How Personality-Based AI Personalizes Customer Journey Mapping in CRM Systems

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Abstract

This research explores how personality artificial intelligence (AI) can be used to tailor customer journey mapping within Customer Relationship Management (CRM) systems. Traditional CRM frameworks often segment users based on demographic or behavioral data, but this study investigates the added value of integrating psychographic profiling using the Big Five (OCEAN) personality traits. With the rise of AI, there is a growing demand for hyper- personalized marketing and the need for more emotionally intelligent customer engagement strategies. To address this, a two-part artefact was developed: a rule-based CRM prototype built in Airtable and a machine learning model trained in Google Colab to classify customer journey flows based on personality scores. The study draws on real-world data, academic literature, and case evaluations to compare traditional versus personality driven CRM strategies. Results suggest that tailoring customer journey touchpoints to personality traits improves alignment between customer needs and CRM communication, offering businesses more relevant and effective customer interactions. This work contributes to the fields of AI for business and customer engagement by showcasing a practical framework for integrating personality-based AI into CRM. It highlights the potential of personality-aware systems to improve customer retention, satisfaction, and long-term engagement, while also outlining ethical considerations around psychological targeting.

1. Introduction

In today’s increasingly competitive digital landscape, businesses are under pressure to deliver highly personalized customer experiences at scale in order to maintain a competitive edge. Customer Relationship Management (CRM) systems play a crucial role in managing these experiences by organizing customer data, centralizing communication, and guiding engagement strategies throughout the customer lifecycle. An analysis on CRM technology investment, not only identifies CRMs as an important tool, but as “strategic disposition that enables them (companies) to outperform their rivals in what are otherwise fiercely competitive markets” (Coltman, 2006). Traditionally, CRM systems were used to track sales, contact history, and answer questions. These systems had the ability to store customer information such as name and contact info and were used primarily as sales management and not for customer relationships. However, with the significant evolution of artificial intelligence (AI), CRM systems have also transformed and become “a central part of most businesses and many organizations” (Grant, 2025). Today, they function as strategic tools that enable companies to manage every interaction with their clients, including the ability to automate marketing and deliver targeted messaging. Despite these advancements, many modern

CRM systems still rely on basic segmentation strategies, such as demographic data, purchase history, or website behavior. These limited approaches increasingly struggle to meet rising customer expectations. and often result in shallow, transactional experiences rather than meaningful brand engagement. To remain competitive, businesses must evolve their CRM strategies to offer truly personalized experiences, which is now possible through personality AI.

AI personality profiling uses machine learning to infer psychological traits by analyzing digital behaviors like text inputs, browsing patterns, and survey responses. It has the ability to "analyze millions of online data points to identify someone's personality, before you ever meet them" (Skloot, n.d.). These traits derived from the technology can be categorized into frameworks for segmentation, one example being the Five-Factor Model (OCEAN). This is a widely recognized framework in psychology that identifies five core dimensions of personality, consisting of: "extroversion, neuroticism, conscientiousness, agreeableness, and openness" (Feng, 2024). When personality-based AI is integrated into CRM systems, it enables businesses to go beyond simply deciding what message to send. It allows them to tailor how, when, and through which channel the message is delivered, aligning each interaction with the customer's communication preferences and emotional drivers. AI powered CRM systems are already in use by major platforms such as Salesforce, HubSpot, Microsoft Dynamics 365, and Zoho. They use AI in their systems to offer features like personalized content recommendations, lead scoring, and AI-generated communications. However, most of these systems rely on behavioral data or general predictive models rather than explicitly incorporating personality-based profiling grounded in psychological frameworks like the Five-Factor Model (OCEAN). The five-factor Model is such as commonly used framework because psychologists have identified that these 5 traits "do not correlate with each other across any population, each trait with its own causes and observable behaviors" (Skloot and D'Agostino, 2019).

While personality-based AI is gaining traction, many companies still lack clear guidance on how to integrate it meaningfully into customer journey mapping. There is a need for applied frameworks that show how personality insights can be used to tailor CRM touchpoints, such as timing, tone, and channel to enhance customer retention and acquisition. This study aims to fill that gap by exploring practical strategies for implementing personality-based AI in CRM systems, its benefits, challenges, and the ethical considerations involved. The central research question guiding this study is: How can personality-based AI be used to tailor customer journey mapping in CRM systems to improve customer retention and acquisition?

This paper is structured in a way that guides the reader through the motivation, design, implementation, and evaluation of a personality-based AI approach to CRM journey mapping. Section 2 reviews literature on CRM systems, customer journey mapping, AI in CRM systems and personality AI using the OCEAN model. Section 3 outlines the research methodology; detailing data preparation and the tools used to build and evaluate a personality-based CRM system prototype. Section 4 defines the systems architecture, explaining how CRM flows were structured using rule-based logic and machine learning. Section 5 describes the implementation of the Airtable prototype, and the Random Forest Classifier used in Google Colab. Section 6 evaluates both approaches through visual comparison and practitioner feedback. Section 7 summarizes key findings, addresses ethical considerations, and suggests directions for future research.

Figure 1: OCEAN personality traits

The core traits used in this study to personalize CRM customer journeys

2. Related Work

To frame this research, it's important to examine the existing literature on AI-powered CRM, customer journey mapping, and the use of personality traits in shaping user experiences. The literature reviewed is organized around four key themes that directly support the structure of this paper: the evolution and purpose of CRM systems, the relationship between CRM and customer journey mapping, how AI has been used to enhance personalization within CRM, and the growing application of personality-based AI to improve engagement. Each section reviews relevant studies, highlighting what has already been explored, where gaps remain, and how this research builds on or challenges previous approaches.

2.1 Purpose and Function of CRM Systems

Customer Relationship Management (CRM) systems, simply put, are software systems used "for managing all of your company's interactions with current and potential customers" (Salesforce, 2024). They are designed to improve customer relations through streamlining operations, communication, and "tracking interactions across every touchpoint for a 360- customer view" (Salesforce, 2024). CRM systems acquire data from various customer touchpoints, such as websites, phone calls, social media, direct marketing, etc. Customer data is the backbone of all CRM capabilities because it enables the system to segment customers, identify behavioral patterns, and deliver relevant, timely interactions.

Embedding detailed customer data into the system is very important, as it enables the ability for personalization, automation, and strategic decision-making. A review on the benefits and implementation of CRMs for SMEs backs up the important of this by stating "having the customer's information, CRM implementation allows the organization to focus its time and resources on its most profitable customers" (Idrus et al., 2011). Modern CRM solutions have evolved significantly from their early days, beginning as only contact databases. According to historical analysis by Databeys, CRM began in the 1950s with customer satisfaction research, then expanded to database marketing in the 1980s, developed into CRM software platforms in the 1990s, and grew further in the 2000s and 2010s with the integration of marketing automation, analytics, and social media engagement, As the tech industry continues to advance, we are already seeing CRM systems significantly improve through the use of artificial intelligence.

The functionality of CRM systems can be divided into several core types: operational, analytical, collaborative, and social (Jelonek, 2015, p.29). Operational CRMs manage day-to-day interactions such as sales, marketing, and service tasks. Analytical CRM uses data from operational systems and other sources for deeper insights and decision-making. Collaborative focuses on managing communication and interactions across multiple channels, and social CRM (s-CRM) adds a newer dimension. This incorporates two- way communication and engagement through social platforms (Jelonek, 2015, p.29). Recent studies report that CRM usage is nearly universal among medium to large businesses, with "91% of companies with 10 or more employees relying on CRM tools" (Lukic, 2025). Popular platforms like Salesforce, which serves over 150,000 companies globally, demonstrate the scale and impact of CRM today. (Lukic, 2025).

AI's ability to process data, learn, and automate decisions has turned CRM into a more dynamic, intelligent platform. Studies note that "CRM is capable of storing enormous customer data for better understanding of their customers," and that smart devices now enable "real-time access of services and products related information anytime anywhere" (Sathyavani et al., 2025). Additionally, integrating AI into CRM activities has shown measurable business benefits. "AI provides advanced automation, predictive analytics, and smarter customer insights," contributing to a 15% increase in repeat sales and customer retention (Lukic, 2025). The integration is expected to generate over $1.1 trillion in business value globally by 2021 (Chatterjee et al. (2019). CRM platforms lay the foundation for long-term engagement and customer-centric growth. As these systems continue to evolve with AI and automation, they offer businesses powerful tools to anticipate customer needs, personalize interactions, and strengthen loyalty

2.2 CRM Customer Journey Mapping

Customer Relationship Management (CRM) systems play a vital role in structuring the customer journey by enabling businesses to track interactions across every stage of engagement. The customer journey is widely understood as a process composed of a series of touchpoints that represent a specific interaction with the brand, product, or service. The customer journey shapes their "cognitive, affective, emotional, social, and physical responses to a company" (Følstad and Kvale, 2018) These touchpoints are typically grouped into three stages: pre-purchase, purchase, and post-purchase (Lemon & Verhoef, 2016). Mapping these interactions is essential for building long-term customer relationships and improving both customer satisfaction and operational efficiency. Lemon and Verhoef (2016) propose a comprehensive framework for understanding the journey by identifying four categories of touchpoints: brand-owned, partner-owned, customer-owned, and social/external/independent. They argue that "the customer might interact with each of these touch point categories in each stage of the experience," with the relative importance of each touchpoint varying depending on the product, service, or customer (p. 74). These mappings allow firms to identify pain points and opportunities for improvement.

Small and medium-sized enterprises (SMEs) also benefit from customer journey mapping (CJM). Okeke, Opara, and Onwuegbuzie (2023) define CJM as “a strategic tool used by organizations to visualize and understand the various stages and experiences that customers undergo when interacting with a business,” emphasizing its role in improving satisfaction and supporting growth. According to their study, effective journey mapping uses touchpoint analysis through technology like CRM systems and sentiment analysis tools. These systems allow SMEs to gather real-time data across communication channels and analyze patterns, enabling “data-driven decisions that enhance customer experiences” (Okeke et al., 2024) Additionally, they note that “collaboration across departments is crucial for effective. touchpoint analysis,” since marketing, sales, and customer service teams all engage with different stages of the journey (Okeke et al., 2024).

This concept is reinforced by Deshmukh (2024), who conducted a case study of Globetrot Travels to examine the impact of mapping customer touchpoints within a CRM framework. The study demonstrated that “touchpoints span various channels, both online and offline, including website visits, social media interactions, email communications, phone calls, in- person interactions, and more” (Gupta, Deshmukh and Kumar, 2024) By mapping these points into a unified CRM platform, the company improved internal communication and personalized its service. This directly influenced customer satisfaction, especially when customer service teams were trained to be more responsive and empathetic: “The findings… underscore the critical role that this touchpoint plays in influencing customer experiences and ultimately driving loyalty and retention” (Gupta, Deshmukh and Kumar, 2024) The integration of AI tools and real-time analytics further enhanced personalization by equipping representatives with deeper behavioral insights. These findings highlight that CRM-supported customer journey mapping is more than is a strategic process that helps firms to tailor experiences across touchpoints, foster engagement, and enhance loyalty. Journey mapping powered by CRM helps businesses gain a complete and structured understanding of customer needs which is a foundation for the AI-driven personalization strategies discussed in the following section.

Feature | Traditional CRM | AI Powered CRM

Customer Journey Mapping	Manual or semiautomated	Real-time, adaptive mapping
Segmentation Basis	Demographics, spending purchase history	Behavioral data, psychographics, personality
Personalization Depth	Limited	High (dynamic, tailored experiences)

Data Use	Static	Predictive and adaptive
Automation	Rule-based campaigns	AI-powered journey orchestration

Table 2.2
This table outlines the key differences between traditional CRM systems and AI-driven CRM models.

2.3 AI Driven CRM Systems

The integration of artificial intelligence into CRM systems has opened the door for a new era of data driven personalization, transforming how businesses understand and engage with customers. The capabilities of AI driven CRM systems includes, but is not limited to "data management, multi-channel integration, and tailored service offerings, each underpinning the nuanced integration of AI into CRM practices" (Khadija Khamis Alnofeli, Akter and Venkata Yanamandram, 2025). AI powered CRM systems use a combination of Natural Language Processing (NLP) and Machine Learning (ML) to analyze unstructured customer data and generate actionable insights.

A 2023 study by Łukasik-Stachowiak examined the readiness of 104 companies to integrate AI into their CRM systems by conducting a pilot survey. The findings revealed that more than half of the surveyed enterprises (51%) had already implemented AI tools in their CRM strategies, particularly more common among medium and large-sized firms. The study emphasized AI's growing role in customer engagement, noting that "the integration of AI capabilities with CRM is recognized as one of the key factors for improving the speed and efficiency of customer service" (Łukasik-Stachowiak, 2023, p. 212). However, it also pointed out that adoption is often slowed by a lack of technical knowledge and internal readiness, especially in smaller businesses. The research concluded that digital transformation, including AI-powered CRM, is no longer optional but a necessary step for maintaining competitiveness in evolving markets. AI capabilities can be used to predict buying patterns, personalize communication, and suggest next-best actions for sales or service interactions. As CRM adoption grows, AI tools are expected to play an even more central role in automating campaign planning and strategic decision-making.

Another study conducted by Sharma, Patel, and Gupta (2025), emphasizes that NLP and ML are essential in extracting value from complex customer data. NLP enables systems to interpret the emotional tone, sentiment, and intent in emails, chat transcripts, and social media posts. ML models then use these insights to segment customers, predict churn, and generate personalized recommendations. Their study reported an 85% accuracy in sentiment analysis, a 15% reduction in churn, and a 25% increase in upselling through AI-driven personalization strategies. (Sharma et al., 2023). This level of insight allowed CRM systems to adapt messaging and offers based on behavior and mood, not just demographics or transaction history. Beyond surface-level engagement, deep learning techniques have further improved CRM personalization across diverse markets. These technologies support real-time chatbot assistance, multilingual comprehension, and continuous model learning based on evolving customer preferences (Sharma et al., 2023). As businesses scale, such features enable CRM platforms to retain a human-like understanding of customer needs, but at a pace and scale only possible through automation. Despite these benefits, challenges remain. Both articles point out that implementing AI in CRM requires significant technical resources and must be done in compliance with privacy regulations such as GDPR. Smaller firms may face barriers due to the expertise and cost involved. Still, the literature agrees that when executed responsibly, AI- driven CRM systems hold immense potential for delivering tailored, high-impact customer experiences.

2.4 Research Niche

While many CRM systems use demographic or behavioral data for personalization, recent research points to a deeper layer of insight: psychographic profiling. Integrating personality- based AI into CRM workflows allows businesses to tailor communication, content, and engagement flows in ways that resonate with individual psychological tendencies, not just observable behavior. For instance, Alamsyah, Nadhila, and Izumi (2024) demonstrated that complaints shared on social media can be mapped to Big Five personality traits using AI tools like the Personality Measurement Platform (PMP). This enables companies to recognize patterns in dissatisfaction tied to certain traits and respond accordingly. Rather than treating all complaints with uniform scripts, companies could adjust tone and strategy based on how customers may respond. For example, it would be able to differ if a customer is more neurotic, conscientious, or open and companies. Companies can use this information to adjust their responses in ways that directly support more effective customer retention. Shumanov, Cooper, and Ewing (2022) extended this personalization to advertising. Their mixed method study found that consumers were more responsive to ads tailored to their inferred dominant trait. For example, neurotic individuals preferred messages that lowered risk, while extraverts responded to status and goal-oriented cues. These findings support the integration of personality modeling into CRM journeys, where outreach, messaging, and loyalty tactics can reflect the customer's motivational drivers.

Orangzab, Hussain, and Sajiid (2025) examined how Big Five traits moderate the effectiveness of online promotions. Openness, agreeableness, and extraversion increased impulse buying behavior when paired with sales or scarcity messages, while conscientiousness and neuroticism had a dampening effect (metatags generator, 2025). This kind of insight suggests that CRM flows could be segmented not just by behavior but by underlying psychographics. A broad applied sciences review (2024) also emphasized that AI-enhanced CRM requires strategic design that goes beyond simple automation. The study outlined success factors like ethical data governance, personalization through segmentation, and predictive analytics as essential to CRM maturity. This aligns with your thesis direction: the next evolution of CRM isn't just faster or more automated, but more psychologically intelligent.

Finally, Naz et al. (2025) provided technical validation that AI can reliably predict traits like extroversion using social media behavior and user-generated content. Their work illustrates how personality signals can be extracted from textual patterns, supporting the feasibility of integrating trait-based logic into CRM flows. As many know from personal experience, AI can already detect digital preferences leading to tailored advertising on social media. A study on the AI's role in marketing effectiveness sin social media ads has the AI tools at what people "like, where they comment, and their type in the search fields on their social media" and through their study found "proven to increase marketing activities' effectiveness" (Dwi Santy et al., 2021)

3. Research Methodology

This research follows a structured methodology that combines both rule-based and machine learning techniques to explore how personality AI can be integrated into CRM systems to personalize customer journey mapping. The primary goal was to assess whether tailoring journeys based on psychographic profiles provides deeper personalization and potential business value compared to traditional CRM methods.

3.1 Overall Research Methodology

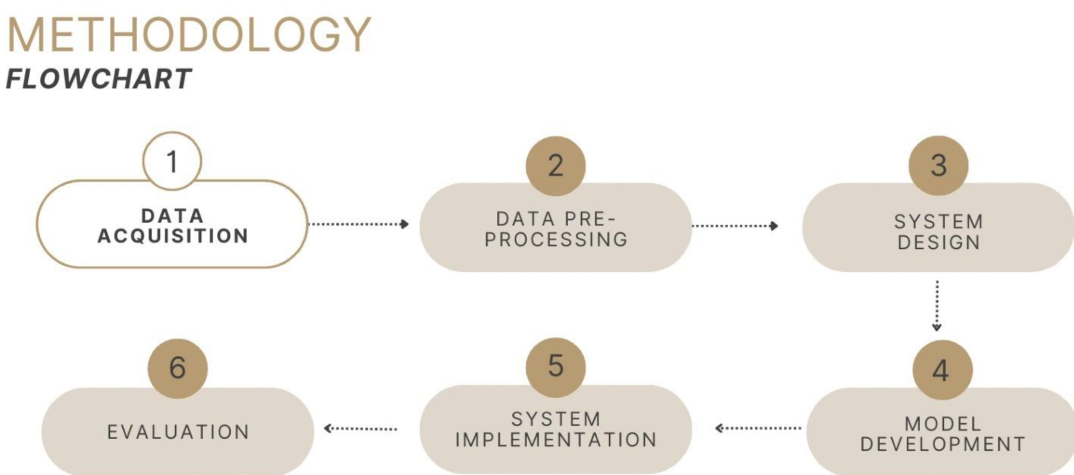

Figure 3.1: Methodology Flowchart

This diagram outlines the six main stages of the research process, from data acquisition to system evaluation.

Data Acquisition and pre-processing

The dataset used for this study was the Customer Personality Analysis dataset sourced from Kaggle, created in 2023. It contains demographic and transactional information for over 2,000 customers of an online retail platform. It includes demographic information (age, marital status, income), behavioral data (web visits, purchases), and spending data (total spending on various product categories). Although this dataset is not originally designed for personality-based AI research, it provides nearly all of the necessary behavioral, demographic, and transactional data required for simulating a CRM system. The only missing component is OCEAN personality scores, which I was able to simulate and integrate into the dataset.

I downloaded the dataset in CSV format and began the cleaning process using Microsoft Excel. To start the data cleaning and pre-processing, I removed unnecessary columns, such as transaction IDs and invoice. Then, I started creating new columns to simplify the dataset and highlight key factors. For example, I added a column titled "Total Spending" by summing the individual product category values for each customer. This helped capture overall buying behavior in a single figure, making it easier for the model to interpret. Another key step in the process was simulating personality traits using the OCEAN model (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism). I used the Excel formula "=RANDBETWEEN(20, 90)" to generate realistic scores on a 0–100 scale for each trait. These random values acted as placeholders since I didn't have access to real psychographic data. Adding them to each customer profile helped me demonstrate how personality traits could influence customer journey mapping in the CRM system.

Customer_ID	Age	Education	Marital_Status	Income	Total_Spending	NumWebPurchases	NumStorePurchases	NumWebVisitsMonth	Response	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism	Assigned Journey
5524	1957	Graduation	Single	58138	1617	8	4	7	1	76	40	59	22	65	VIP Loyalty Flow
2174	1954	Graduation	Single	46344	27	1	2	5	0	78	53	39	27	25	Introvert CRM Flow
4141	1965	Graduation	Together	71613	776	8	10	4	0	23	50	67	55	27	Extrovert CRM
6182	1984	Graduation	Together	26646	53	2	4	6	0	88	49	32	86	25	Introvert CRM Flow
5324	1981	PhD	Married	58293	422	5	6	5	0	87	85	32	81	59	Introvert CRM Flow
7446	1967	Master	Together	62513	716	6	10	6	0	22	77	61	21	43	Extrovert CRM
965	1971	Graduation	Divorced	55635	590	7	7	6	0	82	45	77	50	36	Extrovert CRM
6177	1985	PhD	Married	33454	169	4	4	8	0	50	73	85	38	59	Extrovert CRM
4855	1974	PhD	Together	30351	46	3	2	9	1	79	31	70	46	70	Extrovert CRM
5899	1950	PhD	Together	5648	49	1	0	20	0	75	22	71	70	56	Extrovert CRM
1994	1983	Graduation	Married		19	1	2	7	0	29	54	20	72	50	Introvert CRM Flow
387	1976	Basic	Married	7500	61	2	3	8	0	54	60	65	25	25	Extrovert CRM
2125	1959	Graduation	Divorced	63033	1102	3	8	2	0	74	89	32	24	62	VIP Loyalty Flow
8180	1952	Master	Divorced	59354	310	6	5	6	0	52	61	79	81	76	Extrovert CRM
2569	1987	Graduation	Married	17323	46	1	3	8	0	52	49	83	82	74	Extrovert CRM
2114	1946	PhD	Single	82800	1315	7	12	3	1	22	34	55	68	50	VIP Loyalty Flow
9736	1980	Graduation	Married	41850	96	3	3	8	0	43	20	51	23	28	Standard CRM Flow
4939	1946	Graduation	Together	37760	317	4	6	7	0	65	45	51	86	65	Standard CRM Flow
6565	1949	Master	Married	76995	1782	11	9	5	0	64	31	70	54	28	VIP Loyalty Flow
2278	1985	2n Cycle	Single	33812	133	2	3	6	0	67	29	77	79	48	Extrovert CRM
9360	1982	Graduation	Married	37040	316	4	5	8	0	36	70	23	87	72	Introvert CRM Flow
5376	1979	Graduation	Married	2447	1730	0	0	1	0	29	64	29	24	71	VIP Loyalty Flow
1993	1949	PhD	Married	58607	972	2	9	8	0	90	61	50	86	88	Innovator CRM
4047	1954	PhD	Married	65324	544	6	9	4	0	77	52	57	27	48	Innovator CRM
1409	1951	Graduation	Together	40689	444	7	5	8	0	73	63	73	60	56	Extrovert CRM
7892	1969	Graduation	Single	18589	75	2	3	7	0	90	44	34	63	45	Introvert CRM Flow
2404	1976	Graduation	Married	53359	257	5	4	7	0	76	31	86	58	68	Extrovert CRM
5255	1986	Graduation	Single		637	27	0	1	0	58	63	31	61	89	Introvert CRM Flow
9422	1989	Graduation	Married	38360	131	2	4	3	0	59	44	37	77	53	Introvert CRM Flow
1966	1965	PhD	Married	84618	1672	6	10	2	0	23	36	67	51	51	VIP Loyalty Flow
6864	1989	Master	Divorced	10979	30	3	3	5	0	43	24	49	66	32	Standard CRM Flow
3033	1963	Master	Together	38620	318	2	3	3	0	87	35	30	89	36	Introvert CRM Flow
5710	1970	Graduation	Together	40548	120	2	4	5	0	54	21	87	51	43	Extrovert CRM
7373	1952	PhD	Divorced	46610	302	4	6	6	1	39	58	43	48	31	Standard CRM Flow
8755	1946	Master	Married	68657	1196	3	9	7	0	34	27	63	48	44	VIP Loyalty Flow
10738	1951	Master	Single	49389	65	2	3	7	0	33	86	55	50	27	Standard CRM Flow
4339	1970	PhD	Married	67353	913	5	12	2	0	68	27	81	39	56	Extrovert CRM Flow
10755	1976	2n Cycle	Married	23718	81	3	2	7	0	26	77	90	45	23	Extrovert CRM
8595	1973	Graduation	Widow	42429	67	1	3	5	0	57	20	65	50	60	Extrovert CRM
2968	1943	PhD	Divorced	48948	902	7	5	6	1	31	34	54	50	39	Standard CRM Flow
8601	1980	Graduation	Married	80011	1395	8	5	4	0	86	52	27	90	59	VIP Loyalty Flow
503	1985	Master	Married	20559	53	2	3	8	0	85	66	55	36	33	Innovator CRM
8430	1957	Graduation	Together	21994	22	0	3	5	0	83	49	58	68	32	Innovator CRM
7281	1959	PhD	Single		186	1	4	2	0	73	64	20	79	78	Introvert CRM Flow
2139	1975	Master	Married	7500	31	2	3	5	0	39	24	59	20	29	Standard CRM Flow
1371	1976	Graduation	Single	79941	984	2	9	1	0	90	51	59	78	76	Innovator CRM
9909	1996	2n Cycle	Married	7500	122	3	3	9	1	30	69	82	42	85	Extrovert CRM
7286	1968	Graduation	Together	41728	55	2	2	10	0	31	70	29	26	43	Introvert CRM Flow
7244	1951	Graduation	Single		124	2	4	6	0	24	50	64	34	74	Extrovert CRM
6566	1954	PhD	Married	72550	1319	5	12	8	0	48	31	72	89	48	VIP Loyalty Flow
8614	1957	Graduation	Widow	65486	507	4	10	2	0	69	81	75	39	51	Extrovert CRM Flow
4114	1964	Master	Married	79143	1693	6	13	3	0	51	26	79	51	44	VIP Loyalty Flow
1331	1977	Graduation	Single	35790	72	2	3	7	0	73	59	35	69	28	Introvert CRM Flow
2225	1977	Graduation	Divorced	82582	1617	4	7	1	1	41	50	44	31	85	VIP Loyalty Flow
9381	1978	Graduation	Married	66373	606	4	10	3	0	65	48	85	46	80	Extrovert CRM
6260	1955	Master	Together	82384	1957	3	13	1	1	62	46	78	65	44	VIP Loyalty Flow
10383	1966	Graduation	Divorced	70287	1093	5	10	3	1	67	54	42	54	23	VIP Loyalty Flow

Image 3.1

Cleaned Dataset including the OCEAN traits and associated assigned journeys

System Design and Model Development

This project is built using a dual-system design that incorporates both rule-based logic and machine learning to personalize CRM customer journeys using psychological trait data from the OCEAN personality model. The purpose of this hybrid structure is to demonstrate the potential of AI-enhanced customer segmentation compared to traditional CRM logic, which typically relies on static demographic or behavioral rules. The rule-based system was developed in Airtable, chosen for its flexibility in creating relational databases, formula fields, and linked records within a low-code environment. Customers are assigned to journey flows using two different approaches: a traditional CRM method based on spending thresholds and a personality-based approach, based on the customers' dominant personality trait. To complement the rule-based prototype and introduce automation, a machine learning model was built in Google Colab using Python and scikit-learn. The selected algorithm was a Random Forest Classifier, chosen for its high classification accuracy and interpretability. The model was trained on the OCEAN personality data and the CRM journey flows that were previously assigned in Airtable using rule-based logic. I also built and tested a Convolutional Neural Network (CNN) to compare its performance with the Random Forest model, which will be described mrpe int he implementation phase.

3.2 Technical Methodology

The technical methodology outlines the tools, data processing steps, and model choices used to build the CRM personalization systems.

Tools and Platforms

The tools used to build the prototype included Microsoft Excel, Airtable, and Google Colab. Excel was utilized for initial data cleaning and simulating personality traits. Airtable was chosen to build the rule-based CRM prototype because of its low-code environment and support for conditional logic and relational data. Google Colab was used to implement and test machine learning models in Python. Pandas and scikit-learn were key libraries used for the Random Forest model, and tensorflow/keras for the CNN.

Data Preparation

The cleaned and prepped dataset was used for training the machine learning models. It included five OCEAN personality traits as input features and the CRM journey labels assigned in Airtable as the target variable. First, I converted the journey labels into numeric values using label encoding because machine learning algorithms require numerical input. Once the data was fully prepared, it was split into training and testing sets, with 80 percent of the data used to train the models and the remaining 20 percent reserved for evaluating their performance on new and unseen examples.

Model Selection

I selected a Random Forest Classifier because of its reliability in classification tasks and its ability to handle numeric data. It also provides clear feature importance metrics. To further test the mode, I developed a Convolutional Neural Network (CNN) to see whether a more complex, deep learning model could outperform the Random Forest. The CNN was trained using a one- hot encoded version of the CRM labels and reshaped OCEAN feature data. The CNN architecture included convolutional, pooling, dropout, and dense layers.

Evaluation Plan

One of the ways the model's performance was evaluated was through test accuracy. Line charts were used to illustrates the model’s accuracy during training and validation. The blue line represents training accuracy, which steadily increases and shows gradual progress. The orange line represents validation accuracy, which also improves over time, reaching about 73% by the final epoch.

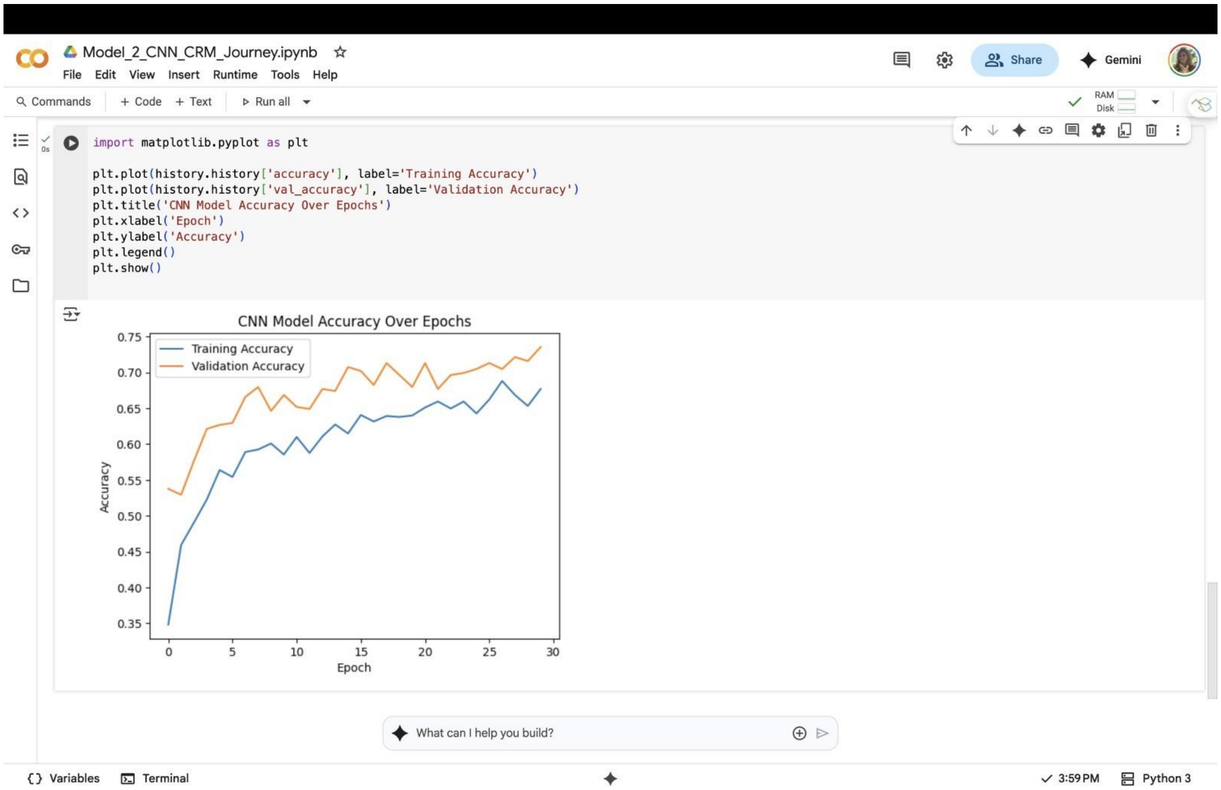

Figure 3.2

CNN model's accuracy during training and validation over 30 epochs

Metric	Random Forest	CNN
Test Accuracy	77.1%	72.1%
Training Time	~3 seconds	~60 seconds
Model Type	Classical ML	Deep Learning

Chart 3.2

Compares key metrics between the Random Forest and CNN models trained on the same dataset

The Random Forest model achieved higher test accuracy at 77.1%, compared to CNN's 72.1%. The CNN model required significantly more training time of 60 seconds compared to about 3 seconds for Random Forest. The table also highlights the difference in model types, with Random Forest representing classical machine learning and CNN utilizing deep learning.

4. Implementation

This section outlines how the prototype was built, including the coding environment, data preparation steps, rule-based logic, machine learning model development, and design decisions. It also includes pseudo-code to explain the logic behind each stage of the implementation process in a clear and accessible way.

Coding Environment and Tools

As mentioned in the previous section, the tools and models used included excel, Airtable, Google Colab, Random Forest Classifer, CNN and various libraries. To go further into the details of this:

- Excel was used to carry out the data cleaning process, including the removal of unnecessary columns and the creation of new variables such as Total Spending. It was also used to simulate OCEAN personality traits by generating randomized values between 20 and 90 for each customer profile.
- Airtable functioned as the interface for building and visualizing the rule-based CRM system. Using its formula fields and linked records, customers were assigned to journeys based on either spending thresholds or dominant personality traits. Airtable also enabled comparison between traditional and personality-based assignments through calculated fields.
- Google Colab was used to develop, train, and evaluate machine learning models. The environment allowed for the use of Python with integrated support for powerful libraries:
- pandas and scikit-learn were used for data handling and building the Random Forest model (RFC) tensorflow and keras were used to define and train the CNN, allowing for experimentation with deep learning techniques

Pseudo-Code

Data Processing:

1. Load raw CSV dataset from Kaggle

2. Remove irrelevant columns (e.g., transaction IDs)

3. Create a 'Total Spending' column by summing all product category columns

4. Generate simulated OCEAN personality traits: For each trait (O, C, E, A, N), assign a random integer between 20 and 90

5. Export cleaned and enriched dataset to use in Airtable and Colab

Airtable Code:

```
IF Total Spending > 1000 → assign to "VIP Loyalty Flow"

IF Extraversion > 60 → assign to "Extrovert CRM Flow"

IF Extraversion < 40 → assign to "Introvert CRM Flow"

IF Openness > 70 → assign to "Innovator CRM Flow"

IF NumWebVisitsMonth < 3 → assign to "Low Engagement Nurture Flow"

ELSE → assign to "Standard CRM Flow"

Create a "Match?" column:

 IF (AI Journey Assignment == Traditional CRM Assignment) → "Yes"

 ELSE → "No"
```

Random Forest Model:

1. Import libraries: pandas, scikit-learn, matplotlib

2. Load the cleaned dataset

3. Encode CRM journey labels into numerical format

4. Split dataset into training and testing sets

5; Initialize a Random Forest Classifier

6. Train the model on training data using OCEAN trait features

7. Test the model and record accuracy

8. Output predictions for evaluation

```
CNN Implementation

1. Import libraries: TensorFlow, Keras, numpy, sklearn

2. Load dataset and scale OCEAN features to 0-1

3. One-hot encode CRM journey labels

4. Reshape input data to fit CNN input layer

5. Define CNN architecture:

 a. Conv1D layer b. MaxPooling1D c. Dropout d. Flatten e.Dense output layer
with softmax

6. Compile model with appropriate loss and optimizer

7. Train the model over 30 epochs

8. Evaluate accuracy and compare with Random Forest
```

Design considerations

Choosing the design of the prototype involved various considerations. The dual-system structure of thhe Rule-Based function combined with Machine Learning model allows for direct comparison between manual logic and automated prediction. This structure reflects real- world CRM environments, where businesses (especially SMEs) often start with rule-based segmentation before adopting AI for greater personalization and scalability. Comparing the RFC and CNN models allowed for a visual representation of trade-offs between performance, interpretability, and training time. The OCEAN personality traits were simulated using randomized but constrained values to reflect realistic personality variation. Although, in an ideal scenario, these would have been taken in real time from user's digital footprint, but for the sake of time and coding knowledge, the simulation approach allowed for meaningful testing without compromising user privacy or requiring advanced data collection methods.

5. Evaluation

To assess the effectiveness, accuracy, and practical value of the personality-based CRM system developed in this project, a comprehensive evaluation was conducted through both system testing and user feedback. The evaluation focused on three core areas: (1) comparing traditional CRM flow assignments to those generated using psychographic data, (2) testing whether a machine learning model could accurately replicate the rule-based logic of the personality-based journey mapping, and (3) capturing user perceptions of the system's value, ethical concerns, and personalization potential through a structured survey. Together, these experiments provide a multi-faceted assessment of the artefact's technical functionality, alignment with business goals, and perceived ethical acceptability.

The following subsections detail each evaluation stage and its findings.

5.1 CRM Journey Assignment Comparison

Figure 5.1
Traditional CRM View showing different customer journeys: Loyalty or Standard

Traditional CRM View
This visual illustrates how customers were segmented using a traditional CRM assignment model, which relied on basic demographic and transactional rules (e.g., total spending, marital status). The bar chart shows that the majority of customers were placed in the "Standard Journey," with fewer directed to the "Loyalty Journey." The pivot table breaks down these assignments by marital status, offering a demographic snapshot.

Key Takeaway: Traditional CRM logic does not consider deeper psychographic or behavioral factors like personality traits. This results in broad segmentation that may overlook opportunities for more personalized and effective engagement. This graph serves as a baseline for comparing the impact of the AI-powered model.

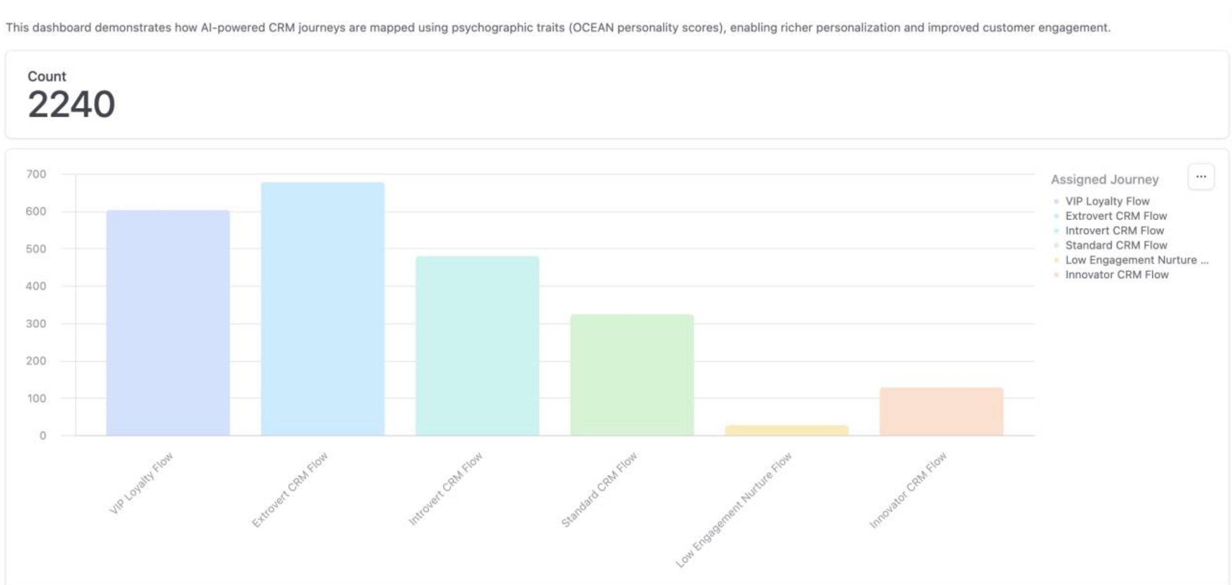

Figure 5.2

AI Based CRM View showing different customer journeys: 6 different depending on dominant OCEAN trait

Pivot table

Assigned Journey, Marital...	(Empty)	Single	Together	Married	Divorced	Widow	Total
VIP Loyalty Flow	2	130	160	218	64	29	603
Extrovert CRM Flow	1	149	175	258	75	20	678
Introvert CRM Flow	2	97	110	212	44	15	480
Standard CRM Flow	1	65	92	123	34	9	324
Low Engagement Nurt...	0	5	7	12	2	1	27
Innovator CRM Flow	1	34	36	41	13	3	128
Total	7	480	580	864	232	77	2240

Figure 5.3

Pivot table of the AI based CRM

Personality-AI View

This dashboard showcases how CRM journeys were assigned using AI-driven personality trait scores (based on the OCEAN model). Instead of relying on basic business rules, this model maps customers to flows like "Extrovert CRM Flow" or "VIP Loyalty Flow" using psychographic data. The bar chart illustrates a more diverse distribution of journeys, while the pivot table provides a demographic breakdown by marital status.

Key Takeaway: The AI-powered approach results in more nuanced segmentation across six distinct journey flows, enabling deeper personalization. Unlike the traditional model, this method reflects individual personality traits, which can lead to more tailored engagement strategies and higher customer satisfaction.

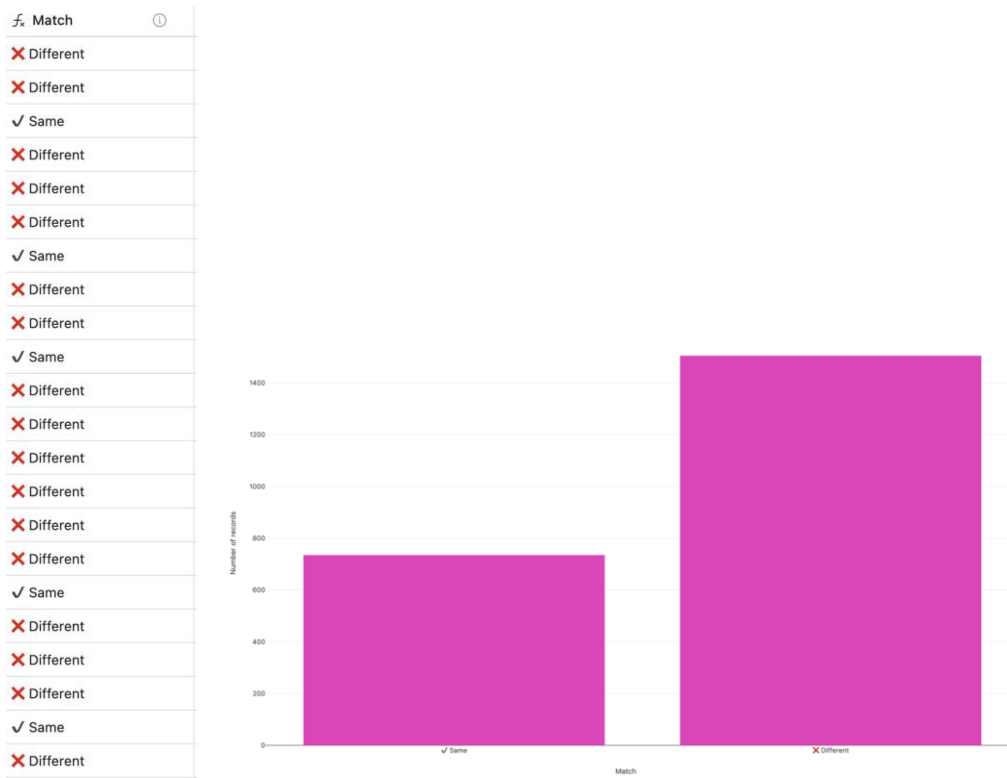

Figure 5.4
Data and Chart results from the Match formula

This experiment demonstrates that the AI-personality-based CRM approach led to more differentiated segmentation. The traditional CRM model oversimplified customer assignment by focusing on basic financial thresholds, while the personality-driven model reflected individual psychological profiles. The results suggest that personality-based flows may better align with customer engagement preferences, offering companies more meaningful, emotionally attuned CRM strategies.

Traditional vs. AI Journey Match Comparison
This bar chart compares how often the personality-based AI model assigned the same customer journey as the traditional CRM method versus a different one. The “Match” column was calculated using a formula in Airtable that flagged whether the two models aligned ("Same") or diverged (“Different") for each customer record. Out of 2,240 total records, only 735 (32.8%) received the same journey in both models, while 1,505 (67.2%) differed. This strong divergence highlights the impact of personality-based segmentation, revealing that the AI model significantly alters customer flow assignments. It suggests traditional logic may overlook critical psychographic nuances that AI can capture for deeper personalization

5.2 Psychographic Trait Variation

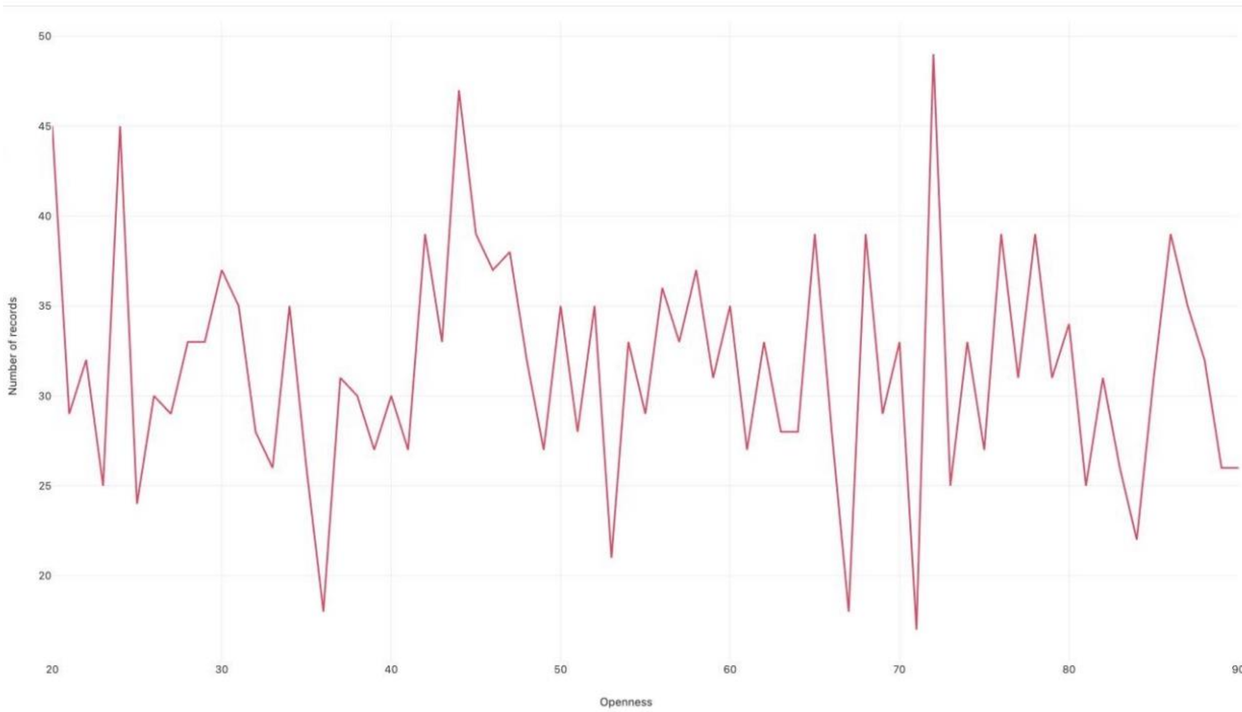

Figure 5.5

Variation in Openness Scores Across Customers

This line graph visualizes the distribution of "Openness" scores among customers, one of the 5 OCEAN personality options. The data was extracted from the CRM table, where each record had an assigned Openness value (ranging from 20–90), and the number of records was counted per score bucket.

Key Takeaway: The wide variance in Openness highlights the diversity in how customers perceive and engage with new ideas and experiences. This variation reinforces the importance of psychographic segmentation, as a one-size-fits-all CRM journey would fail to effectively engage such a diverse audience. AI-powered systems can leverage these traits to deliver tailored messaging, improving both engagement and conversion.

5.3 ML Model Accuracy in Replicating CRM Rules

After training the model, it achieved 100% test accuracy when predicting the journey labels, which confirmed that the model could successfully replicate the logic from my original Airtable rules. This showed that the CRM journeys I designed based on personality traits were consistent enough to be learned.

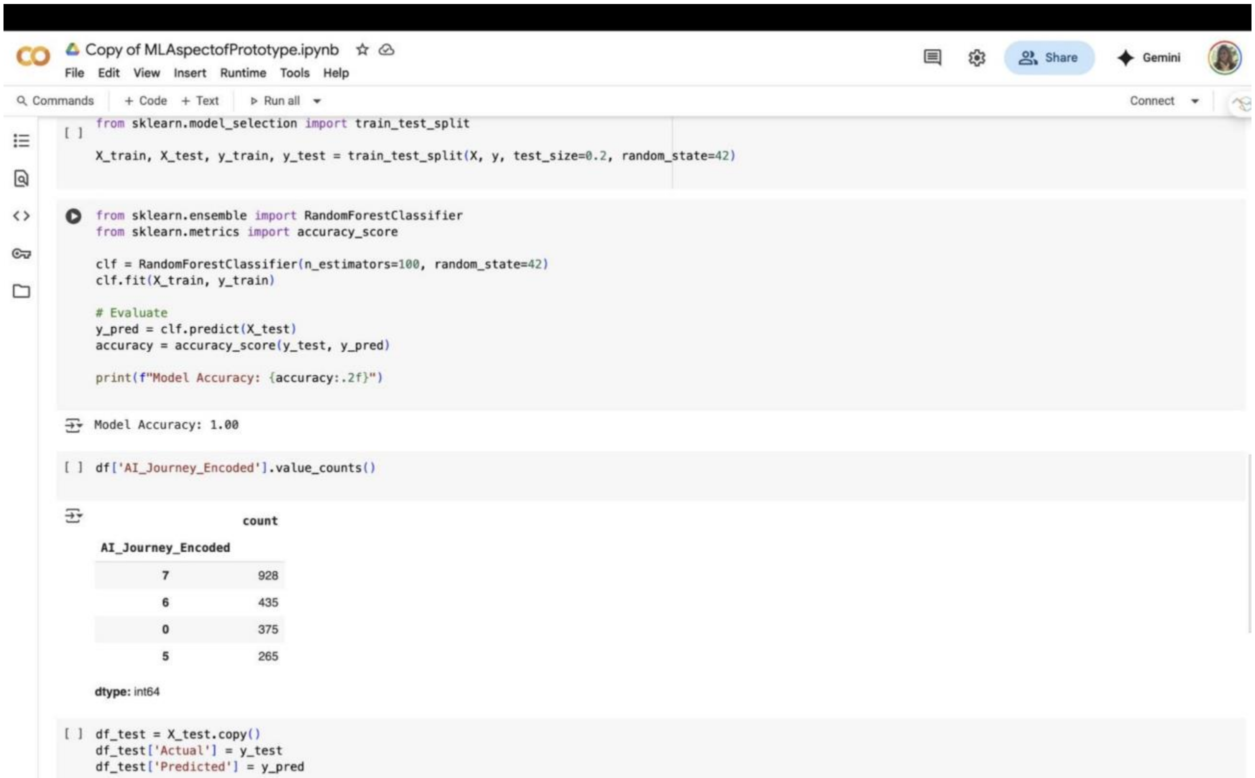

Figure 5.6

Random Forest Model Training and Evaluation in Google Colab

To simulate new customer inputs, I applied a trained model to predict CRM flows on unseen data by implementing the code "y_pred = model.predict(X_test)". The model successfully assigned journey flows (e.g., "Support-Seeking CRM Flow," "Explorer CRM Flow") based purely on the customers' OCEAN traits. This demonstrated how the model could be used in a real-world system to assign journey flows based solely on personality data automatically, and at scale. These predictions were exported into a new .csv file, showing each customer ID, their trait scores, and the machine-predicted journey.

predicted_customer_journeys

Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism	Actual	Predicted
84	35	32	58	39	7	7
21	24	48	62	21	7	7
29	53	32	53	24	7	7
45	73	61	33	66	7	7
57	67	86	68	30	7	7
68	60	84	59	54	0	0
47	76	37	43	48	7	7
52	63	76	40	60	7	7
27	44	40	72	50	6	6
45	65	81	66	50	7	7
46	60	20	71	33	6	6
26	65	28	70	26	7	7
44	84	20	21	55	7	7
24	20	23	58	70	5	5
52	35	41	63	68	7	7
51	64	86	76	75	6	6
83	31	22	53	46	7	7
65	87	20	90	88	5	5
61	40	59	77	77	6	6
44	28	21	80	57	6	6
27	38	49	20	43	7	7
52	59	84	76	72	6	6
86	31	53	58	34	7	7
57	37	46	84	62	6	6
81	23	58	31	34	7	7
58	86	55	47	23	7	7
55	28	43	53	48	7	7
78	50	82	69	24	0	0
37	85	26	41	63	5	5
72	72	72	22	28	0	0

Figure 5.7

Google Colab result of Predicted CRM Journey Assignments Based on OCEAN Personality Traits

This table shows the outcome of google collab. It presents a side-by-side comparison between the machine learning model's predicted CRM journey flow and the actual journey label based on the dominant OCEAN trait. The identical values across the "Actual" and "Predicted" columns further confirm the model's 100% accuracy score. While such perfect accuracy is rare in real-world applications, this output demonstrates that the model has fully learned the pattern from the data provided.

5.4 Survey-Based Feedback

Evaluation Methodology

To further my research, I conducted a survey using Google Forms with the intent of understanding the perceived value and concerns of AI in CRM systems from people in related fields. I received over 45 responses, focusing on responses from people in a business or tech-related field. I acquired voluntary participants through posting on LinkedIn, contacting classmates, old bosses / professors, and family and friends who this may be relevant to. The survey included 12 questions covering a range of topics such as demographics, perceived value, and ethical concerns. Both quantitative responses and qualitative were collected. Below is the link to the survey presented below:

https://forms.gle/ETfN1Fpqe6F4UF8e7

Findings

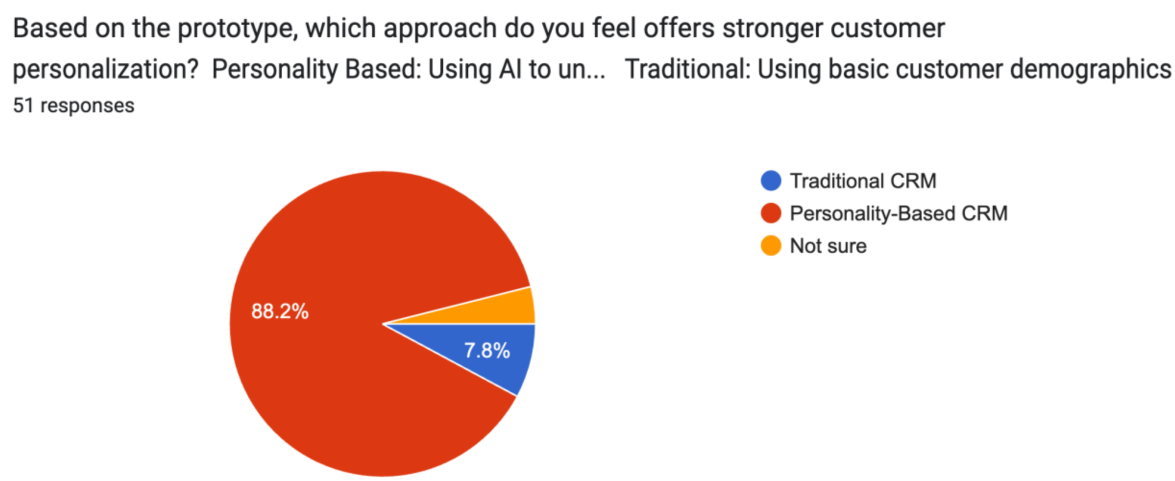

Figure 5.8

Pie chart of perceived value

A clear majority of respondents (88.2 percent) indicated that the personality-based approach offered stronger customer personalization than the traditional CRM. After this question, participants were asked to explain their choice. Many respondents highlighted how personality-based systems create stronger engagement and more meaningful customer experiences. One respondent noted that "more personalized will drive better engagement," while another explained that "customers are attracted to conversations and people that are personal." Several participants pointed out that personality profiling goes beyond static demographic data, and that "traditional CRM is far more basic and generic and doesn't use nearly as much personalization."In addition to the customer experience benefits, this also translates to the business value of Personality-based CRM. For example, one person stated that, "AI can help us identify key personality traits that will close deals faster," and another shared that "working for a large U.S. airline, we are constantly looking for an advantage on our competition, and using progressive tools has kept us #1."

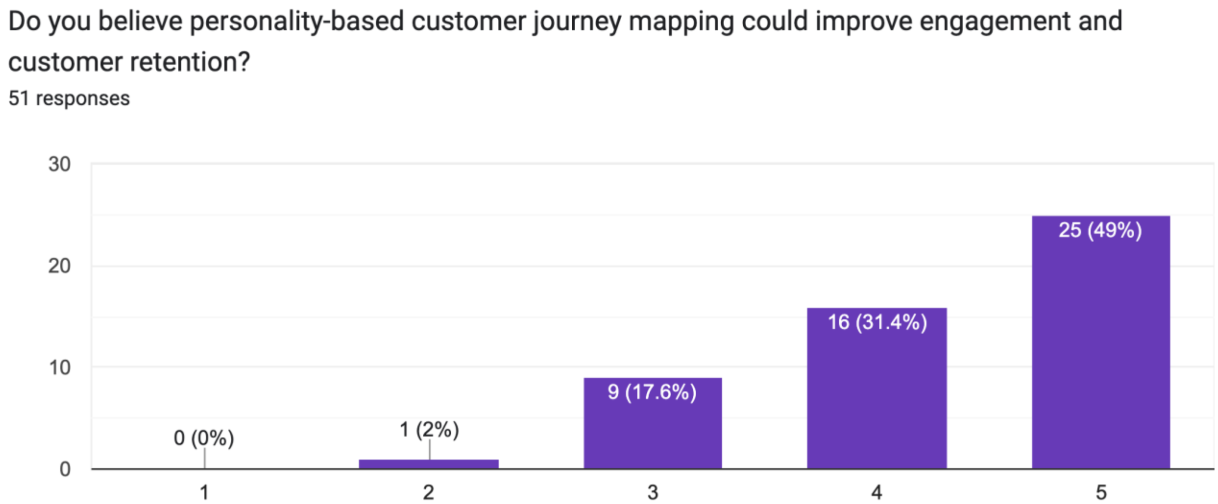

Figure 5.9
Scale of perceived value on customer engagement and retention

This question focuses on the main research question of this thesis paper: How can personality-based AI be used to tailor customer journey mapping in CRM systems to improve customer retention and acquisition?

Most respondents believe personality-based customer journey mapping can significantly improve engagement and retention. Almsot half of participants (49 percent) selected the highest rating of 5, while 30.4 percent selected 4. In total, over 80 percent of responses were positive, with very few participants expressing doubt and no one choosing the lowest rating. The key takeaway from this result is that most respondents see clear value in using personality traits to tailor customer journeys. This indicates strong confidence that personality-based CRM systems can enhance both customer satisfaction and long-term loyalty.

The follow-up question asked about the biggest advantage of personality-based AI in CRM. 35 respondents highlighted recurring themes of stronger personalization, improved engagement, time savings, and the ability to build lasting customer relationships. Many people said that tailoring experiences "creates a more personalized customer experience" and helps "create lasting relationships with customers." Others emphasized practical benefits like "lower customer acquisition costs" and "time saved as opposed to doing it the traditional way." Several also described it as a powerful tool for marketing and sales, with one participant stating that "CRMs are sales tools and psychology/personality is part of that process."

Ethics

The next set of questions focused on the ethical perception of using AI in CRM systems. This project acknowledges several important ethical considerations related to the use of personality-based AI in CRM personalization. One key concern is privacy and data protection. In this prototype, personality traits were simulated; however, in real-world applications, deriving psychographic profiles would require the collection of real behavioral data and/or psychometric assessments. This raises questions around transparency, consent, and compliance with data protection regulations such as GDPR. To mitigate these concerns, customers should be fully informed about how their data is being used and should explicitly consent to personality-based personalization. Asking questions from people in related fields about ethical perception was key to part of this research project.

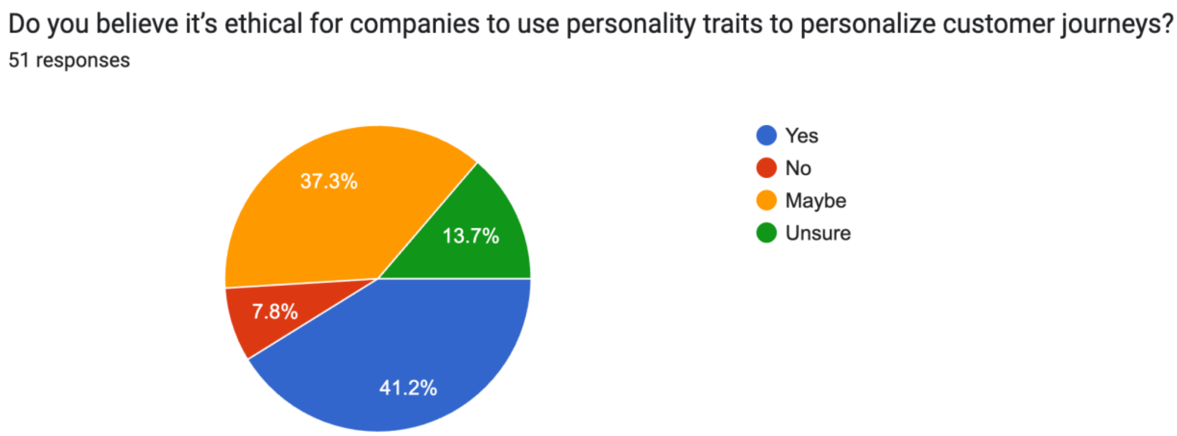

Figure 6.0
Pie chart representing ethical viewpoints

There were a mixed set of results from this question, with nearly 40 percent stating it is ethical for companies to use personality traits to personalize customer journeys, 51 percent stating unsure or maybe, and 7.8 percent stating no, it is not ethical. The follow up question to this aimed toidentify what the ethical reservations associated with these answers would be.

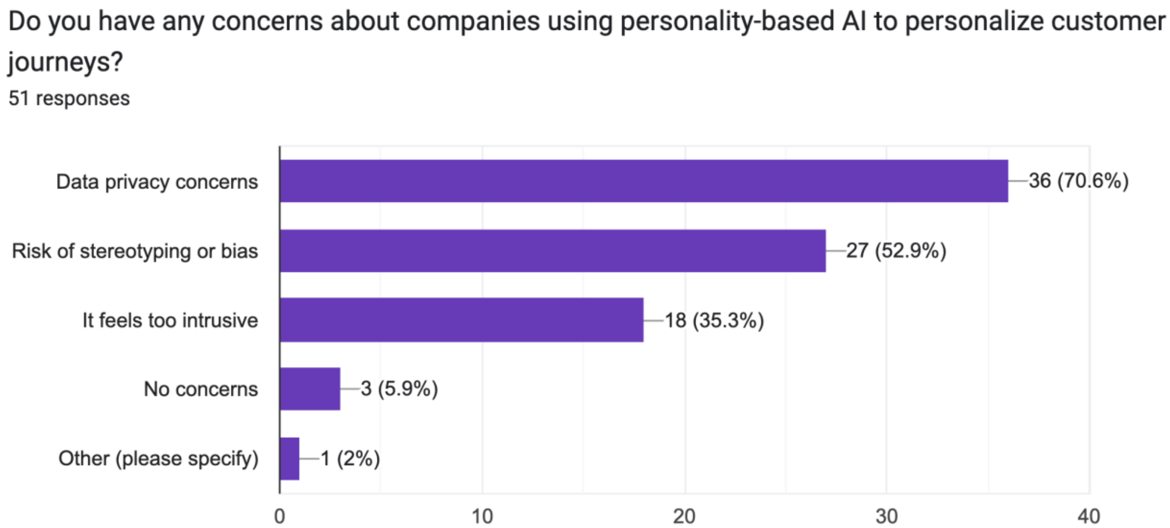

Figure 6.2
Chart representing main ethical concerns of personality-based AI usage

Predicted CRM Journey Assignments Based on OCEAN Personality Traits Most respondents (70.6 percent) stated that data privacy is their top concern, followed by the risk of stereotyping or bias (52.9 percent). Nearly one-third (35.3 percent) also felt that personality-based approaches could be too intrusive, while only 5.9 percent indicated they had no concerns.

This information is important because it shows the hesitation from professionals and why there might be a lack fo adoption. Even though earlier findings indicated strong support for its ability to improve engagement and retention, many participants still questioned whether it could be used responsibly. The high percentage of privacy and bias concerns suggests that companies will need to prioritize transparency, informed consent, and fairness in implementation. Without addressing these issues, organizations risk losing customer trust, which could undermine the very engagement and loyalty they are trying to build.

Another consideration is fairness and bias. There is a risk that personality-based personalization could reinforce stereotypes or lead to discriminatory outcomes (such as a certain personality profile receiving fewer offers or lower-quality experiences). It is essential that systems are designed to ensure inclusive and equitable treatment across all customer segments. This can be done through having diverse datasets, bias testing, etc. There are also concerns related to manipulation and autonomy. While personalization aims to enhance the customer experience, it needs to ensure that it does not exploit individual psychological vulnerabilities for commercial gain. The system should aim to provide value to the customer, not just maximize short-term business outcomes. These considerations will be explored further during the evaluation section of the project, where ethical perceptions of the prototype will be addressed through survey questions. Next, we move onto the design of the model.

4. Conclusion and Future Work

This research explored how personality-based AI can enhance customer journey mapping within CRM systems by comparing a rule-based prototype with machine learning models. The dual-system approach highlighted both the interpretability of rule-based flows and the scalability of AI-driven methods. Using OCEAN personality traits as the foundation, the prototypes demonstrated that tailoring CRM journeys to psychological profiles can offer more personalized and engaging customer experiences compared to traditional demographic-based approaches.

The evaluation revealed that while the Random Forest Classifier delivered higher accuracy than the CNN, both models confirmed the potential of personality-aware CRM personalization. The survey feedback further indicated that customers perceive personality-based personalization as valuable, though concerns about ethics and data use must be carefully addressed. Overall, the findings support the argument that integrating psychographic insights into CRM systems can strengthen long-term customer relationships and improve customer retention and acquisition.

In the future, with more time and resources, it would be beneficial to do a study while gathering real-world customer data, including digital footprints and behavioral patterns, that could provide more accurate insights compared to simulated OCEAN trait values. Ideally, having an AI model that tracks online data and determines users' personality metrics instead of simulating the OCEAN personality traits would offer more intelligent results. By incorporating real-time personality detection methods, such as sentiment analysis or natural language processing, to adjust customer journeys dynamically.

Additionally, developing an Ethical Framework would be important to continue work in this area. As we have identified previously, ethics is an important factor and data privacy is a relevant concern for many, as personality-based personalization raises privacy and fairness concerns, future research should design clear ethical guidelines and compliance measures to ensure responsible use of psychographic data.Overall, this thesis provided valuable insight into how personality-based AI can reshape CRM personalization and customer journey mapping. With the integration of AI and business being my desired area of work, this research process aided in preparing me for the next step in my career path.

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