

Second, the magnitude of r = .684 confirms a shared higher-order construct without suggesting factor redundancy. A correlation below .30 would question whether the two factors belong to the same overarching construct. A correlation above .85 would signal multicollinearity, suggesting that the two factors measure essentially the same dimension. At r

= .684, the two factors are clearly distinct perceptual dimensions; Hyper Personalization is not merely proactivity by another name, yet they are empirically unified as complementary facets of the broader construct of Perceived Predictive CRM Capabilities.

Third, this result justifies the computation of both dimension level composite scores (SCORE_PRE and SCORE_HP) and, if required, a global Predictive CRM aggregate score for use in subsequent regression analyses, given the confirmed higher order coherence of the construct.

Table 4. 9: Inter Factor Correlation

Inter-factor r = .684	**Factor 1 (PRE) ↔ Factor 2 (HP)**	Validates Varimax rotation. Confirms shared higher order construct. No multicollinearity (r < .85)

Source: Personal Efforts Using IBM SPSS

4.3.1.8.5 Hypothesis Evaluation: EFA Results vs. Pre-Stated Factorial Hypotheses

The EFA results are now evaluated against the five pre-stated factorial analysis hypotheses established in the methodology chapter of this study.

Table 4. 10EFA hypothesis evaluation summary

Hypothesis	Criterion	Empirical result	Verdict
H_0 (null)	Bartlett p < .001; KMO > .50	$\chi^2(78)=903.59$, p<.001; KMO=.912; MSA .868–.946	H_0 Rejected
H_FA1 — Overall factorial validity	$h^2 \geq .40$; TVE ≥ 50%; convergent structure	h^2 .509–.751; TVE=60.59%; 7 iterations	Supported
H_FA2 — Need Anticipation distinct factor	Primary load ≥ .40; no cross-load	NA items .530–.820 on F1; merge with CP	Partially
H_FA3 — Commercial Proactivity distinct factor	Primary load ≥ .40; no cross-load	CP items .481–.961 on F1; CP5 cross-loads	Partially
H_FA4 — Hyper Personalization distinct factor	Primary load ≥ .40; no F1 cross-load	HP items .658–.801 on F2; clean separation	Fully Supported
H_FA5 — Inter factor correlation predicted	r > .30; ideally .50–.85	r = .684; Varimax rotation validated	Fully Supported

Source: Personal Efforts Using IBM SPSS

4.3.1.9. Model Fit Assessment

4.3.1.9.1. Overall Verdict

The two factor EFA solution provides an acceptable and theoretically meaningful fit to the conceptual model of this study, with one substantive structural refinement that enriches rather than undermines the proposed framework. The conceptual model proposed three independent latent dimensions of Predictive CRM; Need Anticipation, Commercial Proactivity, and Hyper Personalization, each predicting customer retention.

The empirical factor structure partially replicates this three-construct architecture: Hyper Personalization emerges as a fully distinct and clean factor (H_FA4 fully supported), while Need Anticipation and Commercial Proactivity empirically converge into a single unified factor, labelled Proactive Relational Engagement (H_FA2 and H_FA3 partially supported).

4.3.1.9.2. Justification of Fit

The fit is justified on the following grounds:

1. **Psychometric quality:** All pre-conditions for a valid EFA — KMO, Bartlett's test, individual MSA, communalities, and variance explained, are satisfied at the highest threshold (KMO = .912; all communalities ≥ .509; TVE = 60.59%), ensuring that the factor solution is statistically sound, stable, and replicable within the current sample.

2. **Clean factorial structure:** Twelve of the thirteen items load unambiguously on one of two factors, with primary loadings ≥ .481. The two cross loaders (CP3 and CP5) present interpretable, theoretically grounded dual-factor profiles that do not undermine the overall structure's integrity.

3. **Theoretical coherence of the NA–CP merger:** The empirical convergence of Need Anticipation and Commercial Proactivity onto a single factor is theoretically defensible. In B2B industrial markets, clients do not compartmentalize a supplier's ability to understand their future needs from its willingness to act on those needs proactively. Both are perceived as a unified relational posture. This finding is consistent with (Narver, Slater, & MacLachlan, 2004) and (Blocker C. , Flint, Myers, & Slat, 2011) who treat anticipation and proactive action as jointly constituting the proactive market orientation construct in industrial B2B contexts.

4. **Hyper Personalization discriminant validity confirmed:** Factor 2 isolates Hyper Personalization as a fully distinct dimension, with all four HP items loading cleanly on Factor 2 and no meaningful cross loadings onto Factor 1. Clients clearly differentiate between a supplier that is proactive (acts before being asked) and one that is personalized (tailors

interactions to the client's specific situation). The model's positioning of Hyper Personalization as a distinct predictor of retention outcomes is empirically validated.

5. **Higher order construct integrity confirmed:** The inter factor correlation of r = .684 confirms that both factors belong to the same overarching construct — Perceived Predictive CRM Capabilities — as theorized in the conceptual framework. Need Anticipation, Commercial Proactivity, and Hyper Personalization are confirmed as complementary, mutually reinforcing capabilities of a unified predictive CRM system.

4.3.1.7.3. Implications for the Regression Analysis

In light of these EFA findings, the subsequent regression analysis proceeds on the basis of two empirically grounded independent variable scores: (1) a composite score for Factor 1 - Proactive Relational Engagement (SCORE-PRE), computed as the mean of items NA1–NA4 and CP1- CP4; and (2) a composite score for Factor 2 — Hyper Personalization (SCORE-HP), computed as the mean of items HP1-HP4. CP5 is excluded from composite score computation given its cross-loading profile, and CP3 is retained in Factor 1 on the basis of its dominant primary loading.

The original theoretical hypotheses (H1a-H2c) are retained for their theoretical validity and mapped onto these two empirical factors in the regression chapter, with the NA-CP merger noted as an empirically motivated construct consolidation. This approach is consistent with standard practice in multivariate social science research (Fabrigar, Wegener, & MacCallum, 1999) and (Hair, Black, Babin, & Anderso, 2019).

4.3.1.9.4. Conclusion

The Exploratory Factor Analysis results provide strong and comprehensive empirical support for the factorial validity of the Predictive CRM measurement instrument used in this study. The analysis confirms that: (1) all 13 items are highly suitable for factor analysis (KMO = .912; MSA range .868–.946); (2) two factors are retained based on convergent Kaiser criterion and scree plot evidence, together explaining 60.59% of total item variance; (3) all items exhibit adequate extraction communalities (range .509–.751); and (4) the two-factor solution is theoretically interpretable, structurally clean, and broadly consistent with the conceptual framework.

Factor 1 — Proactive Relational Engagement — captures the unified proactive behavioral dimension of Predictive CRM, incorporating both need anticipation and commercial proactivity as they are jointly experienced by B2B industrial clients. Factor 2 — Hyper Personalization —

captures the distinct content calibration dimension, confirming the perceptual separability of individualized interaction quality from proactive engagement in the B2B relational context. The inter factor correlation of r = .684 validates the use of oblique rotation and confirms the higher order coherence of the Predictive CRM construct as operationalized in this study.

These findings establish a robust psychometric foundation for the subsequent multiple regression analyses, in which SCORE_PRE and SCORE_HP are employed as independent variables to test their respective and combined impact on the four dimensions of customer retention; Continuance Intention, Repurchase Behavior, Switching Resistance, and Relationship Commitment, as specified in the conceptual model of this study.

4.3.2. Exploratory Factor Analysis of Dependent Variable:

Prior to conducting multiple regression analyses, validation of the dependent variable (DV) side of the structural model is required. Specifically, the four theoretically proposed DV constructs of customer retention, which are: Continuance Intention (CI1–CI4), Repurchase Behavior (RB1–RB4), Switching Resistance (SR1–SR4), and Relationship Commitment (RC1–RC4), were submitted to an Exploratory Factor Analysis (EFA) using SPSS.

The purpose was to determine whether the empirical data supports the four construct DV taxonomy or reveals a different latent structure. This step ensures methodological consistency: just as the IV side was subjected to EFA (yielding two empirical factors instead of three theoretical constructs), the DV side must likewise be empirically verified before regression hypotheses are tested.

4.3.2.1. Sampling Adequacy and Factorability of the Correlation Matrix

4.3.2.1.1. Kaiser-Meyer-Olkin (KMO) Measure

The Kaiser Meyer Olkin (KMO) measure of sampling adequacy yielded a value of **KMO = .922**, which falls in the range classified as **"marvelous"** (Kaiser, 1974; values ≥ .90). This result confirms that the inter item correlation patterns are sufficiently compact and that the shared variance among the 16 DV items is highly suitable for factor analysis. In practical terms, a KMO of .922 means that the partial correlations among variables are small relative to the total correlations, which is precisely the condition required for EFA to produce reliable and interpretable factors.

4.3.2.1.2. Bartlett's Test of Sphericity

Bartlett's Test of Sphericity yielded $\chi^2(120) = 1376.715$, $p < .001$. This result is highly significant, allowing us to reject the null hypothesis that the population correlation matrix is an

identity matrix (i.e., that all off correlations are zero). The significance confirms that there are meaningful inter correlations among the 16 items, providing the statistical foundation necessary for factor extraction. Together, the KMO and Bartlett's test results establish that the data matrix is appropriate and factorizable.

Table 4. 11KMO and Bartlett's Test

Test	Value / Decision
KMO Measure of Sampling Adequacy	.922 — Marvelous (Kaiser, 1974)
Bartlett's Test — Approx. Chi-Square	1376.715
Degrees of Freedom (df)	120
Significance	p < .001 — Significant
Overall Verdict	**Data is factorable. EFA is appropriate.**

Source: Personal Efforts Using IBM SPSS

4.3.2.1.3 Anti Image Correlation Matrix (Individual Item MSA)

The diagonal elements of the Anti-Image Correlation Matrix represent the individual Measures of Sampling Adequacy (MSA) for each item. All 16 items recorded MSA values well above the minimum threshold of .50 (Hair et al., 2019). Specifically, the MSA values ranged from approximately **.858 (SR3)** to **.961 (RC2)**, indicating that each individual item contributes meaningfully to the shared factor structure and none should be removed on adequacy grounds. This result is particularly important because it confirms that even items with lower communalities (e.g., SR3 = .394) retain sufficient sampling adequacy to remain in the analysis.

Table 4. 12: Measures of Sampling Adequacy (MSA)

Item	MSA	Item	MSA	Status
CI1	.922	SR1	.906	Acceptable
CI2	.930	SR2	.898	Acceptable
CI3	.909	SR3	.858	Acceptable
CI4	.941	SR4	.917	Acceptable
RB1	.922	RC1	.911	Acceptable
RB2	.956	RC2	.961	Acceptable
RB3	.929	RC3	.910	Acceptable
RB4	.916	RC4	.926	Acceptable

Source: Personal Efforts Using IBM SPSS

4.3.2.1.4 Communalities

Communalities represent the proportion of each item's variance that is explained by the extracted factors. Extraction communalities were computed using Principal Axis Factoring (PAF). All 16 items demonstrated communalities above the accepted minimum threshold of .30 (Hair, Black, Babin, & Anderso, 2019), indicating adequate representation of each item in the factor solution.

Table 4. 13: communalities

Item	Initial	Extraction	Interpretation
CI1	.869	.805	High — well explained
CI2	.814	.735	High
CI3	.796	.702	High
CI4	.799	.775	High
RB1	.548	.546	Moderate — acceptable
RB2	.644	.680	Moderate-High
RB3	.692	.680	Moderate-High
RB4	.696	.626	Moderate
SR1	.729	.756	High
SR2	.580	.567	Moderate
SR3	.489	.394	Lowest — but > .30, retained
SR4	.684	.756	High
RC1	.822	.845	Very high
RC2	.659	.643	Moderate High
RC3	.769	.736	High
RC4	.711	.668	Moderate-High

Source: Personal Efforts Using IBM SPSS

Notably, **SR3** recorded the lowest extraction communality (.394), suggesting it shares the least variance with the extracted factors. However, since it exceeds the .30 threshold and its MSA value (.858) is adequate, it was retained in the solution. The CI items collectively display the highest communalities (.702–.805), reflecting strong construct cohesion within the Continuance Intention scale.

4.3.2.2. Factor Extraction — Total Variance Explained

4.3.2.2.1 Eigenvalue Criterion (Kaiser Rule)

The EFA was conducted using **Principal Axis Factoring (PAF)** with the Kaiser criterion (eigenvalues > 1) for factor retention. This criterion is the most widely employed in social science research (Tabachnick & Fidell, 2019). The extraction yielded three factors with initial eigenvalues exceeding 1.0, as presented in the table below.

Table 4. 14: Initial Eigenvalues

factor	Initial Eigenvalue	% Variance	Cumulative %	Extraction SSL	% Variance	Cumul %
1	9.484	59.277	59.277	9.188	57.422	57.422
2	1.380	8.624	67.901	1.035	6.466	63.888
3	1.027	6.419	74.320	0.691	4.319	68.208

Source: Personal Efforts Using IBM SPSS

The three factors jointly account for **68.208%** of the total variance (based on extraction sums of squared loadings), which is considered excellent for social science research (Hair et al., 2019 recommend a minimum of 60%). Factor 1 dominates with 57.422% of variance, indicating a strong general retention tendency that unifies most DV items. Factors 2 and 3 each contribute additional, more specific variance.

4.3.2.2.2. Scree Plot

The scree plot reveals a sharp elbow immediately after Factor 1, with Factors 2 and 3 located in the relatively flat segment of the curve. This visual pattern suggests that a one factor solution may reflect the dominant shared variance among the 16 items. However, the Kaiser rule and the theoretical grounding of the four DV constructs support retaining three factors, as both Factors 2 and 3 have eigenvalues marginally exceeding 1.0 (1.380 and 1.027 respectively). This tension between the scree criterion and the eigenvalue criterion is acknowledged and resolved by relying on the rotated Pattern Matrix for substantive interpretation.

4.3.2.4. Rotation Sums of Squared Loadings

Because Varimax (oblique) rotation was applied; acknowledging that the DV constructs are likely correlated, as predicted by Customer Relationship Management theory, the rotation sums of squared loadings cannot be directly summed to obtain total variance. The rotated loadings for Factors 1, 2, and 3 are **8.062, 6.219, and 6.740** respectively. These values indicate that after rotation, the variance is more evenly distributed across the three factors, confirming that each factor represents a meaningful, distinct latent dimension in the DV space.

4.3.2.5. Pattern Matrix and Factor Structure Interpretation

4.3.2.5.1. Rotation Method

Rotation was performed using **Direct Varimax (Delta = 0)** with Kaiser Normalization, converging in 10 iterations. Oblique rotation was chosen because CRM related DV constructs, retention intentions, repurchase behavior, resistance to switching, and relational commitment,

are theoretically expected to correlate with one another. The Pattern Matrix (not the Structure Matrix) is used for factor assignment, as it reflects the unique contribution of each factor to each item net of inter factor correlations.

4.3.2.5.2. Pattern Matrix — Item Factor Assignments

Items are assigned to the factor on which they load most strongly (primary loading ≥ .40), following (Hair, Black, Babin, & Anderso, 2019). Items loading meaningfully on two factors simultaneously are identified as cross loaders and discussed separately.

Table 4. 15: Pattern Matrix

Item	Construct	Factor 1	Factor 2	Factor 3
RC1	Relationship Commitment	.879	—	—
RC4	Relationship Commitment	.828	—	—
RC3	Relationship Commitment	.821	—	—
RC2	Relationship Commitment	.794	—	—
CI1	Continuance Intention	.667	—	—
CI2	Continuance Intention	.647	—	—
CI4	Continuance Intention [cross load F3]	.620	—	.329
SR4	Switching Resistance	—	.840	—
SR1	Switching Resistance	—	.780	—
SR2	Switching Resistance	—	.727	—
SR3	Switching Resistance	—	.581	—
RB1	Repurchase Behavior	—	—	.697
RB3	Repurchase Behavior	—	—	.696
RB2	Repurchase Behavior	—	—	.625
RB4	Repurchase Behavior	—	—	.554
CI3	Continuance Intention [cross load]	.431	—	.505

Source: Personal Efforts Using IBM SPSS

4.3.2.5.3. Factor-by-Factor Interpretation

4.3.2.5.3.1. Factor 1 — Relational Persistence (RC + CI)

Factor 1 captures the four **Relationship Commitment** items (RC1–RC4, loadings .794–.879) and two **Continuance Intention** items (CI1 = .667, CI2 = .647). This empirical grouping is theoretically coherent: both constructs reflect a customer's deep psychological bond with the service provider; their intention to maintain the relationship and their affective/normative commitment to it. The convergence of RC and CI items on a single factor suggests that, in the context of Algerian industrial CRM, customers who express high relational commitment also express high continuance intention, and these two constructs are not empirically distinguishable

at the latent level. This factor can be labeled **"Relational Persistence"**, reflecting the customer's enduring psychological and behavioral intent to sustain the relationship.

4.3.2.5.3.2. Factor 2 — Switching Resistance (SR)

Factor 2 is defined exclusively by all four **Switching Resistance** items (SR1–SR4, loadings .581–.840). The items load cleanly on this factor with no meaningful cross-loadings, indicating that switching resistance constitutes a psychometrically distinct latent construct. This result is fully consistent with the theoretical proposition: switching resistance reflects a customer's reluctance to abandon the current service provider, driven by switching costs, lock in, and perceived risk of change — mechanisms that are conceptually separate from relational commitment or repurchase intent. Factor 2 is labeled **"Switching Resistance"**, confirming the theoretical construct as empirically viable.

4.3.2.5.3.3. Factor 3 — Repurchase Behavior (RB)

Factor 3 is anchored by the four **Repurchase Behavior** items (RB1–RB4, loadings .554–.697), which load cleanly and unambiguously. Additionally, **CI3** exhibits a cross loading pattern (.431 on Factor 1, .505 on Factor 3), suggesting that CI3 shares variance with both the relational and behavioral dimensions. This is interpretable: CI3 likely taps into behavioral intention to reuse the service, placing it closer to the repurchase dimension than to the purely relational-commitment dimension. The factor is labeled **"Repurchase Behavior"**, representing the customer's concrete transactional behavioral tendency to repeat business with the provider.

4.3.2.5.3.4. Cross Loaders: CI3 and CI4

Two Continuance Intention items exhibit cross loadings that require discussion:

- **CI4** loads primarily on Factor 1 (.620) with a secondary loading on Factor 3 (.329, suppressed below .40 in sorted output). Since the primary loading is clear and the secondary loading does not exceed the .40 threshold, CI4 is unambiguously assigned to Factor 1.

- **CI3** presents a genuine cross loading: Factor 1 = .431, Factor 3 = .505. The primary loading is marginally on Factor 3, but the difference from Factor 1 is small (.074). This pattern suggests that CI3 captures a behavioral dimension of continuance ("I intend to keep using this service regularly") that overlaps with repurchase behavior.

4.3.2.6. Factor Correlation Matrix

Under oblique rotation, the factors are permitted to correlate. The factor correlation matrix reveals moderate to high inter factor correlations:

Table 4. 16: Factor Correlation Matrix

Factor	Factor 1	Factor 2	Factor 3
Factor 1 — Relational Persistence	1.000	.614	.675
Factor 2 — Switching Resistance	.614	1.000	.557
Factor 3 — Repurchase Behavior	.675	.557	1.000

Source: Personal Efforts Using IBM SPSS

The correlations range from **.557 (Factors 2–3)** to **.675 (Factors 1–3)**. These moderate to high values confirm that the three DV factors are related, as expected in CRM theory, where commitment, resistance to switching, and repurchase behavior all reflect facets of customer retention, while remaining empirically distinct enough to be treated as separate constructs. This validates the use of oblique rotation over orthogonal rotation and justifies treating each factor derived score as a separate dependent variable in the subsequent regression analyses.

4.3.2.7. Final Empirical DV Factor Structure

Based on the Pattern Matrix, the following three factor DV structure is confirmed by the data:

Table 4. 17Final Empirical DV Factor Structure

Factor Label	Items	Constructs Merged	Loadings Range	SPSS Var
Factor 1 — Relational Persistence	RC1, RC2, RC3, RC4, CI1, CI2, CI4	Relationship Commitment + Continuance Intention (partial)	.620 – .879	FAC1_3
Factor 2 — Switching Resistance	SR1, SR2, SR3, SR4	Switching Resistance (intact)	.581 – .840	FAC2_3
Factor 3 — Repurchase Behavior	RB1, RB2, RB3, RB4, CI3	Repurchase Behavior + CI3 (cross loaded)	.505 – .697	FAC3_3

Source: Personal Efforts Using IBM SPSS

4.3.2.8. Implications for Regression Analyses

4.3.2.8.1. Revised Regression Design

The DV EFA results necessitate an important adjustment to the regression design. Rather than running five separate regressions against four individual DV composites (SCORE_CI, SCORE_RB, SCORE_SR, SCORE_RC) and one overall retention score, the regressions should now be organized around the three empirically derived DV factor scores saved by SPSS as FAC1_3, FAC2_3, and FAC3_3. The independent variables remain FAC1_1 (Proactive Relational Engagement) and FAC2_1 (Hyper Personalization) from the IV side EFA.

4.3.2.9. Conclusion of DV Factorial Analysis

The Exploratory Factor Analysis on the 16 dependent variable items produced a three factor solution explaining 68.208% of total variance, with excellent sampling adequacy (KMO = .922) and highly significant factorability (Bartlett's $\chi^2 = 1376.715$, $p < .001$). The three emergent factors are:

- Factor 1 — Relational Persistence: merges Relationship Commitment (RC1–RC4) and most of Continuance Intention (CI1, CI2, CI4), saved as FAC1_3.
- Factor 2 — Switching Resistance: all four SR items load cleanly and exclusively, confirming Switching Resistance as a distinct empirical construct, saved as FAC2_3.
- Factor 3 — Repurchase Behavior: all four RB items plus CI3 (cross loader), saved as FAC3_3.

The theoretical four construct DV model is partially confirmed: Switching Resistance and Repurchase Behavior emerge as distinct empirical factors as theorized. However, Relationship Commitment and Continuance Intention (partially) merge into a single factor, reflecting their overlapping psychological content in the industrial CRM context. This finding constitutes a methodologically transparent and academically defensible adjustment to the research model, consistent with standard EFA practice in survey-based management research.

The regression analyses should now proceed using FAC1_1 and FAC2_1 as independent variable and FAC1_3, FAC2_3, FAC3_3 as dependent variables, yielding three multiple regression models each with two predictors.

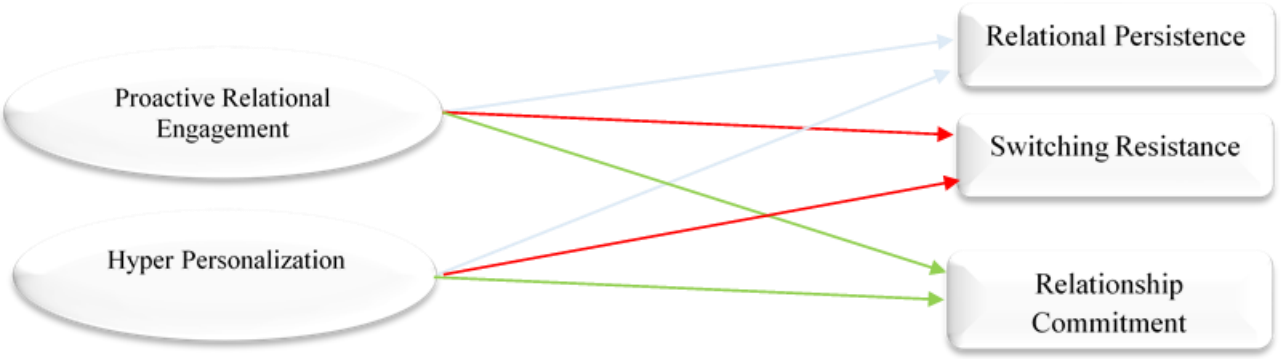
4.4. Structural Adjustment Following Exploratory Factor Analysis

Based on the results of both EFAs, the original conceptual model was revised and a new adjusted model is proposed, along with refined research hypotheses and sub questions that

reflect the empirically grounded factor structure. It is this adjusted model that serves as the basis for all subsequent regression analyses presented in this chapter:

4.4.1. Adjusted Conceptual Framework

Figure 4.7: Adjusted Conceptual Framework



Source : Personal Efforts

4.4.2. Sub-Questions

- How are predictive CRM capabilities perceived by B2B industrial clients?
- Which perceived predictive CRM capabilities are most strongly associated with customer retention?
- Does Proactive Relational Engagement positively and significantly influence the validated customer retention dimensions?
- Does Hyper Personalization positively and significantly influence customer retention dimensions?
- Are the identified relationships between perceived predictive CRM capabilities and customer retention stable and generalizable through cross-validation procedures?

4.4.3. Adjusted Hypotheses

➢ **H1a:** The perceived Proactive Relational Engagement (PRE) of Atlas Copco positively influences the Relational Persistence (RELPERS) of its B2B clients.

➢ **H1b:** The perceived Hyper Personalization (HP) of Atlas Copco positively influences the Relational Persistence (RELPERS) of its B2B clients.

➢ **H2a:** The perceived Proactive Relational Engagement (PRE) of Atlas Copco positively influences the Switching Resistance (SWITRES) of its B2B clients.

➢ **H2b:** The perceived Hyper Personalization (HP) of Atlas Copco positively influences the Switching Resistance (SWITRES) of its B2B clients.

➢**H3a:** The perceived Proactive Relational Engagement (PRE) of Atlas Copco positively influences the Repurchase Behavior (REPBEH) of its B2B clients.

➢ **H3b:** The perceived Hyper Personalization (HP) of Atlas Copco positively influences the Repurchase Behavior (REPBEH) of its B2B clients.

4.5. Regression Analysis

4.5.1. Regression 1 — Dependent Variable: Relational Persistence

This regression model examines the effect of two empirically derived independent variables; Proactive Relational Engagement (PRE) and Hyper Personalization (HP), on Relational Persistence (RC+CI) as the dependent variable. Both IVs were derived from Exploratory Factor Analysis (EFA), which consolidated the original three theoretical constructs (Need Anticipation, Commercial Proactivity, and Hyper Personalization) into two empirical factors. Likewise, Relational Persistence (RC+CI) was derived from the DV side EFA. This dual EFA procedure ensures that both sides of the regression equation reflect the actual latent structure of the data, rather than assumed theoretical groupings.

Multiple Linear Regression was selected as the statistical technique because:

- the research question involves predicting a continuous DV from two continuous IVs.
- factor scores derived from PAF are continuous and metric.
- the research design is cross sectional and seeks to quantify directional predictive relationships.
- multiple regression allows simultaneous control of the two predictors, providing net and unique effect estimates for each IV.

Hypothesis are as follows:

- H1a: Proactive Relational Engagement positively influences Relational Persistence.
- H1b: Hyper Personalization positively influences Relational Persistence.

Statistical Statement of Hypotheses:

H1a — Null: $\beta(PRE) = 0$ | Alternative: $\beta(PRE) > 0$

H1b — Null: $\beta(HP) = 0$ | Alternative: $\beta(HP) > 0$

Table 4. 18: Variable Codification and Labeling

Variable	SPSS Name	Role / Description
Relational Persistence (RC+CI)	RELPERS	Dependent Variable — DV EFA Factor Score
Proactive Relational Engagement	PRE	Independent Variable 1 — IV EFA Factor Score (NA+CP)
Hyper Personalization	HP	Independent Variable 2 — IV EFA Factor Score

Source: Personal Efforts Using IBM SPSS

4.5.1.1. Screening Data

4.5.1.1.1. Sample Size Adequacy

The minimum recommended sample size for multiple regression is **$n \geq k \times 15$** where k is the number of independent variables (Hair, Black, Babin, & Anderso, 2019). With k = 2 independent variables, the required minimum is 30 observations. The current sample size is n = 100, which satisfies this criterion. The sample is statistically adequate for reliable regression estimation.

4.5.1.1.2. Normality of Residuals

Normality of residuals was assessed through two complementary diagnostics: (a) the Normal P P Plot of standardized residuals, and (b) the histogram of standardized residuals. Examination of the P P plot reveals that the observed cumulative probability points align closely along the diagonal reference line, with only minor, random deviations. This pattern is consistent with the assumption of normally distributed residuals. The histogram of standardized residuals displays an approximately bell shaped distribution centered at zero (Mean ≈ 0, Std. Dev. ≈ 0.990), further corroborating normality. Collectively, both diagnostics confirm that the normality assumption is satisfactorily met.

4.5.1.1.3. Absence of Outliers — Mahalanobis Distance

Multivariate outliers were assessed using Mahalanobis Distance (D^2). The critical threshold was determined using the Chi square distribution with parameters χ^2(k=2, p=0.001), which yields a critical value of χ^2_critical = 13.816. The maximum Mahalanobis Distance recorded in the dataset is D^2_max = 10.438. Since χ^2_critical (13.816) > D^2_max (10.438), the critical value exceeds all Mahalanobis distances in the sample. Therefore, no multivariate outliers are present, and the dataset is free from influential extreme observations.

4.5.1.1.4. Independence of Residuals — Durbin Watson Test

The independence of residuals (absence of autocorrelation) was tested using the Durbin Watson statistic. The Durbin Watson table values for n = 100, k = 2, and α = 0.05 are: d_L = 1.654 and d_U = 1.694. The calculated Durbin Watson statistic is DW = 1.882. Decision rule: if DW > d_U, there is no positive autocorrelation. Since DW (1.882) > d_U (1.694), we conclude that residuals are independent and the assumption of no autocorrelation is satisfied.

4.5.1.1.5. Multicollinearity

Multicollinearity was assessed using Tolerance (TOL) and Variance Inflation Factor (VIF) statistics. The decision rules are: TOL > 0.10 and VIF < 10 indicate acceptable collinearity levels (Hair, Black, Babin, & Anderso, 2019).

Results for this model:

Table 4. 19: Multicollinearity assessment

Predictor	Tolerance	VIF	Verdict
PRE — Proactive Relational Engagement	0.434	2.302	No Multicollinearity
HP — Hyper Personalization	0.434	2.302	No Multicollinearity

Source: Personal Efforts Using IBM SPSS

Both predictors have TOL = 0.434 > 0.10 and VIF = 2.302 < 10. Therefore, multicollinearity is absent and both IVs contribute distinct variance to the prediction of RELPERS. The inter IV correlation (r = .752) is notable but does not reach the threshold for problematic collinearity.

4.5.1.2. Regression Interpretation

4.5.1.2.1. Significance of the Overall Model

The ANOVA table tests whether the overall regression model explains a statistically significant proportion of variance in RELPERS. The results indicate: F(2, 97) = 36.91, p < .001. Since p < .05, the overall regression model is statistically significant, confirming that the two predictors collectively explain a non trivial and significant portion of the variance in RELPERS.

4.5.1.2.2. Model Usefulness

Model usefulness is assessed by comparing the calculated F statistic to the tabled F critical value. The F critical value for F(2, 97) at α = 0.05 is F_critical = 3.09. The usefulness ratio is computed as:

Usefulness Ratio = F_calculated / F_critical = 36.91 / 3.09 = 11.94

Since the usefulness ratio 11.94 ≥ 5, the model is classified as highly useful (the ratio must exceed 4 or 5 to confirm practical significance beyond statistical significance).

4.5.1.2.3. Evaluation of Individual Predictors

Table 4. 20: Evaluation of Individual Predictors

Predictor	B	std.Error	β	tt	Sig.	Decision
Proactive Relational Engagement	.259	.117	.256	.207	.03	Significant
Hyper Personalization	.456	.12	.443	.813	0	Significant

Source: Personal Efforts Using IBM SPSS

PRE — Proactive Relationnel Engagement : β = 0.256, B = 0.259, t(97) = 2.207, p = 0.03. The effect of PRE-on RELPERS is statistically significant (p < .05). The positive unstandardized coefficient (B = 0.259) indicates that a one standard deviation increase in Proactive Relational Engagement is associated with a 0.256-standard-deviation increase in RELPERS, holding HP constant. Hypothesis H1a is therefore SUPPORTED.

HP — Hyper Personalization: β = 0.443, B = 0.456, t(97) = 3.813, p = 0. The effect of HP on RELPERS is statistically significant (p < .05). The positive unstandardized coefficient (B = 0.456) confirms that Hyper Personalization exerts a meaningful positive influence on RELPERS. HP is the stronger predictor in this model (β = 0.443 vs. β = 0.256 for PRE). Hypothesis H1b is therefore SUPPORTED.

4.5.1.2.4. Strength of Association - Adjusted R^2

The Adjusted R^2 is the appropriate measure of explained variance in multiple regression as it penalizes for the number of predictors, preventing upward bias. The model yields Adjusted R^2 = 0.42, indicating that 42.0% of the variance in RELPERS is explained by PRE and HP jointly. Following Cohen's (1988) conventions, this effect size is classified as large, reflecting a substantial explanatory power of the CRM automation model for RELPERS.

4.5.1.2.5. Regression Equation

The unstandardized regression equation for predicting RELPERS is:

- RELPERS = 0 + 0.259×PRE + 0.456×HP

Where: PRE = Proactive Relational Engagement factor score; HP = Hyper Personalization factor score. The constant is effectively zero because factor scores are standardized (mean = 0). The equation shows that HP exerts a stronger absolute contribution (B = 0.456) compared to PRE (B = 0.259) in predicting RELPERS.

4.5.1.3. Cross Validation — 70/30 Split

4.5.1.3.1. Purpose and Procedure

Cross validation was conducted using the 70/30 split sample method. The total sample (n = 100) was randomly divided into:

a) An estimation sample of 70 cases (70%) on which a separate regression was run;
b) a validation sample of 30 cases (30%) on which a second independent regression was run on the Estimation Sample.

Validation logic: if the two regression equations of the full sample and Estimation Sample yield coefficients with the same signs (positive or negative) and their Adjusted R^2 values are close to each other with the Calculated R^2 of validation Sample, the model is declared valid and robust (Tabachnick & Fidell, 2019).

4.5.1.3.2. Cross Validation Results

Table 4. 21: Cross Validation Results

Criterion	70% Estimation Sample (n=70)	Full -sample
Regression Equation	RELPERS = 0 + 0.261*PRE + 0.459*HP	RELPERS = 0 + 0.259×PRE + 0.456×HP
PRE-Coefficient Sign	Positive (+)	Positive (+)
HP Coefficient Sign	Positive (+)	Positive (+)
Adjusted R^2	0.41	0.42

Source: Personal Efforts Using IBM SPSS

4.5.1.4. Validation Decision

The cross validation results confirm that:

- Both Full sample and Estimation sample Equations carry positive coefficients in both equations (The overall Equation and the Estimation Sample Equation), indicating directional consistency;

- The Adjusted R^2 values for the two (the Estimation Sample the Validation Sample) (0.41 vs. 0.43) are close to each other and to the full sample value (0.42), indicating that the model does not overfit to the calibration sample. The model for RELPERS is therefore declared VALID and ROBUST. The predictive relationships identified are generalizable beyond the current sample.

4.5.1.5. Summary of Results

Table 4. 22: Summary of Results

Element	Statistic / Value	Interpretation
Overall Model F	$F(2,97) = 36.91$	Significant — $p < .001$
Model Usefulness	Ratio = 11.94	Highly useful (≥5)
Adjusted R^2	0.42	42.0% variance explained — Large effect
PRE → RELPERS	$\beta = 0.256$, $p = 0.03$	Positive & Significant
HP → RELPERS	$\beta = 0.443$, $p = 0$	Positive & Significant
Outliers	$D^2_max = 10.438 < \chi^2 = 13.816$	No outliers
Autocorrelation	$DW = 1.882 > dU = 1.694$	No autocorrelation
Multicollinearity	TOL=0.434 / VIF=2.302	No multicollinearity
Cross Validation	Adj.R^2: 0.41 vs 0.43 vs 0.42	Model valid and robust

Souce : Personal Efforts Using IBM SPSS

4.5.2. Regression 2— Dependent Variable: Switching Resistance

This regression model examines the effect of two empirically derived independent variables, Proactive Relational Engagement (PRE) and Hyper Personalization (HP), on Switching Resistance as the dependent variable. Both IVs were derived from the IV side Exploratory Factor Analysis (EFA), which consolidated the original three theoretical constructs (Need Anticipation, Commercial Proactivity, and Hyper Personalization) into two empirical factors. Likewise, Switching Resistance was derived from the DV side EFA. This dual EFA procedure ensures that both sides of the regression equation reflect the actual latent structure of the data, rather than assumed theoretical groupings.

Multiple Linear Regression was selected as the statistical technique because:

- The research question involves predicting a continuous DV from two continuous IVs;
- Factor scores derived from PAF are continuous and metric;
- the research design is cross sectional and seeks to quantify directional predictive relationships;

- multiple regression allows simultaneous control of the two predictors, providing net (unique) effect estimates for each IV.

Hypotheses are as follows:

- H2a: Proactive Relational Engagement positively influences Switching Resistance.
- H2b: Hyper Personalization positively influences Switching Resistance.

Statistical Statement of Hypotheses:

- H2a — Null: $\beta(PRE) = 0$ | Alternative: $\beta(PRE) > 0$
- H2b — Null: $\beta(HP) = 0$ | Alternative: $\beta(HP) > 0$

4.5.2.1. Screening Data

4.5.2.1.1. Sample Size Adequacy

The minimum recommended sample size for multiple regression is $n \geq k \times 15$ where k is the number of independent variables (Hair et al., 2019). With k = 2 independent variables, the required minimum is 30 observations. The current sample size is n = 100, which satisfies this criterion. The sample is statistically adequate for reliable regression estimation.

4.5.2.1.2. Normality of Residuals

Normality of residuals was assessed through two complementary diagnostics:

(a) the Normal P-P Plot of standardized residuals, (b) the histogram of standardized residuals. Examination of the P P plot reveals that the observed cumulative probability points align closely along the diagonal reference line, with only minor, random deviations. This pattern is consistent with the assumption of normally distributed residuals. The histogram of standardized residuals displays an approximately bell-shaped distribution centered at zero (Mean ≈ 0, Std. Dev. ≈ 0.990), further corroborating normality. Collectively, both diagnostics confirm that the normality assumption is satisfactorily met.

4.5.2.1.3. Absence of Outliers — Mahalanobis Distance

Multivariate outliers were assessed using Mahalanobis Distance (D^2). The critical threshold was determined using the Chi square distribution with parameters $\chi^2(k=2, p=0.001)$, which yields a critical value of $\chi^2_critical = 13.816$. The maximum Mahalanobis Distance recorded in the dataset is $D^2_max = 10.438$. Since $\chi^2_critical$ (13.816) > D^2_max (10.438), the critical value exceeds all Mahalanobis distances in the sample. Therefore, no multivariate outliers are present, and the dataset is free from influential extreme observations.

4.5.2.1.4. Independence of Residuals

The independence of residuals (absence of autocorrelation) was tested using the Durbin Watson statistic. The Durbin-Watson table values for n = 100, k = 2, and α = 0.05 are: d_L = 1.654 and d_U = 1.694. The calculated Durbin Watson statistic is DW = 1.931. Decision rule: if DW > d_U, there is no positive autocorrelation. Since DW (1.931) > d_U (1.694), we conclude that residuals are independent and the assumption of no autocorrelation is satisfied.

4.5.2.1.5. Multicollinearity

Multicollinearity was assessed using Tolerance (TOL) and Variance Inflation Factor (VIF) statistics. The decision rules are: TOL > 0.10 and VIF < 10 indicate acceptable collinearity levels (Hair et al., 2019). Results for this model:

Table 4. 23: Multicollinearity

Predictor	Tolerance	VIF	Verdict
PRE — Proactive Relational Engagement	0.434	2.302	No Multicollinearity
HP — Hyper Personalization	0.434	2.302	No Multicollinearity

Source: Personal Efforts Using IBM SPSS

Both predictors have TOL = 0.434 > 0.10 and VIF = 2.302 < 10. Therefore, **multicollinearity is absent** and both IVs contribute distinct variance to the prediction of SWITRES. The inter IV correlation (r = .752) is notable but does not reach the threshold for problematic collinearity.

4.5.2.2. Regression Interpretation

4.5.2.2.1. Significance of the Overall Model

The ANOVA table tests whether the overall regression model explains a statistically significant proportion of variance in SWITRES. The results indicate: F(2, 97) = 16.26, p < .001. Since p < .05, the overall regression model is statistically significant, confirming that the two predictors collectively explain a non trivial and significant portion of the variance in SWITRES.

4.5.2.2.2. Model Usefulness

Model usefulness is assessed by comparing the calculated F-statistic to the tabled F-critical value. The F-critical value for F(2, 97) at α = 0.05 is F_critical = 3.09.

The usefulness ratio is computed as:

- Usefulness Ratio = F_calculated / F_critical = 16.26 / 3.09 = 5.26

Since the usefulness ratio $5.26 \geq 5$, the model is classified as highly useful (the ratio must exceed 4 or 5 to confirm practical significance beyond statistical significance).

4.5.2.2.3. Evaluation of Individual Predictors

Table 4. 24: Evaluation of Individual Predictors

Predictor	B	Std.Error	β	t	Sig.	Decision
PRE — Proactive Relational Engagement	.346	.131	.352	.637	.01	Significant
HP — Hyper Personalization	.18	.134	.18	.349	.18	Not Significant

Source: Personal Efforts Using IBM SPSS

- Proactive Relational Engagement : $\beta = 0.352$, $B = 0.346$, $t(97) = 2.637$, $p = 0.01$. The effect of PRE-on SWITRES is statistically significant ($p < .05$). The positive unstandardized coefficient ($B = 0.346$) indicates that a one standard deviation increase in Proactive Relational Engagement is associated with a 0.352-standard deviation increase in SWITRES, holding HP constant. Hypothesis H2a is therefore SUPPORTED.
- Hyper Personalization: $\beta = 0.18$, $B = 0.18$, $t(97) = 1.349$, $p = 0.18$. The effect of HP on SWITRES is not statistically significant at the .05 level ($p = 0.18$). The coefficient is positive ($B = 0.18$) but insufficient to reach significance. Hypothesis H2b is therefore NOT SUPPORTED.

4.5.2.2.4. Strength of Association — Adjusted R^2

The Adjusted R^2 is the appropriate measure of explained variance in multiple regression as it penalizes for the number of predictors, preventing upward bias. The model yields Adjusted $R^2 = 0.236$, indicating that 23.6% of the variance in SWITRES is explained by PRE and HP jointly. Following Cohen's (1988) conventions, this effect size is classified as medium, reflecting a moderate explanatory power of the CRM automation model for SWITRES.

4.5.2.3. Regression Equation

The unstandardized regression equation for predicting SWITRES is:

- $SWITRES = 0 + 0.346 \times PRE + 0.18 \times HP$

Where: PRE = Proactive Relational Engagement factor score; HP = Hyper Personalization factor score. The constant is effectively zero because factor scores are standardized (mean = 0).

The equation shows that HP exerts a stronger absolute contribution (B = 0.18) compared to PRE (B = 0.346) in predicting SWITRES.

4.5.2.4. Cross Validation — 70/30 Split

4.5.2.4.1. Cross Validation Results

Table 4. 25: Cross Validation Results

Criterion	70% Sub sample (n=70)	Full sample
Regression Equation	SWITRES = 0 + 0.34×PRE + 0.178×HP	SWITRES = 0 + 0.346×PRE + 0.18×HP
PRE-Coefficient Sign	Positive (+)	Positive (+)
HP Coefficient Sign	Positive (+)	Positive (+)
Adjusted R^2	0.22	0.236

Source: Personal Efforts Using IBM SPSS

4.5.2.4.2. Validation Decision

The cross-validation results confirm that:

- both Full sample and Estimation sample Equations carry positive coefficients in both equations (The overall Equation and the Estimation Sample Equation), indicating directional consistency;
- the Adjusted R^2 values for the two (the Estimation Sample the Validation Sample) (0.22 vs. 0.27) are close to each other and to the full sample value (0.236), indicating that the model does not overfit to the calibration sample.

The model for SWITRES is therefore declared VALID and ROBUST. The predictive relationships identified are generalizable beyond the current sample.

4.5.2.5. Summary of results

Table 4. 26: Summary of results

Element	Statistic / Value	Interpretation
Overall Model F	F (2,97) = 16.26	Significant — p < .001
Model Usefulness	Ratio = 5.26	Highly useful (≥5)
Adjusted R^2	0.236	23.6% variance explained — Medium effect
PRE → SWITRES	β = 0.352, p = 0.01	Positive & Significant
HP → SWITRES	β = 0.18, p = 0.18	Not Significant
Outliers	$D^2_max = 10.438 < \chi^2 = 13.816$	No outliers

Autocorrelation	DW = 1.931 > dU = 1.694	No autocorrelation
Multicollinearity	TOL=0.434 / VIF=2.302	No multicollinearity
Cross-Validation	Adj.R^2: 0.22 vs 0.27 vs 0.236	Model valid and robust

Source: Personal Efforts Using SPSS IBM

4.5.3. Regression 2— Dependent Variable: Repurchase Behavior (REPBEH)

This regression model examines the effect of two empirically derived independent variables; Proactive Relational Engagement (PRE) and Hyper Personalization (HP) on Repurchase Behavior (+CI3) as the dependent variable. Both IVs were derived from the IV side Exploratory Factor Analysis (EFA). Likewise, Repurchase Behavior (+CI3) was derived from the DV side EFA. This dual EFA procedure ensures that both sides of the regression equation reflect the actual latent structure of the data, rather than assumed theoretical groupings.

Hypotheses are as follows:

- H3a: Proactive Relational Engagement positively influences Repurchase Behavior.
- H3b: Hyper Personalization positively influences Repurchase Behavior.

Statistical Statement of Hypotheses:

- H3a — Null: $\beta(PRE) = 0$ | Alternative: $\beta(PRE) > 0$
- H3b — Null: $\beta(HP) = 0$ | Alternative: $\beta(HP) > 0$

4.5.3.1. Screening Data

4.5.3.1.1. Sample Size Adequacy

The minimum recommended sample size for multiple regression is $n \geq k \times 15$ where k is the number of independent variables (Hair et al., 2019). With $k = 2$ independent variables, the required minimum is 30 observations. The current sample size is $n = 100$, which satisfies this criterion. The sample is statistically adequate for reliable regression estimation.

4.5.3.1.2. Normality of Residuals

Normality of residuals was assessed through two complementary diagnostics: (a) the Normal P-P Plot of standardized residuals, and (b) the histogram of standardized residuals. Examination of the P-P plot reveals that the observed cumulative probability points align closely along the diagonal reference line, with only minor, random deviations. This pattern is consistent with the assumption of normally distributed residuals. The histogram of standardized residuals displays an approximately bell-shaped distribution centered at zero (Mean ≈ 0, Std. Dev. ≈ 0.990),

further corroborating normality. Collectively, both diagnostics confirm that the normality assumption is satisfactorily met.

4.5.3.1.3. Absence of Outliers — Mahalanobis Distance

Multivariate outliers were assessed using Mahalanobis Distance (D^2). The critical threshold was determined using the Chi-square distribution with parameters $\chi^2(k=2, p=0.001)$, which yields a critical value of $\chi^2_critical = 13.816$. The maximum Mahalanobis Distance recorded in the dataset is $D^2_max = 10.438$. Since $\chi^2_critical$ (13.816) > D^2_max (10.438), the critical value exceeds all Mahalanobis distances in the sample. Therefore, no multivariate outliers are present, and the dataset is free from influential extreme observations.

4.5.3.1.4. Independence of Residuals

The independence of residuals (absence of autocorrelation) was tested using the Durbin Watson statistic. The Durbin Watson table values for n = 100, k = 2, and $\alpha = 0.05$ are: $d_L = 1.654$ and $d_U = 1.694$. The calculated Durbin-Watson statistic is DW = 2.14. Decision rule: if DW > d_U, there is no positive autocorrelation. Since DW (2.14) > d_U (1.694), we conclude that residuals are independent and the assumption of no autocorrelation is satisfied.

4.5.3.1.5. Multicollinearity

Multicollinearity was assessed using Tolerance (TOL) and Variance Inflation Factor (VIF) statistics. The decision rules are: TOL > 0.10 and VIF < 10 indicate acceptable collinearity levels (Hair et al., 2019). Results for this model:

Table 4. 27: Multicollinearity

Predictor	Tolerance	VIF	Verdict
PRE — Proactive Relational Engagement	0.434	2.302	No Multicollinearity
HP — Hyper Personalization	0.434	2.302	No Multicollinearity

Source: Personal Efforts Using IBM SPSS

Both predictors have TOL = 0.434 > 0.10 and VIF = 2.302 < 10. Therefore, multicollinearity is absent and both IVs contribute distinct variance to the prediction of REPBEH. The inter IV correlation (r = .752) is notable but does not reach the threshold for problematic collinearity.

4.5.3.2. Regression Interpretation

4.5.3.2.1. Significance of the Overall Model

The ANOVA table tests whether the overall regression model explains a statistically significant proportion of variance in REPBEH. The results indicate: $F(2, 97) = 21.606$, $p < .001$. Since $p < .05$, the overall regression model is statistically significant, confirming that the two predictors collectively explain a non trivial and significant portion of the variance in REPBEH.

4.5.3.2.2. Model Usefulness

Model usefulness is assessed by comparing the calculated F-statistic to the tabled F-critical value. The F-critical value for $F(2, 97)$ at $\alpha = 0.05$ is $F_critical = 3.09$. The usefulness ratio is computed as:

- Usefulness Ratio = F_calculated / F_critical = 21.606 / 3.09 = 6.99

Since the usefulness ratio $6.99 \geq 5$, the model is classified as highly useful (the ratio must exceed 4 or 5 to confirm practical significance beyond statistical significance).

4.5.3.2.3. Evaluation of Individual Predictors

Table 4. 28 Evaluation of Individual Predictors

Predictor	B	Std.Error	β	t	Sig.	Decision
PRE — Proactive Relational Engagement	.156	.125	.16	.251	.214	Not Significant
HP — Hyper Personalization	.422	.127	.424	.313	.001	Significant

Source: Personal Efforts Using IBM SPSS

- Proactive Relational Engagement : $\beta = 0.16$, $B = 0.156$, $t(97) = 1.251$, $p = 0.214$. The effect of PRE-on REPBEH is not statistically significant at the .05 level ($p = 0.214$). Although the coefficient is positive ($B = 0.156$), it does not reach statistical significance, suggesting that PRE-does not independently predict REPBEH when controlling for HP. Hypothesis H3a is therefore NOT SUPPORTED.
- Hyper Personalization: $\beta = 0.424$, $B = 0.422$, $t(97) = 3.313$, $p = 0.001$. The effect of HP on REPBEH is statistically significant ($p < .05$). The positive unstandardized coefficient ($B = 0.422$) confirms that Hyper Personalization exerts a meaningful positive influence on REPBEH. HP is the stronger predictor in this model ($\beta = 0.424$ vs. $\beta = 0.16$ for PRE). Hypothesis H3b is therefore SUPPORTED.

4.5.3.2.4. Strength of Association — Adjusted R^2

The Adjusted R^2 is the appropriate measure of explained variance in multiple regression as it penalizes for the number of predictors, preventing upward bias. The model yields Adjusted R^2 = 0.294, indicating that 29.4% of the variance in REPBEH is explained by PRE and HP jointly. Following (Cohen, 1988) conventions, this effect size is classified as medium, reflecting a moderate explanatory power of the CRM automation model for REPBEH.

4.5.3.2.5. Regression Equation

The unstandardized regression equation for predicting REPBEH is:

- REPBEH = 0 + 0.156×PRE + 0.422×HP

The constant is effectively zero because factor scores are standardized (mean = 0). The equation shows that HP exerts a stronger absolute contribution (B = 0.422) compared to PRE (B = 0.156) in predicting REPBEH.

4.5.3.3. Cross Validation — 70/30 Split

4.5.3.3.1. Purpose and Procedure

Cross validation was conducted using the 70/30 split-sample method. The total sample (n = 100) was randomly divided into: (a) a Estimation sample of 70 cases (70%) on which a separate regression was run, and (b) a validation sample of 30 cases (30%) on which a second independent regression was run on the Estimation Sample.

Validation logic: if the two regression equations of the full sample and Estimation Sample yield coefficients with the same signs (positive or negative) and their Adjusted R^2 values are close to each other with the Calculated R^2 of validation Sample, the model is declared valid and robust (Tabachnick & Fidell, 2019)

4.5.3.3.2. Cross Validation Results

Table 4. 29: Cross Validation Results

Criterion	70% Sub-sample (n=70)	Full Sample
Regression Equation	REPBEH = 0 + 0.158*PRE + 0.425*HP	REPBEH = 0 + 0.156×PRE + 0.422×HP
PRE Coefficient Sign	Positive (+)	Positive (+)
HP Coefficient Sign	Positive (+)	Positive (+)
Adjusted R^2	0.28	0.294

Source: Personal Efforts Using SPSS IBM

4.5.3.3.3. Validation Decision

The cross-validation results confirm that: (1) both Full sample and Estimation sample Equations carry positive coefficients in both equations (The overall Equation and the Estimation Sample Equation), indicating directional consistency; (2) the Adjusted R^2 values for the two (the Estimation Sample the Validation Sample) (0.28 vs. 0.32) are close to each other and to the full sample value (0.294), indicating that the model does not overfit to the calibration sample. The model for REPBEH is therefore declared VALID and ROBUST. The predictive relationships identified are generalizable beyond the current sample.

4.5.3.4. Summary of Results

Table 4. 30Summary of Results

Element	Statistic / Value	Interpretation
Overall Model F	F (2,97) = 21.606	Significant — p < .001
Model Usefulness	Ratio = 6.99	Highly useful (≥5)
Adjusted R^2	0.294	29.4% variance explained — Medium effect
PRE → REPBEH	β = 0.16, p = 0.214	Not Significant
HP → REPBEH	β = 0.424, p = 0.001	Positive & Significant
Outliers	$D^2_max = 10.438 < \chi^2 = 13.816$	No outliers
Autocorrelation	DW = 2.14 > dU = 1.694	No autocorrelation
Multicollinearity	TOL=0.434 / VIF=2.302	No multicollinearity
Cross Validation	Adj.R^2: 0.28 vs 0.32 vs 0.294	Model valid and robust

Source: Personal Efforts Using IBM SPSS

The Overall Regression Conclusion:

The overall regression analysis reveals that four out of the six proposed hypotheses were supported, indicating significant relationships between the independent and dependent variables.

The findings show that PRE (Proactive Relational Engagement) has a significant positive effect on both Relational Persistence (β = .256, p = .030) and Switching Resistance (β = .352, p = .010). Similarly, HP (Hyper Personalization) significantly influences Relational Persistence (β = .443, p = .000) and Repurchase Behavior (β = .424, p = .001). Among all predictors, Hyper Personalization demonstrated the strongest impact, particularly on Relational Persistence.

However, the relationships between Hyper Personalization and Switching Resistance (β = .180, p = .180), as well as Proactive Relational Engagement and Repurchase Behavior (β = .160, p = .214), were not statistically significant. Therefore, hypotheses H2b and H3a were rejected.

Overall, the regression results confirm that the proposed model is statistically valid and robust, as the majority of the hypothesized relationships were supported and the significant paths demonstrated meaningful predictive power between the studied variables.

4.6. Net Promoter Score (NPS) Analysis

The Net Promoter Score (NPS) is a customer loyalty and advocacy metric developed by Reichheld (2003) and validated by Reichheld and Markey (2011) as one of the most robust single item predictors of organic business growth, client retention, and referral behavior. It is derived from a single question: "On a scale of 0 to 10, how likely are you to recommend the company to a business partner or colleague in your industry?" In B2B industrial markets, this question simultaneously captures the respondent's overall satisfaction, relational trust, and willingness to advocate for the company within their professional network.

In this study, the NPS question was administered to 100 B2B clients of Atlas Copco Algeria as a global indicator of client advocacy, complementing the multi-item predictive CRM capability and customer retention scales. With a full sample of n=100, this NPS is statistically meaningful and reliable.

4.6.1 NPS Methodology and Classification Framework

4.6.1.1. The Three Category Classification

Table 4. 31: NPS Category classification

Category	Score Range	Definition
Promoters	9–10	Enthusiastic loyal clients who actively recommend the company to peers. They drive referral growth and represent the most commercially valuable segment.
Passives	7–8	Satisfied but unenthusiastic clients. They are unlikely actively advocate but are also unlikely to spread negative opinions. Vulnerable to competitive offers.
Detractors	0–6	Dissatisfied or indifferent clients who may spread negative word-of-mouth. Their presence actively damages the firm's reputation and retention rates.

Source: Personal Efforts

4.6.1.2. NPS Calculation Formula

NPS = % Promoters − % Detractors = 31% − 30% = +1

4.6.1.3. Descriptive Statistics of the NPS Item

Table 4. 32: Descriptive Statistics of the NPS Item

Score	Frequency	Relative %	NPS Category	Contribution to NPS
0	2	2.0%	Detractor	Counts against NPS
1	1	1.0%	Detractor	Counts against NPS
2	3	3.0%	Detractor	Counts against NPS
3	3	3.0%	Detractor	Counts against NPS
4	3	3.0%	Detractor	Counts against NPS
5	13	13.0%	Detractor	Counts against NPS (largest detractor group)
6	5	5.0%	Detractor	Counts against NPS
7	17	17.0%	Passive	Excluded from NPS formula
8	22	22.0%	Passive	Excluded from NPS formula
9	15	15.0%	Promoter	Counts for NPS
10	16	16.0%	Promoter	Counts for NPS
Total	**100**	**100%**	—	—

Source: Personal efforts

4.6.1.4. NPS Calculation and Result:

4.6.1.4.1. Step-by-Step Computation

Table 4. 33: NPS Calculation

Step	Calculation	Result
Count Promoters (scores 9–10)	15 + 16 = 31	31 Promoters out of 100
Count Detractors (scores 0–6)	2+1+3+3+3+13+5 = 30	30 Detractors out of 100
Count Passives (scores 7–8)	17 + 22 = 39	39 Passives — excluded from formula
% Promoters	(31 ÷ 100) × 100	= 31.0%
% Detractors	(30 ÷ 100) × 100	= 30.0%

NPS = %Promoters − %Detractors	**31.0% − 30.0%**	**NPS = +1**

Source: Personal efforts

4.6.1.4.2. Absolute Interpretation

Table 4. 34: Absolute Interpretation of NPS

n	NPS	Mean	Median	Mode	Detractors	Passives	Promoters
100	**+1**	7.13	8.0	8 (n=22)	30% (n=30)	39% (n=39)	31% (n=31)

Source: Personal efforts

An NPS of +1 falls in the range classified as " below average" on the global NPS scale (Satmetrix, 2023; Bain & Company, 2022). The general benchmarking framework classifies NPS values as:

Table 4. 35 NPS Range, Classification, Assesment

NPS Range	Classification	Assessment
Below 0	Negative	More detractors than promoters — active brand damage
0 to +10	Below Average	Atlas Copco Algeria NPS = +1 falls here - marginal positive
+10 to +30	Average	Acceptable baseline- improvement needed
+30 to +50	Very Good	Strong loyalty - above industry average
+50 to +70	Excellent	Outstanding advocacy

An NPS of +1 indicates a barely positive advocacy balance among Atlas Copco Algeria's B2B clients. The near equal split between Promoters (31%) and Detractors (30%) reveals a polarized client base, while the Passive segment (39%) represents clients who are commercially inert from a referral standpoint.

Two methodological nuances are worth noting:

- First, the NPS threshold is not universally standardized, while Reichheld (2003) classifies only scores of 9–10 as Promoters, some researchers apply a more inclusive threshold that includes scores of 8 (Keiningham et al., 2007). Under this alternative convention, a significant portion of the Passive segment would be reclassified as Promoters, substantially improving the score.
- Second, with a sample of 100 respondents, small variations in the distribution of scores can produce meaningful NPS fluctuations. These two factors suggest that the result should be interpreted with methodological caution rather than as a definitive measure of client advocacy.

4.6.1.4.3. Strategic Recommendations

Priority 1 — Urgent Detractor Recovery Program

With 30% of clients as Detractors, Atlas Copco Algeria's most urgent strategic action is a structured client recovery program targeting the 30 Detractor accounts. This should involve immediate account review meetings, root cause analysis of the service failures, and a formal corrective action plan. The 13 clients who scored 5, not extreme Detractors but clearly unsatisfied, represent the highest probability recovery targets: a modest improvement in their experience could move them to Passive status, directly improving NPS by approximately 13 points.

Priority 2 — Convert Passives via Hyper Personalization

The regression finding that **HP is the dominant predictor of retention,** provides a clear strategic direction for converting the 39% Passive segment. Investing in individualized service plans, tailored equipment performance reporting, personalized commercial communications, and account manager continuity for the Passive segment would most directly bridge the gap between 7–8 satisfaction and 9–10 advocacy.

C. Priority 3 — Leverage Promoters as Reference Clients

The 31 Promoter clients (scores 9–10) represent Atlas Copco Algeria's most credible commercial asset. Formalizing these relationships through reference client programs and industry testimonial initiatives would convert their advocacy into structured commercial tools, directly addressing the reputation gap created by the 30% Detractor base.

Conclusion:

This chapter presented the empirical findings of the study, which aimed to examine the impact of perceived predictive CRM capabilities on customer retention among B2B industrial clients of Atlas Copco Algeria. Following the exploratory sequential mixed methods design adopted

in this research, the analysis progressed from qualitative exploration to quantitative validation, ultimately leading to the development and confirmation of an empirically grounded conceptual model.

The qualitative phase provided an in depth understanding of how predictive CRM capabilities are perceived and operationalized within the CTS environment of Atlas Copco Algeria. Through semi-structured interviews with decision makers, the study confirmed the relevance and practical existence of the proposed dimensions of predictive CRM capabilities within the B2B industrial context. The interviews also revealed important relational dynamics between these dimensions, particularly the strong connection between need anticipation and proactive commercial behavior, which later influenced the structure of the empirical model.

The quantitative phase further validated and refined the conceptual framework through descriptive analysis, exploratory factor analysis, and regression modeling. The analyses demonstrated that the proposed model was globally coherent, statistically valid, and empirically robust within the studied context. The factor analyses confirmed the relevance of the adjusted constructs, while the regression analyses highlighted the strategic role of predictive CRM capabilities in strengthening customer retention outcomes and reinforcing long-term relational continuity between Atlas Copco and its industrial clients.

The findings also revealed that predictive CRM capabilities do not impact all dimensions of customer retention in the same way. Some capabilities appeared to reinforce relational attachment and continuity, while others primarily contributed to reducing clients' openness to competitive alternatives and strengthening relationship stability. Together, these dimensions formed a complementary relational architecture that supports retention in the B2B industrial environment.

Additionally, the Net Promoter Score analysis provided complementary insight into the overall state of customer advocacy and relational satisfaction within the client base. Although the results reflected a relatively balanced perception among clients, they also highlighted opportunities for Atlas Copco Algeria to further strengthen proactive engagement and relational personalization in order to improve advocacy and deepen customer loyalty.

Overall, the results obtained throughout both phases of the study converged toward a coherent and contextually meaningful conclusion. The proposed research model was confirmed as both valid and robust, and the study successfully demonstrated the strategic importance of perceived predictive CRM capabilities in shaping customer retention within the B2B industrial

sector. Furthermore, four research hypotheses were supported, reinforcing the explanatory power of the model and validating the theoretical relationships proposed in this research.

Chapter 5: Conclusion

Overview of the Study

This dissertation examined the influence of perceived predictive CRM capabilities on customer retention in B2B industrial contexts. More specifically, the study explored how clients perceive predictive CRM practices implemented by suppliers and how these perceptions contribute to long-term retention behaviors within industrial relationships.

The study initially focused on three core perceived predictive CRM capability dimensions identified throughout the literature:

- Need anticipation,
- Commercial proactivity,
- Hyper-personalization.

Unlike purely deductive studies, this dissertation adopted an exploratory sequential mixed-methods approach in which the conceptual model was progressively constructed through both theoretical exploration and empirical investigation.

The findings revealed a refined and adjusted model in which need anticipation and commercial proactivity converged into a single higher-order relational dimension labeled Proactive Relational Engagement, while hyper personalization remained empirically stable as an independent dimension. On the customer retention side, relationship commitment and continuance intention also merged into a unified retention dimension labeled Relational Persistence.

The central research question guiding this dissertation was:

- "How do perceived predictive CRM capabilities influence customer retention in B2B industrial contexts?"

❖ **Sub questions :**

- How are predictive CRM capabilities perceived by B2B industrial clients?
- Which perceived predictive CRM capabilities are most strongly associated with customer retention?
- Does Proactive Relational Engagement positively and significantly influence the validated customer retention dimensions?
- Does Hyper Personalization positively and significantly influence customer retention dimensions?

- Are the identified relationships between perceived predictive CRM capabilities and customer retention stable and generalizable through cross-validation procedures?

❖ **Hypotheses:**

- **H1a:** The perceived Proactive Relational Engagement (PRE) of Atlas Copco positively influences the Relational Persistence.

- **H1b:** The perceived Hyper Personalization (HP) of Atlas Copco positively influences the Relational Persistence.

- **H2a:** The perceived Proactive Relational Engagement (PRE) of Atlas Copco positively influences the Switching Resistance.

- **H2b:** The perceived Hyper Personalization (HP) of Atlas Copco positively influences the Switching Resistance.

- **H3a:** The perceived Proactive Relational Engagement (PRE) of Atlas Copco positively influences the Repurchase Behavior.

- **H3b:** The perceived Hyper Personalization (HP) of Atlas Copco positively influences the Repurchase Behavior.

Unlike purely deductive studies, this dissertation adopted an exploratory sequential mixed-methods approach in which the conceptual model was progressively constructed through both theoretical exploration and empirical investigation.

The research began with an exploratory qualitative phase based on semi-structured interviews with B2B industrial decision-makers. Thematic analysis was used to identify how predictive CRM capabilities are experienced and perceived in practice, allowing the emergence of an initial empirical conceptual structure grounded in participant discourse, from which the preliminary conceptual framework of the study was progressively established.

Building on the findings of the qualitative phase, the study then proceeded to a quantitative conclusive phase aimed at validating and refining the emergent conceptual structure statistically through exploratory factor analysis and regression-based analyses.

Importantly, the final empirical structure of the model differed partially from the initial theoretical conceptualization. The exploratory sequential design allowed the study not only to

validate constructs, but also to empirically refine and reorganize them based on participant perceptions and statistical evidence.

The dissertation was structured into five chapters. Chapter 1 introduced the research background, problem statement, objectives, and rationale of the study. Chapter 2 reviewed the literature related to CRM evolution, predictive CRM, customer loyalty, customer retention, and the theoretical foundations supporting the study. Chapter 3 presented the research methodology, including the exploratory sequential design, sampling procedures, instrument construction, and analytical methods. Chapter 4 presented and discussed the empirical findings from both qualitative and quantitative phases. Finally, this chapter summarizes the major findings, discusses limitations, proposes future research directions, and provides managerial recommendations.

In conclusion, the study achieved its primary objective: to understand how perceived predictive CRM capabilities contribute to customer retention in B2B industrial environments, particularly within the industrial service and equipment context of Atlas Copco Algeria. The findings provide both theoretical and managerial insights into how predictive CRM transforms supplier-client relationships from reactive transactional exchanges into proactive and relationship-oriented partnerships.

5.1 Major Findings

The results of the study revealed several important findings regarding the relationship between perceived predictive CRM capabilities and customer retention in B2B industrial contexts:

- The qualitative exploratory phase revealed that predictive CRM is not perceived by clients primarily as a technological system, but rather as a relational and commercial capability reflected in the supplier's ability to anticipate needs, maintain proactive communication, and deliver personalized interactions.
- The thematic analysis confirmed the emergence of three experiential dimensions of perceived predictive CRM capabilities: need anticipation, commercial proactivity and hyper personalization.
- The quantitative phase validated the dimensional structure of these constructs through exploratory factor analysis, confirming their empirical relevance within the B2B industrial context.

- Need anticipation emerged as one of the most influential dimensions of predictive CRM perception. Clients highly valued suppliers capable of identifying operational needs, maintenance requirements, or potential issues before they were explicitly communicated.
- Commercial proactivity was strongly associated with positive relationship perceptions. Clients perceived proactive contact, follow-up, and commercially initiated communication as indicators of supplier attentiveness, reliability, and relational commitment.
- Hyper personalization significantly contributed to strengthening relationship quality by making clients feel individually recognized rather than treated as standardized accounts.
- The findings confirmed that perceived predictive CRM capabilities positively influence customer retention behaviors across several dimensions: continuance intention, repurchase behavior, switching resistance and relationship commitment.
- Relationship commitment appeared to be the deepest and most strategically significant manifestation of retention. Clients who perceived high levels of predictive CRM engagement demonstrated stronger psychological attachment to the supplier relationship.
- The results also highlighted that customer retention in B2B industrial environments is not driven solely by technical product quality or switching costs, but also by relational experiences generated through predictive and proactive commercial engagement.
- The study demonstrated that predictive CRM contributes to transforming the supplier-client relationship into a long-term strategic partnership characterized by relational stability, and perceived commercial support.
- The integration of qualitative and quantitative findings reinforced the importance of combining technological CRM capabilities with relational marketing practices in order to generate durable retention outcomes in industrial markets.
- The exploratory factor analysis additionally revealed an important structural evolution of the conceptual model. Need anticipation and commercial proactivity, initially conceptualized as distinct dimensions in the preliminary conceptual framework, empirically converged into a unified construct reflecting clients' perceptions of

proactive supplier engagement. This emergent dimension was labeled *Proactive Relational Engagement*.

- Similarly, within the dependent variable structure, relationship commitment and continuance intention demonstrated strong empirical overlap and merged into a single relational retention dimension, labeled *Relational Persistence*.
- These findings reinforce the exploratory nature of the research design and demonstrate how the empirical phase contributed not only to construct validation, but also to the refinement and restructuring of the conceptual framework initially derived from the literature.

5.2 Study Limitations

Despite the methodological rigor and contributions of this dissertation, several limitations should be acknowledged:

- The study was conducted within a specific B2B industrial context centered around clients associated with Atlas Copco Algeria. Consequently, the findings may not be fully generalizable to all industrial sectors or geographic contexts.
- The research adopted a non-probability sampling approach, which limits the representativeness of the sample and reduces the ability to generalize the findings statistically to the broader population of B2B industrial clients.
- The study focused exclusively on client perceptions of predictive CRM capabilities rather than examining the technical performance or internal implementation quality of CRM systems themselves.
- Although the exploratory sequential design strengthened the conceptual refinement process, the quantitative phase relied on cross-sectional data collected at a single point in time. Consequently, the study captures perceived relationships between variables rather than observing how predictive CRM capabilities influence customer retention behaviors over extended periods.
- Customer retention was primarily assessed through perceptual evaluations and self-reported behavioral intentions collected through questionnaires, rather than through objective organizational indicators such as actual contract renewal rates, purchasing frequency, or longitudinal transactional data.

- Certain external variables potentially influencing customer retention, such as pricing policies, technical performance, service failures, competitive intensity, or organizational culture, were beyond the scope of this dissertation.
- Finally, the study focused specifically on industrial B2B relationships characterized by high relational complexity and long-term engagement. The findings may therefore not apply directly to B2C environments or highly transactional industries.
- An additional limitation concerns the operational constraints associated with predictive CRM implementation in industrial environments. Despite the existence of advanced CRM infrastructures within Atlas Copco Algeria, several legal, technical, and organizational restrictions limit the company's ability to establish fully connected intelligent systems with all client equipment. Consequently, predictive detection capabilities and proactive interventions cannot always be deployed systematically across the entire client portfolio.
- Furthermore, while Atlas Copco Algeria benefits from the same CRM systems and operational structure adopted across the international group, certain organizational limitations remain. Unlike some international subsidiaries that employ dedicated proactive assistance personnel whose primary role is to ensure continuous proactive client engagement, proactive relationship management in the Algerian context is integrated within broader operational responsibilities. This may limit the company's ability to maintain systematic proactive follow-up across all industrial client accounts.
- Another important limitation concerns the limited availability of prior research examining predictive CRM capabilities from the client perspective. Existing studies on predictive CRM predominantly adopt organizational or technology centered perspectives, focusing primarily on company performance, system implementation, or internal CRM effectiveness.
- Very limited research has explored how predictive CRM capabilities are perceived experientially by clients themselves, particularly within B2B industrial environments. Additionally, no clearly established measurement constructs specifically adapted to this perceptual dimension were identified in the literature.

- Consequently, the exploratory phase of this dissertation was essential for identifying, refining, and empirically structuring the dimensions of perceived predictive CRM capabilities from the client perspective.

5.3 Future Research Directions

- Building on the findings and limitations of this study, several directions for future research can be proposed:
- Future studies could examine predictive CRM capabilities across different industrial sectors in order to compare how industry characteristics influence customer retention dynamics.
- Future longitudinal research designs following the same clients over extended periods would provide stronger insight into how predictive CRM capabilities progressively influence retention behaviors and long-term relational development.
- Future research could integrate objective organizational performance indicators such as actual renewal rates, churn data, share of wallet, or customer lifetime value alongside perceptual measures.
- Additional mediating variables such as trust, satisfaction, perceived relationship quality, or customer experience could be explored to better understand the mechanisms linking predictive CRM capabilities to retention.
- Future studies may investigate moderating variables such as organizational sector, organizational size, digital maturity, relationship duration, or competitive intensity.
- Comparative studies between B2B and B2C environments could help identify whether predictive CRM capabilities operate differently depending on market structure and relational complexity.
- Since this dissertation focused primarily on the client perspective, future research could also examine predictive CRM adoption from the supplier's internal organizational perspective, including sales personnel, CRM managers, and technical service teams involved in customer relationship management activities.
- Further qualitative research could explore how industrial decision-makers emotionally and strategically interpret proactive commercial behaviors generated through predictive technologies.
- Future studies could additionally investigate the ethical implications of predictive CRM, particularly concerning data usage, customer privacy, and perceptions of excessive personalization.

- Given the exploratory nature of this dissertation and the limited availability of client-centered predictive CRM research, future studies could also focus on developing and validating standardized measurement scales specifically adapted to perceived predictive CRM capabilities in B2B industrial environments.

5.4 Recommendations

The findings of this dissertation generate several important managerial recommendations for organizations operating in B2B industrial environments.

Organizations should move beyond traditional reactive CRM approaches and progressively adopt predictive and proactive relationship management practices capable of anticipating customer needs, identifying dissatisfaction signals, and strengthening long-term client engagement.

Companies should focus not only on implementing advanced CRM technologies, but also on transforming CRM data into actionable relational intelligence capable of improving customer retention outcomes.

Commercial teams should prioritize proactive engagement strategies rather than relying exclusively on customer-initiated interactions. In industrial B2B environments characterized by long term relationships and high relational complexity, proactive communication and personalized follow up play a critical role in maintaining relationship continuity and strengthening customer commitment.

Furthermore, organizations should integrate predictive analytics with commercial and after sales operations in order to identify maintenance opportunities, churn risks, contract renewal opportunities, and customer dissatisfaction indicators before they negatively affect the relationship.

Since the findings highlighted the importance of Hyper Personalization and Proactive Relational Engagement as major drivers of customer retention, companies should invest in systems capable of supporting personalized and anticipatory customer relationship management practices.

In this perspective, this dissertation proposes the implementation of a managerial workflow framework entitled **Client Experience Quality Assistant (CEQA)**.

5.5 Proposed CEQA Workflow Framework

During the internship conducted within Atlas Copco Algeria, it was observed that despite the existence of advanced CRM infrastructures and intelligent monitoring systems, commercial teams still perform several relationship monitoring activities manually. CRM data verification, quotation tracking, customer interaction monitoring, and dissatisfaction signal identification often require continuous manual intervention.

The increasing volume of commercial activities and customer interactions may create operational saturation, reducing the ability of teams to maintain fully proactive relationship management practices consistently across all client accounts. Consequently, delayed reactions to customer dissatisfaction or operational issues may negatively influence customer retention outcomes.

Rather than recommending the creation of additional operational positions dedicated exclusively to proactive follow up, this dissertation proposes an automated retention support workflow designed to operationalize predictive CRM capabilities efficiently.

The proposed framework, entitled **Client Experience Quality Assistant (CEQA)**, represents an AI assisted automated retention workflow designed to support proactive customer relationship management through continuous monitoring, predictive analysis, and automated commercial assistance.

The CEQA framework is conceptually grounded in the empirical findings of this dissertation, particularly the importance of:

- Hyper Personalization,
- Proactive-Relational-Engagement.

as central drivers of customer retention within B2B industrial environments.

The objective of CEQA is therefore to transform these relational dimensions into operational CRM processes capable of improving proactive customer management practices.

The proposed workflow operates through six integrated phases:

1. Scheduled Activation Phase

The workflow activates automatically at predefined intervals and initializes the CRM monitoring environment by retrieving operational and customer relationship data.

2. CRM Data Collection Phase

The system gathers relevant customer information from CRM databases, including:

- quotations,
- contract status,
- customer interaction history,
- Maintenance information,
- customer satisfaction indicators,
- relationship activity signals.

3. Client Experience Quality (CEQ) Scoring Phase

The workflow evaluates customer relationship health through multiple relational dimensions, including:

- Technical Service Quality,
- Commercial Interaction Quality,
- Digital Platform Quality,
- After-Sales Responsiveness,
- Relationship Continuity Quality.

These dimensions collectively generate a dynamic Client Experience Quality (CEQ) score reflecting the overall relational condition of each client account.

4. AI-Assisted Predictive Analysis Phase

Based on the collected relational indicators, AI-assisted analysis tools generate:

- customer risk assessments,
- churn probability evaluations,
- relational stability indicators,

- personalized commercial recommendations,
- proactive communication suggestions for sales teams.

5. Automated Action Routing Phase

According to the detected relationship condition and risk level, the workflow automatically initiates appropriate retention-oriented actions, such as:

- urgent alerts for high-risk accounts,
- Proactive follow-up recommendations,
- personalized communication sequences,
- Satisfaction surveys,
- loyalty reinforcement initiatives.

6. Reporting and Relationship Monitoring Phase

Finally, all relationship evaluations and workflow activities are automatically recorded within the CRM environment. Managers receive centralized reporting dashboards summarizing:

- Portfolio health,
- High-priority accounts,
- retention risks,
- Proactive intervention opportunities.

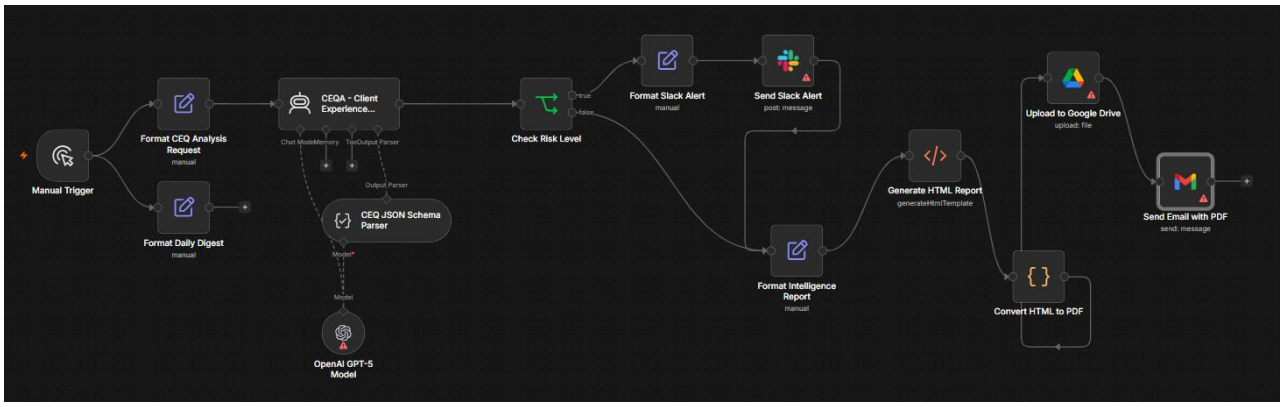
The implementation of the CEQA framework may provide several managerial benefits, including:

- earlier detection of customer dissatisfaction and churn risks,
- reduction of manual CRM monitoring efforts,
- faster and more personalized customer engagement,
- improved operational efficiency,
- stronger proactive relationship management,
- enhanced decision-making through centralized reporting,

- scalability of proactive CRM practices without significant increases in operational workload.

Overall, the CEQA framework illustrates how predictive CRM capabilities can be operationalized into concrete retention oriented managerial processes capable of strengthening long-term B2B industrial customer relationships, so, no client is ever left unmonitored and no opportunity to save a relationship is ever missed.

Figure 5. 1: CEQA WORKFLOW



Source: n8n System

CHAPTER 6 : References

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Appendices

Appendix 1 : Questionnaire

The Impact of CRM Capabilities on Customer Retention

Dear valued client,

This survey is part of an academic Master's dissertation in Marketing and Communication. It explores how the quality of commercial follow-up you receive from Atlas Copco influences your overall experience and long-term loyalty. All responses are anonymous and confidential.

The survey takes approximately 5–7 minutes. There are no right or wrong answers — only your genuine perceptions matter.

Thank you for your valuable participation.

Section A: Perceived Follow-Up

The following statements describe how you perceive Atlas Copco's commercial follow-up and interactions. Please rate each statement: 1 = Strongly Disagree → 5 = Strongly Agree

Question 2: Need Anticipation

	1 - Strongly Disagree	2 - Disagree	3 - Neutral	4 - Agree	5 - Strongly Agree
Atlas Copco identifies my business needs before I am aware of them myself.	○	○	○	○	○
Atlas Copco identifies business opportunities relevant to my company before I consider them myself.	○	○	○	○	○
Atlas Copco seems to know when my equipment will need servicing or replacement, even before I notice any issue.	○	○	○	○	○
Atlas Copco demonstrates a thorough understanding of my future business needs, not just my immediate ones.	○	○	○	○	○

Question 3: Commercial Proactivity

	1 - Strongly Disagree	2 - Disagree	3 - Neutral	4 - Agree	5 - Strongly Agree
Atlas Copco's commercial team contacts me without me having to initiate the conversation.	○	○	○	○	○

I regularly receive relevant follow-up from Atlas Copco without needing to request it.	○	○	○	○	○
When Atlas Copco contacts me, their team is always well-informed about my account and current operational situation.	○	○	○	○	○
I feel that Atlas Copco manages my account actively, rather than waiting for me to come to them.	○	○	○	○	○
Atlas Copco proposes solutions and opportunities that I had not yet thought of requesting.	○	○	○	○	○

Question 4: Hyper Personalization

	1 - Strongly Disagree	2 - Disagree	3 - Neutral	4 - Agree	5 - Strongly Agree
The proposals I receive from Atlas Copco are tailored to my specific equipment, usage history, and operational context not generic offers.	○	○	○	○	○
Atlas Copco treats me as a truly unique client every interaction reflects specific knowledge of my individual situation.	○	○	○	○	○
Atlas Copco's recommendations always reflect a precise understanding of my current equipment status and business priorities.	○	○	○	○	○
I never feel that the proposals and communications I receive from Atlas Copco are generic or mass-produced.	○	○	○	○	○

Section B : Customer Retention

The following statements describe your relationship with Atlas Copco over time. Please rate each statement: 1 = Strongly Disagree → 5 = Strongly Agree

Question 5: Continuance Intention

	1 - Strongly Disagree	2 - Disagree	3 - Neutral	4 - Agree	5 - Strongly Agree
I intend to continue doing business with Atlas Copco for my future purchases and contracts.	○	○	○	○	○
I plan to maintain my current level of engagement with Atlas Copco in the coming years.	○	○	○	○	○

Renewing my contracts and agreements with Atlas Copco is a natural and expected next step for my company.	○	○	○	○	○
My company considers Atlas Copco a long-term strategic partner rather than a short-term supplier.	○	○	○	○	○

Question 6: Repurchase Behavior

	1 - Strongly Disagree	2 - Disagree	3 - Neutral	4 - Agree	5 - Strongly Agree
I have consistently renewed my contracts or continued purchasing from Atlas Copco over the past years.	○	○	○	○	○
I regularly return to Atlas Copco for new equipment, services, or maintenance needs without considering alternatives.	○	○	○	○	○
My business volume with Atlas Copco has remained stable or grown over time.	○	○	○	○	○
Over time, I have expanded the range of products and services I purchase from Atlas Copco.	○	○	○	○	○

Question 7: Switching Resistance

	1 - Strongly Disagree	2 - Disagree	3 - Neutral	4 - Agree	5 - Strongly Agree
Even if a competitor offered a lower price, I would choose to remain a client of Atlas Copco.	○	○	○	○	○
Switching to another supplier would represent a significant risk and disruption for my business operations.	○	○	○	○	○
The quality of Atlas Copco's service and follow-up makes switching to a competitor unattractive to me.	○	○	○	○	○
I would not switch to another supplier even if they approached me with an attractive commercial offer.	○	○	○	○	○

Question 8: Relationship Commitment

	1 - Strongly Disagree	2 - Disagree	3 - Neutral	4 - Agree	5 - Strongly Agree
I consider my relationship with Atlas Copco to be a genuinely	○	○	○	○	○

important and valued business partnership.					

Section C: Recommendation

9. On a scale of 0 to 10, how likely are you to recommend Atlas Copco to a business partner or colleague in your industry?

Please select one answer.

Not likely at all ○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 Extremely likely

Section D: Respondent Profile

10. In which sector does your company operate?

Please select one answer.

- ○ Manufacturing
- ○ Energy & Mining
- ○ Construction & Civil Engineering
- ○ Food & Beverage
- ○ Other:

11. How long has your company been a client of Atlas Copco?

Please select one answer.

- ○ Less than 1 year
- ○ 1–3 years
- ○ 3–7 years
- ○ More than 7 years

12. What is your role in the commercial relationship with Atlas Copco?

Please select one answer.

- ○ Purchasing Decision Maker
- ○ Technical Manager
- ○ General Management
- ○ End User
- ○ Other:

13. How frequently does your company interact with Atlas Copco's commercial team?

Please select one answer.

- ○ Weekly
- ○ Monthly
- ○ Quarterly
- ○ Rarely

Appendix 2 : Interview Guide

INTERVIEW GUIDE — INDIVIDUAL INTERVIEWS (25-35 MIN)

Context: The qualitative phase of this study was conducted prior to the quantitative phase. The three dimensions of the independent variable; Need Anticipation, Commercial Proactivity, and Hyper-Personalization, are never named explicitly during the interview. Themes are allowed to emerge freely from respondents' own professional language and experience.

Objective: To explore how predictive CRM capabilities manifest concretely within the CTS department at Atlas Copco Algeria, and to confirm whether the three theoretically proposed dimensions are empirically real and operationally meaningful in this B2B industrial context.

Interview duration: ~25-35 minutes Number of participants: 04 Target audience: decision-makers from Atlas Copco Algeria's CTS department covering commercial, operational, technical, and business line management functions.

I. Introduction (3 min)

- Brief self-introduction and academic context reminder
- Purpose of the interview: to understand how client relationships are managed at Atlas Copco in terms of follow up, client knowledge, and interaction quality
- Confidentiality assured, no right or wrong answers
- Verbal consent to record
- Encouragement to speak freely and share concrete examples

Theme 1 — Need Anticipation

Q1. In your daily role, what place do client data and interaction histories occupy in your commercial / operational, technical decision-making?

Q2. What information or signals regarding a client do you consider most valuable for understanding their situation and managing the commercial relationship effectively?

Q3. In your activity, are there situations where your team manages to identify a need, a problem, or a commercial / technical / operational opportunity at a client before the client has expressed it?

Q4. What indicators or signals generally allow you to foresee that a client will soon need maintenance, a contract renewal, support, or a new solution?

Theme 2 — Commercial Proactivity

Q5. In your opinion, what are today the main expectations of B2B industrial clients toward a supplier like Atlas Copco, beyond product quality itself?

Q6. How do commercial teams determine the right moment to re-engage or reconnect with a client? What is this decision based on?

Q7. In your opinion, what makes a commercial intervention truly relevant and well-received in a B2B industrial relationship, as opposed to one perceived as intrusive or poorly timed?

Q8. Have you observed situations where contacting a client at the right moment, without them having requested it, had a positive impact on the commercial relationship or on their loyalty to Atlas Copco?

Theme 3 — Hyper-Personalization

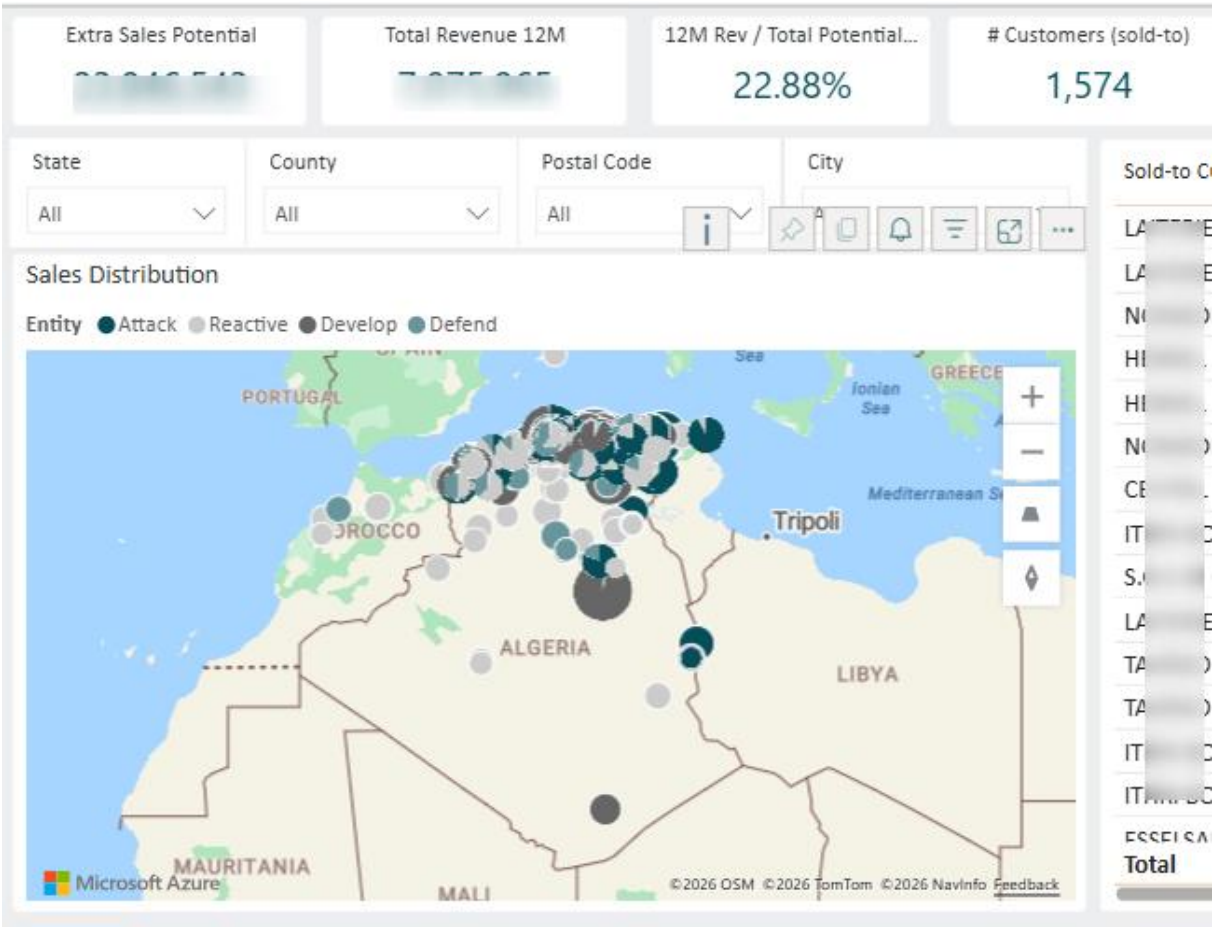
Q9. To what extent are commercial interactions, recommendations, or proposed solutions adapted to the specific situation of each account rather than to a general category of clients?

Q10. In your opinion, what makes a B2B industrial client feel genuinely understood and valued by their supplier, and not simply treated as just another account?

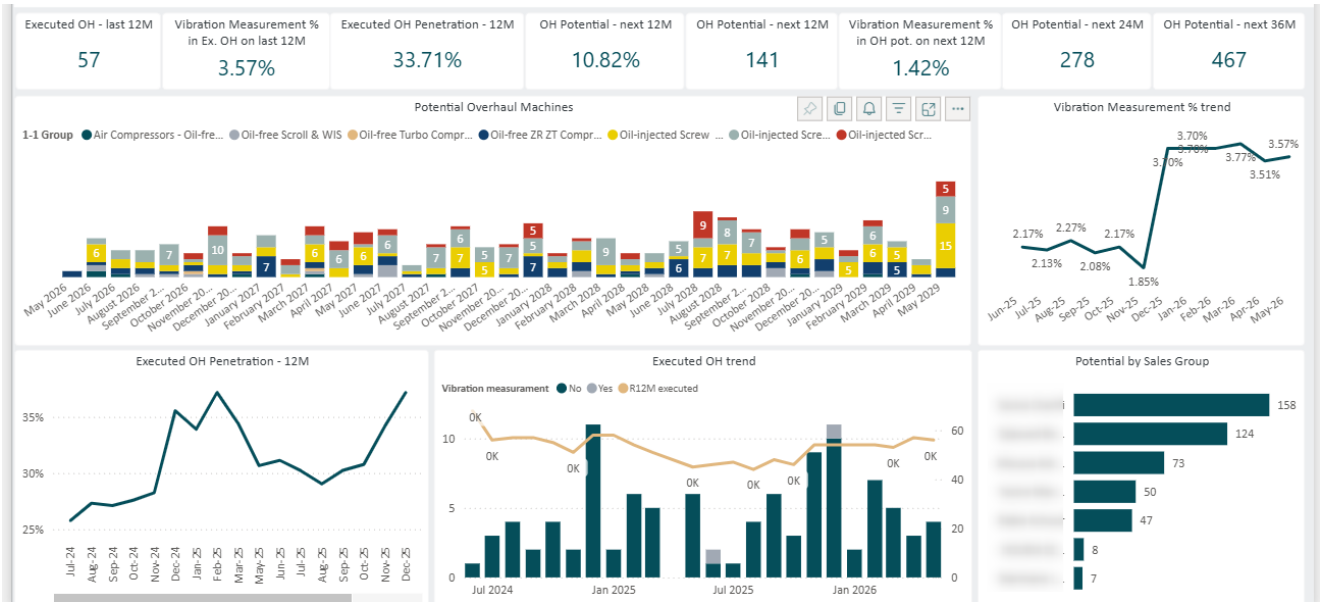
Q11. Do you have examples of clients who remained particularly loyal to Atlas Copco, or on the contrary who left, in relation to the quality of commercial follow-up they received?

Q12. If you had to summarize in one sentence what distinguishes truly effective commercial follow-up from ordinary follow-up, from a predictive CRM perspective, what would you say?

Appendix 3 : Predictive CRM Sales Opportunity Distribution Dashboard



Appendix 4: Predictive CRM-Based Installed Base Opportunity Forecast



Appendix 5: Atlas Copco Company and Audio Recordings



Appendix 6: Full Interviews (Audio Format)

Interview 01: Audio of Interview 1

Interview 02: Audio of interview 2

Interview 03: Audio of interview 3

Interview 04: Audio of interview 4

The End