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Master of Science International Business Management

Master's Thesis

Topic

Coupling of Sentiment Analysis and Topic Modelling to foster product adoption by understanding customer purchase intentions

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Name of AI tool	**URL**	**Type of use in the text (with selection menu)**	**Pages in the text**
Chatgpt	**https://chatgpt.com/**	Generation of ideas and/or topic suggestions	**17-21, 30-32, 43, 22**
Chatgpt	**https://chatgpt.com/**	Text generation with own editing (incl. review based on scientific sources)	**46, 49**

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Abstract

In today's rapidly evolving digital and technological landscape, understanding consumer behaviour is an essential factor for businesses to enhance product adoption and craft effective marketing strategies. Traditional market research often is the result of qualitative analysis and rely on small sample size to comprehend the motivation of customer purchase behaviour. This result is more likely to be prone to human error bias and misleading solutions. Therefore, to solve this issue this study leverages Natural Language Processing (NLP) as a powerful tool in extracting consumer behaviour and purchase intentions from a large-scale of data. Specifically, this research will focus on understanding customer purchase intentions to foster product adoption using two most important techniques of NLP i.e. Topic Modelling (TM) and Sentiment Analysis (SA). This research also outlines a comprehensive framework for value creation aiming to provide accurate data-driven insights on customer perception and behaviour to enhance decision-making, customer engagement and foster product acceptance across industries.

Keywords: customer purchase intention, customer behaviour, natural language processing, product adoption, product acceptance, sentiment analysis, topic modelling, perceived value, customer decision journey

List of Abbreviations:

Abbreviation	Full Form
CPI	Customer Purchase Intention
AI	Artificial Intelligence
NLP	Natural Language Procession
SA	Sentiment Analysis
TM	Topic Modelling

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1. Introduction

In today's modern era, understanding consumer behavioural patterns and purchase intention is the cornerstone for companies to drive their way towards a successful product. With the market becoming extremely consumer-centric, there is a significant increase in challenges for brands to not only make their product visible but also appealing for potential buyers. Making the product acceptable is the most challenging part for companies these days. ‘A strong brand name works as a sort of halo effect, a spill-over phenomenon that offers a perceived enhanced solution to the overall product’ (Dahlen et al., 2009). In the light of these difficulties, marketers are gradually turning to Natural Language Processing (NLP), which is gradually becoming a replication of human intelligence, to gain more profound comprehension of consumer behaviours throughout the customer journey, especially in the most critical phases such as consideration, purchase, and post-purchase to guide customers towards adopting a product. Traditional methods of gathering insights—through surveys, focus groups, or manual review of customer feedback—fail to capture the real-time, nuanced needs of modern consumers. Lemon and Verhoef (2016) stated that “customer journey analysis should understand and map the journey from the customer perspective and, therefore, requires customer input." Consequently, to understand this input, NLP serves as a powerful tool for bridging the gap between brands and customers by providing valuable data-driven insights at each stage of the customer decision-making process. For instance, even well-known brands like Meta, Apple, Amazon, and Netflix invest heavily in analysing customer feedback, and reviewing or collecting customer data in various forms to ensure success.

This research delves on understanding the importance of NLP in analysing CPI and their behaviour while considering a product and making purchasing decisions, with the goal of enhancing product adoption. This paper adopts a qualitative approach, incorporating two major NLP techniques, namely Sentiment Analysis (SA) and Topic Modelling (TM) to uncover valuable insights hidden patterns, trends, and correlational aspects of customers using dynamic online marketplaces and other unstructured textual data that influences decision-making. For instance, SA can access customer sentiments, and preferences, while TM can detect recurring themes in customer feedback, social media, web analytics, and transaction data, offering businesses valuable insights to make more informed decisions.

Additionally, this discusses the integration of NLP techniques with relevant theoretical models such as Customer Decision Journey (CDJ) and the PERVAL (PERceived VALue) model to offer a comprehensive framework leading towards product success. This research aims to provide a holistic understanding of

NLP's potential to analyse consumer perception and drive product success across industries by comprehending the existing literature, theoretical framework structures, and engaging in qualitative, in-depth interviews. These insights enable businesses to unlock new pathways to recognize individual customer thinking processes and behavioural patterns to create effective targeted marketing strategies and improve customer satisfaction, leading towards product acceptance by utilizing the transformational potential of NLP.

1.1. Motivation (Problem Indication & Gap spotting)

The long-term survival of business in today's dynamic and data-driven market environments is strongly dependent on understanding customer behaviour and purchase intentions for a successful product acceptance. The customer's perception of a company is highly related to the product and thus influences the buying behaviour, resulting in product success or failure. The traditional methods of market research, which rely solely on manual methods of collecting data to understand customer purchase intentions, can be limited in their ability to capture a full spectrum of customer perception and behaviour towards a product. Due to human interventions in analysing the data sets, these approaches can result in biases due to limited resources, thereby not being relevant for broader consumer groups. The increasing use of digitalization has led to increased competition, thereby imposing marketers to analyse vast quantities of unstructured data such as social media interactions, product reviews, and feedback throughout the customer journey. These data provide the marketers with an understanding of their product positioning and allow them to modify their marketing strategies accordingly.

SA and TM drive businesses to build successful products, where SA helps to understand customer opinions towards a product using product reviews, customer feedback, web analytics, or social media interactions, while TM discovers the underlying themes and topics and groups them using large-scale textual data, making it easier for marketers. Despite a significant growth of NLP in marketing, there is a distinct gap in gauging the deeper meanings and interpretations behind CPI and providing distinctive personalized experiences to achieve customer satisfaction using the integration of both techniques together.

There is limited research on the intersection of NLP techniques with theoretical models such as the Customer Decision Journey (CDJ) and PERVAL (PERceived VALue) model. The existing research escorts to partial insights, concentrating on either customer sentiments or product adoption separately.

Consequently, marketers are struggling to discover a comprehensive tool that can help in understanding “why” customers behave a certain way and “how” these emotions can be utilized to guide customers towards product adoption.

This thesis aims to address this gap by discovering the interplay of SA and TM within the CDJ and PERVAL model to develop a comprehensive framework that can be used as a tool to understand customer purchase intentions (CPI), empowering marketers and businesses to craft more personalized, targeted and effective customer engagement strategies enhancing product adoption.

1.2. Objective

The primary objective of this research is to investigate -- How NLP can be leveraged to enhance the understanding of CPI and thereby facilitate foster product adoption. This paper aims to use specific NLP techniques such as SA and TM to do in-depth research to understand the psychological and behavioural aspect of customers and its impact on decision-making processes to further nurture product acceptance. It also emphasizes the importance of NLP as a strategic tool for enhancing customer engagement, curating data-driven marketing strategies, and driving product success in competitive markets.

This study will majorly deal with two key sub-questions as follows:

- How can companies leverage the role of NLP to understand customer purchasing behaviour towards a product?

This sub-question is focused on uncovering the underlying reasons, “why” customers behave certain way, factors influencing purchase intentions based on data-sets especially during consideration and purchase phases of customer journey.

Understanding customer perception and behaviour towards a product is essential for companies to tailor their product and marketing strategies accordingly. NLP offers a vast number of tools and techniques to delve into intricacies of customer purchasing intent. NLP driven SA can gauge customer sentiments such as emotions, opinions towards a product by analysing vast amounts of textual data from customer feedback, reviews, web analytics and social media interactions to uncover implicit sentiments such as tone, context, language, and pain points to identify the trends and patterns which can provide a deeper understanding into customer preferences. On the other hand, the TM can play a role in grouping these textual data and extracting their underlying patterns. Overall, leveraging NLP, makes it easier to empower business to make data-driven decisions and enhance customer satisfaction.

- How can companies leverage NLP techniques to guide customers in decision-making and enhance product adoption?

This sub-question will explore “how” companies can guide the customers towards product adoption following various methods by utilizing the results obtained in first sub-question. It will particularly deal with consideration, purchase, post-purchase phases.

In today’s competitive world guiding customers in decision-making is a critical objective for companies to enhance product acceptance. NLP is changing the face value of dealing and understanding nature of problems. This part of the research will focus on practical applications, by leveraging NLP, companies can analyse customer data to tailored product suggestion, create real-world applications like chatbots and virtual assistants, handle dynamic pricing for providing a personalized experience to foster product adoption.

Overall, this paper’s major aim is to exhibit NLP’s exceptional capacity to create a change in modern marketing and customer engagement strategies. NLP can serve as an influential and transformative tool for marketers to better understand, engage, and convert their potential customers throughout the customer journey.

1.3. Structure of thesis

This thesis is structured into seven key chapters as follows.

Chapter 1: Introduction

The first chapter introduces the budding importance of understanding CPI in today’s new age data-driven environment. It outlines the motivation of this study, including identifying the problem and research gap, and defining the main research objectives. This section also delves into setting a clear objective for this research, integrating NLP techniques in marketing.

Chapter 2: Literature Review

The second chapter consists of four major sections which deals with a comprehensive review of existing literature on Customer Purchase Intentions (CPI), product adoption, AI, and the latest trends in NLP and marketing. Furthermore, a literature review on NLP is discussed and has two sub-sections which consists of SA and TM. This chapter acts as a connecting dot to provide a solid foundation for this research.

Chapter 3: Theoretical Framework / Conceptual Model

In this chapter, the theoretical models, CDJ and PERVAL models that underpins this research are introduced extensively discussed in relation to their applications and relevance in understanding CPI and CB using SA and TM. This chapter provides a foundation and acts as a building base for the integration of NLP techniques into these models to analyse customer perceptions and guide customer decision-making process. It also includes case studies on practical applications across industries to enhance product adoption using NLP-driven personalized marketing strategies and recommendations.

Chapter 4: Research Methodology

This chapter provides a detailed research design, emphasizing on the NLP techniques and their applications and contribution to the theoretical frameworks. Additionally, it describes a structural methodology of combining SA and TM. It also describes the data collection and data analysis processes, explaining from where and how the insights are derived.

Chapter 5: Findings and Analysis

In this chapter, the study presents the findings and analysis from the qualitative interviews, to ideally illustrate how NLP techniques have been used to extract information and data to understand CPI. This chapter broadly divided into phases where first phase discusses customer journey throughout the process of research, second phase value creation to enhance the CPI using NLP and the final phase consists of result analysis where leveraging NLP to enhance customer decision-making and purchase intentions and product adoption are two main parts.

Chapter 6: Discussion and Reflection

This chapter is a reflection of the findings of this research where the implications for both academic research and practical application are discussed. It evaluates the extensive use of NLP in marketing, it also highlights the limitations and benefits of the entire research including the potential areas for future research.

Chapter 7: Conclusion

This is the final chapter that summarizes the entire research and its key contributions. It concludes how NLP can be used as a powerful tool to understand CPI, guide product adoption and discusses the practical approaches for marketers.

This structured approach forms a coherent flow, from the initial problem statement to the practical applications of the findings. Each chapter is built as an addition to the previous one to harness better understanding of NLP driven decision-making and brand-consumer connection.

2. Literature Review

The literature review discusses the domain related to the research study. It ponders upon extensive literature review on the major areas of this research such as CPI, product adoption, SA, and TM.

2.1. Customer Purchase Intentions (CPI) / Customer Behaviour

Purchase intention is the preference of consumer to buy the product or service which has become a central focus of marketing research over the years due to the changing landscape. In another words, purchase intention has another aspect that the consumer will purchase a product after evaluation (Younus, Rasheed and Zia, 2015). Psychographic factors, including lifestyle, personality traits, and attitudes, help to gain a profound understanding of consumer decision-making (Jothimani et al., 2023). Knowledge about the product by the consumer plays an integral role during product purchase decision (Jayachandran, Hewett, and Kaufman, 2004). It is a conclusion that higher the perceived value resulting higher the intention of purchase (Younus, Rasheed and Zia, 2015). The user's intention is considered a determinant of a user's behaviour hence the actual behaviour can also be measured by user's intention. However, to fully understand the user's actual behaviour, it becomes very important to firstly focus on the user's intention (Eid, 2011). Since its appearance in marketing research, purchase intention has been the subject of great attention in the academic environments. Customer behavioural intentions are considered as signals of actual purchasing choice, thus are desirable to be monitored (Rehmani and Khan, 2011). Consumer decision journey maps are commonly conceptualized as dynamic processes and structured based on previously developed process models (Farah et al., 2019).

The study of consumers' actions as they choose whether to buy a certain good that satisfies their wants is known as CPI. It is a study that analyses consumer behaviour and their perceptions towards buying and utilizing a particular product. For marketers it is essential to determine CPI in terms of what customer's purchase, why they purchase it, when they purchase it, how frequently they purchase it, and many other factors (Biswas & Patra, 2023). Predicting purchase intention is an extremely complex process for marketers which is associated with many factors such as customer decision making, such as consumer attitude and perceived value, social influence, perceived risk and trust, brand loyalty, customer satisfaction, and including the balance of cost (Cozer, 2018, Jothimani et al., 2023).

With the convenience of technology and the improvement of buying efficiency CPI always acts as a dependent variable which can improve consumer satisfaction, enhance purchasing desire, and promote re-purchase (Yin & Qui, 2021). Study suggests the intentions of the consumer behaviour is an indicator of the extent to which people are willingness to pay or consider and the need of a specific product (García et al., 2020).

2.2. Product Acceptance/Adoption

Product adoption is considered as a process where customers decide to purchase a product and begin to continuously use it. It is a step-by-step process to make users comfortable with a new product. Technological advancement can lead to high level of market uncertainty, technology uncertainty and competitive volatility. This high level of uncertainty adds to the difficulty of determining the timing of product introduction. Both firms' (innovator) and consumers' (adopter) points of view are pivotal in investigating the factors that enhance innovation adoption. Omitting one actor's viewpoint will lead to potential misspecification and misinterpretation of empirical conditions (Frambach et al., 1998). Exploration of enhancing and excelling product adoption of a service-oriented technology is an imperative research agenda (Ostrom et al., 2010). The adoption of a product is highly dependent on consumer's intent towards it. An organization can attempt to create a brand, but it is customers who will determine whether a brand comes alive or not (Timacheff and Rand, 2001). A brand is a business strategy to persuade customers to choose to consume their product over its competitors and it is a meaningful symbol that customers choose to consume because they relate to it (Williams, 2000).

Adoption and acceptance of a product within consumers strongly depend on customer values, beliefs and perception, rather than the product functionality. Customers firmly relate to the feelings, fantasies and fun factors involved in the actual experience of the product (Emilien et al., 2017). Product branding, packaging and positioning can also contribute a lot towards the product acceptance process (Jansberg et al., 2018). These factors have started to play a crucial role in the entire product adoption journey of customers. In the recent years more studies are being done on product adoption after the adaptation of social media platforms which plays a significant role in moulding customer intentions and enhance product adoption (Marong et al., 2020). In today's digital age functional and tangible aspect of the product is valued more, as customers can get a clear picture of the product through various mediums (Cozer, 2018, Cao & Mokhtarian, 2007).

Product acceptance is challenging yet an extremely pivotal component for marketers and business, this depends on multiple ingredients such as social influences, consumer individual characteristics, marketing efforts and product attributes – compatibility, complexity, tribality, observability and unprecedented relative advantages over other products. The combination of these elements strongly defines the acceptance of a product by consumers in the market (Venkatesh et al., 2003).

2.3. Artificial Intelligence

AI is a vast and ongoing technological evolution with far-reaching consequences. The world is undergoing a profound transformation following the advent of AI. Human intelligence, such as thought, deep learning, adaptation, engagement, and sensory understanding are the assisting mechanisms which are emulated by the computational technologies of AI (Tran et al., 2019). Firms rely on AI to gain a competitive edge through digitalization (Jang et al., 2021). With the increasing technological advancement AI can process information faster, makes better decisions in compared to humans (Samara et al., 2020). Companies use AI to create a large volume of digital information, referred to as big data by gathering customer activities data from multiple sources such as chatbots, location-based advertisements, social media, e-mails, and websites (Yang, Henthorne and George, 2019).

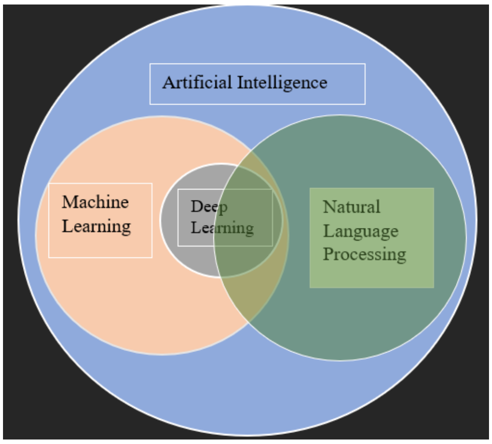

Figure 1: Venn Diagram Representation of Artificial Intelligence (Chen & Baxter, 2022)

AI is an expansive domain within computer science, with the objective of developing machines capable of executing tasks that traditionally necessitate human intelligence. These tasks encompass areas like visual perception, speech recognition, decision-making, and language translation (Haleem et al., 2022). Machine Learning (ML) is a subfield of Artificial Intelligence, involves training algorithms to learn from data, enabling them to make predictions without explicitly programming various outcomes (Sarker, 2021). Deep Learning (DL) is a branch of Machine Learning that obtains promising result object detection, semantic segmentation, edge detection and number of other domains by automating the extraction of high-level features via hierarchical feature learning mechanism wherein the upper layer of features are generated on the previous set of layer/layers (Ganaie et al., 2022). Natural Language Processing (NLP) is a subset of AI that has recently gained attention for representing and analysing human language computationally. It is further classified into two parts Natural Language Understanding (linguistics) and Natural Language Generation (NLG) (Khurana et al., 2022).

2.3.1. Natural Language Processing (NLP)

Natural language processing (NLP) is a specific field within the domain of Artificial Intelligence (AI) that sets out to provide the ability to comprehend and analyse human language. In recent years, NLP has seen substantial progress, mostly driven by the incorporation of machine learning and deep learning methodologies (Sun et al., 2019; Ricketts, 2023). NLP utilizes computational linguistics, statistical analysis, and machine learning techniques to enable computers to interpret the meaning, intention, and sentiment of textual input (Sharma et al., 2023). NLP has been increasingly employed in analysing data sources, including unstructured input from customer satisfaction surveys and electronic medical records (EMR) notes. Academic studies have demonstrated the ability of NLP to understand the fundamental ideas and analyze the content of large unstructured data (Vishwakarma et al., 2023). Furthermore, NLP has the capacity to significantly reducel the time and costs affiliated with analytical processes.

NLP strives to achieve dominance in human-to-machine interaction as to a point where conversing with machine is as seamless as human conversations. It thrives to process unstructured data, and converting it into a machine understandable language. According to International Data Corporation (IDC) latest prediction, the volume of data analysed by cognitive systems will significantly impact the industries worldwide by 2025 (Dale, 2017). It will further considerably a boon for industries such as robotics, healthcare, finance, connected vehicles, retail, e-commerce, smart home, education, automotive, manufacturing and many more. With the rise of its use, NLP has become an aid and gained predominant support in customer service and understanding customer behaviour by using “chatbots” or virtual assistant”. Conversational systems, Text Analytics, Machine translation are broadly considered as three major categories of NLP for industrial applications (Kalyanathaya et al., 2019). The adaptation of NLP models with continuous evaluation and improvements can uncover commonalities, refine the essential information, predict outcomes thereby helping industries to understand and meet customer needs (Just, 2023).

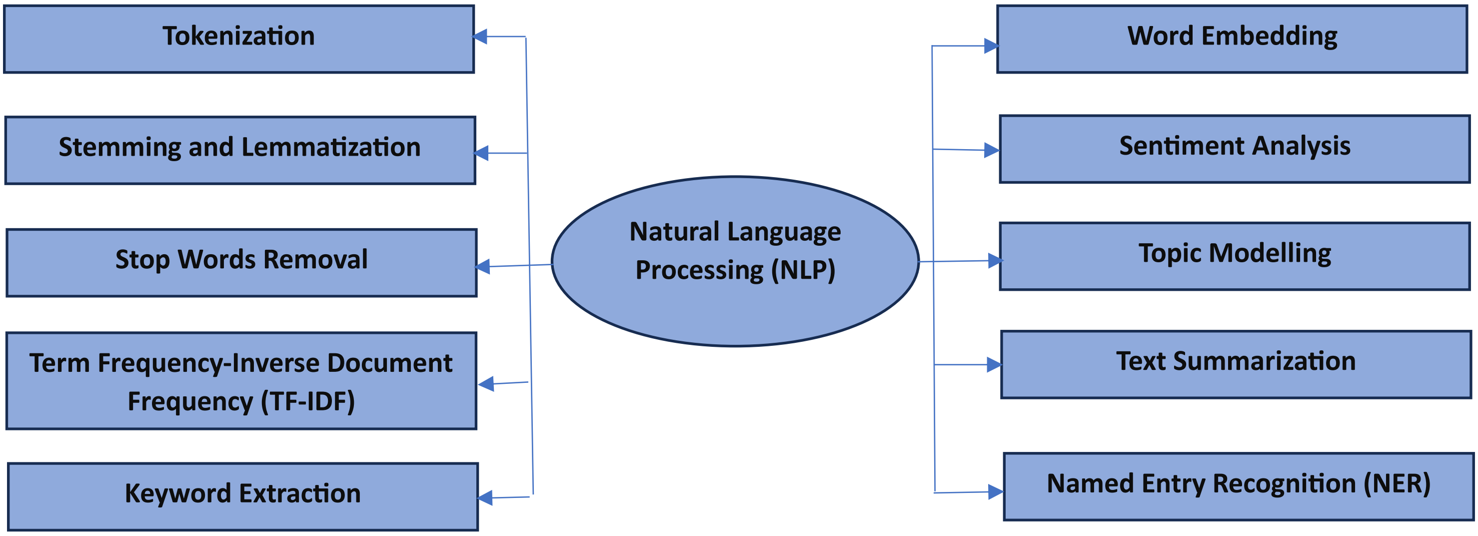

Figure 2: Techniques of Natural Language Processing (NLP) (Anjum & Yadav, 2024)

NLP's one of the core techniques in text categorization and classification which is used to analyse predefined categories to textual data as per its content. The advent of machine learning algorithms is unmeasured throughout this process to classify text into discrete classes or labels, which is essential for many applications such as spam detection, subject classification and intent recognition (Perumalsamy et al., 2022). To preprocess and standardize the text for subsequent analysis techniques such as tokenization, stemming, and lemmatization are implied. Term Frequency-Inverse Document Frequency (TF-IDF) is widely adopted to convert textual data into numerical forms which can be understood by machine learning algorithms. Keyword Extraction is an advancement of NLP which uses TF-IDF method to balance term frequency by identifying and reducing the impact of common words from the text data efficiently. Stop Word Removal is a preprocessing step in NLP which targets to focus on text classification and information retrieval by concentrating on important terms (Eloundou et al., 2023, Jurafsky & Martin, 2020). Named Entity Recognition (NER) technique accelerate the data retrieval efficiently and uphold the decision-making throughout underwriting and claim management (Perumalsamy et al., 2022). Word Embeddings captures contextual and semantic information thereby enhancing NLP performance (Mikolov et al., 2013).

2.3.1.1. Sentiment Analysis (SA)

SA is a technique of NLP, also known as opinion mining is one of the most active fields of text classification and mining which helps organizations to examine and extracts consumer emotions, opinions, attitudes, etc. towards the product. With the increasing internet media such as e-commerce, and social media customer's perception is changing with each day, as a result, user's emotional, behavioural analysis to identify the trends using textual data has become an important aspect of marketing industry (Tubishat et al.,2018, Kwon et al.,2021). SA lays a strong foundation for a sentiment dictionary, which consists of customer's emotional parity, reflecting the degree of positive, negative, or neutral sentiment of each word. These dictionaries play a critical role in accurately quantifying emotions, as they interpret the sentiment conveyed in textual data in a structured format. The factuality of SA strongly depends on the quality and comprehensiveness of these sentiment dictionary. Customer opinions and sentiments is changing in the span of a moment with the abundance of information available on web these days. It has become extremely important for organizations to collect and analyse the opinions of multiple costumers rather than the opinion from one single person (Liu, 2012). Over the years marketing and advertising industry has experienced a significant progress and advancement in the areas of neuroscience, AI, which is transforming the consumer perceptions and experience to ten folds. With respect to these changes the focus on opinion mining, SA, and emotional understanding of customer preferences to predict the CPI and acquire customers using smart and contextual marketing is at a significant rise (Nunez et al., 2020).

With the surge in digital age, SA has evolved beyond just traditional text-based methods. Multimodal approach enables the businesses to gain a holistic understanding of sentiments by analysing diversified sources of information, such as video, audio, and images. Multimodal SA is a data-driven technique that integrates multiple data streams to access and analyse customers' emotional states. The application of deep neural networks in this approach surpasses conventional SA which solely relies on textual data; by incorporating visual analysis it targets to infer latent emotions of users based on the emotion word tag (Hu et al., 2018; Jim et al., 2024). This comprehensive approach enables organizations to synthesize information in a full spectrum of human emotions using diversified contexts, including verbal reviews, vlogs, human-machine interactions, tone of voice, facial expressions; however, a primary challenge is to analyse and interpret such varied features across different forms of communication utilizing advanced mythologies, such as deep learning (Bansal et al., 2022; Hartmann & Netzer, 2023).

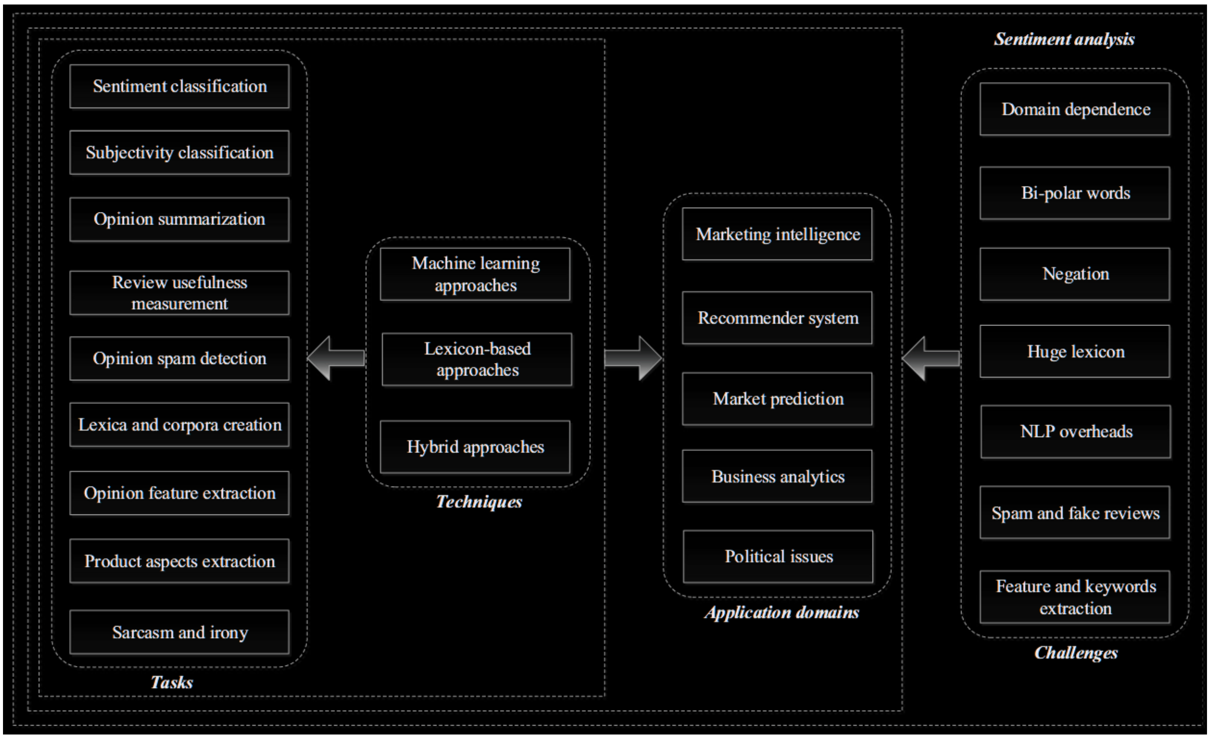

Figure 3: Main tasks, techniques, application domains, and challenges in SA research (Chen, Xie, 2020)

Organizations must subjectively classify the customers based on based on their opinions and sentiments using the gathered textual data or hidden documents, however; subjectivity classification is more complicated as compared to sentiment classification. Furthermore, spam detection and review usefulness measurement in SA is equally important as it helps in identifying the original feedback in compared to the fake reviews used to promote a product while the sarcasm and irony detection targets to identify emotions and expressions including sarcasm and irony data. In addition to it accumulating these opinions, sentiments, habits or emotions lexica and corpora creation uses a series of directory named WordNet to understand the positive, negative, or neutral sentiments of customers towards a product by extracting the synonyms or antonyms of an individual word. N-grams and parts-of-speech tags allows the recognition of word combination or phrases and grammatical structure of sentences which allows the businesses to take on board, the customer's overall sentiments and emotions (Guerrero et al., 2015; Li et al., 2019; Liang et al., 2018; Li et al., 2017; Bharadwaj, 2023). Thus, the sentiments of customers must be extracted and explored from various different sources to gain a diversified understanding of customer. With the rapid evolution of technology and social media or cookies becoming the centre of opinion collection, it is still a monetary challenge to gather data from various domains and train the model as per the organization need (Babu and Kanaga, 2021, Liu et al., 2016, Wu et al., 2016; Moslmi et al., 2017).

2.3.1.2. Topic Modelling (TM)

Topic modelling (TM) is one of the most important branches of NLP that helps in information retrieval by discovering hidden meanings and themes to understand overall trend of words co-occurrence in large collection of data sets or corpus. It introduces a semantic meaning into the vocabulary and group words into "topics" by identifying patterns within the data sets allowing organizations to understand customers' thought process and insights for a certain product that influence their purchasing behaviour. This process is done by selecting a corpus and using the modelling tool to group a cluster of similar words together (Graham et al., 2012; Lin & He, 2009; Ban & Kim, 2019). This allows the businesses to extract and identify similar patterns across various documents and categorize them to relevant documents within a large number of datasets thereby streamlining the process resulting in organizing, classifying, collaborating, retrieving information and reducing the time spent finding related information (Zhou et al., 2019; Uys et al., 2008). TM dramatically reduces the problem such as finetuning the textual data into coherent groups, thus, it is considered as a reduction tool (Hartmann & Netzer, 2023).

The most widely used methods are Latent Dirichlet Allocation (LDA), Latent Semantic Analysis (LSA), and Non-negative Matrix Factorization (NMF). LDA is most widely utilized method of TM, which has demonstrated its efficiency across various applications, including information retrieval and document classification. This is fundamentally based on assumptions that documents are as equable as mixtures of topics, and each topic is a composition of words thereby providing full generative models and handling long-length documents (Farkhod et al., 2021; Blei et al., 2003). Additionally, in LSA there is no document level models, each word in a document is modelled as a sample of mixture model. LSA is considered to work at a term-document matrix and can be used in information retrieval, recommendation systems, or, educational technologies (Landauer, 2006, Lee et al., 2010).

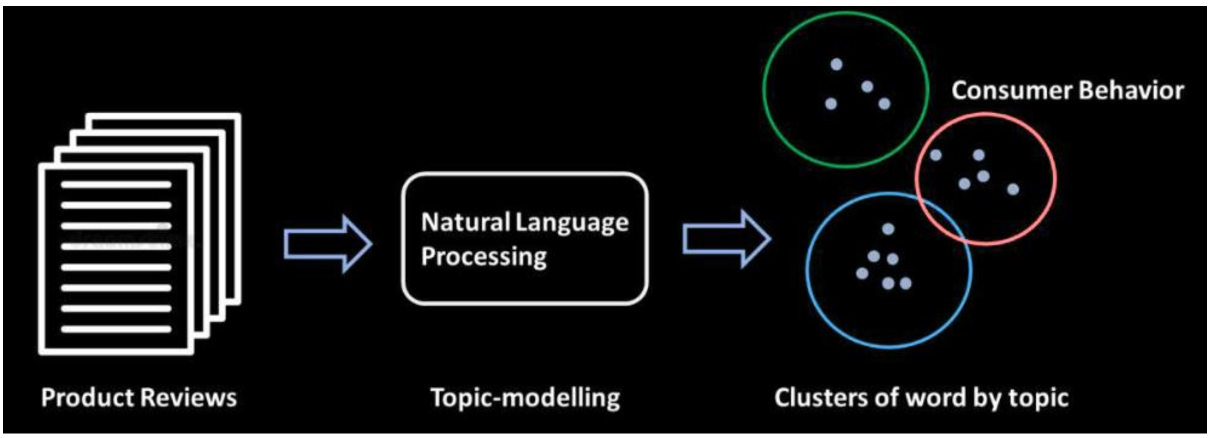

Figure 4: Extraction of consumer behaviour using TM (Netsiri & Lhotáková, 2023)

TM can be utilized to extract meaningful insights within the unstructured data-sets on consumer behavioural patterns and perceptions towards a product by automatically identifying similar word patterns. With the surge in technological enhancement, by automating the analysis of customer feedback on specific features of the product, leveraging detection of patterns such as word frequency, proximity of words, thereby clustering the feedbacks depending on themes and highlighting the most frequent occurrences, TM has seamlessly made it easier for marketers. TM thus has significantly reduced the processing time while handling large data-sets (Vaid et al., 2023; Netsiri & Lhotáková, 2023).

2.4. State-of-the-Art Trends in NLP and Marketing

With the wave of digitalization technology is transforming the traditional marketing practices towards a more data-driven modern approach by enhancing an organization's ability to analyse and interpret textual data. Over the years the learning models of NLP has been improved so as to guide marketers to better understand customer behaviour or perception towards a product, personalize interactions, and optimize marketing strategies based on consumer purchasing intentions.

NLP in marketing is revolutionizing industry standards on how businesses gain insights into CPI. NLP algorithms are being integrated in advanced analytics tools and trained extensively by businesses, using textual data from various sources to capture precise identification of trends and consumer sentiments. For instance, the latest SA and TM models achieves state-of-the-art performance as they are now trained to interpret even more complicated emotional expressions and provide a detailed visualization of customer sentiments while identifying the themes and topics aids marketers to curate as per consumer needs and interests (Cambria & White, 2014, Zhou et al., 2017).

As per Google stated in developer's website "a recommendation system helps users find compelling content in a large corpus". SA and TM models are proficient in providing personalized product suggestions and content with the help of social media listening, thereby ensuring targeted marketing and enhanced conversion rates due to increased user engagement. For instance, around 60% of watch time on YouTube comes from recommendations and around 40% of apps downloaded on Google play comes from recommendations (Google, n.d.; Wanjale et al., 2023). Furthermore, the chatbots and virtual assistants play a key role in interacting with users in real-time in customer service industry. These bots can handle inqueries or advice customers with personalized product recommendations based on their purchasing needs thereby improving customer satisfaction and fostering positive brand image (Adamopoulou, & Moussiades, 2020; Gnewuch et al., 2017).

NLP enriches the content generation and optimization processes with the use of SA and TM advancements. For example, the latest automated content generation technologies such as OpenAI, Gemini provide high-quality relevant content with the use of prompts. This technology reduces the time, resources and efforts needed by marketers for content creation, however; still provides high-caliber content related to marketing copy, product descriptions or articles (Brown et al., 2020). Moreover, SA and TM are instrumental for Search Engine Optimization (SEO) processes as well which are used for refining keyword strategies and understanding user intent or perception. These tools assist marketers to enhance the product visibility and ranking (Särkiö, 2019).

Marketers in today's modern world use SA and TM extensively to aid customer purchase decisions and drive them towards product adoption.

3. Theoretical framework & Conceptual Model

3.1. Overview of Theoretical Models in Customer Purchasing Behaviour

In today's rapidly evolving technological landscape driven by product and process innovation, the need for organizations to stay competitive and up-to-date with the current trends is also increasing. This has led to an increasing demand for a comprehensive framework and developing cutting-edge products that can guide organizations in identifying and leveraging the attributes that create the most value for their customer is the utmost priority. The fast-paced change in technology has also led to an increased intricacy of consumer behaviour, thereby posing challenges for the businesses in identifying and understanding the factors influencing customer decisions, satisfactions, and loyalty. The vital prerequisite for effectively addressing these challenges there is a crucial requirement of a comprehensive theoretical framework or conceptual model that can direct organizations in comprehending, recognizing and enhancing the factors that influence customer perceptions and behaviours. Understanding these conceptual models can guide the organizations a step closer towards their target customers which in turn will provide a significantly higher quality Return of Investment (ROI).

This paper presents a unique and comprehensive approach to identify and influence CPI by the integration of two key theories and models which are Customer Decision Journey (CDJ) model and the PERVAL (PERceived VALue) model. These two models are integrated with NLP specifically the two techniques – SA and TM to understand the customer behaviour. Each component plays a vital role in addressing the complexities of new world customer interactions. The main aim of this is paper is to integrate these models with NLP techniques to create a unified and dynamic framework that provides more profound knowledge on customer decision-making processes and value perception.

In this framework, CDJ model functions as a fundamental element, which provides a systematic and structured roadmap that delineates the several different stages of customer journey while making a purchase decision. With a thorough understanding of these phases – starting from initial consideration stage to post-purchase stage, businesses can interact and engage with customers and curate effective marketing strategies for their customers. This helps the organizations to understand the ever-evolving customer demands and expectations.

PERVAL model complements the CDJ model, which delves with the complex and diversified perceived value of customers. PERVAL model provides an in-depth awareness and understanding of factors by deconstructing the notion of value in various different dimensions, such as functional, emotional, social, and epistemic value which influences customer satisfaction and loyalty. The incorporation of the PERVAL model into the framework enables the businesses to not only pinpoint the essential characteristics but also to customize their products and services so as to resonate far more profoundly with their intended customer base.

This framework is even more enhanced with addition of analytical capability by NLP which plays a role of powerful tool by facilitating the processing and interpretation of extensive amount of unstructured data, such as, such as customer feedback, product reviews, web analytics, transaction data and social media interactions. NLP augments this framework by providing valuable insights into consumer behaviours and attitudes by revealing hidden patterns, sentiments, and themes within a specified dataset. The strategies guided by CDJ and PERVAL models can be enhanced and optimized as per these insights, thereby guaranteeing that organizations can effectively customize their responses as per customer needs and preferences in real-time.

This paper depicts the robust and integrated framework created by the collective use of CDJ model, PERVAL model, and NLP which not only investigate but also decodes the complicated processes that governs customer decision-making and value perception. In today’s ever-changing market landscape this strategy provides businesses with a dynamic toolkit that enables them to more adequately comprehend, anticipate and shape customer behaviour.

3.2. PERVAL Model:

Perceived Value of a product is directly proportional to individual customer perceived benefits and cost. Product perceived value is determined by a consumer based on long-term cost impact and benefits of the product for a consumer (Morar, 2013). In contemporary era of marketing and evolving consumer behaviour, user empathy has become extremely predominant for businesses aiming to improve customer satisfaction, nurture loyalty and gain an edge over competitors. Netsiri & Lhotáková (2023) states in his research that "Consumer perceived value refers to consumers' overall assessment of the utility of a product based on their perceptions". Sweeney and Soutar (2001) proposed a widely adopted framework for evaluating customer perceived value which is said as **PERVAL model**. This multi-dimensional conceptual model provides a comprehensive approach in understanding customer perceptions towards a product which is conceptualized based on five dimensions: **functional value, economic value, emotional value, Epistemic value, social value** (Pires et al., 2024). As the consumer behaviour evolves, particularly the digital commerce, PERVAL model remains relevant including these dimensions which gives a robust understanding of customer perceived value (CPV) of a product (Zolkepli et al., 2020). Micu et al. (2019) believes "the perceived value (PV) framework is consumers' perceptual gap between what they pay (price and sacrifice) and what they get (quality, benefits and utility). A positive gap promotes repurchase intention, and a negative gap impedes purchase intention".

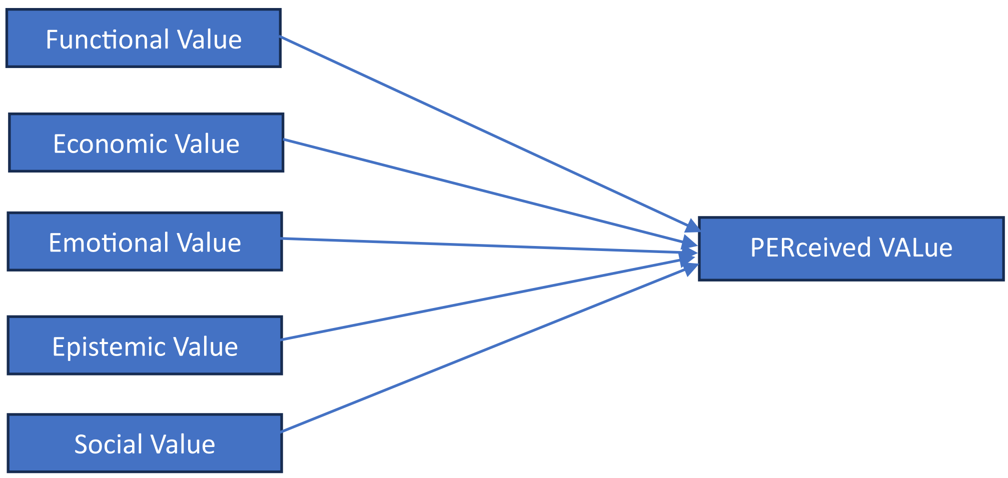

Figure 5: Dimensions of the PERVAL Model (based on Netsiri & Lhotáková, 2023)

Functional Value:

Sweeney and Soutar (2001) states that "Functional value pertains to the utilitarian benefits of a product or service, including its quality, performance, and price fairness". Functional value defines the usefulness and expected performance of a product and is a critical determinant where product performance is directly related to customer satisfaction (Boksberger & Melsen, 2011). Functional value plays a crucial role in various industries such as technology, automotive, health care sectors as these industries are strongly reliant on quality and pragmatic utility of product (Chiu et al., 2009). Consumers analyse the functional value of a product strongly before moving to decision-making, hence this value of a product drives a strong CPI rate (Zolkepli & Tan, 2020).

Economic Value:

Sweeney and Soutar (2001) states that economic value emphasizes on the perceived economic benefit of a product or service, focusing on the cost-benefit ratio from the consumer's perspective. As per the recent studies the value for money is an integral part of purchase intentions, especially when customers are becoming more aware and the markets are turning to be price-sensitive. This dimension relates to the consumers' prospective of whether the price paid for a product is substantiated by the benefits received (Chiu et al., 2009). Research investigations suggests that the price fairness and transparency are moulding consumer perceptions of economic value, thereby exerting a substantial influence on their ultimate purchase decisions (Xia et al., 2004).

Emotional Value:

Sweeney and Soutar (2001) in their research states that "Emotional value is derived from the affective responses a product elicits, such as pleasure, excitement, or comfort". This dimension of PERVAL model has garnered exponential relevance as customers not only seek for functional benefits but also emotional gratification derived from their purchases. This value focuses on feelings of customers (Boksberger & Melsen, 2011). For instance, as per studies this dimension is a mediating factor between perceived quality and customer satisfaction in industries such as hospitality and service management, while it is more pronounced in the domains such as tourism, entertainment, and luxury goods as customers find a sense of feelings and emotions attached (Manthiou et al., 2018). As per research emotional value can act as a key differentiator for businesses in the market and have a profound impact on customer satisfaction, brand attachment, and long-term loyalty leading towards product adoption (Pham, 2013, Schmitt et al., 2009).

Epistemic Value:

Sweeney and Soutar (2001) states that "epistemic value refers to the value derived from novelty, curiosity, or the desire for knowledge and exploration". This dimension explores the product uniqueness and the ability to provide new experiences, thereby satisfying consumer curiosity and elevating the customer engagement and adoption (Morar, 2013). Research suggests that epistemic value significantly drives customers' willingness to try new products in dynamic markets, thereby enhancing the impact of product adoption of interesting cutting-edge technologies or luxury goods (Zhang et al., 2021)

Social Value:

Sweeney and Soutar (2001) states that “Social value refers to the consumer's perception of how a product enhances their social standing or contributes to their self-image”. The increasing dynamic culture of social media, use of internet and brand communities have transformed the aspect of social value. Customers strongly engage with brands that safeguard their social status; this plays a crucial role in influencing purchase intentions (Netsiri & Lhotáková, 2023). This value potently refers to the customer’s cognitive framework on acceptability at an individual level and relations with social environment, thereby leading towards purchase decisions and adoption of product (Morar, 2013).

In conclusion, customer behaviour and perceived value strongly revolves around these five dimensions of PERVAL model which can provide accurate insights on customers’ intentions and perceptions towards a product. This paper will use PERVAL model as one of the conceptual frameworks to identify CPI and understand the guidance process towards product adoption with the help of SA and TM.

3.3. Customer Decision Journey (CDJ) Model:

The concept “customer decision journey” was initially introduced with the aim to describe a dynamic consumer decision-making process emphasizing the role of digital channels, as the customers became more unpredictable and fragmented (Court et al., 2009a). Subsequently, Edelman et al. (2023) refined the model, emphasising a shift of customers towards an iterative, non-liner journey. In this advanced CDJ model, the post-purchase phase like promotion and loyalty played an influencing product adoption and shaping customer perceptions and decisions of potential customers through various channels such as reviews, social media and traditional word-of-mouth communications.

The Customer Decision Journey (CDJ) model is gaining significant importance in understanding decision-making processes of consumers. This interest primarily is derived from the embracing importance of adopting a consumer-centric philosophy in the service and marketing fields to enhance customer experience (Santos and Goncalvez, 2021). Consumer experience includes various aspects that focuses on the consumer's cognitive, behavioural, social, emotional, and sensorial response to the offerings of a firm during the entire consumer decision journey (Lemon and Verhoef, 2016). Over the last decade, many marketing researchers and practitioners have shifted away from the traditional AIDA (Awareness, Interest, Desire, Action) model of thinking, toward a model that emphasizes the importance of consumer relationships (Budiawan, Satria, and Simanjuntak, 2017). When consumers are satisfied with the total value that a firm has provided throughout these four stages, they are likely to skip steps one and two of their buying journeys the next time a buying need arises and go directly to step three—making a purchase (Vollrath and Villegas, 2021).

The CDJ is conceptualized into four-step orientation where customers act in a specific way during the entire customer decision journey. Initially consumers compile a list of brands they intend to take into account. This list is then refined as per their evaluation based on their needs and then they either add or remove the brands from their consideration list. On the third stage customers proceed to make the purchase. Lastly, consumers cultivate expectations based on their experience related to the product and services, which also in a way influences their future buying behaviour and expectations (Court et al., 2009b). When the organizations deliver a satisfactory result throughout all the four stages during the first purchase, the customers are most likely to skip the first two steps of their decision journey during the subsequent purchases. The modern customer decision journey necessitates to the marketing strategies and tactics that adopts a customer centric approach where the consumer needs is at top most priority aligning to create value at each of the four stages (Vollrath & Villegas, 2021).

With the advent of digitalization such as mobile devices, social media, e-commerce platforms every aspect of CDJ is being gradually reshaped as consumers are now extremely well informed about the product with the help of reviews, influencer content and personalized online recommendations. For instance, Amazon and Netflix are two major players who have successfully integrated the data-driven insights into the CDJ model to provide a personalized experience to customers at every stage and to guide them towards product adoption (Hoyer et al., 2020, Lemon & Verhoef, 2016).

Due to the strong presence of web and digital media consumers are moving outside the marketing funnel or traditional AIDA model by changing the way they research and buy products, hence the presence of CDJ model widely revolves around the consideration phase (need recognition, information search, evaluation of alternatives), purchase phase and post-purchase phase to fulfil this gap. In conclusion, CDJ can provide an in-depth understanding of insights on customer's intentions and perceptions towards a product.

This paper will use CDJ model as a strategic tool along with PERVAL model to identify CPI and understand the guidance process towards product adoption with the help of SA and TM.

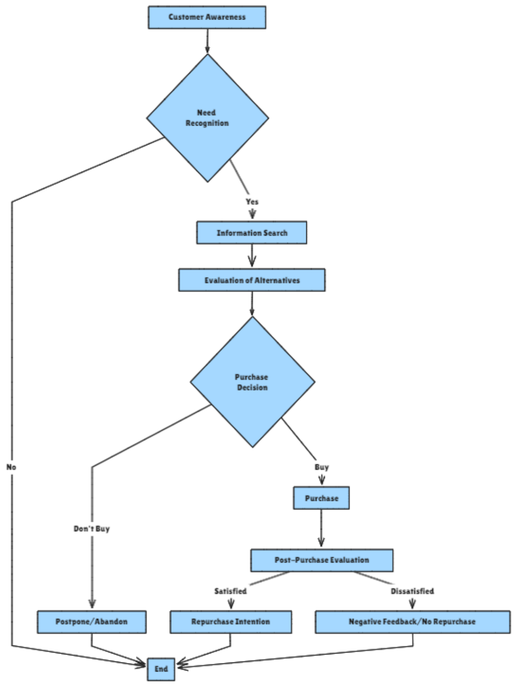

Figure 6: Customer Decision Journey Model (own representation)

Need Recognition (Initial Consideration):

This phase encompasses the first touch point of CDJ, where consumer becomes aware of a need or design and begins to seek information from multiple channels comparing a potential list of brands (Court et al., 2009c). Research suggests that in contrast to traditional models of customer journey, CDJ is more dynamic and interactive, hence the need can be triggered by internal or external stimuli such as personal need or emotional engagement, advertising or recommendations (Kotler et al., 2016). These factors significantly influence consumers to enter the consideration phase incorporating past experience of a brand and the chance of moving forward in customer decision-making journey increases.

In today's marketplace, brands that maintain a strong presence in social media or search engines with personalized ads, email or influencer marketing in this phase are more likely to be recognized and considered by consumers and successful in fostering the perception of consumer needs (Foroudi et al., 2018; Lemon & Verhoef, 2016). CDJ model puts forward that consumers begin with considering smaller set of brands which they already have in mind due to the potent presence of digital media and web, in contrast to the traditional model, where consumers started with multiple options and gradually narrowed them down.

Active Evaluation:

In this phase consumers start actively seeing for more information to explore potential solutions for the recognized needs. This stage can comprise of extensive internal (past experience, personal knowledge) and external (ads, social media, online reviews) perceived risks, where consumers gather details to aid their decision-making (Towers & Towers, 2021). Consumers more often compare and evaluate alternative options they have gathered during the information search based on features, prices, reviews, quality, customer service and other key factors. This phase also includes addition and subtraction of brands from consumers initial consideration list (Baláková et al., 2023).

With a surge in digital media, consumers heavily rely on search engines, product reviews, social media, and website comparison (Towers & Towers, 2021). The rise of NLP techniques has provided a golden opportunity to understand customer preference and offer personalized recommendations, in turn increasing chances of the positive evaluation. Additionally, businesses must follow an omnichannel behaviour alongside social proof such as Search Engine Optimization (SEO), targeted ads, and ensuring the presence of testimonials to shape consumer decision by offering persuasive yet valuable content across channels to build trust (Jothimani et al., 2023).

Purchase Decision:

This is the most pivotal stage in CDJ model where all the marketing effort leads a consumer to the decision of purchasing the product or according to digital standards clicking the "buy now" option. This stage emphasized various factors that influence a customer to buy the product, such as price, convenience, trust, promotional offers. In e-commerce setting, customers might still hesitate due to certain concerns such as payment security, return policies, additional cost leading to higher cart abandonment rates. However, with the rise of digitalization, business can create frictionless checkout experience by using NLP techniques to provide real-time customer services, such as live support, chatbot, thereby, enhancing the chance of completing the purchase (Kannan & Li, 2017).

Post-Purchase Evaluation:

With the technological advancement it is becoming extremely crucial for the businesses to determine the long-term customer retention and advocacy towards the brand. After purchasing a product consumers access the credibility of the product based on their expectations. As a result, a positive experience can increase the repeat purchase, thereby leading to customer loyalty and a negative experience can result in dissatisfaction, product returns, or negative reviews (Foroudi et al., 2018). To access these experiences and foster customer satisfaction, business must implement Customer Relationship Management (CRM) and post-purchase engagement strategies such as follow-up emails or surveys, customer services, loyalty programmes (Kannan & Li, 2017). By investing in after sales support businesses can guide customers towards product adoption cultivating long lasting relationships with customers.

3.4. Understanding Customer Perception and Behaviour using NLP

With the advent of digital transformation modern marketing is taking a leap in customer behaviour analysis, through strategic employment of NLP techniques like TM and SA. These tools are especially valuable in understanding customer perception and behaviour throughout the customer journey. Marketers treat these techniques as effective tool to extract valuable insights and facilitate the creation of finely-tuned marketing strategies and enhance product adoption and customer satisfaction. Understanding customer perception (CP) and customer behaviour (CB) with reasons gives businesses an inevitable pathway to track customer loyalty or churn, and act upon it accordingly to guide prospective customers.

Consumers seek variety of information, opinion and knowledge about a brand or product from various sources to be confident about their choice of product and reduce the risk. Online review plays a major role in shaping brand's perception, while this also assists businesses to gain deeper understanding of diverse customer perspective towards the product, consequently improve strategies (Ban & Kim, 2019). CP is an epitomic tool for product enhancement, brand development, or quality improvement, claim reduction, or gathering information of customer views; hence, CP data is collected through diverse channels in textual format in the form of product reviews, ratings, social media reviews (Ramaswamy & DeClerck, 2018). Angelov (2024) describes how businesses track the individualized Application Programming Interface (API) for each customer and then run NLP techniques to generate a score for understanding customer purchasing intent. In this study, this paper aims to bridge the gap between business expectations and technology with the use of SA and TM to further understand CPI.

NLP Technique	**Practice**	**NLP Capability**	**Process Outcome**
Sentiment Analysis	Emotion/Sentiment Recognition	Text classification as positive, negative, or neutral	Understanding customer emotions and reactions
	Feedback Analysis	Compiling sentiments from various sources	Comprehensive view of customer satisfaction
	Trend Analysis	Detecting shifts in sentiment over time	Dynamic updates to business strategies
	Contextual Analysis	Evaluating sentiment in specific contexts	Tailored responses and improvements to customer service
	Aspect-Based Sentiment Analysis	Identifying sentiment related to specific features	Targeted enhancements in products and services

Topic Modelling	Trend Analysis	Uncovering temporal latent themes in social media	Anticipation of emerging opportunities
	Idea Shortlisting	Measuring the diversity of ideas based on themes	Streamlined innovation processes
	Idea Component Analysis	Identifying main features of an idea	Enhanced idea development and refinement

Table 1: NLP Technique and Capabilities (own representation)

3.4.1. Capturing customer sentiments with Sentiment Analysis

SA is an essential NLP technique which marketers can utilize to gauge the emotional tone, and sentiments of customer interactions in the context of textual data. SA algorithms categorize customer reviews, social media posts and interactions, ratings, and feedback into positive, negative, or neutral sentiments, thereby enabling marketers to understand CPI and customer satisfactions at various stages of customer journey (Bharadwaj, 2023).

For cross-domain sentiment classification an automated technique is used to construct a sentiment-oriented lexical data-base thesaurus employing both labelled and unlabelled data from various source domains to determine the relationship between words that convey similar emotions across different contexts, and then utilized this thesaurus to expand the original feature set for training a binary sentiment classification model (Moslmi et al., 2017). A method for transferring sentiment knowledge from multiple source domains to multiple target domains by distinguishing between domain-specific and domain-independent word sentiments (Yoshida et al., 2011). Andreevskaia & Bergler (2017) proposed a methodology employing an ensemble comprising two distinct classifiers, with the first classifier built using a lexicon and the second classifier trained on a small amount of in-domain data. Dealing with conditional sentences is challenging in compared to single sentence; therefore, part-of-speech (POS) tags for sentiment words, tense structure, and conditional connectives, etc. was introduced to address the issue by utilizing collection of linguistic features, including sentiment words and phrases along with their positions (Liu, 2012).

For instance, SA can evaluate how customers feel about a product's marketing campaign or using the product, which in turn highlights the areas for improvement assisting marketers to enhance their product features or customer services.

3.4.2. Identifying Key Themes with Topic Modelling

TM allows businesses to count and organize data into thematic clusters, resulting in quicker interpretation of large number of unstructured data-sets such as product reviews, customer feedback, social media comments based on the probability distribution. Thus, TM serves as an effective tool for reducing the cognitive load on humans. Marketers can enhance their products based on consumer needs and preferences utilizing these themes to verify the performance metrics, ultimately stemming in customer purchase, satisfaction and product adoption (Netsiri & Lhotáková, 2023; Just, 2024). The modifications and innovations in supervised, unsupervised, and semi-supervised approaches have modified the application of TM. Therefore, TM algorithms can be used for information retrieval of customers in document repositories by text mining, text classification, machine learning, and recommendation systems (Devrath et al., 2024). Given the rapid evolution of the digital landscape, this approach is applicable across various industries due to its scalability which acts as a catalyst to help businesses track customer preferences to understand purchase intentions and facilitate data-driven decision-making to foster product adoption.

For instance, in the context of customer journey, customers evaluate various product features, prices, brand perceptions, etc., In this scenario, TM algorithms help marketers to identify and reveal concerns or interest of their product by collecting and clustering the textual data into thematic categories. Additionally, if marketers want to analyse what their customers say about a particular feature or the entire product, they can use TM to detect pattern such as word frequency and distance between words from customer's similar product reviews appearing frequently, thereby reducing the manual effort (Vaid et al., 2022).

3.5. Analytical Framework

This paper aims to achieve the goal of product adoption through an understanding of CPI. Therefore, in this chapter a conceptual model is developed to serve as a functional tool for marketers by integrating SA and TM with key marketing theoretical models, CDJ and PERVAL models. This model not only sheds light on how consumer sentiments and key themes influence purchase decisions but also enables marketers to garner insights from complex, large-scale datasets and provide a structured roadmap for decision-making.

By integrating theoretical models to NLP techniques this chapter delves into extracting deeper insights on CPI, specifically during the consideration and purchase phases, and their role in driving product adoption. Furthermore, it extends to the post-purchase phase, focusing on how these insights can aid marketers in crafting strategies that foster sustained product adoption and customer loyalty. The discussion below elaborates on each element, linking these theoretical models with data-driven analytical techniques providing a nuanced understanding of the consumer mindset during these critical phases.

3.5.1. Sentiment Analysis across CDJ model

SA can track customer emotions and attitude towards a specific product across different stages of CDJ such as consideration phase (how customers feel about a product), purchase phase (emotional triggers that leads to purchase), and the post-purchase phase (satisfaction levels that leads to product adoption). It plays an integral role for marketers and product teams to identify potential pain points in the customer journey, capture the emotional triggers of customers influencing purchase decisions and to gauge the overall sentiments towards the product (Manassero, 2024).

Business can make use of online platforms, encompassing social media, customer service interactions (CRM tools), and product reviews on blogs, forums, shopping websites etc. to analyse customer data. This text-based data uses SA techniques such as machine learning classifiers or lexicon-based approaches on a labelled data-set, to categorize the text into various sentiments based on polarity, emotions, urgency, intentions (Marong et al., 2020). Sentiment is a subjective emotion that has the power to influence an individual's thoughts and judgments. Thus, these findings can be visualized through sentiment trend charts, illustrating changes in customer perception throughout the journey. This visualization aids in pinpointing areas where interventions might be necessary to enhance the customer journey. Marketers can proactively visualize where interventions are needed and modify strategies based on this data addressing customer concerns and elevate the overall customer experience, ultimately influencing higher product adoption rates (Sun et al., 2024).

During the consideration phase, while consumers evaluate a product based on available information via various different mediums, marketers can track the shift in sentiments using analytics of customer data to analyse consumer opinions and the emotional behaviour towards product features, quality, pricing, functionality, or brand reputation. In purchase phase, SA can be applied by marketers to track consumers direct emotions such as positive reactions toward ease of purchase, clear pricing, or effective customer support that drive purchase completion, and negative reactions related to complexity during checkout or hidden costs that can lead to risk of churn or cart abandonment and become barrier in purchase decision (Khoo & Johnkhan, 2017). While positive sentiment can determine a strong alignment between customer expectations and product perceived value, on contrary negative sentiments highlights the price dissatisfaction or concerns about usability specified as obstacles to purchase.

For instance, as depicted in the figure, “nice”, and “bad” can be considered as sentiment expressions that can automatically sorted with the help of SA (Amazinum, 2024). These emotional indicators can help marketers to continuously monitor and refine the customer journey thus leading towards customer satisfaction and product acceptance.

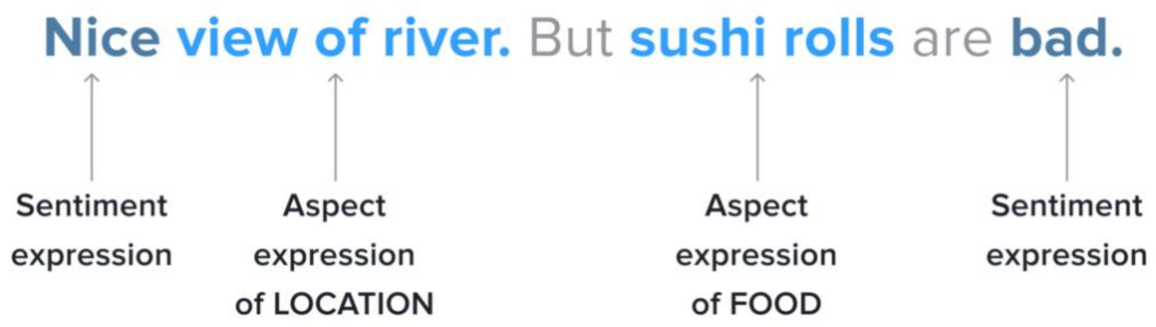

Figure 7: Aspects of Sentiment Analysis (Amazinum, 2024)

3.5.2. Identifying key themes in CDJ model with Topic Modelling

TM is another valuable method that can improvise the understanding of CDJ model by identifying underlying themes within large amount of unstructured customer data-sets, decoding the complex factors and the frequency of particular customer feedback by uncovering what customers are thinking when considering or purchasing a product. This result can be used to augment the original set of features for classification and help businesses to enhance their marketing strategies and emphasize on strengthening the product (Liu, 2012).

Ban & Kim (2019) in their research states that, due to the advancement in technology, customers now seek for variety of information, opinion and knowledge about a product before making a purchase decision. In contrast, during the post-purchase phase customer service experience, delivery or product satisfaction parameters play a crucial role in shaping product success. Based on past studies TM offers marketers an opportunity to look back and forward at the same time by providing a flexibility in selecting the type of textual data that can be used for analysis (Vaid et al., 2023).

Businesses can implement TM algorithms to analyse a corpus of text to understand complex data structures and identify clusters of co-occurring words, grouping them together based on semantic similarity. For instance, in a well-functioning topic model, coherent and meaningful word clusters are generated, such as “army”, “tank”, “captain" or “wheat”, “farm”, “crops”. These data can uncover hidden patterns and also can be used to group similar data together (Zhou et al., 2017). Therefore, to understand complex purchasing behaviour TM serve as a versatile and valuable tool for the unsupervised analysis of textual data (Netsiri & Lhotáková, 2023).

In conclusion, TM in the CDJ model provides a structured way to reveal the answer to “what” specific features or issues customers care about the most while considering a product. This dual approach not only enables businesses to access the most relevant themes but also provides actionable insights to improve marketing strategies, thereby ensuring smooth journey towards product adoption.

3.5.3. Evaluating PERVAL model with Sentiment Analysis

The PERVAL model accesses customers based on functional, emotional, social, epistemic, and economic value thereby helping marketers to understand purchase intentions. Combining SA algorithms with PERVAL model marketers gain valuable insights on how consumers perceive these dimensions when considering a product purchase.

In the context of customer journey, consumers mostly go through all the phases of perceived value, during this phase when SA is utilized as a tool, it has the power to discern customer sentiments and analyse their purchase intentions. Text mining facilitates the identification of expressions of PERceived VALue within customer feedback and social media content. Concurrently, SA, utilizing either pre-built tools or machine learning algorithms, evaluates the emotional value associated with these identified categories. For instance, favourable sentiments regarding “product quality” and “price comparison” signify elevated functional and economic value, references to “customer satisfaction” correlate with emotional value, emotions like “pride” or “social status” reveals social value; lastly, the “curiosity” and “novelty” towards a product address to epistemic value (Tubishat et al.,2018, Kwon et al.,2021, Pires et al., 2024). Luxury cars serve as a prime example of the confluence of PERceived VALue dimensions, embodying all the values (Netsiri & Lhotáková, 2023). By employing SA to PERVAL model, marketers can gain deeper understanding of consumer preferences and how perceived value impact the decision-making at different stages. Thus, this convergence can guide marketers with dimensions most valued to customers and craft their marketing strategies to increase the likelihood of purchase.

3.5.4. Addressing PERVAL model with Topic Modelling

In additional to SA, this paper deals with the valuable insights on addressing PERVAL model with TM. Several scales can effectively measure different facets of value: value consciousness, value of the offer, value of the product, value of the transaction, social value (Pires et al., 2024). The intersection of these facets of value with TM aids marketers uncover the key attributes consumers associate with different aspects of perceived value during the decision-making process.

During consideration phase, TM can identify the heterogeneous factors influencing functional value (“product”, “performance”, “durability”, “product specifications”), economic value (“price”, “value for price”, “affordability”), and epistemic value (“innovation”, “cutting-edge design”). Alternatively, in purchase phase, TM can unveil determinants impacting emotional value (“personal satisfaction”, “enjoyment”, “attachment”) and social value (“identity”, “status”, “belonging”). These themes reflect the broader narratives which enables marketers to predict customer behaviour and by addressing these attributes marketers can effectively position their brand and refine their marketing methodologies to enhance customer confidence in the purchase decision, fostering product adoption (Zhou et al., 2017).

3.5.5. Coupling of Sentiment Analysis and Topic Modelling with CDJ and PERVAL model

This study aims to demonstrate that TM technique can be utilised on SA process to comprehend consumer buying intent. While TM elucidates "what" text deals with in the consumer behaviour context by grouping the topics and generating a theme, SA provides an additional dimension of understanding by assessing the emotional responses associated with these themes by answering "how" customers feel about a certain product (Zhou et al., 2017). Brody & Elhadad (2010) first proposed to identify aspects using topic models and then identify aspect-specific sentiment words by considering adjectives only. TM technique becomes more powerful when combined with SA, facilitating the detection of hidden patterns for the categorization of extensive datasets (Zhou et al., 2017). For instance, a joint model approach, topic-sentiment model approach can be designed which results in sentiment words and topic at the same time, due to the observation that every opinion has a target (Liu, 2012).

The coupling of topic-sentiment model with CDJ and PERVAL model, authorize businesses to endorse a systematic approach. This chapter discusses an analytical framework developed for comprehending customer sentiments and identifying the particular features and attributes that are most significant to them providing a profound insight into purchase intentions.

Social media and internet are extremely rich source of contextual information related to its users as it can track the record of user behavioural patterns in the form of feedbacks, surveys, social media posts, or product reviews, and construct a substantial amount of data. SA and TM are technologies that are widely used in today's date across multiple industries to extract customer behavioural pattern to understand the purchase intent. Analysing such social media data is significant and far-reaching as it generates insights on public opinions, societal unrest and nation-wide SA (Oshogbunu et al., 2021; Xu, Zhang, & Luo, 2010; Zhou, Qian, & Ma, 2012; Atefeh et al., 2017).

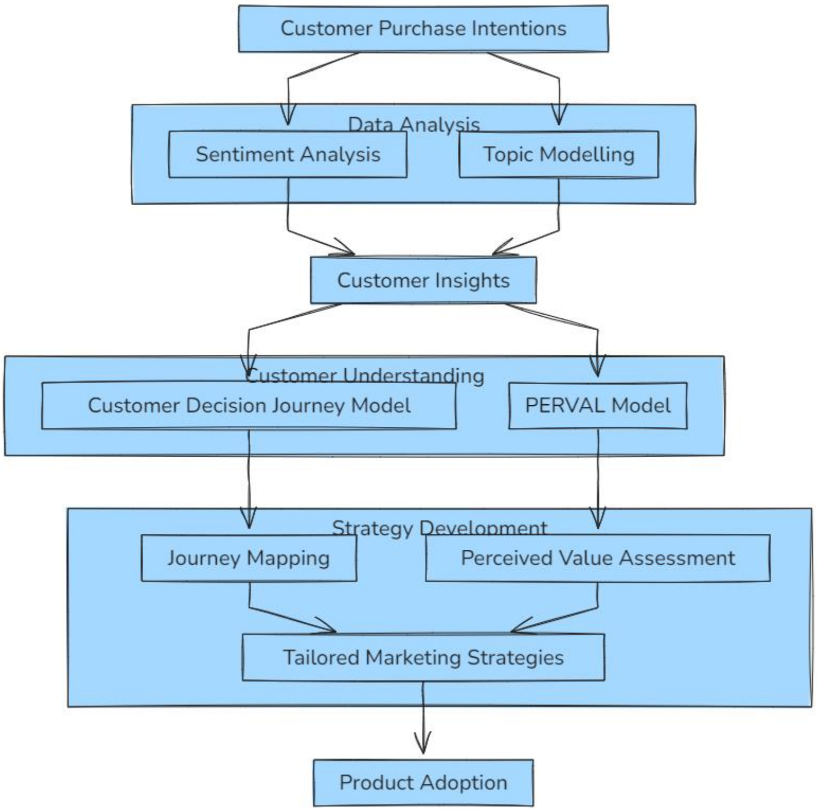

Figure 8: Conceptual Model for this study (own representation)

In this study the process of coupling involves integrating analytical techniques to enhance understanding of customer behaviour. The gathered customer data is used for data analysis by utilizing two primary analytical techniques i.e. SA and TM to derive the customer insights. These customer insights provide the emotional aspect of customer behaviour by using key topic indicators in the textual data collected, thereby offering a nuanced understanding of the multidimensional perceived value outlined in the PERVAL model throughout CDJ specifically in the consideration and purchase phases. Together, this method can provide a substantial history on consumer behaviour and help marketers to develop a strategy based on journey mapping and perceived value assessment to tailor marketing campaigns and influence customer purchase. Furthermore, it is essential to concentrate on the post-purchase phase by delivering outstanding customer service to enhance customer retention, ultimately facilitating successful product adoption.

3.5.6. Integrating Sentiment Analysis and Topic Modelling to foster Product Adoption

In the fast-paced realm of technological advancement, where consumers are constantly inundated with various options, product adoption depends on delivering a seamless and interesting user experience. Simply acquiring a new customer is no longer enough; customer retention is now the primary challenge for marketers. To prevent and reduce the churn rate brands must put in an effort in post-purchase phase equally as in consideration and purchase phases to actively nurture relationships and exceed customer expectations. In an increasingly competitive world, this necessitates a deep understanding of customer needs and preferences, personalized communication, and continuous value delivery to foster loyalty and advocacy in an increasingly competitive landscape (Jothimani et al., 2023). Thus, this paper aims to develop a model that leverages SA and TM to enhance product adoption strategies.

Social listening plays a crucial role in gaining these insights, marketer can gather customer-oriented textual data, such as customer reviews, to understand and learn more about customers. These data include the historical information, which can be used to analyse product feedback, thereby enabling businesses to build personalized user personas and improve their product/services by targeted promotions. This allows businesses to create a "framing effect" which influences customer to purchase a product (Gooljar et al., 2024; Vaid et al., 2023). For instance, the coupling of SA and TM can be used by marketers to deliver precision marketing such as intelligent product recommender algorithms, "you might also like" feature in online shopping platforms (Yin & Qiu, 2021).

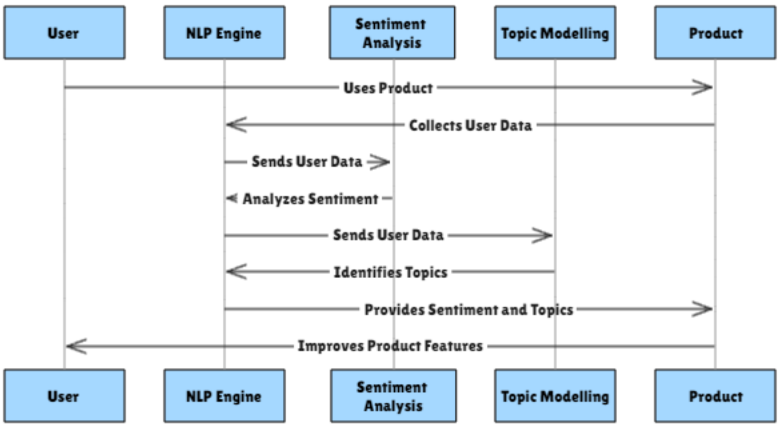

Figure 9: Integration of SA and TM into Product adoption (own representation)

The real-world applications lie on AI-powered tools such as chatbots, virtual assistants, or dynamic pricing, equipped by SA and TM. These tools can often simulate human-like conversations proving real-time customer services and personalized product recommendations. For example, SA to use for virtual assistants to gauge customer emotion during interactions and then tailor responses accordingly. Additionally, TM can help to identify recurring product-related issues or customer interests, allowing marketers to recommend specific products. Furthermore, businesses can strategically optimize dynamic prices of product according to the algorithmic results (Gattani et al., 2023, Yin & Qiu, 2021).

In conclusion, the integration of SA and TM into the product adoption process provides valuable perceived value (PERVAL) of customers to understand purchase intent.

3.6. Application in Various Industries

This chapter discusses the case studies from various industries where TM and SA are applied in accordance with PERVAL model throughout the customer journey to give a holistic approach towards the research.

Retail & E-commerce:

Myntra an Indian retail e-commerce giant uses TM and SA to enhance purchase conversion by identifying common behaviour and concerns towards CPI. For example, Myntra provides a seamless online shopping experience through features such as visual search, virtual trial rooms, and personalised recommendations or chatbots to address customer needs based on their application surfing behaviour, and product review with respect to PERVAL model throughout the customer journey. These features allow Myntra to train their algorithmic models and augment better CRM strategies along with tailoring marketing champaigns for customer advocacy paving the way towards product success (Krishna et al., 2023).

Consumer Electronics:

Huang (2022) explained in the paper, “product attributes have a greater impact on consumer purchasing decisions than does social influence”. Alimi (2022) performed a survey on “a topic-sentiment analysis on consumer’s preference on Samsung and iPhone phones using twitter data”. A detailed process was carried out throughout the customer journey starting from data collection, processing, viewing and removing the common stop words and finally top 20 terms were extracted based on the frequency. These terms were then narrowed down to top 10 terms after visualization. The most common words for iPhone included “apple”, “pro”, “android”, and “iOS”, while Samsung had “galaxy”, “android”, “google”, “Bibiana”, and “NASA”. It was concluded that SA showed high percentage of positive reaction, anticipation and joy, while there was a low percentage of negative reactions, sadness and fear.

This case study depicts a strong use of TM and SA in accordance to PERVAL model, the consumer electronics industry tries to understand intentions behind customer purchasing behaviour and proactively craft marketing strategies.

Finance:

Fintech companies are at the forefront by analysing customer feedback utilizing topic-sentiment analysis-based solutions for customer relationship management (CRM), such as chatbots and virtual assistants to deliver efficient and personalized customer support, particularly for digitally savvy demographics. Fintech businesses use technology to provide financial services; they develop and set up their offerings and use marketing-related stimuli to attract and surprise clients (Barbu et al., 2021). This focus on NLP techniques throughout the customer journey to understand the perceived value broadens businesses customer service automation, allowing fintech companies to scale their operations efficiently while addressing customer inquiries promptly leading towards successful customer retention.

Education:

Ray et al. (2019) followed an NLP-based approach to explore the values that affects customer decisions for e-learning platform, Coursera. The result generated themes like, "value addition", "easy to follow", "topic cover", "reliability of course", "course quality", "recommend the course", "videos to watch", "good deals", "value for money", "facilitator skills", "discussion forum", "review scores", etc. in customer reviews are few important factors that relates to customer sentiments showcasing their intentions to take up the course and drives towards adopting these platforms.

Hospitality:

Zhang et al. (2021) used Airbnb as an example in their paper to analyse "The impact of consumer perceived value on repeat purchase intention based on online reviews: by the method of text mining". This paper was a quantitative analysis by classifying the topic into different hypothesis, PERVAL model was used as a strong baseline to understand customer perceived value through text mining process. Overall, this research showed that functional, economic, social, epistemic, emotional value all significantly influenced consumers' repeat purchase behaviour thereby forcing marketers to understand customer behaviour before curating marketing strategies and adapt towards more personalized recommendation systems.

Tourism:

Ali et al. (2022) performed a survey on TripAdvisor by "Analysing tourism reviews using an LDA topic-based SA approach". A thorough steps of data collection and pre-processing, extracting latent topics using LDA algorithm on collected reviews, and applying SA to each topic was followed. The result depicted the underlying topics and sentimental polarity reflected in online reviews to guide tourism companies to understand customer purchasing behaviour.

4. Research Methodology

4.1. Research design

This aim of this research was to achieve remarkable research results by developing a comprehensive framework that integrates SA and TM with Customer Decision Journey (CDJ) and PERVAL models. The SA and TM systems in this paper are presented to leverage advanced methods of extracting specific themes driving those emotions to understand CPI. This extensive framework can help organizations to gain valuable insights on customer purchasing behaviour and make informed decisions to enhance their products, marketing strategies, and overall customer satisfaction gradually leading towards product adoption at a higher level. The confluence of these NLP techniques along with the models provides a holistic view of customer feedback by highlighting both "what" customers think and "how" they feel about a product.

This paper is designed to delve into an in-depth analysis of problem statement, introduce the basics, and discuss data sources and customer acquisition techniques by adopting a qualitative analysis. This approach allows to explore complex, context-dependent consumer behaviour by provides an in-dept understanding of CPI throughout CDJ and product adoption, which are often influenced by various factors considered as perceived value. This study also discusses on various case studies (see chapter 3.6) to understand and contextualize the findings within specific industries. The selected case studies focus on real-world businesses **consumer behaviour** plays a critical role in product success, such as Retail & E-commerce, consumer electronics, automotive, food, hospitality, finance, education, tourism. Some case studies on food & beverage, healthcare and automotive industries are discussed in chapter 5. The combination of qualitative analysis and real-world application case studies provides a robust explaination for understanding how companies can leverage customer feedback to understand CPI and enhance product offerings or marketing strategies.

4.2. NLP State-of-the-Art Techniques: Synergy of Sentiment Analysis and Topic Modelling

TM is a powerful tool when combined with SA techniques as both the tools of NP complement each other to understand consumer purchase intent. While SA focuses on the emotional aspect of customers, TM helps to uncover underlying themes and group them into topics. Thus, the synergy of SA and TM enables businesses with exceptional power to understand customer behaviour and influence purchase decisions (Zhou et al., 2017; Graham et al., 2012; Hu et al., 2018; Jim et al., 2024).

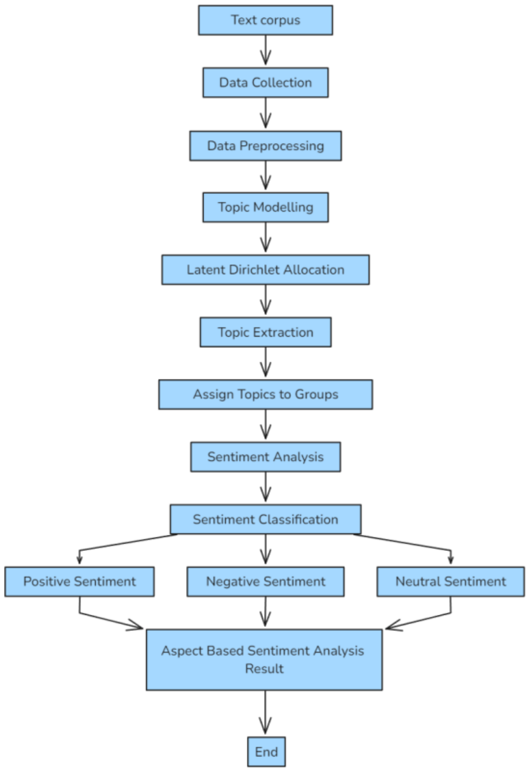

Figure 10: Methodological process for Topic-Based Sentiment analysis approach (own representation)

To understand purchase intentions businesses, follow a series of steps: firstly, businesses gather relevant data from various sources, also known as **data collection** step. The next is **data processing** where the data is cleaned and structured for analysis by utilizing punctuation removal, stop word removal, lemmatization and word embedding (see chapter 2.3.1.). Following to that the data is sent to LDA (see chapter 2.3.1.2) for topic extraction and assign it to groups. Finally, the sentiment classification as positive, negative or neutral is done based on the topics (Tan et al., 2023, Ali et al., 2022). A positive word can be assigned as +1, while a negative word can be -1 to score and sum up the orientation of words. This is also termed as aspect-based SA. By consistently refining their algorithms to track and analyse customer historical data, businesses can gain a deeper understanding of customer behaviour and purchase intent. This enables them to implement strategic tactics that encourage customers to adopt their products (Ali et al., 2022).

For example, in the consideration phase, topics related to product attributes such as "durability" or "affordability" may emerge. During the purchase phase, themes like "customer service" or "payment process" might dominate. By identifying these recurring themes, businesses can tailor their messaging and improve product offerings in line with customer priorities to prevent churning of customers (Khurana et al., 2022).

4.3. Data Collection

This research has followed a systematic conceptual qualitative study approach. In the first block of phase one of the research methodology, relevant literature has been searched, and filtered down to analyse the key aspects of CPI and categorize them into logical groups. The literature review was performed. Databases and search engines are utilized to perform relevant keyword combinations related to CPI, customer behaviour, decision making and product adoption. First, a keyword combination of “customer purchase intention” OR “customer decision making” OR “customer purchasing behaviour” OR “Product adoption” OR “Product acceptance” OR “Customer Decision Journey” OR “PERVAL model” OR “Perceived Value” OR “Natural Language Processing” OR “Sentiment Analysis” AND “Topic Modelling” was searched in the Title, Abstract, or Keyword in the recent publications. The emphasis was placed on recent publications to ensure the incorporation of up-to-date knowledge.

Additionally, industry reports, white papers, and thought leadership articles from reputable consulting firms and industry experts were considered to learn more on the buying behaviour and product adoption. The acquired repository initially of 284 papers was cleaned for duplicates, then the abstract of all the publications were read to understand its compatibility with framed research questions, and then the final literature collection of 117 papers were used for primary study and assessment. The content of the academic papers was studied to gather the theory introduced, the qualitative indicators discussed and analysed for relevancy to this thesis. This structured review methodology was supplemented with exploratory search of the academic papers in the quality assessment step. Subsequently, the literature for the use of NLP techniques in understanding the purchase intention and product adoption, review of methods for imbalanced multi-label classification, and evaluation criteria for benchmarking multiple NLP models along with scope of performance improvement was carried out using exploratory search of published academic papers with emphasis on recent articles.

King (2021) highlights the application of qualitative research guidelines, advocate for a more flexible and appropriate pathway for researchers. In this context, furthermore, information was gained by interviewing focus groups and organizations. The interviewees were selected from various different industries to understand how NLP use cases vary among industries.

Name	Company	Industry	Background	Location
Boyan Angelov	Exxtra	Technology and Consulting	Principal Data and AI Strategy with over 14 years of experience	Video Call
Alberto Manassero	Rows.com	Business/Productivity Software (SAAS services)- AI powered spreadsheet	Head of Product Growth with over 12 years of experience	Video Call
Bishwajeet Samal	Volkswagen Group, Germany	Automotive	Head of Marketing Campaigns with over 20 years of experience	Video Call
Mohamed Elbasueny	Regent Branding	Digital Advertising Services	Head of AI department with over 4 years of experience	Video Call
Ronak Sharma	Bisleri International Pvt. Ltd.	Food and Beverage Services	Head of D2C & Digital Marketing with over 11 years of experience (Former Brand Marketing Manager at Flipkart – Indian E-commerce)	Video Call
Simonetta Batteiger	Self-employed	Product Coaching community	Product Coach with over 27 years of experience (Former VP Growth at Eyeo)	Video Call
Ulf Greiner	Self-employed	Product Coaching community	Product Coach with over 22 years of experience	Video Call
Dr. Kinda El Maarry	Prima	Insurance	Director Data Governance and Business Intelligence with over 10 years of experience	Speak at ProductLab event (no interview was conducted)

Table 2: Interviewee Participants (own reprensentation)

4.4. Data Analysis

This methodology was followed throughout the thesis to develop the answer for the main research question and sub-questions. After a careful analysis of data collected using the above methods the first and second sub questions were answered respectively - how NLP can be leveraged to comprehend customer and how companies can guide customers to foster product adoption and change brand perception by personalized recommendations and marketing campaigns.

To analyse these data various tools were used for better understand of the literature. Firstly, “Zeroto” was used extensively as a personal research assistant to collect, organize, and annotate the collected academic papers. This tool helped to analyse the research papers, highlight important parts, use tags to group the papers for later purpose which provided a systematic structure to the entire research. Secondly, “Turboscribe” was used to transcribe all the interviews and “Taguette” which is an open-source document tagging tool was used for qualitative data analysis. Finally, tools like “Scribber” and “Mybib” were used for citation purposes.

This paper followed a qualitative approach with all the interviews conducted in a semi-structured way, where the interview style allowed the interviewers to ask follow-up questions and the interviewees to explain their thoughts by going deeper into the issue. This method enhanced the research process by allowing to gain deeper insights on specific subject matters (Kallio et al., 2016). Additionally, an interview guide was developed for the semi-structured interview composed of 17 questions (see appendix) with the objective of answering the research question RQ1 and RQ2. For a semi-structured interview, interviewer was allowed to ask follow up questions to dive deeper into the subject matter. As a part of qualitative analysis 8 industry experts such as product managers, marketing leaders, Data and AI experts from various different industries were considered for the interview process. Additionally, one product event talk was taken into consideration with respect to product adoption (see table 4.3). The entire data collection process helped to gather information on impact of NLP techniques to understand customer perception, behaviour and preferences towards a product and the relevance of CDJ and PERVAL model in gauging CPI and guiding customers towards adoption of product.

This data analysis for this study was done in a 3-step process using all the tools mentioned previously: **(1) Reduce the data:** Here all the duplicates and irrelevant data collected were removed and only the required data was kept. This helped to deepen the knowledge for further research on the topic. **(2) Summarize the data:** In this part the data was summarized and coded into an easier format by using Zeroto highlights or tags to group together and utilize later for relevant search. (3) Conclude: The collected data was concluded and used to do the further research to identify the patterns including the interviews to draw a conclusion for the entire research conducted. Ultimately, this study has tried to achieve the goal of developing a comprehensive framework for marketers to understand CPI and provide a roadmap to guide customers towards product adoption.

5. Findings and Analysis

In today's fast changing marketing dynamics and consumer behaviour, having business understanding and user empathy relates strongly to product sense which can only come from data. This chapter discusses the interviews conducted, analysing how SA, TM, CDJ and PERVAL model can be integrated to enhance PA.

5.1. Customer Journey throughout (A step towards product acceptance)

The customer journey is an essential framework for product acceptance. According to **Sharma (2024)**, at every phase, businesses have the opportunity to engage with customers and employ targeted strategies to facilitate the acceptance of the product. He further highlights the importance of CDJ facilitated by real-time feedback loops. For many customers, the purchase decision happens long after initial consideration, influenced by interactions with digital marketing campaigns and personalized content.

Manassero (2024) explains that customer interactions across different touchpoints enables Rows to understand the user footprints. He further elaborated Rows uses TM for feature-tracking and customer engagement analysis to forecast customer retention using "power workspace" (users active more than 3 days a week), thus, the company can assess the probability of customer purchase. He also discussed about a case study on Rows client, the issue was the need to analyse large volume of Google reviews from Google My Business. Rows provided a solution to combine Google My Business and OpenAI, employ SA to build a dashboard. This insight empowers them to prioritize product improvements and track branded conversions that will highly impact customer satisfaction, ultimately leading to product adoption through their customer-centric approach.

Similarly, **Angelov (2024)** emphasized the importance of capturing data such as social media, product reviews, CRM systems and integrating the analytics into customer journey touch points. He pointed out by applying SA and TM companies can follow a data-driven approach to align their products with customer needs and influence purchase decisions. This dynamic approach of following the data canvas throughout the CDJ can equip business to foster stronger customer loyalty and product adoption.

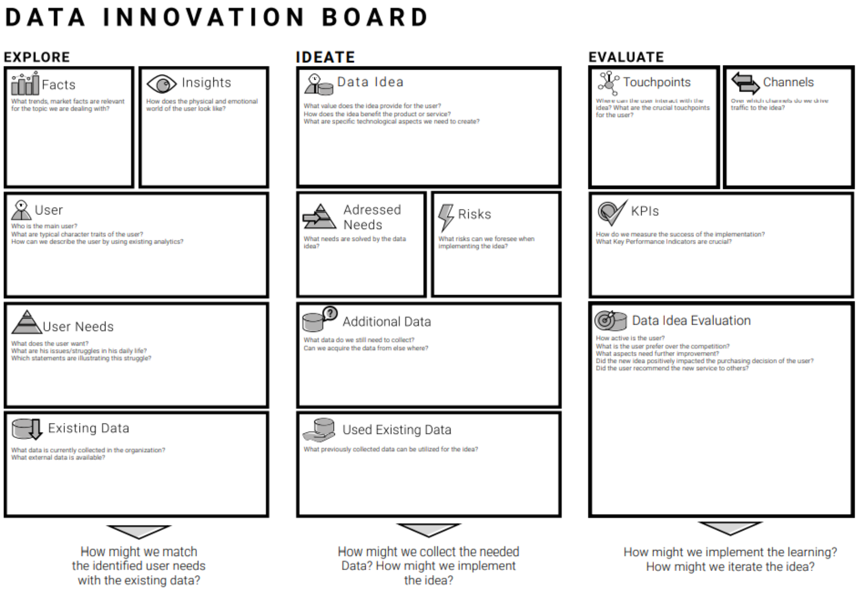

Figure 11: Data Canvas (cited by Angelov, 2024)

Batteiger (2024) stressed, there's always a problem to solve which exemplifies and relates to customers' need. Furthermore, to support this arguement, **Elbasueny (2024)** underscored the use of TM in developing chatbots for personalized recommendations and importance of precision. The chatbot provides customers with real-time, contextually relevant information, which helps build trust in the brand's product offerings, enhancing CDJ. Moreover, **Samal (2024)** added optimization in content generate throughout the customer journey is done with the use of SA and TM tools.

5.2. Value Creation to enhance customer purchase intention using NLP

The PERVAL model assesses consumer value through functional, emotional, social, epistemic, and economic dimensions, significantly influencing customer decision-making. Interviewees indicated that SA and TA can improve these dimensions, enabling companies to tailor their marketing strategies.

Functional value was the most cited value across all interviews. **Manassero (2024)** described how Rows utilized AI to improve user experience by simplifying complex data integration tasks, thereby enhancing functional utility. He further added, week-on-week retention metrics allow them to understand perceived value of the product, resulting in driving product stickiness and purchase intentions. Additionally, **Angelov (2024)** supported this argument by illustrating how SA may segment reviews and classify consumer feedback according to functional requirements, such as product reliability or performance.

Emotional value was particularly mentioned by **Samal (2024)**. He stressed, Volkswagen's future vision of utilizing chatbots for personalized user interaction within cars can trigger emotional engagement. He added, customer feedback allows Volkswagen to understand customer sentiments towards design and technology, which enables them to adjust its offerings to strengthen emotional bonds, influencing customer perception and brand loyalty. This was further supported by **Sharma (2024)**, emotional value is a key driver in choosing a brand over competitors in industries like FMCG (Fast-Moving Consumer Goods).

Angelov (2024) underscored SA & TM can evaluate by accessing customers' willingness to pay by identifying patterns, companies can curate their pricing strategies by offering targeted promotional discounts in term of push notifications. **Elbasueny (2024)** highlighted the significance of NLP in monetizing chatbot interactions through appropriate ads and offers, derived from real-time TM data of customer inquiries, further augmenting the perceived **economic value** of product.

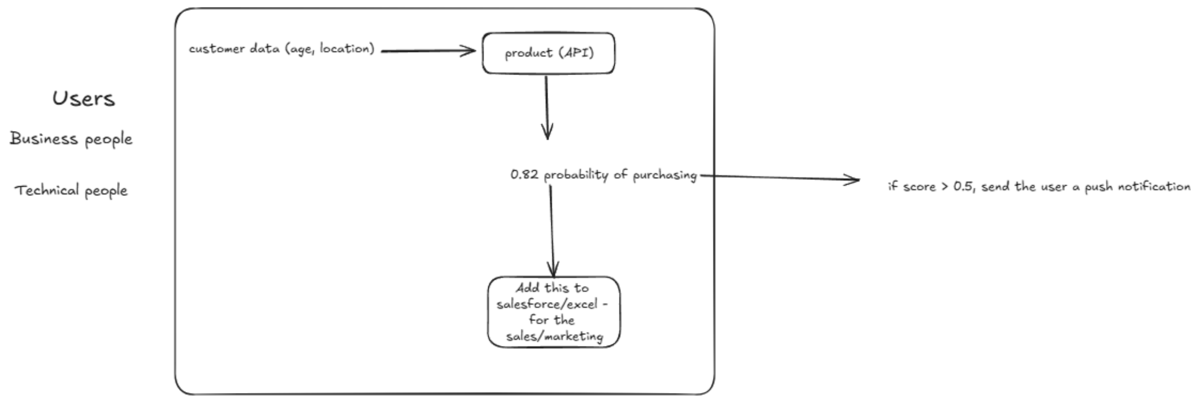

Figure 12: Targeted Promotions (Angelov, 2024)

Sharma (2024) elaborated how Bisleri used SA and TM to track social media data for understanding customer perceived social value of their product. He added this data allows them to modify marketing plans to resonate with the **social dimension** of product. Furthermore, **Samal (2024)** focused on automotive industry, where brand identity is closely related to social status; therefore, understanding customer perceptions can help Volkswagen to tailor their approach towards customer.

Elbasueny (2024) articulated that NLP-driven chatbots collects customer data using by tracking "question ID" can provide epistemic value by delivering accurate, expert-level responses to customer inquiries. Their veterinarian chatbot, offers information from reliable sources, providing both functional and **epistemic value**. This stimulates customer curiosity and encourages them to engage more deeply with the product or service.

5.3. Result Analysis

This chapter dig deeper into the interviews to understand the importance integration of of SA and TM with CDJ and PERVAL models to provide actionable insights to improve decision-making and product adoption.

5.3.1. Leveraging NLP to enhance Decision-Making

NLP technologies offer substantial insights into consumer behaviour. For instance, SA permits businesses to evaluate customer opinion, feedback, and general emotions toward a product. In accordance to this, **Samal (2024)** elaborates Volkswagen's plan on testing SA into their chatbots, where real-time feedback can shape future product innovations, marketing tactics, and customer service improvements.

Additionally, TM assists businesses to comprehend the dominating themes using customer feedbacks. As highlighted by **Elbasueny (2024)**; by using TM in a product like chatbot, companies can identify vital pain points using the individualized question ID. This allows companies to tailor and provide real-time accurate data, which boosts both customer trust and product utility improving customer satisfaction. Furthermore, he added by using "like" and "dislike" buttons in the search bar of their chatbot they track customer feedback and analysis the data to further enhance the product and there by promoting CPI.

Moreover, NLP can play a pivotal role in forecasting future purchase intentions**. Angelov (2024)** discussed about predictive models based on SA and TM to anticipate future buying behaviour, thus enabling businesses to adopt prescriptive analytics **to** guide customers through their journey—from initial consideration to decision-making.

5.3.2. Leveraging NLP to enhance Product Adoption

SA and TM play a pivotal role in fostering product adoption by enabling marketing to offer personalized and relevant customer interactions. Marry (2024) explained the importance of user-centric approach by following data customer mapping, value proposition and feedback loops. She further added to manage the collected customer data as a product leveraging continuous model improvements. This method can help businesses to improve the customer experience throughout CDJ, thereby resulting in product adoption.

Angelov (2024) highlighted, forecasting future purchase intentions by analysing customer sentiments which empowers businesses to understand customer needs and increase conversion rates.

Furthermore, the trust-building and precision aspect was underscored by Elbasueny (2024) depicted that reliable data provided through chatbots can enhance customer loyalty and post-purchase behaviour.

Sharma (2024) emphasized on the significance of feedback loop in-ecommerce. Brands like Flipkart, rely heavily on NLP tools to gather customer feedback which informs their customer needs and guide marketers to craft marketing strategies or recommend individualized ads. This adaptive marketing approach enhance product adoption.

Samal (2024) elucidated that brand loyalty can be augmented through individualized interactions facilitated by NLP. Offering personalized content, such as recommendations systems in vehicles, enhances customer affinity for the business, hence elevating the probability of customer retention.

Finally, Manassero (2024) stressed analysing customer usage data, Rows is able to feature updates and offerings align with customer needs by identifying which features are most valuable to users. This continuous optimization of the product offering enhances long-term customer retention leading to successful product adoption.

6. Discussions and Reflection

6.1. Discussions

The findings from this research demonstrate a comprehensive understanding of SA and TM can be integrated with CDJ and PERVAL model to significantly influence customer purchases and enhance product adoption by providing real-time actionable insights to consumer behaviour.

This study unveils the importance of data-driven decision-making based on real-time customer feedback. Interviewees addressed that SA and TM can provide information on customer emotions, feelings and attitude towards a product. Through the analysis of consumer reviews and social media engagement, businesses can pinpoint areas for enhancement and tweak their offerings to align with customer requirements. Continuous improvement and training of models results in capability of adaptive responsiveness based on customer needs, thereby enhancing purchase intentions.

It was evident that SA and TM play a significant role in product adoption by influencing customer decision by employing data-driven personalization. This enables marketers to create tailored customer journeys that guide users from initial consideration to adoption. Moreover, the importance of accurate and reliable chatbots is a critical factor in driving product adoption. By providing tailored individualized recommendations and addressing customer requirements, marketers can markedly enhance engagement and conversion rates.

Looking ahead, with technological advancement, SA and TM will continue to play a major role in shaping the marketing dynamics of products by understanding CPI; however, the importance of real-time input data will become increasingly essential to maintain competitiveness. The interviews underscored that although businesses are starting to adapt NLP, there is still much remains to be accomplished in terms of integrating these tools with traditional marketing models for influencing purchasing behaviour or product adoption. Conversely, Greiner (2024) and Batteiger (2024) highlighted ethical concerns stemming from extensive sharing of customer personal data.

6.2. Reflections

Despite the valuable insights generated by this research, several limitations should be acknowledged. First, the study primarily relies on specific NLP techniques such as SA and TM, which are based on the analysis of textual data. As a result, non-textual data, including images, videos, and other multimedia forms of consumer expression, were not considered, which may limit the understanding of the full spectrum of customer behaviour. Another limitation is due to the qualitative analysis of data the accuracy of SA and TM algorithms, may not be captured, a quantitative analysis of similar research is suggested for a predominantly in-depth result. Lastly, further research can be conducted on ethical considerations with the use of large-scale customer data, such as privacy concerns or data bias.

7. Conclusion

The overall purpose of this research was to highlight the importance of NLP techniques, especially SA and TM, in comprehending purchase intentions and encouraging product adoption by influencing customer decision-making process. By integrating CDJ and PERVAL model, this study was oriented to develop a roadmap for marketers and businesses to analyse customer behaviour efficiently specifically during initial consideration, purchase and post-purchase phases. The confluence of these techniques along with marketing models allows businesses to understand “how” customer feels revealing emotional aspect and “what” customer thinks unveiling the themes behind emotions about a product by analysing the continuous feedback.

This study explored the significance of SA and TM in strengthening brand-consumer relationship by persuading customer decision-making and simulating product adoption. Companies can craft more personalized and targeted marketing strategies by analysing real-time data from various customer touchpoints. To conclude, this research provides a roadmap to businesses to understand “why” customers behave certain way and learn user empathy to adapt to the ever-evolving consumer needs, improve customer satisfaction, and effectively comprehend “how” they can promote product adoption in a progressively competitive market.

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Appendix: Interview Transcript

Location: Online meeting via Teams, Berlin.
Date: 22nd Aug. 2024
Interviewers: Panda. S,
Interviewee: Angelov. B, (Principal Data and AI Strategy, Exxtra)

Interviewer: Thank you for taking sometime for this discussion. I will share a bit about my thesis. The aim of this thesis is coupling of sentiment analysis and topic modelling to foster product adoption by understanding customer purchase intentions.

Interviewee: Okay, yeah and this is the topic of your thesis right as far as I understand, this is what you want to do?

Interviewer: Yes, kind of like the first part I want to talk more about how they can do it and the second part like more into curating the marketing strategies, what are the strategies that they can follow.

Interviewee: Okay, that's a good structure. But do you plan to write code for this? Do you have like a data centre?

Interviewer: No, mostly no, it will be more of a solution

Interviewee: So basically, you want to describe how such a thing would look like, right? How such a solution would look like. Yeah, okay, so I think the best way to do it is actually to draw it somehow. Let me see if I can quickly draw something. Just give me a second and I'll share my screen. So, can you explain the business problem again?

Interviewer: So, let's say that there's a retail company or maybe e-commerce company, right? So how they target basically, let's take an example of social media. So, these days mostly like I think sentiment analysis and topic modelling is a part of social media more towards it.

Interviewee: Okay, so let me just share the screen and we can try to draw this thing. I mean such things the best way to do them is basically really to draw. So, purchasing customer, purchasing intent analysis, right? And you get the data from social media or something?

Interviewer: Yeah, like maybe topic modelling is more towards the text base, so maybe the customer reviews or yeah, those things.

Interviewee: So, can you remind me like are you like more technical person? So, like can you code as well? Because I need to understand how much I should go into the technical things.

Interviewer: I am a technical person, I can understand the technicality, but I don't have to include the technical things into it.

Interviewee: Okay, that's good. Okay, so basically the most important thing is what data do you have available, right? So, it all starts from there. You have some kind of text data which would be like perhaps reviews. Can you describe me what data sets do you think are possible here? Like do customer reviews of products, is that like an interesting data set?

Interviewer: Yes.

Interviewee: Okay, so this is what you need to draw here. Okay, so this is good and you're right that you said about the topic modelling, right? So spacy is a technology. Maybe you know the library, right? Do you know spaCy, the library?

Interviewer: Yes, but not a depth of the library.

Interviewee: Okay, it's really nice just you check it out.
Interviewer: Yeah, sure.

Interviewee: It's like a Python library. It's like also Berlin-based, like the people who develop it are in Berlin. So, it's a lot of interesting things you can learn there. So, one data set is the product review text, but is there another data set which could be interesting?

Interviewer: Maybe the emails or the push notifications, if that customer, for example, like if customers are reading the push notifications or the email by any apps that we send.

Interviewee: Okay, push notification data. Okay, how about CRM data? Like is this like data from some kind of CRM like Salesforce or something like that?

Interviewer: Yeah, that would work too, customer relationship. Yeah, I mean that would basically include all of it actually. So that also works.

Interviewee: Exactly, so that's that all comes from there. So yeah, probably you mean the CRM contains all of those things, yeah?

Interviewer: Yeah.

Interviewee: Okay, so like it's always good to focus what is the end result that you want to do like this this type of, so this is a bit like in technologies. The end result of such an analysis, right? You can have like you can split it may be different buckets, you know, you can say there's descriptive results and then you have like predictive results. You have prescriptive, sorry, and then you have predictive. So, I'll maybe cover in a second. So, this is kind of the end result from the whole project. I will say that you want to make some kind of, you can split it into those three results and they're very different. So descriptive basically would mean just describing, describing stuff like you could describe like how many five-star reviews we have, you know?

Interviewer: Yeah.

Interviewee: So, it's not, it's not very useful, right? It's kind of the most basic analytical thing. Prescriptive means basically, you know, most people who review whatever with four stars and above, we can say they want to purchase something. And predictive are kind of like the sentiment stuff, the topic modelling where you have more machine learning, right? So, you can group like the results like this. I think it's a nice structure.

So obviously like any data project, you can structure with, you have data and then you have the end result. It's always good to make sure that the end result would make sense that you can, what is the product and who are the users of this, you know, because maybe like you have more like business people are interested. I actually have to think about the users here, all the users of those products.

They have the users and here you have kind of the, just escaped my mind, uh, the products and you have different products. For example, here you might have like, an API. So basically, a backend system and here you have like a dashboard, you know?

For example, you just describe how the data looks like, and here you have maybe a report for prescriptive, you know? So, I'm just finding like a way for you to structure the idea a bit like, uh, and there's all, of course there are different types of people, technical business, but you can, you know, you can have even deeper personas here. I don't know.

Just have to think a bit about this. So, this is about the end result. Um, in the middle you have like, uh, uh, a data, sorry, data processing. Obviously, this data needs to be processed somehow. Uh, you have another important topic, which is, uh, data mining. Um, data, all of this is kind of data mining, right? Those first steps are data mining. I mean, I don't like the data mining because it's like a bit, old school. I think you can use like newer methodology. You could say like there's data enrichment.

Interviewer: Do you crisp DM methodology, like for data?

Interviewee: It's basically, like a very big word, like it's cross-industry standards for data mining. You know, it's like a big, big, big word, but it's like a very traditional way to, uh, structure like data, projects, you know, so you can follow that for example. Uh, so basically then you have, uh, and then following the processes, then you have like, three data analysis. So basically, visualizing data. Uh, then you have the final steps are like, here you have like a data analysis, uh, here, for example, you have like the topic, uh, maybe the sentiment analysis that, so data analysis slash machine learning, right.

Interviewer: Okay.

Interviewee: You have sentiment analysis, topic modelling, what you mentioned. Very nice idea, churn prediction. There's a lot of things you can do here, right? For example, you have also things, in natural language processing, for example, you have like a named entity recognition, part of speech tagging stuff that you can have a look in a spacey. I think it's dot IO. I think you check like they described how those things work. So, this is kind of the, the flow of your, project, you know, like from here to here. I think this is the concept that you can, present a bit, you know?

Interviewer: Oh, okay. Actually, thank you so much for this complete model. That looks really good.

Interviewee: It's, nice to draw. Do you have questions?

Interviewer: Yes, so, can you please let me know how exactly, like from the, this side, the data side of it, let's say if you're trying to do something, where, you want to see something, how exactly is going on the user side of it, who are people who are actually using the product, right? If it is an e-commerce website, for example, if I'm using a product and, uh, like we see on a daily basis, the targeted ads that we get on Instagram or something like that. So how exactly it can happen on the behind, like in the background using all of these.

Interviewee: So, this, I mean, the first thing that you need to do is really this process, right? It's exactly this process. Um, you start with the business question and the business question is your title here. That's the business question, right? This is what you need to do. Uh, and then you start to understand the data, right? You have to understand what data do we have available and you have to gather it, right? data insight of the company, data outside of the company. Let me show you, I think I shared this in my, that was in my, talk actually. You can do a canvas like this actually. I think this is something that you can, share and use, this canvas. So basically here, um, with the business idea that you have, you have to understand. So, who is the user of this? We did it a little bit here, but then you kind of collect like, what kind of data is available for this, right?

It all starts with data. So, if you have like text data, for example, if you find out that there's data like this available, or you, you can buy this data, you can collect it, you know, um, there's many ways you can do it. The first thing you try to do is in the company, it is somewhere.

This data, you go to the CRM, check. Do we have this data? Maybe we have this data in our social media profiles, right? You have to look for it.

Interviewer: How much of a big role does Google cookies play here? Do they like play any kind of roles here?

Interviewee: They do. I think, I mean, I'm not a big expert on cookies, but there's a lot of useful data. So, they allow you to track user behaviour, right? So that data is not text data. It's like more tabular data, right? You have different types of data. You have like a text, you have tabular, you have image, video, time series, right? spatial data. There are all kinds of data types, right? You can imagine, for example, you can have the location of users that could be interesting somehow. So, you have to collect all possible data types. And based on this, you can decide what you can do. Because with the text data, you can do sentiment modelling, right? With the spatial data, you can do like more like spatial analytics. So, then you can go to here, like how can you clean the data, right? How can you, some of the data will be wrong, you know, maybe you need to aggregate it. There's most of the time you spend here. And then you do here, like the, in topic modelling part, then you do the general model, the sentiment prediction.

Interviewer: Can you share an example of how your company does it generally?
Interviewee: for example, you can do here, but this is not a hard problem for sentiment prediction. There's a lot of technologies available. So, most of the work actually is here at the beginning of the data understanding.
Like 80%. The modelling part, it's, there's a lot of tools available, a lot of models, deployment basically, you know, right? At the end, you have to, I mean, in this case, I'm not sure if you're going to have like, what kind of product you want to build. Maybe your product here. That's why I described them here. Because if your product is an API, which tells you for every customer, how likely they are to, to purchase something, right?

That's like, you can imagine you get customer data in, maybe let's throw it like you have customer data in, and then you get the score, right? So, you have like something like, customer data. So it could be, like age, location. So, this data is being sent to your model, to the API. So basically, the product and, then out of this, you get like a score, right?

For example, to tell you for this customer, there's like, 0.82 probability of purchasing, right? So, this is what your product outputs. And this, this then can be added to Salesforce, or be used by marketing teams. Yeah. This is one product. I mean, your product could be, like a dashboard to a report, you know, and the report you can generate like, once a month or something. Did it answer your question a little bit? This is kind of the connection, because at the end, what you see, like in, those apps, right.

Interviewer: Yes, it did, thank you! Could you please share some insights on recommendation in apps?

Interviewee: For example, they're basically, connecting to some kind of backend system like this, you know, some kind of API and they, knowing you, for example, if, if you are a user who has this high probability, they will send you something to only to you, right? So, this is automatically for every user, you get this score. So, for this score, if score is more than, 0.5, send the user, uh, push notification.

Interviewer: Do you think depending on the domains or industry, this kind of like the NLP experiences varies or the situation where he's like maybe healthcare industry or finance industry versus the e-commerce industry and the target percent.

Interviewee: Yeah. The, the marketing industry, right. So, like typical normal businesses, they have tools to do this. So, I don't think many of those companies are building such products because you can just buy them. I think Salesforce probably has stuff like this inside, you know, so nobody would build such a thing unless it's a very big company, you know, some very big, e-commerce business might need like a special data team to build this. So, for all other domains, they need this because the data is more private, you know, it's more specific, the data formats they have, there's some regulation around it. And then the maturity of those companies is lower in terms of data. So, they, they normally build those things.

So healthcare, because there's a lot of legal regulation, basically, and, laws and whatever about what data you can track, for example, and collect. So, in that sense, it's, they build those things normally.

Interviewer: As an AI engineer, how would you define your typical workday duties? Specifically, how would you work with marketing experts and analyse datasets to adjust to the changing industry standards in AI for targeted marketing and product positioning? I would like an example.

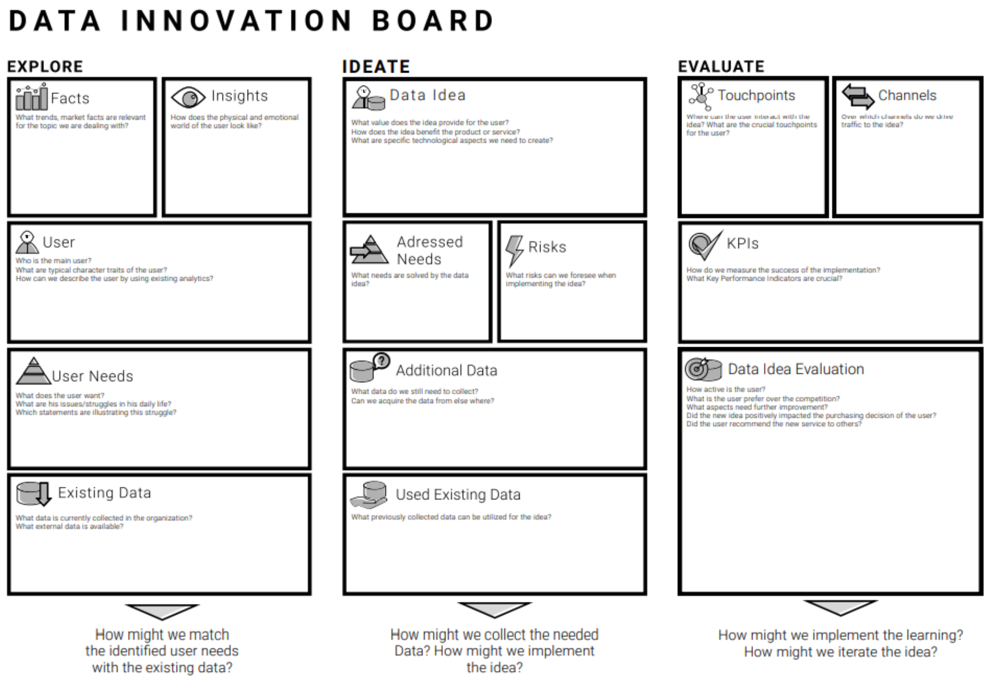
Interviewee: I mean, my specific role is like as a principle, I mean, my role is to be at the beginning of conversation with big clients to see what's possible. Sometimes it's automotive companies, sometimes it's like a mobility, sometimes it's a bank, energy, anything, it could be anything. And they normally come to my company and me in my role, to ask what can we do. Normally they come with the idea of some kind of AI and say we have a marketing problem, can you help? Normally they want like a bigger strategy problem, but sometimes, very normally with them, I look at the whole company and they, every company has a marketing and sales team, almost every company, right?

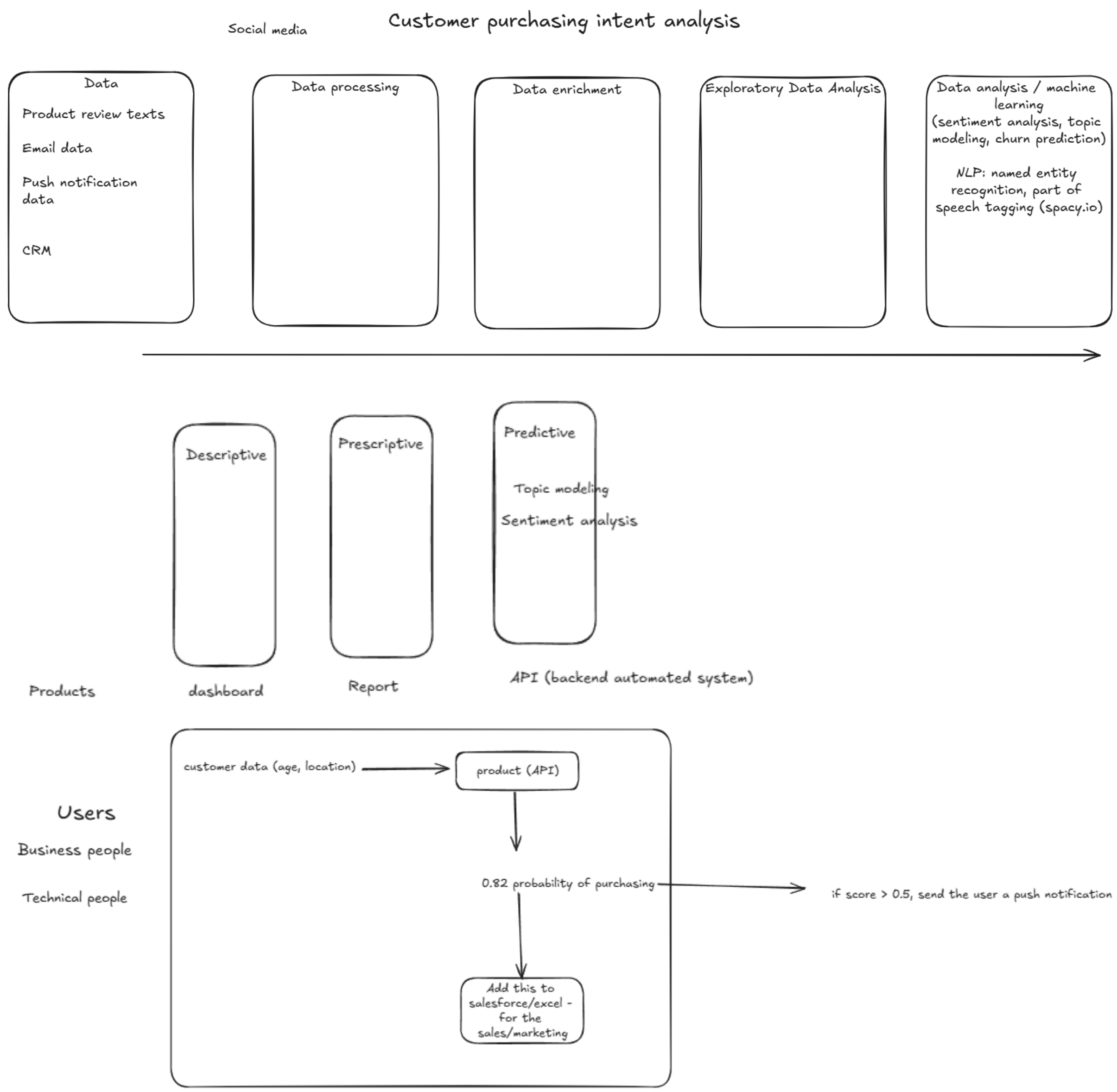
And then I will look at them and normally I'll tell the customer, all right, like, in that team, in your organization, you have enough data. The infrastructure is good. You know, you have Salesforce, you have good CRM systems. I would advise you to, do this to build a product like this, right? So, this is what happens. Sometimes, I would advise, the company where's the most useful place to start making money with AI and analytics. And often is this type of things because they're very, easy to build. This is like a sentiment analysis, for example, topic modelling. These are very standard things.

But normally I work with like a bit tougher client, which have like a bit more, as I said, in this field, there's a lot of products already. Normally they talk to the vendor, you know, they don't talk to a consultancy, right? So, to me, they talk when they have like, let's say they want to build a predictive maintenance for their cars, the cars they want to predict which car is going to break, for example. I'm focused a bit more on like harder problems, I would say. but sometimes you do work with analytics, as well.

It more towards business, understanding, like dealing with Business Analysts and product managers. I mean, I have to take care of everything. I mean, like we are a big company and those clients are big. Normally I, because I know the technology, the business, all those parts, but it depends on the business. I will take different people together with me. I'm there normally to make sure the whole thing happens, me specifically. But normally you take a marketing expert, you take like a developer.

I will share the drawings with you for your reference.





Interviewer: Thank you so much for an insightful talk. To conclude, would you like to add anything else that can be really helpful or not off the top of my head?

Interviewee: No, I think that's pretty much from my side.

Interviewer: Okay, thank you so much!

Location: Online meeting via Teams, Berlin.
Date: 28nd Aug. 2024
Interviewers: Panda. S,
Interviewee: Manassero. A, (Head of Product Growth, Rows.com)

Interviewer: Thank you so much for taking sometime out! Can you please share a little bit of your background?

Interviewee: Sure! Happy to help! I am working in the growth team at Rows basically about like growing the user base, understanding how the people are using the product, if they're sticking to the product, if they're activating. So basically, think of it of like overseeing the entire funnel from acquisition to retention.

Interviewer: So, do you also in a daily basis see the customer's perceptions, how it exactly changes depending on your products or your marketing strategies?

Interviewee: Well, I think the way we have to understand if people are liking our product is basically looking at a few metrics. And specifically, we are basically checking the number of power workspaces. Workspaces are basically accounts to our product. The power workspaces are accounts that are using Rows for more than three days a week. And this, I think, is a very good sign of people that are actually really liking the product. And on a more granular level, obviously, we are also looking at the funnel for a couple of our key products. First one being the data integration. So, Rows is a spreadsheet with two main pillars.

The first one is that you can ingest data automatically instead of like from file or clipboard. So, you have integration, API integration with providers that allows you to ingest data directly in the spreadsheet. The second one is AI. Now, AI is helping you in making sense of data and simulating some actions that would otherwise need very complex syntaxes. And the third one is how people are sharing. The idea that the UI of Rows is quite nice to be shared. So, we are bridging the gap with our different reporting tool. And so those three main features, we are looking at how people are actually using them.

So, in the first case for data integration, we are looking at the funnel. How many people click on the first, on connecting integration up to how many people actually use the data coming from integration. On the AI part, we are looking at how people are using, how many people, how long they're using our AI functions, or how many people are using our analyst, which is basically an AI compiler, AI components that allows you to run analysis on your data. And so how many questions they are asking, if they're getting errors, the type of questions they're asking. And on the sharing side, we are tracking how many people use this embed, which is one of our sharing features. And how many people are, how many tables are using per spreadsheet and this kind of stuff. So those are all micro, more micro metrics, KPIs that we are tracking to understand if people, and obviously we want to have, we have like ratios between them. So many people are using that, that specific feature out of those people who started using that feature. How many people are using after five days out of how many people started using the first day. And all those ratios are actually helping us understand, yeah, how many people are actually using our feature and how long are they using their feature. And we think the best proxy to understand if they like the product or not.

Interviewer: Do you have any idea of the conversion metrics? Like how many exactly, like starting from the first phase of awareness phase till the end of acquisition phase, how many customers actually get converted and is it more into the B2B side or B2C side?

Interviewee: Well, it's a B2B product, but it's a B2B product in the sense that the account is most likely held by a company or a professional. I mean, a single person company. But obviously what we are tracking is like single user, so like employees in the companies. And in terms of conversion rate, our funnel is pretty, so we, one year ago we decided to get rid of the homepage. So, once you land on rows.com, you start using the product right away. So, we have a huge amount of like, we really open up the funnel at the very first, the very first steps. We, we have now, we have now roughly, well, like so far, so we basically took, I think this metric is more relevant. So, it took us five years to get to 50k users. Now we are more, in a year we got more, over a million.

And actually people, what we see is the main bottleneck of our products so far is using an integration. So, if the people manage to get to use an integration, then the likelihood of sticking to the product and to upgrade basically, which is our norm right now, is quite high. So, if you look at the, meaning that like could be around 10%. And while if people are just like not using the integration, they are way more likely to churn after a week, basically five days or so. So, I would say our name, I think this is, and this is basically boils down to how we actually drive those and guide those people to try out the first integration, which is by the way, the, the, the, the key value proposition of Rows. So, yes, I will say our name 8%, 10% is the percentage of people who actually, end up upgrading once they tried once integration.

Interviewer: What are your services post-purchase and how do you see it exactly like for your customers later on? How do you track and analyse it? Whether they are liking it or not? Do you really like talk to them in person to understand it or how do you take the feedback?

Interviewee: Yeah. So, we have, we have a day which is scheduled on Monday every week in which we see how many people churn from being paying users. And we go through, one-on-one interviews with them. And it's very useful to understand if there was something really, really important from them we actually missed or, or we did bad. Then we measure, measure week one retention, which is the most important part, the most, most interesting predictor for us. Week three retention, then we have a core model in which we measure week by week, the decaying of active user. So many active users were in, in three weeks ago, five weeks ago, 10 weeks ago. And then we, and then we check this metric obviously. And what we do is like, and then, and then whenever, other than this personal interview, we have also a form that we submit every time everyone, everyone churns and, and plus churn from being paying user.

And then we also have a set of emails actually that are triggered whenever you don't have any action or don't have any activity in the last 30 days or something or so. And, and those emails are useful to understand, understand actually the trend. Plus, we have a once per quarter MPS survey in which we basically ask the key question of the survey. Survey is not really; would you recommend this? Would you recommend this to a friend? This is more, it's more like, it's more cantered and revolves around this question: how would you feel? How bad would you feel if Rows would not exist anymore tomorrow? There's also a different way to phrase it, but it's also very revealing of how people feel about the product. And, and we also ask for the most used features and the most missing feature. And we use those inputs to inform quarterly, quarterly roadmap basically.

So overall, I would say personal interview with people that churn plus, plus form churn from being paying users. Then we have like standard email flow for people who churn not being a paying user. And then we have these, these MPS survey every quarter.

Interviewer: So basically, the perceived value of your customers also plays a very important role in the entire process.

Interviewee: What do you mean?

Interviewer: I mean, like what customers exactly think or what kind of perception they have for your product also means a lot to your company basically.

Interviewee: Well, I will say, yeah. I mean, it's really, we take into account because those people are providing us very strict feedback and very straight to the point and straightforward feedback. So, if this price is not fast enough, if people table miss specific feature, those are very, those are like, well, of course, like they're not really perception. They're just something that they care about. Being a very horizontal tool is very common to miss something that people really like. And, and we take this very seriously. And it is very important for us to understand where to, of course, we have our, our idea because like the risk for this kind of horizontal tools is that you get plotted by feedback. And most of them are like basically asking for everything. You cannot just leave out everything you need to prioritize. And the prioritization is key and the focus is key, especially. And you can only prioritize if you have a very clear idea in mind of which kind of tool and which kind of user niche you want to chase. But yes, we are taking them very seriously. So those are really proper feedback on the product.

Interviewer: Do you use any kind of maybe AI techniques to, for your marketing strategies or maybe to create more targeted and personalized customer experience? Any kind of tools that you use in general?

Interviewee: Well, let's start by the assumption that, that what we are still in the phase in which we need to work a lot on the product can make the product even better than it is right now. So, we don't really focus on what I would call like cosmetics of the marketing part. Okay. We are working, of course, on the way we market some products. And, what we understood so far is that said the phrasing and the wording and the way we make product and feature discoverable is not really, doesn't move the needle right now. So right now, we are still in the, in the phases in which we heavily invest on the product. We need to either the product is 10x better than the alternative or it won't work. So, it's basically to deliver better feature better, something that is usable, something easy to use, something that can really improve the life of hundreds of millions of people using Spreadsheet.

What we use AI for is to, it's not really using AI, it's more trying to offer AI specific target of users of customers and to improve their, their experience on the Rows. For example, if you're encountering a marketing user, we're most likely offering them AI use case or how to use AI to improve their marketing strategies. So we have, for example, a sentimentalizes function that allows you to run sentiment on text. And this is what we'll actually promote to marketing users whenever they sign up or whenever they start using the product through some tours or whatever.

Interviewer: How do you exactly promote, let's say, like you said, an example of if it's a marketing user, you will promote the sentiment analysis tool or something like that. So then how do you exactly do it? Is someone sitting over there and connecting to the users or the customers to talk about it based on their requirements? Or is it your tool that directly, like kind of if they provide their details, it directly starts learning from it and like it gives the result that they really want to see?

Interviewee: No, I mean, like it's just like it's a product itself that recommends based on, for example, what people picked in the onboarding. So, if the people pick marketing as a user, as a role, then you will see marketing integration on top. You will see a specific use case that we promote through our checklist in the onboarding and whatever. So on and so forth. Our templates, our group of like email flow at the signups.

Interviewer: As you mentioned that it kind of like still needs a lot of improvement for your application, right? So how do you see the future of your application and the usage of like the wave of AI that is actually coming in? How do you see your application in the future in accordance to the AI?

Interviewee: And maybe it's even more in a couple of weeks from now, we will be releasing to the public a new version of our AI analyst. We call it analyst because it's basically a companion for you to understand, make sense of data, transform data, slice data, people data. And it will have a huge amount of more like huge amount of capabilities, more than the previous version. So, you will be actually a co-pilot. And I think the role of AI on spreadsheet would be even more focused on co-piloting. So, allows you to do stuff that usually people are not comfortable with. Do complex syntaxes for you, do complex formulas, do complex pivot table for you. And on the other side, it will be, it will be really, really be a companion for how to make sense of data. Right. If you have multiple tables, you will need to, AI will be soon able to have multi-table, multi-table context about multi-tables, really understand the relationship between tables, allows you to draw insight, make prediction about your data. So, I see two main avenues here, from one end is basically co-piloting you, allows you to make spreadsheets simpler in terms of creating everything charts, pivot tables, complex syntaxes and whatever. And on the other side, makes sense of making sense of data. So, more data analysis capabilities, more statistical capabilities, more prediction, forecast capability, and having context of multi-tables and this kind of stuff.

I think we are getting there really fast with Rows. And in two weeks, we will be seeing huge, improvement and huge release about this. So, I think we are on the right, on the right, on the right avenue. And yeah, that's it. And if I may touch a bit of a technical point, we will. The way we will do it is to create different standalone single agent. We will take care of single task one by one. You won't have a unique, of course, the perception for the user, it will be a unique entry point or a unique feature. But on the back, a different AI agent, everyone, each of one focus on a specific task. You will have one AI agent, namely one prompt doing a specific task. And the key is to have, the key is to being able to orchestrate these different agents on your, on your page based on the request of the user. That would be the best thing, the biggest challenge right now.

Interviewer: Given a chance, this is a bit different question that I would like to understand. Given a chance of talking about your product, will you say that your company in general follows a product first approach or a user first approach?

Interviewee: Yeah, yeah. It's a difficult question. It looks, it sounds fluffy, but it's no, definitely not. So, I would say both, but on a different scale and different level. So, most of the company will probably say both, but I will try to articulate why both is an answer for us, for ROSE and at which level. So, you need to be user centric. All the company needs to be user centric. And especially you need to be user centric on one specific aspect of our product, which is its horizontality, or how would you call it? How horizontal is our product? Spreadsheet is a tool they use to take notes, run financial model, run code, build table, build reports. So, there's such a wide range of use cases. You need to learn and you need to listen to your users whenever it comes to feature that you cannot not add. You could miss. So, when you build a spreadsheet, you're facing competition from companies like 40 years old company, 20 years old company, Google Sheets, who make competitors. So those are people who invest a shitload of money on those products.

You need to understand, to listen to your user when it comes to build the baseline, the benchmark of your experience. So, you need to have pivot table. You must have pivot table if you're building a spreadsheet. You must have conditional formatting. You must have charts. You must have aggregations. This kind of like example of like very horizontal, very mandatory feature. But then you need product. You need to have a product orientation. You need to have a product approach because whenever you have a horizontal product, you need to start somewhere. And you can position yourself in a horizontal product, but you need to have a niche to start with. And you need a very strong vision of what to do with that niche. The first niche was marketing users. And so, we need to have a very strong product direction and very strong product vision to say we need to make life of marketers 10x easier using Roles and Excel or Google Sheets. And you need to ask yourself which kind of feature you need to put in your product vision to reach this goal.

And you have this user-centric vision for the baseline, the feature that you cannot not have, you cannot miss. And then you have a very strong product vision and product orientation whenever you want to create on top of it, build on top of it and create the best spreadsheet for that specific niche. Or, for example, like we are doing now, I think there is a huge market and strategic-wise, we want to, I think there is room to bridge the gap between spreadsheet and data visualization tool. So right now, the typical workflow is basically moving from a spreadsheet, a thinking tool, which is a thinking tool, to Looker or Tableau or those data visualization tools. And the workflow itself is a nightmare. Maintaining dashboard is super, super tough and super time-consuming.

And I think what Rows was born for is to bridge this gap. And so here we need to have a strong product vision because people will not demand, they don't have in mind, they don't know that they could use a spreadsheet to build a nice report. So, what we need to have been a strong product vision to make it happen, to create those features that allow people to use spreadsheets as a report tool.

Interviewer: How do you differentiate yourself from, like, Microsoft has Power BI, as well as they have Excel, they have both of it. And you are trying to bring both of them together in one single application, which is a really great thing. But then how do you manage at the same point of time to create the user awareness that we are giving both of them in one single application?

Interviewee: I think it's all about starting, first of all, about speaking to the right people. So, we won't be able to replace Tableau right away for a company like Cisco, probably. But what we can do is just choose to start small and think of, like, why don't we teach our marketing marketers, our marketing user in a small-scale startup or app, how to report their data. And this is actually, it's all about, like, having the right niche in mind and a feasible objective in mind and then create a feature that is, like, as easy as that, like bringing and appealing components from other people. But everything is actually born with Rows, to be honest. And Rows was born and started with this vision to make the spreadsheet look good and look good when shared.

I think this is not really parting away from the original vision of Rows. This is something that is already doable in Rows. It's all about finding the right niche, add a few more features, allow users to make dashboards very easily, like by drag and drop, by adding a couple of new components that we still miss. And then everything else is based on a spreadsheet. So compared to adding a column in a table on Tableau or adding a series on a bar chart in Tableau, you will have this simplicity of a spreadsheet. You will have just gone to the table, add a column, you add a column, then you include the column in the chart, and then your dashboard will update. If you have data on SQL, you want to display on a chart, you can do it because Rows is integrated with SQL or Postgres or BigQuery. All you need to do is to go to the table integrated with BigQuery, use the same spreadsheet-like functions to add a column, to add a column or whatever. And you don't need to go through the typical workflow that you need to connect again the integration or to connect again the template. Sorry, to connect again the database as you do on Looker, which is much way easier.

Interviewer: One last thing from my end would be, let's take a hypothetical situation where a lot of users are requesting a certain kind of change in your product. At that point of time, do you have room to add that feature to your product or how do you see or do you take some time to understand if this is going to work out when you release it or not?

Interviewee: Well, it's a good question. We have a portion of our website, it's called feedback.rows.com, and it's basically a recording, like collecting people, the feature asked by people. And then we go through it, every roadmap, and based on our specific focus, we decided to include it into the roadmap. But most of them make a lot of sense. Most other are maybe a big leap, too much of a big leap for us at the moment. And so, we keep it aside, either aside or basically for the next quarter. But we take this communication with the user quite seriously. And we usually ask people to motivate why they are looking for that specific feature, and then we analyze all the motivation, and we see if there actually is overlap with our specific niche or our focus user, basically the user we are focusing on right now. Obviously, we have upvotes in this mechanism, so we can see actually how many people have voted for a feature, and this is a very good indicator of how popular it needs to be, how hot is the feature request, and yeah, that's it. And we progressively tackle it one by one. In the last quarter, we even built a new team, a small team in our company, focused mainly on tackling those issues that the current structure of ROSE actually doesn't have time to deal with.

Interviewer: Do you use any AI or maybe NLP tools, which is basically a part of AI techniques to like segregate all of these feedbacks from the customers, or do you do it manually, right?

Interviewee: We use Rows, actually, of course. So, we have, I think we have a type form, like our tech stack includes type form as a form, as a form, and we send this form every quarter. For example, let's take the MPS survey, so every quarter, end of the quarter, we send this MPS survey through type form. We have an integration with type form, and we can basically fetch data, actually. The type form save is only on their dashboard, directly into Rows, so we have the integration. We fetch data as soon as a new response, a new answer just comes in.

We have a spreadsheet, which just basically collects all replies from previous and current surveys, and then we do a bit of analysis. So, we have our function to measure the sentiment of the feedback, so send a rating from one to five, or from very negative to very positive, and then we have, obviously, we have like numerical questions, numerical answers, and then we have the answer about the feature that's very important to navigate, and those features, on those, basically, what feature we would like to see in Rows, what feature will help you use more

Rows, which kind of integration we are missing, and all those stuff, and we use those, we use a couple of our proprietary functions, which are extractOpenAI, and summarizeOpenAI, and we use them to extract a key point for each question, and then we classify them, and we also use classifyOpenAI to classify them into, I don't know, UX, UI, computation, and to understand for each quarter what basically the trend of features in each of the buckets, so this quarter, we have a lot of questions about UI, next quarter, we have a lot, the previous quarter, we have a lot of feedbacks on the computational side, maybe we did something that reduces the performance, and so we have a way to really make sense of the data to Rows, yeah.

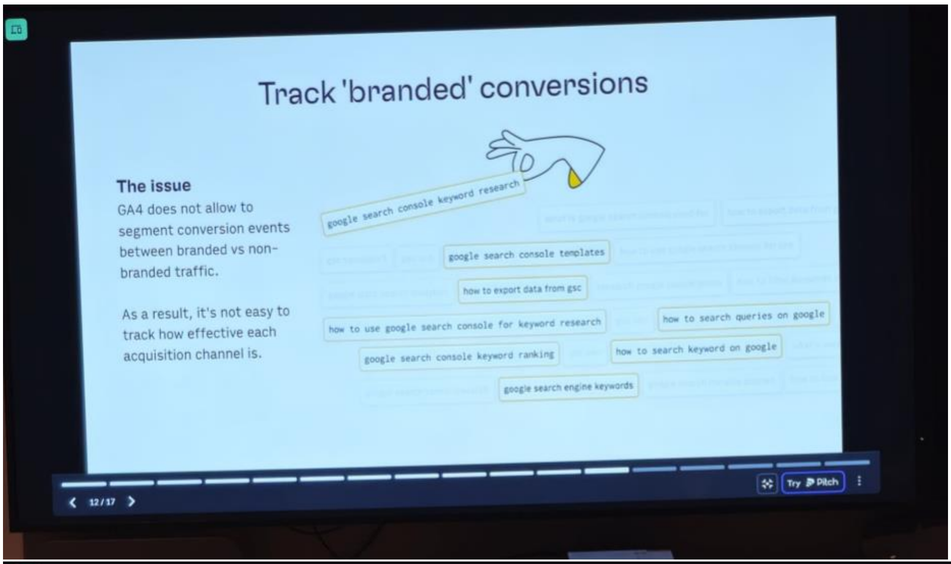
Interviewer: Okay, I think that kind of answers all of my questions. Thank you so much. Would you like to add anything else?

Interviewee: I think it was a nice chat. Yes, for Rows, I think AI, just to summarize, AI plays a role within Rows, and within the way we are using Rows, mainly on classifying customer feedback, categorizing bugs, and try to make sense of data, make sense of like, of course, and this actually very, actually opens up, I think it really opens up a new market in the sense that before AI, you had basically, you had a trade-off, you have to face this trade-off, either you ask for open-ended questions which are very hard to manage, okay, or you ask for closed questions, but these usually tend to bias, to provide the user with your bias, right, because it's hard to predict all the type of questions, all the type of answers, and you're somehow channelling the answer of the user into your, what you think are the main problems, okay, and AI actually solved this trade-off, because it allows you to keep it very open, and this actually helps people to express themselves, to be more, be more authentic, and be more reliable on their answers. On the other hand, AI helps to make sense of this data, by summarizing, instructing the key points, and make your analysis way, way easier, so we're using, we're using, this way we use Rows, and we use AI Rows, and then obviously we provide AI features to our users, and on two main, two main like domains and dimensions, they mentioned before, so on one end is co-piloting people using Excel, making spreadsheet easier, and on the other sense, on the other, on the other dimension, making sense of data, so analyzing data, making statistical analysis, comparing data, and this kind of stuff.

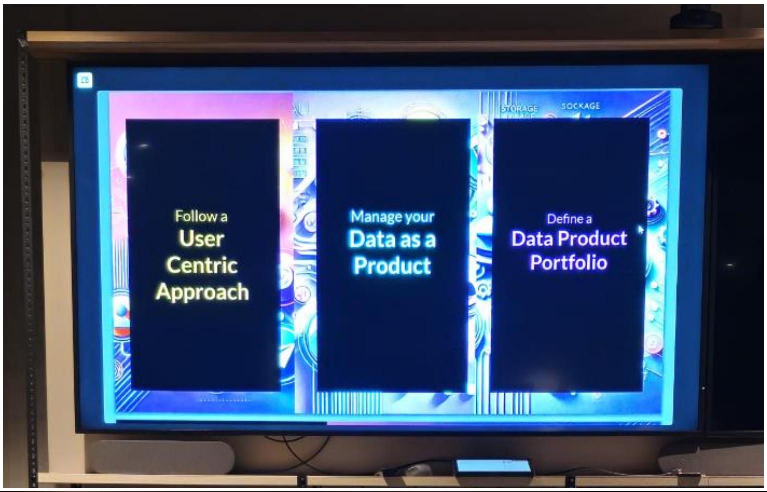
Interviewer: Thank you so much.

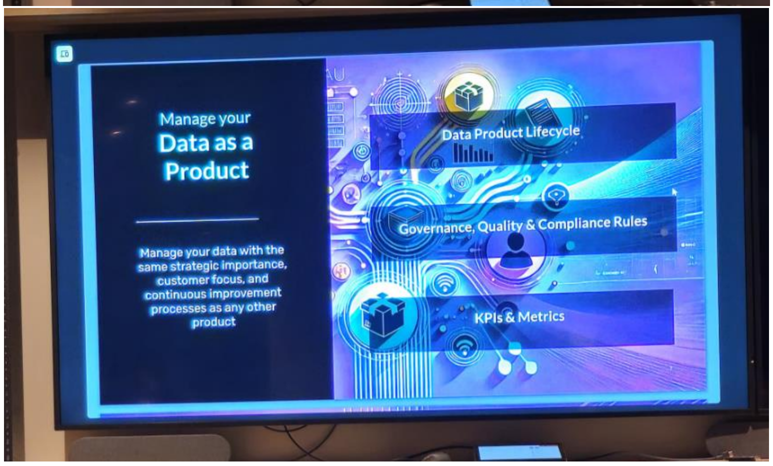
Interviewee: You're welcome. Let me know if you need more.

Location: ProductLab event, Berlin.
Date: 27th Aug. 2024
Interviewers: Panda. S,
Interviewee: Manassero. A, (Head of Product Growth, Rows.com)



Location: ProductLab Event, Berlin.
Date: 27th Sept. 2024
Interviewers: Panda. S,
Interviewee: Maarry. K, (Director Data Governance and Business Intelligence, Prima)





Location: Online meeting via Teams, Berlin.
Date: 7th Sept. 2024
Interviewers: Panda. S,
Interviewee: Samal. B, (Head of Marketing Campaigns, Volkswagen Group)

Interviewer: The aim of my thesis is how exactly companies can use NLP to understand customers purchase behaviour throughout the customer journey and their intentions. And according to that, how they can curate the marketing strategies.

Interviewee: Okay. I can share some of my experiences. Obviously, within our company, we haven't started using NLP full-fledged. That's a very basic stages of using like we are experimenting still. So, nothing that has been really rolled out to customers. Obviously, there is an inbuilt car information system, which understands voice commands and reacts like call this thing, answer this message or whatever. Those things are there, but those are very basic. Now, it is not really with the advent of AI, like what it should be, you know, technological changes, which would enhance people's lives. This is something which has not been yet integrated into a car.

So, it is a plan for the next phase. I don't know about Mercedes or BMW, if they have already done something. But high level of interactivity, which is like we have something called EDA. EDA is a voice assistant, and you can ask anything. It is linked to ChatGPT. It is available in our cars, but it is basically using ChatGPT as a background, as an interface, which gives answers and EDA is just saying it, telling it to people, customers. So, if ChatGPT is good in responding, EDA is good in responding. For example, if you are going to, let's say, you're going to Bosnia or someplace like Montenegro, let's say, and you want to know which is the best Japanese restaurant around. If you ask, because the ChatGPT version that is available in the cars right now is not the latest. It gives you information which is old. Like from a consumer's expectation, they would expect that you will give the recent most. Like if you do a Google search, you'll get the most recent. But the challenge with car industry is the compatibility of, let's say, the new versions of ChatGPT to the existing platform that are available in the cars. So, that is one challenge that Volkswagen faces. I can talk about our systems. Which we want to overcome.

So, if you say whether NLP has been fully implemented or has been, is being used up to the mark, I would say not yet, because we are still trying to find solutions. Like, you can go to any Volkswagen dealer, you can exchange ChatGPT in a car, you can ask questions, people answer. But those are, if it is about history, I think it does a good job. But if it is about something which needs updating, new restaurant which has come up, or new event place, or new event which is happening, those are the restrictions in the car. So, that is the first point about, let's say, in-car usage of NLP to enhance people's lives.

Then there is a second aspect which is about consumer interface where people are calling or people want to interact, let's say, with the chatbots. Those are the things which we are still working on, because we being in Germany, obviously there is a huge focus in German language. At the same time, UK and also folks here are experimenting with English to come up with solutions which is appropriate in terms of giving replies, giving feedback, it should be appropriate. I haven't experienced it yet. I maybe would request you to do some research, see what is available, maybe you will find out about Volkswagen, about Mercedes, about BMW. But this is something which is, I would say, it is still being worked upon.

Mercedes is also offering, if I am not mistaken, ChatGPT now in two of their cars, one or two of their cars, I am not very sure about BMW. Those are the few couple of things, pointers I wanted to share upfront with you. Different industry if we talk about, I of course interact with few chatbots, I try to talk to them.

Interviewer: Not related to only NLP because I also need to understand how you understand customer behavior. So let us discuss a bit more on it. Can you describe how your company currently understands customer perceptions of your product, perceptions of our product? So, we have different researches.

Interviewee: So, there are two things. One is we do product clinics. Before the launch of the product, we test the product with different customer groups. We get their feedback, how to improve, what they expect. So, how do you decide these customer groups? So, like, you know, there is a limited amount of money, limited amount of time. So, you pick your customer groups. Few who are driving competitor cars. Few who are old folks and owners. And few who are in the market and not decided on what they want to buy. And they're not loyal to any particular brand. So, that could be a good mix of people that are in the room to give feedback on the cars. The second is there are global researches in place across markets. So, we have, let's say, two waves in a year. Where we are asking customers different questions about different cars, all models, all features. Their views on how we are tackling sustainability, et cetera, et cetera. So, there also, we get feedback on the products.

So, for example, there is feedback on folks under the leader in electric vehicle. Which is, let's say, a summary question. Which is, what do you call it? It's an umbrella question. And there are also particular questions like, what is your perception of IDP as an EV? What is your perception of an ID4 as an EV? What about the interiors? What about the design? What about the drive quality, range, et cetera? And there also they give feedback. So, majorly, if you ask me, one is when the product is getting developed, there are a couple of instances where we get feedback from customers. Computers, people who are driving computer cars. People who have been driving for certain ICs from the past. And people who are not loyal to any particular brand, but are in the market to look for cars. And this global research, which has been in place since many, many years. So, these are, let's say, two important touch points or milestones where we collect feedback from the customers. And another small thing I could say is post-campaign analysis. So, once you do a campaign, product campaign, we highlight certain features, then we ask people what is their perception. So, there also they give us some feedback.

Interviewer: Yeah, so, when you decide about these customers, right? How do you get to know that these are the particular, because you might do some kind of analysis, maybe the personas. How do you decide on that exactly? I mean, whom to exactly choose? Because there will be a number of customers from your competitor brand also.

Interviewee: Yeah, no, no, no. So, basically, it depends on availability. Obviously, we give it to an agency who recruits for us. We give certain parameters. This is what we want. There's a mix. These are the kind of people we want. They do headhunt or they go and talk to people, whoever are willing, available on that particular date. That is how it was.

Interviewer: Does your company use AI technology to understand sentiments of customers?

Interviewee: Sentiments of customers, not yet, I would say. There's advance. But we'll come, let's say, in the near future. So, it's not there yet. We don't have a solution.

Interviewer: How do you track the post-purchase? Do you take the customer feedback from each of the customers? Or do you select a few of them? Are you selective in that?

Interviewee: Yeah, yeah. It's like, again, given to an agency to get a few customers from whom we can get feedback. So, yeah, that is done. We also organize events like we have ER, like the motor shows. Also, there are questionnaires where people give feedback. And we have tests, like TTI fan test we did recently. There is ID tests or ID drives where we get feedback from customers, from journalists. We call journalists for drives. We get their feedback because they're experts. They know all the cars and they give their open feedback about what they feel about the cars and the features.

Interviewer: How about the customer reviews? Do you try to consider them to customize your marketing campaigns?

Interviewee: It is very seriously taken. Obviously, our product department, our design department, marketing also, we take feedback. And we, of course, want to improve on if there is negative feedback. So, it's like done with all seriousness, I would say. At least, I hope so. Obviously, journalists are the close, let's say, the industry experts. One big point of our contact where we get feedback. At least for automobile, that is how it works. And they are taken very seriously.

Interviewer: What aspects of customer value, emotional, social function, and monetary do you think are the most important to your customers?

Interviewee: Of course, a car is a huge purchase like it's a big figure item so monetary makes a lot of difference. Like the tactical we give where we talk about finance schemes or you know discounts they have a huge impact like everyone does it across automobile companies. I would say first point is monetary, the second point is experience reliability. So, there are three things, one is likeability, let's start with money obviously pricing, then comes the product, how good is the product features, you know interiors, exteriors, whatever they like. Then the third thing is reliability and trust if that's what's the brand and the fourth topic which is let's say one umbrella again talking likeability, likeability for the brand if you prefer the brand. I don't think many of us would prefer to be seen in a Dodge or what do you call it Dacia. If I would buy a car it has to be from a good brand, a brand with good reputation.

If I'm French I'll go for Renault or Peugeot, if I'm German I'll go for Volkswagen, yeah if I'm Spanish I'll go for Cupra maybe. So, brand reputation or likeability is another important point.

Interviewer: How do you kind of measure the dimension of customer value for your products? Which dimension do you think is more effective for your customers versus with your products?

Interviewee: As I said, you know, like, because, yeah, so because functionality is one thing. So especially for EVs now, what is the range? How fast does it charge? What is the price, you know, interiors, all the features, software upgrades are one big thing nowadays. How compatible the software is, if there are any issues with it, et cetera. How do you see the stages of customer decision journey awareness conservation design with three-dimensional functional monitoring? As in, so when you're doing, or when you're planning, starting from the launch of the product at the world premiere till the time, obviously, during the life cycle, as many number of waves as needed to sell the car, there is a launch phase, or there is a pre-launch phase, there is a launch phase, there is a sustain phase.

We think through the funnel. So, the mix changes. If you're in the launch phase, obviously focus is on awareness. In the sustain phase, focus is on consideration and purchase. Post-purchase is always ongoing. Let's say that's the always on thing. So that remains throughout. People who buy, what is their feedback is important. And so, we keep an eye on that. And emotional, social, functional, monetary, I think it's all combined. As I said, first point is what is the pricing. Then comes, you know, whether, you know, the likelihood of the brand is there. If they prefer this product from this brand, they trust the brand and the product. So emotional is, the monetary is rational, let's say. And then there is emotional.

If you ask me, which is stronger, any day it is emotional. The likelihood for the brand, the emotional appeal of the brand is, has to be stronger than the monetary aspect. So even if a Dacia would reduce their price by 30% on a particular product, that won't bring them substantial more sales because people do not like the brand. It is seen as a workhorse brand. People who are carpenters, plumbers, or, you know, transporters, maybe they would use it because it is low on cost. It is highly functional. And there is, there may not be any emotional aspect that they need to consider before making a purchase decision. So that is how it works for a brand like Volkswagen or Audi or BMW or Mercedes or the good brands, emotional aspect is important. And then obviously, so it is emotional and then rational. This is which is kept in mind across the funnel, like from awareness till purchase, post-purchase. So that is what is kept in mind.

Interviewer: Can you think of any specific points in the customer journey where understanding personal value of the products could be significantly influence customer decision making?

Interviewee: As in, this is, I would say in the sustained phase because the products have been launched. Definitely some people have bought it. Journalists have given their reviews. So, I would say six months after the launch is a good time where the positive value of your product could be measured. And then if there are any weak points that need to be addressed from, you know, from whichever aspect required, if it is design, you can't change it. But if it is something functional, like, you know, which could be, could be improved in the next phase of product development, that should be, taken into consideration because like, it's not that everything is fixed. There are some changes which are possible during the product manufacturing stages, but yeah, they have to be in the next phase, like if there is a facelift, there will be changes and those pain points, we try to overcome them. So yeah, that is, from automobile company point of view, this is how we deal with it.

It's very expensive to change anything in design. The metal like has to be, the design does not change much, like in a facelift, that's the reason, like most of the manufacturers, what they do is they change a bumper because that's a separate part. That dye, one particular dye can be changed. The front bumper, the back bumper, or maybe one particular thing. You cannot change the overall shape of the car and you cannot change the doors. Let's say the body only, maybe you can put some more lines on the bonnet or maybe you can put some, a new bumper or something. So, these are particular, some aspects of the car which could be manipulated a bit.

Interviewer: Could you shed some light on the strategies that you use for product adoption? (marketing strategies)

Interviewee: Yeah, I think, okay, so going back, if I were to say, all your people used to prefer, I'm talking about India now, people used to prefer sedans, okay. In many other markets, that was a trend. People used to prefer sedans at their family cars. Slowly the trend changed and moved towards SUVs. People are preferring SUV body style because it is, you know, it offers you more. It can take you off-roading, it can take you on adventure trips, it can be used as a family vehicle, it can help you go shopping inside the city vehicles, everything. And it's more compact. Even compact SUVs become a major hit, like which Maruti did in India. But also here in Germany, like we have T-Roc, we have T-Cross, smaller cars, compact SUVs are in demand. What I was saying is, yeah, and you need to change your volume mix according to this. So, depending on what is the market demand, you need to keep changing your, let's say, product offerings.

For example, like we have Variants, which is, let's say the, like, you know Variant, right? Passat Variant, which is not a sedan or an SUV, but has got a flat kind of hatch. So, it is a long car or big car, but with more boot space, it is more practical. A lot of Germans have preferred it. And Passat Variant is a high-selling car in Germany, but not in India. In India, it won't work because people do not prefer that body shape. So, depending on market realities, obviously you have to change your product mix, and that is how you plan your strategies, okay? We can sell Variants in Germany or Europe, but this does not apply to India, for example. We can't sell Passat Variant in India.

Interviewer: Does your company use AI in any marketing strategies to get more target and personalized customer experiences? Example future plans, if possible.

Interviewee: So currently we are using AI to produce content, to produce moving images and also static or digital. And what we're doing is we are mapping the environment and creating content around it. But yes, I think other companies are also using AI. Like a lot of brands are using AI to come up with campaigns, content to engage with people like Gucci, like Balenciaga, like other automotive brands. So, from marketing strategy point of view, majorly we are using it to produce content at a low cost and at a faster pace right now. And as in the customer journey, like I was saying, so improving on the chatbots, improving on the, let's say if there will be a Volkswagen representative, which is not there to be honest.

Like if any of the other brands will come up with a brand consultant which is made out of AI, like which is AI-generated and not a real person, he or she needs to be trained. And there obviously, it is a marketing technique obviously, but there will be companies who will use it. Some are already started, they're like these newsreaders who are made out of AI, like generated out of AI, they're not real people. Influencers who are engaging with audiences. It used to be called programmatic, now programmatic is blended with let's say AI. So, it's even more robust, I would say. If you are interacting with any of our assets, it is all automated and you get some more of this campaign assets or more of this car creatives, which engages you even further. But depending on what people are doing with different content elements, it's definitely trackable on the internet. And that makes it easy. And also, we personalize it. So, if it's a family, like someone looking for a family card, we will try to show a creative with family around. If it is someone who is a surfer and looking at a card to fit the surfboard, then there will be a, let's say the same card but with a surfboard so that it is more attractive to this user. So those are the kind of, let's say adaptations or those are kind of automated creative improvement, content improvement, you can say, which is being done and then served to people.

Interviewer: What are the data sources you consider when using NLP to understand customers?

Interviewee: Review social media posts, chatbot interactions. You consider when using NLP to understand customer purchase intentions. So, as I said, it's pretty primitive. Nothing really robust that is at least available for folks. There are a couple of countries which have started with chatbots. I think UK has a chatbot, US has started. So, you take certain feedback, but how it is used right now to understand purchase intentions. Is there a way to target these people back? I don't think so. It is just about collecting data for sure. So many people interacted, so many people asked this question, so many people are interested in ID4, for example. Those are the things we collect, but purchase intentions particularly, like if we go two steps back when AI was not existing, also in during the normal internet phase, we track which IP spent how much time on the website.

So, page visits, model page visits, website visits, time spent on the website. These are KPIs that we track. And also, if they are interacting with particular things on our website, we understand them. And if they allow cookies, then we serve them with those banners to encourage them to buy our product or come back to the website again. So those are the things which are being done. And with chatbots coming in place where people are interacting, I'm sure we will capture those insights to reach out to those people who have interacted more in a certain way to influence them to come back to our website or consider buying our cards.

Interviewer: Can you share examples where NLP insights directly influence changes?

Interviewee: Yeah, not in product positioning definitely right now, but yeah, customer targeting, yes, initial stages, I would say. Envision role of AI in shaping the future of company customer engaging strategies and understanding and influencing customer behaviour. So yeah, like a future would be to create chatbots, to create let's say AI robots to interact with people. There are metaverse environments where you can have avatars talking to people. People do not want to meet human consultants so that they don't, they're not chased. Maybe they're more comfortable talking to AI robots or AI chatbots in a very human way. We need to train them with NLP so that they respond properly. It looks like a human conversation.

At the same time, there is customer comfort that they are not going to be chased because they've spent this time talking to this chatbot. So, all of this could be built. Different countries are working on different solutions, you know, because the language has to be local and the cultural nuances and the local Flavors have to be attached to it. For example, Spanish too. Even if it's Spanish, like in Mexico, it would be a little bit different to what it would be in Spain. There is no central solution or global solution for this, but different countries are working on different things.

Interviewer: Do you see a drawback of not starting to use AI on a full-fledged basis?

Interviewee: I won't say so. We are definitely working to use AI on a full-fledged basis. It's just that, you know, there are different departments, the companies, different companies are going through different phases, let's say. How much do you need to invest into AI is a question. And number of people, resources, money, everything, no? And by the time, like, that's the reason, like, we also tie up with different, let's say, global, we have a tie up with Microsoft, we have a tie up with Vivian for software. But I would say that, you know, we would focus on producing cars, doing the job that we know the best. And these parts maybe are outsourced to different other companies who we can work with as partners. And yeah, we'll buy solutions from them.

Interviewer: Is there anything else you would like to add?

Interviewee: A lot will change, actually, a lot is happening. There is no end to learning, there is no end to usage, there is no end to how AI can be applied to do different things. So, it is a new phase for the whole world. And like we learn to live with the internet, we would get used to living with AI has got its pros and cons. Fake news can easily be built, fake information can be given, people can be politically motivated in a certain way. Companies like, you know, there would be legal departments also looking at different, you know, different messages going out on behalf of companies.

So, if you do something that people in the digital agency for your competitors who are countering what you're doing and trying to do reputation damage, and you need to have reputation management as a technique to counter competitor challenges, let's say. Similar would be with AI, like AI is even going to be more dangerous. Yeah. So marketing is a war, and you need to do whatever is needed to win the war. So, I'm sure the battle is going to be nasty. At the same time, it's equal opportunity for everyone.

So yeah, and you can also use AI to generate new car designs people have not seen. You could take in some things like this is my design and have a copyright on it, like not using publicly available AI, but using AI to develop your own solution and creating designs out of it. Like once you register the design, no one else, even if they generate it, they shouldn't be able to use it. So those kinds of laws, which are still not existing, but should come in place and is a big challenge now, at least for many of the industries.

Interviewer: Thank you so much!

Location: Online meeting via Teams, Berlin.
Date: 17th Sept. 2024
Interviewers: Panda. S,
Interviewee: Elbasueny. M, (Head of AI department, Regent Branding)

Interviewer: If you can just give a background of yourself and then we go ahead.

Interviewee: We work in, we're using basically LLMs to create chatbots. And we're currently also building product. It is like the new AI shopping product for people that it should be like understanding people needs or clients' needs without any, you know, without any harsh or any work. And we are using LLM as a recommendation engine in it. And the last product of our company is called VidBuzz.

VidBuzz is like a chatbot like that's using some LLMs on the ground to answer veterinary data. Yeah, I think we have talked about it. Yeah, we have. Yeah, our country is ahead of development in that. It's a small company, but we're trying to survive in that world.

Interviewer: it more of a B2B, I think?

Interviewee: Yeah, we're offering marketing, marketing products and also like AI solutions to people.

Interviewer: The aim of my thesis is how can sentiment analysis and topic modelling be leveraged to understand customer purchase intentions ultimately fostering product adoption. The end goal that I'm targeting towards is how can exactly marketers or maybe businesses get help of NLP to guide customers towards the product adoption.

Interviewee: Yeah, that's amazing. It's a really nice one.

Interviewer: let's say you are building a chatbot, right? So, for example, if you're building it, then you must like kind of have done your market research on it already. And you must know what kind of product exactly does your customers need?

Interviewee: We got to know that the clients need more accurate answers to their questions. And they also need the like, you know, an accredited source for that. And they needed to be so up to date. They don't need like, a paper or like, because we are collecting our answers from papers, also from scientific papers. And they don't need to get an answer from, you know, a weak paper, a weak accredited paper. So, if I need to summarize that they need first, like, correct, correct answers to the questions. Second, up to date answers to the questions. And the third ones you needed to be accredited. So, they need sources for that. Okay. Yeah. So that's the three first three feeds. We summarize our feedback from the customers and also from the advertisement campaign. And we found out that these are the more like, the three important stuffs that people that our clients' needs from us. And so, we are currently working on that.

Interviewer: How do you understand these feedbacks? How do you figure out these are the target groups that we want to focus on so that we can understand the feedback? Because based on the feedback?

Interviewee: Yeah, first of all, we have a small part of customers now, because we are a veterinary chatbot. So, we mostly what we have is, is like two kinds of people. First one is the professional ones. And they are all they are like mostly vets. And second ones are like people with a dog, people that have pets, that own pets. And so, we clearly understand what they want. For professional ones, they are a little bit hard. And we have a feedback per question. So, like every question that you can ask, you get an answer for it, like a chat GPT**. But you can have feedback for the exact question. And we are linking that to the question ID. And so, we are filtering the questions with the we name it reviewed questions.** And we get them and we try to send we have some people of some vets that are working with us. So, we send we send that question to them. And they return back with the answers and the exact sources for that. And then we collect that and we retrain the model on it after it. Yeah.

Interviewer: What are some other factors that you really think influence, when you try to acquire a new customer, what exactly do you think influence those customers to consider your product?

Interviewee: I believe I believe it's I think I have an answer for it. I believe it's trust. Okay, because people, our clients need to trust us in that we are providing them with correct answers for their questions. So, I think that we need to have like a high accuracy more than ChatGPT because we have pre trained our models on perspective data that's related to the data from really accurate sources and the needs that like, maybe out of 100 questions, one or two is wrong. So, they need to trust our, our products so that they can they use it. Because we are in a big market and there's a lot of chatbots out there. And so, they need to trust us. And by trusting us is that we use the perfect sources to use. And also, we are we are always up to date. Because sometimes, you know, in medical data, there is a paper that counter another paper. We need to have to be up to date in that. We are answering the questions based on some, based on some papers that we have. And that's also on some sources that we collect. It's it was professionally collected by WITS. And yeah, so it's kind of a RAG if you know what a RAG is. Yeah. So, I believe it's, we target bigger veterinary communities. Maybe, I don't remember the exact sum of them, but we target like the 10 most veterinary communities in Britain. And we're trying to embed that solution in their in their websites. So, people like trust some websites or some communities to ask questions there. And if we manage to put that chatbot there, we have a business customer. Just our big target for, for, for monetizing. I think we have like two matrices**. I believe it's questions per day. And we, we also like have feedbacks per client. We also track if, if like the clients open up our emails or not.** Yeah. And we have also Google Analytics to track like the time spent for per client per day. Yeah.

Interviewer: How exactly do you try to understand your customer base sentiments?

Interviewee: Because you also train your models accordingly, right? So, you of course take the feedback and everything based on that you try to do it. We just have like, and dislike button for every question. Okay. And we have all sorts of feedback, pass on the feedback. We, made like, every month we shipped that sentiment analysis model along with the likes and dislikes comments. And then we, yeah, we can create the overall sentiment on that for the whole client. So, we can see like, if you're getting good or not, but we mostly care about the likes and dislikes.

Interviewer: Does any kind of customer perceived value play a role? For example, do you think these are really important for customers for your product, maybe the current product that you're working on, the previous product that you have?

Interviewee: I think for my current company, I think the functional one is what most now, because we still haven't monetized it yet. So, I think what's care, what they care most about is how functional it is. So, they just don't have any social, you know, do you, do you understand what I mean in it? We are trying, we are trying to monetize from the business itself because we are a B2B people. So, after we gain a lot of customers and we got to acquire a lot of customers, we are trying to market it to the company. I think say, we are on a step now for monetizing that app or chatbot by, you know, we are making something using topic modelling to use to, to detect some situations or like some maybe I gave you an example now. So maybe I'm the client and I'm trying to get like my dog is itching, is itching a lot. So, we are talking now about, we need to provide it with itching medicine, right?

So, using, using topic modelling, we can detect that it's this client is, inquiring about itching medicine. And then we are, we have like a marketing, it's like Google ads. And we use that to, to provide him with, with a, with a specified medicine from, from a specified company. So that's how we monetize it by ads.
you mean emotional, social, and all that dimension.

Interviewer: Are there any other things that you try to do, maybe to curate or maybe to provide to a customer?

Interviewee: We are, if you are talking from the emotional one, we are, we are trying to give an into our UX experience. And from the social ones, our marketing team is also working a lot to, to try to market that and try to market that as a Britain, as a British solution for veterinary. And out from the technology side, we are, we are always in veterinary communities trying to explain how our chatbots working. But it's so hard because we are in the step of, you know, acquiring business customers for us. And we are, our chatbot is just for free. Now you can use it as, as much as you want. Okay. So, we are trying to acquire, maybe I can't have enough data for it because we are trying to acquire, we are trying to build our P2P solutions. And we are just in the step of like getting or acquiring the customers or the end users to show and to show it to the that we are, we want to get some money from.

Interviewer: Except for trust, if you talk about maybe during all of these dimensions or anything else, what is a particular thing that we will actually post and that your customers would love to see in your product?

Interviewee: Okay, let me think about it. If I put myself in the foot of a client and I, want to, I'm using that chatbot you know, what's, what is the, what's the best thing about ChatGPT? It's like, whenever you ask them a question, you just get an approach to that. And also, now they are adding the voice sync in it and, and they're now embedding that chat, that chatbot into our operating systems. And I think if, if we, if we manage to do that our product is being used by vet, by vets in every day, we have a success here. So, it's like, if you are so functional to them that they are using, us every day for like, for students, for veterinary students in, in seas, in their seasons or some stuff like that, or like vets every day that like have got the strange questions that they don't know.
And also, we have in our, in our roadmap that we, you want to add, you want to be, we want that chatbot to not be used as a chatbot because like everyone has a chatbot nowadays. But if, if we manage to like be like the centre solution for vet, for vets, like if you have, if you, if you have a beta and it's not feeling okay, you just, you just give it a foot or some stuff and we can analyse what's going on here. That, that we are trying to reach, you know. I believe we have a social campaign to target vets in Britain now. So, we are sending also emails to, I believe it's like, we have some data of this in Britain. And also, we are, we are having like, for early clients, we are giving vet bots for free for life for them to sign up. And yeah, when we're not using any AI, like directly, but I think the, like the social campaigns now that we're using this, I think we believe, I believe we are using a third parties' solution for that. That's using AI under the hood. So, I believe we are all using AI indirectly. Okay.

Interviewer: How do you train the models? For example, like let's say, take an example of Meta, right? They use social media extensively to train their data sets. What exactly is your way to do so?

Interviewee: So, I believe we, we built our dataset from releasing the model at first without using any RAG. And after it, we collect a lot of questions and we send them to some, to some professional vets and they answered it and provides the sources for that. And then we, we, we have used the sources of the sources, like how we got the sources from, in the RAG process. And we, we trained the model to, to use that answers that we collected. So, we indirectly create a synthesized dataset.
And we're using, we have some agents process here is that we are trying to use in Drench. Drench is a, is a shopping, is a shopping product. And it's, it's going to use that to create like a bathroom, for the questions that the client asks, we use the topic modelling to be able to like direct the agent, because we have like some sorts of agents and for every case we have an agent for it. And so, we have like a, a fashion agent and bathrooms that we detect that by, by classic machine learning. And then we bought that was the process of like, which agent are we using? You know, it's like, if it's so success, we can use it in a lot of other areas, but we're, we are currently targeted fits because we, we, we can't be using that chatbot to target people because we, we, you know, you don't, you don't have the regulations to answer medical questions for people. And we are, we are clearly saying that, you should always ask a vet for your, for your pets and just, just for initial help. Yeah. But maybe in the future, we can have that process also for people if we managed to get zero error chatbot question answers. I'm very keen and I'm very believable that we will be able to do that in our age because AI is going like crazy now.

Interviewer: Thank you so much for your time, I don't have any more questions, if you want to share anything?

Interviewee: No, it's okay. It was really nice to meet you again.

Location: Online meeting via GoogleMeet, Berlin.
Date: 16th Sept. 2024
Interviewers: Panda. S,
Interviewee: Sharma. R, (Head of D2C & Digital Marketing, Bisleri International Pvt. Ltd.)

Interviewer: How did you use the customer journey to track customer perception in e-commerce.

Interviewee: So, you know, whenever there's a brand, right, that goes out in the market. First of all, in online scenario, probably a brand is present physically. And there's much awareness about it. To give you an example, you know about Tim Hortons? So, suppose Tim Hortons is a, you know, a physical store, right? Where you know that it's a cafe around the corner and you go to it and, you know, you order your coffee and your croissant and all of those things, right? Now suppose, so there's well, it's a well-known place in Canada, right? Specifically. However, so now suppose given the digital environment growing, etc.

Suppose they decide to launch their Tim Hortons delivery app, right? Wherein they say that, okay, fine, we will deliver the order to you. So now there for them, there are two things now. One is already need to kind of have to run their offline business wherein they want footfalls to continue to grow, right? So, in two scenarios, offline and online, ensure that in offline people know you. However, how do they choose you over a McDonald's or a Starbucks? If you know they are going for coffee, right? And if they are going for food, you know, why do they choose you over McDonald's, right? Now, so they need to drive that pull, right? People know. So here are the customer journeys. People know you offline, right? But you have to ensure that they come visit your store. So how do you do that, right? So, people generally while going to their office on the corner see that there's a Tim Hortons. Okay. Awesome. You know, it's near to me and I'll kind of walk in and buy my espresso and a bagel, right? And move on, right? To my office. But now there opens a Starbucks. Next to the Tim Hortons in the offline world. Right now, there's a choice for the customer wherein the customer can choose to say, Okay, fuck Tim Hortons. I want to go to Starbucks and, you know, drive their coffee and their croissant instead of my daily coffee and bagel that I used to eat from Tim Hortons. Now as an organization or as a store Tim Hortons, now I need to, you know, while people know about me, they have been here with me. They have, you know, dined with me. I need to now play on the pull, right?

So top funnel is clear wherein there's a top of mind recall for my offline. So, we are talking still about offline. So, I need to create a pull, right? So, what I'll do is in front of my store, I'll put a kind of a standee. You understand a standee, right? It's a kind of a whiteboard or a sticker or a digital screen, right? And I'll say that, oh, okay, you know, a coffee and a bagel, which cost if you buy separately, say $200. Now it is, if you, you know, bagel plus coffee is $410. Now this croissant and coffee, you know, that Starbucks will cost me $150, right? So thereby you now have created a pull for the customer, right? They already know that your coffee is good. Your bagel is good by doing that offer. Now you are ensuring that there's a repeat customer. And also, you know, thereby you are bringing a new customer because you are running an offer outside your store, right? So, this is how you kind of acquire and retain and increase footfall for your offline business. So that's your kind of journey. So, journey is about a new user, a returning user and a user who has kind of, you know, who's gone from you, right? And you bring them back into the ecosystem by doing some kind of offer, some kind of activity, you know, what is your carrot for the customer basis, right?

Now we come to the online world. So, we started by saying that there is a store and then now they have decided that they want to launch their own app, right? So here things become a little bit tricky. Tricky, why? First, you need to tell the whole neighbourhood that, hey, look, I am also online, right? So now in your neighbourhood, probably a hundred customers come into your store, but there are a thousand customers in your locality, right? So probably you'll put in your store a good branding of that, scan this QR code and you can just order it from home and we deliver to your house now, right? But that doesn't help you, right? Because out of hundred, you know that 90 or 80 customers are my repeat customers who go to their office and on their way, they choose to pick it up, right? Or while coming back, they pick up some dinner and eat it once they are home.

So now the job for you is that, how do I kind of first A, drive awareness for my brand, right? First, you need to announce it to the world, right? That, hey, I have an app, right? So, first job of the customer journey in the online world is that you start communicating about your online presence, right? So, we discussed that there are a thousand households, right? In your locality. But out of that, you need to really decide or zero on to the people who can be your potential customers, right? So, defining who is your potential customer is very important. Now, how do you do that, right? Now you need to figure that, okay, this is the demographic of my locality and this is the age group or this is the gender or this is the by interest or preference type, right? Like I am a professional. So, you need to define your personas, right? Who are you as a brand and who is your target audience? So, you need to decide that. Once you do that, out of the thousand households in your locality, you get to know that, okay, 800 people can be my potential customers, right? So now you start telling them about how you are present online. That's how you move ahead with creating awareness because obviously you do not have awareness about your presence online. So, this is driving awareness and deciding who is your customer, etc.

Now, once that is done, you need to move them to the consideration funnel. So, you need to now tell them that, okay, I have the biggest variety of bagels available in Canada, whatever, area of Canada, Kitchener, suppose, right? In Kitchener, we have got the biggest variety of bagels available, right? Now, that will help you. So, suppose I'm a vegan and you are a non-vegetarian, right? So, I'll get to know, okay, fine. Oh, good, they also have vegan, right? So, I'll consider that, okay, fine. Someday I'll order a vegan bagel from there. And after that, that is consideration that I have to, once awareness is done, I want them to come visit me on my app or download my app, right? So, the CTA for my second type of campaigns would be that install the app, visit website, or buy now, right? Now comes the last of the funnel, that is the bottom funnel, and that is for you to kind of drive conversions. Now, out of the 800 households who are your potential customers, 500 kinds of considered you. Like, you know, they interacted with you online, right? They probably could click the ad, went to your website, or even downloaded the app, right? And out of that 500, now you need to focus on those 500 in pushing, you know, how you make them shop, right? So now, the next time you target them, you'll say, hey, look, you know, if you download my app now, I give you a $10 discount, and my bagel plus coffee will be, you know, $410 for you, right? So, you are giving them another reason why they should buy online, right? And giving them an offer. So, you know, probably the people who is going office will order coffee before he leaves from home because he'll save on $10, right? Now, out of that 500, suppose 110 converted with you, right? Over a period of time, generally 3-4 weeks, right?

Now, your job becomes that you have to focus on two things. One is, in the customer journey, people who have transacted with you, you want them to repeat purchase with you, right? And second is that people who have considered you or people who you have reached out to, you need to move them to another funnel. So, we started from awareness, people who are aware, you want them to move to consideration. People who are in consideration, you want them to move into conversion. You do retargeting, remarketing, and all of these things, right? And that's how you kind of ensure that you consistently have returning users, you consistently have new users. And obviously, after all of that, you also need to focus on people who are going to churn, right? So, churn is basically, after 2-3 transactions, I'll stop shopping with you. So, I have to ensure that how do I bring you back again to shop with me. And I work on that journey as well.

This is how both offline and online, you need to focus on multiple steps of a customer's journey with you, right? From creating awareness, to consideration, to conversion, to retargeting, remarketing, to bringing back churned or lapsed customers. This is the whole journey that you need to define. And across touchpoints, you need to capture your audiences.

Interviewer: During this entire journey, let's say, if you are working for any specific audience, how much does the emotional, social, or maybe the monetary aspect plays a role?

Interviewee: Equally. All of this equally. So, to give you an example, I work with Bisseri right now, right? I'm selling water online, right? I'm selling packaged drinking water online. Now, let's talk about emotional, right? I mean, social and economic will touch upon that also. It's a very small thing. But emotion is a big play, you know.

To give you an example, I sell packaged drinking water online. Now, I have different categories of users who have different use cases, right? In terms of emotional play. I can talk to new mothers who have become mothers recently or who have young kids, right? Saying that, okay, you know, hygienic, unhygienic water, tap water, or filter water is not good or not giving your kid the required minerals, right? And I kind of target them and say that, you know, maybe if your kid drinks tap water, he can have dengue, diarrhoea, or whatever, you know, all those things. Which is a fact because, the water is not clean and can impact your gut and your overall health, right? And the similar way, I can target, professionals saying that, oh, you know, packaged drinking water, a good quality water or a properly mineralized water helps you with, you know, keeping you active throughout the day. And your brain functions better. Because we also have pH neutral water, right? Which also helps you with gut health. It decreases acidity. So, that is another kind of water. So, these are the different audiences you kind of dissect and target them basis, emotional, social, and economical.

In economical, I have sparkling water also, right? I also have spring water. Other than normal packaged drinking water. So, economical is packaged drinking water is a mass product. It is for everyone and anyone. Spring water is for, higher up, like more premium customers. And sparkling is like, people who only stays in 7 stars and flies business class and take summer holidays in Europe. So, these are the kind of, different audiences that you define as per the product or services that you provide, right? So, social, economic, and emotional. This is how you bifurcate basis, needs, emotions, demands, and all of these things. Okay.

Interviewer: Let's take an example that you have switched industries. So, how does these factors play a role in both the industries that you have worked together? And what are the challenges that exactly you faced while maybe working with Bisleri or while working with Flipkart?

Interviewee: Right. Oh, absolutely. So, see, I mean, it's, every industry, has got a product or a service to sell, right? Now, that product or services is, defined as per different people. So, for example, I was part of private labels or private brands at Flipkart which is, you know, we were manufacturing our own brand. Flipkart is majorly a marketplace. A marketplace basically where anybody can come and sell their products. So, there we decided that we are going to launch our own brands. And we defined that, okay, fine, you know, our target group, we are going to be entry price point brand. So, suppose, I was in the home category. So, we are going to cater to audience who are wanting to shop something at entry price. So, gas stoves generally start with, you know, 599 rupees. And they go up to, how much ever you are willing to spend depending upon your kitchen.

But we decided that we want to cater to an audience that is aspirational but does not have the means or does not want to spend more. So, they want economical products which look very good in their kitchen, which they can show off to their neighbours and all of that. So, here it shows, clearly shows social and economic both.

They want to impress their relatives and neighbours. But at the same time, they also want to do the consideration based on their economic condition or, you know, adherence. So, this is across industry, product and service.

Interviewer: For example, these days all of the companies are, of course, entering into AI as you already know. Does Bisleri really do something like that or I think when you were with Flipkart also, they already started their chatbot services and everything.

Interviewee: So, I think, see, AI has been around for a while. It's not that AI has just come first. Yeah, so it's just a buzzword. I mean, there have been further enhancement to existing products and services that were AI based, right? For example, you know, at Bisleri, now we have also deployed a chatbot that can understand, your customer queries like on our website and kind of address those. So, that is a basic use case for e-commerce today that they are deploying these AI bots which can kind of understand user language.

They have to train the model, of course. So, we are right now training our bot, right? So, it is not completely open for users to, interact with, but it is learning as per the queries that are, you know, getting by the customers. So, it will take six months. So, learning, you know, training the models is a key thing in today's scenario when it comes to exposing it to end consumer. Earlier, the AI that was used was more, in professional environments. Like, you will have dashboards that kind of reflect that, okay, sales are doing well here or not. What is the insight. So, correct, correct. So, those were applications of AI. Now, AI is getting, because of enhancement like learning models and all of these, right, generative capabilities, it is getting exposed to consumer for further training of the bots.

Interviewer: How do you collect data of your customers, you must be aware of the customer purchase intentions before doing your marketing strategies and you must be curating it accordingly, right? So, how do you collect all those data and does social media play any kind of role in that or what are the major sources that you collect the data for predicting the customer purchase intentions?

Interviewee: Yeah, absolutely. I mean, social media is the key to understanding the intentions. Social media in today's world with AI enablement, like we discussed, how you deploy funnel-based strategies and communications. That is all your social media game wherein you exactly know, okay, these are the potential customers, these are the people who have considered you, these are the people who have high probability of converting with you. So, these are all social media-based, for example, Meta Pay, you know everything. So, the they already have such high-trained algos and, AI-based models that you can predict everything like people, so suppose if you search, you know, shoes, and you'll start getting bombarded with shoe ad.

So, that is that is how social media is getting used to understand customer behaviour and further exploit that to influence consumer behaviour.

Interviewer: Yeah. So, in Flipkart, did you use to like take customer feedback? I mean, of course, we have the reviews in the app, but did you use those to find specific segment of your customer?

Interviewee: Absolutely, absolutely. We used to always have focus groups, wherein we used to call, 6 to 10 customers for a group discussion in terms of reviews, feedback, before launching a product, after launching a product. So, all of this is very strategically planned. You always interact with your end consumers even before you launch your products to after you launch your products.

Interviewer: how do you choose that focus group? Of course, I understand that you take the buyer's persona very seriously and then maybe you do it. But still based on your buyer's persona, there must be like a lot of people in the list.

So, do you see a frequent buyer and based on that, you choose? Because I think Flipkart is being used with everyone out there in India because of its cheap prices, how do you then basically like gauge which kind of customers will you focus on?

Interviewee: Right, so see, you know, you always have to take a mix back, right? Or else you will not have good data points, right? So, you have to take a new user, you have to take a repeat user, you have to take a user who has churned with you to a user who is considering you or probably a customer who has purchased some other category and not the category that you are looking for, right? So, you always have to take a mix back to understand a customer better.

Interviewer: Okay, thank you! If you want to share anything else about your experience or maybe if you want like different industries experience and how are they different from each other?

Interviewee: No, I think this is good enough.

Location: Online meeting via Google Meet, Berlin.
Date: 17th Sept. 2024
Interviewers: Panda. S,
Interviewee: Batteiger. S, (Product Coach)

Interviewer: What are the key factors that I believe influence customer decisions when considering my products?

Interviewee: I can tell you that this is different product by product that I've worked on. It is always a deep knowledge and empathy with the kind of target audience you have and what their realities are, what jobs they have to do, what problems they face doing these kinds of things. And then it could be price. It could be just being perceived as best value to solve a specific problem. They must have a problem. Right. Or they must have a desire to do something. Like a product like Spotify, people buy it because they just like to be entertained. So, it could also be a longing for entertainment. It might not have to be a deep-down problem. The deeper-seated problem could be that they feel lonely or not able to just sit with silence with themselves and they want to fill this void. But it's always like an interaction with your target audience group that is surfacing. What these key drivers are when somebody is considering to buy a product.

Interviewer: How do you track and analyse customer journey from awareness to post-purchase?

Interviewee: Like from the moment in time somebody makes contact, you can like you can track whether you have a conversation, whether they say yes to the offering or not. That part's the easy part to track. In past organizations, when I would again say it depends, right. B2B context, big partnerships. You have a target list of maybe 10 top targets that you want to speak to. You intentionally start building relationships. You reach out on LinkedIn to some business development director. You start a strategic conversation with their CEO. You might target them with ads to get on their radar. There are so many ways how you could slice this. But I think in a B2C context, there's tooling around the stuff. Right. Where you kind of send out tracking pixels with email campaigns or any other newsletters with any kind of ads you send. And you track the journey this way using something like Salesforce or something, some other CRM usually. But it's I have seen it done differently in every single organization I've been a part of. And I don't think that most organizations do this very well.

Interviewer: Ok, so because these days there are a lot of things changing gradually for the entire customer journey. How do you see the role of AI in this entire process right now?

Interviewee: I see new kind of things emerging, like, for example, in a tool like Dovetail that's been used by UX researchers. You upload the video recordings of the conversations you had with customers around anything. And that tool tags and tracks all these conversations. And you can literally go back into the stack of past conversations to say to the tool, give me the sentiment of what people think about this and that. Even if it wasn't the original research question, Dovetail will look through the library of recorded interviews to find the moment in time where someone said something about the thing that you are interested in. And it will tell you and summarize for you the sentiment of the average of what people have said about something. So, I see people starting to do stuff like this. There is a startup also here in Cologne that's called TLDV. What is it called? Something to watch the recording is the second part. And they do the same thing.

They take recordings of sales conversations to give heads up sales and heads up marketing the ability to go back into sales conversations, to identify themes of objections and themes of excitement, maybe also to kind of figure out how to target people. So, I see this happening personally.
So, I just do my own interviews and I don't use AI techniques like this. But I see all larger organizations kind of starting to do stuff like this.

Interviewer: What do you think? How do they exactly gather this feedback? Like as you mentioned about the videos. So how do you how do businesses generally collect this? What kind of audience do they target to get this feedback from customers?

Interviewee: So, it usually starts way earlier. It starts with setting a vision and a strategy where you kind of pick a target audience. And you say you are working. Your solution might be for a scale ups in the region like Germany, Austria, Switzerland. Right. And you are targeting as a buyer the head of sales or whatever. Right. And then you are intentionally looking to speak to those kinds of people from your target population and you're recording those conversations. So, it's like the intentional discovery processes and intentional user research processes gather this kind of feedback. And then also, like if you are a little bit more mature and you have a lot of customer interactions, **the tickets that come in from the support system and the tickets from customer care, they also hold a lot of sentiment.** They hold a lot of knowledge about what customers are actually saying, what's working, what's not working for them. And so, a lot of organizations have that pool of data as well on what their customers like or dislike about their products.

Interviewer: How much do you think customer perceived value play a role in buying a product? Maybe value in the sense of their emotional or social or maybe functional or monetary values?

Interviewee: Nobody buys something unless you either have a problem or you really want it. So, it's like and that's a very emotional thing. For example, you buy a new washing machine because yours just broke and you need to wash your you need to do your laundry. Right. Or you or then because your washing machine broke, you are seeking the service of a laundromat. Because like short term, you have to fix this problem and you don't have the money to buy the new washing machine this month. And so, for the next three months, you're taking your laundry to the local laundromat. Or the example I gave earlier. Right. Like you are maybe lonely and bored and you are seeking some sort of entertainment. And then you're looking at solutions like Netflix or Spotify or reading the news or something. But there's always a need. There is always a problem to solve. That's at the core of why you choose to do something about it. You might want help to understand what product even is and how to be successful in a product role. I'd want a sparrings partner that you can talk to outside of your own organization because you feel insecure and you want a more experienced voice to guide you. Those are all like needs that have to do with your own emotions, with like wanting comfort, wanting safety, wanting something.

So, there's always an emotional part in this. And then sometimes as you are choosing between different choices. Right. Price might be the thing that depends on who you are. Right. Maybe you're super wealthy and then you don't care about the price of things. Or maybe you have to really watch every single euro and then you do care about the price of things. So, depending on where you are playing. If you are Aldi, you're looking for the customers. And maybe if you are Louis Vuitton, that price is not the thing, but it is some sort of like an image of wealth and status that people are after.

Interviewer: Do you also think that all of these values that customers generally perceive, like have a specific impact on how they associate with the product? Because everyone has a different need, as you were mentioning.

Interviewee: Yeah, I do think so. Not everyone buys the same kind of things. Like some people are very attached to their Apple products. Other are like, no, my Android phone is just fine. And the next one says I want a fair phone because I care about the sustainability aspect of things. So, what you personally care about and the kind of things you buy or not or don't buy, they definitely have a relationship. Like it's also like who you choose to vote for. The things that you care about and the candidates you vote for. There's some sort of overlap there. So, of course, it has to do with who the person is that makes this choice.

Interviewer: Just a follow up question on that. So, do you think that any specific value like we were discussing about the social, economic and like emotional or functional values, any one specific value that plays a major role for the customers during the entire customer journey? Or is it like all of them that plays a role?

Interviewee: I think we shift between those things and they play a role. All of them play a role for us in some part of our life and sometimes the same product versus the functional and then it becomes the emotional versus the emotional, and then it becomes the functional and then we lose a job and then out of a sudden price plays a role. You know, it's like life happens. We change. We use things for all kinds of purposes. We might not care about the price. You know, there is not one rule. This is what I found. Everyone's different. Every context is different. Every product is different. What kind of alternative products are out there in this market plays a role? Does it play a role? Is it a lifestyle product? Is it a commodity type product? And that may influence your purchasing decision in one product category and not in the other.

Interviewer: From whatever experience till date, you had in all of the organizations, how do you see the customer decision journey aligning with all of these dimensions?

Interviewee: I think it maps. When I think back into my time at Zito, for example, where we were running a marketplace for trading domain names, right? There were people, sellers who had names to offer that they wanted to get a good price for and buyers that wanted a name because they started a new business and needed a name for their website. Sometimes they were portfolio buyers that just took whole buckets of names off somebody else. But what we found, for example, in the pricing of domain names, right, because every single name was in itself unique, could almost not at all predict what somebody was willing to pay for it because it depended on how badly they wanted that specific name. So, it's like, yes, it's a marketplace, right? So, all sellers have the need that their name is findable, that their name is then displayed together with a price and that the transfer of the name and the transfer of money is functional, secure and safe, right?

But the purchasing decision could come from all kinds of random events happening in the world where somebody out of a sudden has a need for a name. And so, it's almost impossible to predict all the many ways in which somebody out of a sudden can feel the desire to have this kind of product. Obviously, there are themes like people like entrepreneurs starting a new business. They need a name for their website, right? There are scale ups starting to maybe rebrand, having now the resources for a better kind of name for their website. But it's hard to say it's always just one thing. It's usually more than one thing that leads to a purchasing decision. That's how I see this. It's complex. It's not it's not an easy thing.

Interviewer: Would you like to add something, on any specific points in the customer journey where understanding perceived value of the product could significantly influence the customer decision? If you have any specific example to share on it.

Interviewee: I think when you're about to hit that buy button, right. For example, in the case of the buy button for the domain name, you have to think that the money asked for the same is worthwhile spending. And when you're setting up a call to explore coaching, you would want to know if you can trust this person to be a good coach for you. So, something around trust building, something around pricing may influence the decision to move forward at that point in time. But it could also be something like the perceived pressure that if I don't act now, it's going to be gone. Like think of this whole frenzy around the Oasis tickets, right? Like you lined up in this queue forever. You get to the end of the queue. You had a specific price in mind that you were going to be willing to spend on those concert tickets. And then you're given five minutes to make this choice. And you know you're likely not going to go back into this position where you have the luxury to even choose. So, this time pressure might also influence your decision making. Or some sense of scarcity. There's only one left, right? Like if you think about booking flights, right? And they say to you, oh, on this route that day for this price, there's only two seats left, right? You have this idea. It's like, oh, my God, I have to make a decision now because it might be gone tomorrow. So, there's many, many ways how you're being influenced at that point in time where you pull out the credit card and buy.

Interviewer: Coming on to the next one, could you maybe share some of the experiences that you had earlier for the marketing strategies of your product? And how did AI play a role earlier? And with this buzzword right now coming up so much. How will it play a role going ahead and more targeted and personalized customer experience?

Interviewee: So, I mean, quite frankly, only in the last year or so has it become possible at scale to use AI tooling to aid this process. Unless you were kind of building this behind the scenes for a long time, like a Facebook did, right? So, I mean, some big players like Google or Facebook or Amazon, they've been kind of toying with machine learning algorithms and AI aided way to target ads and stuff like this for a long time. Most of the companies are now for the first time ever in this position to utilize something like this for their marketing efforts. So, the way I can say this work is I don't think anything will change about you can convince someone to buy something they don't want. So, there are things in which like if you know who the person is, how they tick and what they want, what they care about and how their psychology ticks, then it's more likely that thing for a long time. Right. This is like targeted advertising is exactly like this.

And AI is supporting this. I think in a B2B context or for more high-priced things like a service like coaching or a partnership deal that you want to close, it's much more important that you build relationship with somebody somehow. And that's usually taking like four or five, six, seven, eight interactions that build trust, that get to know the person.

And yeah, I guess AI could help you keep track of your interactions and prompt you to start doing something again. But if it's not really, really feeling genuine and personal, it's going to do more damage than good. Like I mean, I appreciate like my colleague, Tim Havik, for example, right. He's been doing great work with a lot of conference talks and stuff like that. We know each other personally. He's coming to one of my product tank events in November as a speaker. Right. I just went to one of his workshops and I downloaded a resource from there. And then he starts putting me into his email chain thing. And he just assumes because this is a new email to his system that we don't know each other. So, I get a mass email that speaks to me as if I've never heard of him before. And it's kind of just makes me laugh. And I'm like, OK, come on, dude. I can't even take this email serious. Right. Because I know it's just a system sending it out. And when I know that I'm just talking to a system, I'm like, I don't care. If I'm if I have a feeling like genuinely somebody is really, truly on a human level connecting with me, it's a way different story. So, AI gets it wrong that way. Like they it talks to me in the wrong language or it talks to me in in a way that does not pay attention to the established relationship. And I don't think it actually helps.

Interviewer: What do you think, how much of a role and maybe from where is the data being collected to give a more specific and targeted marketing? Well, I mean, maybe to influence the customer behaviour towards a specific product, for example, like using reviews or social media or chatbots.

Interviewee: The companies that have been collecting this data are all the social media giants. Right. Facebook, LinkedIn, Instagram, Twitter, WhatsApp, Alibaba Group in China. Like there's companies that have been collecting this data for our cell phone providers, web hosting businesses that route your web traffic and understand what kind of content you consume online. Like all of them have data on you. You can build your own data on this kind of stuff by tracking your customer and late and prospect interactions. But unless they're sharing with you all kinds of personal stuff, which would sound very creepy to acquire, you're never going to have as full of a data set on this as Facebook does.

Interviewer: Yeah. That's true. So do you think that AI, all the AI models, maybe because companies have recently started adopting it. So maybe do you think that they need to be trained even more to maybe try to influence the customer behaviour completely?

Interviewee: Personally, I find this morally wrong because it's manipulative. Are companies going to do this? I'm pretty sure they will if they can. And it might cause a huge backlash if you get it wrong. So, I think we'll see more innovation in that direction. But the ethical implications of this are there. Right. And so, some of it is already starting to get regulated in Europe, like the EU AI Act is making some of this stuff illegal. Does that mean that it affects companies based out of the US or China or some other outside EU country? Although the EU is quite good at defining jurisdiction when it affects people living inside the European Union. So there's that. People are still going to do this, break it and then apologize later and just hope that they'll cruise through the lawsuit in some way that they just walk away with a fine that doesn't break their business, probably. And who is collecting all of this, whether we want it or not, all the big organizations that deal with national security based in the States and Israel and in the European Union as well. So, and Russia plus China. Right. All of them are collecting all of whatever they can get their hands on from all of us.

Interviewer: Thank you so much for sharing valuable insights, if you would like to add anything related to it.

Interviewee: I like that there is value and time saving in analysing data that's given to you with consent. I'm pretty sure that companies will use this, but maybe the trick to do it in an ethically good and not weird fashion is to have a human in the loop where it's like maybe you get suggestions for what to write to somebody, but then a human is still looking at this, like looking at this from the perspective of like, OK, would I say things this way? Do I know this person? Is this message right or does it have to be tweaked? My hope is that it would go in this direction and then it can be a time saver for sales teams. But personally, I really think like there is something about an authentically human interaction that comes with integrity. And I don't know to what degree it is ever going to feel like this when you're being targeted by machines, because we're all going to get much better at kind of like smelling when this is just machine talking to us versus a real human being. So that's what I'll add. But we'll see. Well, I hope that machines are not going to take over the world, killing all humans. That's like a doomsday scenario. Some people think that. My vision for the future or where I want to build towards and why I want to say like people with good morals and different perspectives and leadership roles in tech is where we can have like a good co-creation together with decent boundaries of things that are done by machines versus things that we understand should be done by humans.
I think AI has to stay. It's not going to go away. So, it's like we're never going to go back to a time where the Internet doesn't exist. We're never going to go back to a time where the steam machine doesn't exist. We're never going to go back to a time where AI doesn't exist. It's been around since the 70s, right? It's just the LLM stuff is very popular and top of mind for many people right now. But there is still a way to go from a generally intelligent AI. So, we'll see. But the stuff that we have today is not going to go away.

Interviewer: Thank you very much for your time and answering it so patiently.

Interviewee: You're more than welcome. I've done lots of research myself, so I am happy to give back and help you with yours.

Location: Online meeting via GoogleMeet, Berlin.
Date: 20th Sept. 2024
Interviewers: Panda. S,
Interviewee: Greiner. U, (Product Coach)

Interviewer: What was your role like in your previous companies?

Interviewee: I was in a B2B context. Therefore, mostly, I think, we learned about the perception by interacting directly with the customer. So, interviewing them, like, when, like, on trade shows or when visiting them and, yeah, all kind of different situations where there was a possibility to talk to the customer or where there was a certain, yeah, reason to talk, and that was mainly also, I think, where we try to learn, try to understand our customer's view and see our products.

Interviewer: How can AI help in a B2B context to understand customer's sentiments or perceptions towards your product, and how, like, it can be done in a company if you have any experience on it?

Interviewee: Well, what would come to my mind is helping to kind of analyse bigger, bigger sets of data where this kind of information is, can be found. I would say maybe, like, customer support, if emails and chats with interactions with customers that could be maybe crawled and analysed. It could be, like, social media in a professional context, maybe LinkedIn. It could be related, I don't know, platforms where people exchange and talk about the products, thinking of stuff like Reddit, maybe. So, that would be the first that comes to my mind where I think AI would be useful to help and analyse bigger sets of data. Actually, very recent example from what I do now is I also do trainings.

There are feedback forms always that the clients fill. And what the company did is then after, like, a year, use AI to crawl all the feedback that people gave and distil it down and just, yeah, sum up the main points that were mentioned repeatedly.

Interviewer: how do you think, like, the future will look like if we continue doing it? And can it have a positive impact or a negative impact?

Interviewee: Yes. Like, for example, let's talk about understanding customer purchase intentions. Or maybe their perceptions, what motivates them to buy. Like, in today's state, let's take an example of Meta, right? So, Meta is probably recording all of our data to train its gen AI. Mm-hmm. And that's how we get the targeted marketing. All over our social media.

Interviewer: How do you think all the businesses are going to adapt it gradually? Or what do you think the future will be about?

Interviewee: Well, I mean, I'm quite sure that gradually more and more people will use this. How this will look like, I don't know. Good question. I'm generally speaking, I'm a bit afraid of the amount of content that may be created in consequence. So, yeah, that's, from a customer perspective or a consumer perspective, that's a bit more worrying. Yeah. That you're bombarded and manipulated maybe also in a way more and more. From a company perspective, yes, it's great having the possibility, of course, to analyse the huge amounts of data.

Interviewer: What do you think are the key data sources from your experience till now that are generally being used to train these AI models and to understand the customers better?

Interviewee: I have no clue. Yeah. I'm really not an expert in that field. Like all the communication channels that are used, for example, in customer support or like forums, professional platforms, like LinkedIn, Reddit, but what's typically being used, I have no idea.