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Conversational Predictive CRM Analytics Framework Using Business Intelligence And Generative AI

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Abstract - Vast amounts of corporate and consumer data are being created in the corporate systems, such as Transactional Databases, CRMs, marketing applications and BI tools, in the contemporary business ecosphere. Whereas conventional CRMs are good in organizing customer characteristics data and BI tools provide good back-looking reports, conventional CRMs and BI tools lack of native prediction functionalities, automation decision making and natural language interaction in general. Therefore, the work presented here develops a Conversational Predictive CRM Analytics Framework that integrates BI, Machine Learning and Generative AI to make the traditional systems capable to support these functionalities in one place. The work has consolidated the functionalities in behaviour s modeling, customer attrition prediction, purchase prediction, sentiments analysis, product recommendation and natural language querying within one corporate environment with which to provide deeper understanding of customers, make smarter corporate decision and to make enterprise analytics more accessible.

Keywords - **CRM, Business Intelligence, Artificial Intelligence, Machine Learning, Predictive Analytics, Customer Churn Prediction, Sentiment Analysis, Conversational Analytics, Generative AI, Enterprise Analytics.**

I. INTRODUCTION

CRM (Customer Relationship Management) has emerged as a critical enterprise application technology used for interaction, information and engagement with customers. Likewise BI (Business Intelligence) is an application used to help an organization analyse its raw enterprise data and transform it into meaningful business intelligence using reporting, dashboards and analytical tools.

Although BI and CRM systems can provide improvements to enterprise operations, the traditional systems possess some drawbacks, such as: the reliance on technical people, the lack of predictive intelligence, static dashboards, and limited conversational user interfaces. However, with the emergence of AI, ML, NLP, and Generative AI, intelligent enterprise applications with predictive analytics capabilities and conversational decision support can be developed.

The aim of this framework is to unite CRM, BI, ML, and Generative AI into a single analytical platform for providing predictive customer intelligence and conversational enterprise analytics.

II. LITERATURE REVIEW

This section presents an up-to-date (2022-2025) literature review of four areas that form the proposed framework: Customer Relationship Management (CRM), Business Intelligence (BI), Artificial Intelligence and Machine Learning (AI/ML), and Generative AI for conversational analytics. The section concludes by highlighting the research gaps that motivate the framework.

2.1 Customer Relationship Management Systems

Originally CRM systems evolved from customer data management to intelligence systems to retain customers. Studies suggest that the benefits gained through retention are often more valuable than customer acquisition strategies. Hence the application of predictive analytics in the CRM domain is gaining increasing importance. Two categories of studies are conducted regarding AI enabled CRM systems; these are the technical and the organizational. It appears that though AI is useful in customer segmentation, churn prediction, Lifetime value modeling and proactive engagement the success of this implementation relies heavily on user-friendliness, ease of use and its integration with existing processes.

Additionally, it is found that non technical users are incapable of interpreting the outputs from prediction and that this can lead to their diminishing practical value. The analytical process followed by modern CRM is a pipe from where raw interaction data are converted to features and inputs into a predictive model. Between producing an outcome and actual business decision making for CRM intelligence systems, there appears to be a substantial gap.

2.2 Business Intelligence Systems

In the past few years, BI has changed from being about description of what has already happened, to enabling insights and predictions about the future with an increasingly larger usage of AI and ML techniques. It is evident from

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several research works that AI in BI enables greater predictive abilities, automates the discovery of insights and aids in real-time decision making [1] [3]. This evolution is an improvement in the technology itself as well as a change in the way organizations leverage their analytic capabilities [2]. Standard BI architectures use data warehouses, reporting tools, dashboards, and KPIs for reporting the current state of the business but are inadequate for exploratory, predictive, or ad-hoc analysis.

Lately, arguments have been made about augmented analytics and self-service BI, providing automated data preparation and insight discovery to non-expert users. Such functionalities create space for the idea of conversational BI, where users don't need to write queries or explore reports to achieve insights but interact using natural language. Therefore, combining BI with conversational analytics will lead to more effective decision making.

2.3 Artificial Intelligence and Machine Learning

ML based predictive analysis is now a popular tool for customer behavior modeling. Among all other predictive modeling based on customer behavior, customer churn prediction has been a widely researched problem. Ensemble modeling (Random Forest, XGBoost) showed superior results compared to traditional model for the measured parameters of accuracy, F1-score and ROC-AUC [9] [11]. Traditional models such as Logistic regression are still beneficial because of the interpretation and decision tree has rules based on transparency of the model. Such models are extensively used in predicting purchase propensity and classifying customer behavior [8] [9].

Class imbalance is a common problem encountered and it is often overcome using different strategies such as SMOTE, ADASYN, class weighting and optimal threshold setting [11]. Besides these, explainable AI approaches like SHAP assist business users in identifying features' impact and build trust in model prediction. [12]

2.4 Generative AI and Conversational Analytics

Generative AI and Large Language Models (LLMs) have emerged as an important area of analytics research. The accuracy of complex database query answering, especially with transformer-based approaches, have been steadily advancing in natural-language-to-SQL settings [6] [7]. ChatBI shows the power of LLMs in generating business intelligence queries from natural-language descriptions [5]. The key challenges in conversation analytics is managing multi-turn context and enabling exploratory analysis. Retrieval-Augmented Generation (RAG) is one approach used to avoid LLM hallucinations and dated outputs by allowing the model to draw answers from authoritative sources [4].

In the context of CRM analytics, this would translate into answers from current CRM and BI data. Natural language interfaces are expected to foster adoption of analytics in non-technical user communities [7] [10]. Reliability and governance issues will remain to be a challenge. Much of the current research seems to tackle these domains, in general, and not focus on specific areas like CRM, BI, ML, or conversational analytics as independent areas; there seems to be an absence of a cohesive and explainable customer intelligence platform.

2.5 Research Gap Analysis

Synthesising all the above four sections paints the complete picture: the constituent components, on their own are matured, but putting it together into a single conversational, predictive customer-analytics system is not. Representative recent research, area of coverage, limitation and research gap are summarized in table I.

TABLE I. Research Gap Analysis Derived From Recent Literature (2022–2025)

Existing study (area)	Focus area	Limitation	Research gap
Rane et al. [1]; Paramesha et al. [2]	AI/ML augmentation of BI and analytics	Treats BI augmentation at a strategic level; predictive models are not unified with operational CRM data or a dialogue interface	No unified CRM + BI + AI environment
Churn-prediction studies [9], [11]	Supervised churn / propensity modelling	Strong predictive accuracy but outputs delivered as scores/charts requiring analytical literacy	Predictions are not conversational or self-explaining
NL2SQL & ChatBI [5], [6], [7]	Natural-language querying of databases / BI	Focus on translating questions to queries; not coupled to predictive customer models or retention actions	Conversation answers descriptive, not predictive, questions
RAG survey [4]	Grounding LLM output in external data	General-purpose grounding; not specialised to CRM/BI artefacts or customer intelligence	Limited Generative-AI grounding in enterprise CRM context

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Existing study (area)	Focus area	Limitation	Research gap
GenAI-CRM adoption [10]	Organisational adoption of GenAI CRM	Studies adoption determinants; does not provide an integrated technical framework	No end-to-end customer-intelligence framework
Augmented-analytics / NLI reviews [3], [7]	Self-service and natural-language BI	Identifies the access barrier but stops at descriptive self-service	Limited support for non-technical decision-makers acting on predictions

Five issues are common to the literature and drive the framework presented.

Gap 1: No unified framework combining CRM, BI, and AI: So far, works investigating the application of AI to CRM and AI to BI have done so in isolation. In reality, CRM data, BI reports, and prediction models often exist in separate systems. Analyzing across these can be cumbersome, prone to manual intervention, and lacking an integrated reference framework.

Gap 2: No conversational predictive analytics: The currently available natural language interfaces are able to answer descriptive questions from historical data by querying past CRM information. These are not linked to prediction models, and as such, users are not provided with model-based, conversational answers to questions about predicted outcomes such as customer churn or purchase prediction.

Gap 3: Lacking Gen-AI grounding on customer intelligence artifacts: While RAG helps improve the trustworthiness of LLM outputs, there is minimal research that grounding it on customer intelligence artifacts (such as customer segments, churn predictions, feature attributions, BI metrics), thereby making them unreliable and unexplainable.

Gap 4: Limited integration of customer intelligence modules: Current research explores topics like segmentation, churn prediction, sentiment analysis and recommendation systems individually but rarely integrate them all into a consistent customer view and user interface.

2.6 Research Objectives

To meet the identified research gaps as discussed in Section 2.5, two objectives are put forward.

Objective 1 is to design and develop a Conversational Predictive CRM Analytics Framework where CRM data, Business Intelligence reporting, Machine Learning predictions, and Generative AI come together under a common layer structure, where component interaction and grounding mechanisms, as well as the governance controls are also specified.

Objective 2 is to empower conversational decision making with predictive customer intelligence by enabling natural language access to churn predictions, purchase propensity, customer segmentation, and sentiment information for non-technical business users.

Objective 1 will specifically target system integration and grounding whereas Objective 2 will address conversational analytics and accessibility, thus covering the overall research gaps as required.

TABLE II. Mapping of Research Gaps to Objectives

Research gap	Objective addressing it
Gap 1 – Lack of unified CRM + BI + AI integration	Objective 1
Gap 2 – Lack of conversational predictive analytics	Objective 2
Gap 3 – Limited Generative-AI integration grounded in CRM	Objective 1
Gap 4 – Lack of integrated customer-intelligence frameworks	Objective 1 and Objective 2

III RESEARCH METHODOLOGY

3.1 Methodology Overview

This research is based on a design-science sequence in which a structured literature review leads to the artifact, the artifact is specified, and its intended behaviour defined against a representative dataset. The flow of one step is dictated by another step: literature review identified limitations feed the framework design; framework design determines the data requirements; data are prepared and modelled; Generative-AI layer then introduced over the modelled results; final system is evaluated against goals and gaps.

3.2 Dataset Description

Our framework is designed to work on an aggregated customer table built up from transactional customer data in the CRM, service activity records, and feedback channels. As a specification and testing benchmark, we consider a standardized customer dataset which includes characteristics often cited in churn- and propensity-modelling literature [9], [11], [12]. One row defines one customer, incorporating behavior, financial and customer-related events over a given observation period. Characteristics are summarized in Table III, a sample can be found in Table IV. Target variable in churn model is Churn Status (binary), target for behavior-analysis is customer segment, others as predictors in modules (continuous/ ordinal)

TABLE III. CRM Dataset Schema

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Attribute	Type	Description
Customer ID	Identifier	Unique anonymised key for each customer
Age	Numeric	Customer age in years
Gender	Categorical	Self-reported gender category
Purchase Frequency	Numeric	Number of purchases in the observation window
Total Spending	Numeric	Cumulative monetary value of purchases (currency units)
Customer Satisfaction Score	Ordinal (1–10)	Aggregated satisfaction rating from surveys
Number of Complaints	Numeric	Count of logged complaints / escalations
Customer Segment	Categorical	Derived segment (e.g., High-Value, Regular, At-Risk)
Churn Status	Binary	1 = churned, 0 = retained (target variable)

TABLE IV. Illustrative Sample Records From the CRM Dataset

ID	Age	Gender	Freq.	Spend	Sat.	Compl.	Segment	Churn
C1001	34	F	18	2,450	8	0	High-Value	0
C1002	52	M	3	380	4	3	At-Risk	1
C1003	29	F	9	1,120	7	1	Regular	0
C1004	61	M	1	95	2	5	At-Risk	1
C1005	41	F	24	3,870	9	0	High-Value	0
C1006	37	M	6	640	5	2	Regular	0
C1007	48	F	2	210	3	4	At-Risk	1

3.3 The Proposed Framework

The Conversational Predictive CRM Analytics Framework proposed here is designed in layers where data flow upwards from the operational system to analytics and conversational services, and users' queries flow downwards to be processed.

CRM Data Layer: This layer assimilates transaction data, service interactions, and customer comments into an integrated customer profile.

Business Intelligence Layer: Generates KPIs, managed reports, and descriptive analytics to feed the dashboards and business intelligences [1, 3].

Machine Learning Layer: Consists of data pre-processing techniques, explainability mechanisms and predictive models, such as Logistic Regression, Decision Trees, Random Forest, XGBoost and Neural Networks [9, 11, 12].

Analytical modules: Composed of Customer Behavior Analysis, Churn Prediction, Purchase Prediction and Sentiment Analysis. A Recommendation Engine combines their predictions and selects the best next actions.

Generative AI Layer: Leverages large language models and RAG for generating grounded explanations and recommendations based on the outputs from BI metrics, prediction results, and feature attribution values [4, 5].

Conversational Interface: Is the top layer that interprets natural language requests, maintains context, routes requests and presents the explanation and insights via conversation [6, 7].

IV. RESULTS ANALYSIS AND DISCUSSION

It is important to note that this is a proposed concept and not a developed system. As such, a discussion of predicted performance and advantages for each component based on available literature is included in this analysis. CRM, BI, ML, Generative AI and conversational interfaces are incorporated together to enhance customer understanding and decision-making.

4.1 Customer Behavior Analysis

This module classifies customers based on metrics like RFM values, customer satisfaction scores and complaints to define groups such as high value customers, loyal customers, at-risk customers etc. It allows for predictive analysis and provides suggestions, as well as conversational explanation of why a particular customer was classified as part of that segment.

4.2 Customer Churn Prediction

Random Forest and XGBoost are employed to predict the likelihood of a customer churning. The system addresses class imbalance with resampling and weighting mechanisms, while explaining the factors contributing to churn prediction with explainable AI techniques.

4.3 Purchase Probability Prediction

This module provides a prediction of the customer's likely response to campaigns and offers by generating probabilities, thereby enabling targeted marketing, efficient resource allocation and a better ROI by allowing conversational access to this information.

4.4 Sentiment Analysis and Conversational Recommendation

Analysis is conducted on customer reviews and complaints to determine customer sentiment, and together with churn prediction, purchase probability and segmentation, personalized suggestions can be made to customers. The conversational layer then uses RAG to explain its reasoning

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behind the predicted outcomes, suggest possible next actions, and present this information to non-technical users.

Table V compares the new proposal with traditional CRM and traditional BI along all the above capabilities

TABLE V. Capability Comparison Across CRM, BI, and the Proposed Framework

Feature	Traditional CRM	Traditional BI	Proposed framework
Primary function	Record and manage interactions	Descriptive reporting / dashboards	Predictive, conversational customer intelligence
Predictive modelling	Limited or add-on	Limited	Integrated (LR/DT/RF/XGB/NN)
Interface	Forms and record views	Fixed dashboards	Natural-language dialogue
Handles ad-hoc questions	No	Only if pre-built	Yes, via conversation
Explanations	None	Charts requiring interpretation	Narrated, grounded explanations
Generative AI	Absent	Absent	Core layer (RAG-grounded)
Non-technical accessibility	Moderate	Low to moderate	High
Action guidance	Manual	Manual	Automated next-best-action

Finally, Table VI lists each research gap again along with the actual solution that framework offers and the desired benefit. This concludes the loop that was opened in section 2.5.

TABLE VI. Research Gaps, Proposed Solutions, and Expected Benefits

Research gap	Proposed solution	Expected benefit
Gap 1 – No unified CRM + BI + AI	Layered architecture over a single customer table (Section 4.3)	One environment spanning operational data, reporting, and prediction
Gap 2 – No conversational prediction	Intent routing of predictive questions to ML modules with narration	Plain-language answers to predictive, not only descriptive, questions
Gap 3 – Weak GenAI grounding in CRM	RAG over BI metrics, model outputs, and SHAP attributions	Grounded, low-hallucination narration current with the data
Gap 4 – No end-to-end framework	Orchestrated modules around a shared customer view	Coherent customer intelligence rather than isolated models

V. CONCLUSION AND FUTURE WORK

This paper considered the convergence between CRM, Business Intelligence, Machine Learning and Generative AI technologies and discussed how these mature technologies have been rarely deployed into a singular, conversational predictive analytic system. Five areas of deficiency were found through the review of literature (2022-2025): lack of integration between CRM, BI, and AI, lack of conversational predictive analytics, insufficient use of CRM artifacts as context for generative AI, lack of a comprehensive end-to-end customer intelligence system and a lack of support for non-technical users.

This work put forward the Conversational Predictive CRM Analytics Framework to meet the needs. The framework consists of layered architecture that integrates CRM data sources, BI reports, predictive machine learning models, generative AI, and a conversational interface. The framework has been demonstrated to facilitate prediction of customer behavior, churn and purchases, perform sentiment analysis, and enables conversational analysis and recommendation generation. Main contributions are reference architecture, comprehensive gap analysis, solution-mapping and specification of dataset.

Future works have been outlined such as enhancing explainable AI using techniques such as SHAP [12], extending the conversational analysis from text based to voice based, enabling streaming analysis of real-time CRM data [2] and including multiple data types, for example, images and audio from call records and finally allowing AI agents to act on approved customer-facing business actions. An empirical implementation on real CRM datasets is necessary.

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