

Assessing Customer Satisfaction: A Classification Model using Machine Learning

António Luís Silva Ferreira Quelhas Saraiva

A thesis submitted to Faculdade de Engenharia da Universidade do Porto for the
Master's degree in Engineering and Industrial Management

Supervisor

Joana Maria Ferreira Alvura da Hora

June 2023



Abstract

This project was undertaken at Bluwalk (BW), a company with a start-up structure, operating in the gig economy. BW functions as an aggregator service, connecting workers with transportation gigs.

The company was in a situation where management felt that customer retention was poor. Recognizing the critical significance of customer retention for the company's success, it was necessary to understand what the most determining factor was and that's where customer satisfaction emerged. Consequently, the logic behind this project was simple, by increasing satisfaction, retention would increase. To achieve this, it was undertaken a thorough study centered on customer satisfaction. The initial step involved developing a Customer Journey Map (CJM), which provided a holistic understanding of the customers' experiences, encompassing their interactions, the departments involved in each step, and pains and gains throughout their journey.

With a clear understanding of the customer journey, the next crucial task was to identify the factors influencing customer satisfaction during the entire retention phase. This involved a meticulous examination of various touchpoints and interactions. A set of Key Performance Indicators (KPIs) was then identified to measure the identified factors effectively. After this task, the Net Promoter Score (NPS) was then chosen as the control variable to represent satisfaction.

Having the control variable defined, the next task involved collecting all the required data, encompassing the NPS scores and the KPIs. This diligent data collection process resulted in a well-curated dataset, ready to be analyzed and utilized for further exploration.

Finally, a machine learning model was constructed with the collected dataset as the foundation. The objective of this model was to predict the category of the control variable, i.e., customer satisfaction. The obtained model achieved a test accuracy of 76% and an "F1 score" of 71%.

This dissertation details the entire process undertaken to address the challenge of enhancing customer retention at BW. The focus on customer satisfaction as a crucial determinant led to the development of a comprehensive study, incorporating the CJM, identification of key indicators, data collection, and the construction of a machine learning model. This research serves as a foundation for understanding the dynamics of customer satisfaction. The findings and insights obtained pave the way for future investigations and provide actionable recommendations for BW and other organizations facing similar challenges in customer retention.

Resumo

Este projeto foi realizado na BW, uma empresa com uma estrutura de start-up, que opera na “gig economy”. A BW funciona como um serviço agregador dentro da “gig economy”, ligando trabalhadores a serviços de transporte.

A BW encontrava-se numa situação em que a administração sentia que a retenção de clientes estava abaixo do esperado. Reconhecendo o caráter crítico da retenção de clientes para o sucesso da empresa, foi necessário compreender qual era o fator mais determinante e foi aí que a satisfação do cliente assumiu um papel fundamental. Consequentemente, a lógica subjacente a este projeto era simples: ao aumentar a satisfação, por consequência a retenção aumentaria. Para o conseguir, foi efetuado um estudo exaustivo centrado na satisfação do cliente. O passo inicial envolveu o desenvolvimento de um CJM, que proporcionou uma compreensão holística das experiências dos clientes, englobando as suas interações, os departamentos envolvidos em cada passo e as “dores” e “ganhos” ao longo do seu percurso.

Com uma compreensão clara do percurso do cliente, a tarefa seguinte consistiu em identificar os factores que influenciam a satisfação do cliente durante toda a fase de retenção. Isto envolveu uma análise meticulosa de vários pontos de contacto e interações. Foi então elaborado um conjunto de KPIs para medir eficazmente os factores identificados. Após esta tarefa, o NPS foi então escolhido como a variável de controlo para representar a satisfação.

Definida a variável de controlo, a tarefa seguinte envolveu a recolha de todos os dados necessários para a análise, englobando as pontuações do NPS e os dados dos KPIs. Esse processo de recolha de dados resultou num conjunto de dados devidamente estruturado, pronto para ser analisado e utilizado para exploração posterior.

Finalmente, foi construído um modelo de “machine learning” tendo como base o conjunto de dados recolhidos. O objetivo deste modelo era prever a categoria da variável de controlo, ou seja, a satisfação do cliente. O modelo obtido alcançou uma precisão de teste de 76% e um “F1 score” de 71%.

Esta dissertação detalha todo o processo realizado para enfrentar o desafio de aumentar a retenção de clientes na BW. O foco na satisfação do cliente como fator fundamental levou ao desenvolvimento de um estudo abrangente, incorporando o CJM, a identificação de KPIs, a recolha de dados, e a construção de um modelo de “machine learning”. Esta investigação serve de base para compreender a dinâmica da satisfação do cliente. As considerações e conclusões obtidas abrem caminho para futuras investigações e fornecem recomendações acionáveis para a BW e outras empresas que enfrentam desafios semelhantes na retenção de clientes.

Acknowledgements

First and foremost, I would like to express my heartfelt gratitude to Dr. Joana Hora, my supervisor at FEUP, for her unwavering support and guidance throughout the entire duration of this project. Her constant encouragement and attention ensured that I remained on the right path, and I am truly grateful for her dedication and efforts in ensuring the success of this project. In my opinion, she went above and beyond her obligations, and I consider myself incredibly fortunate to have had her as my supervisor. Without her invaluable support, the outcome of this project would not have been the same.

I would also like to extend my sincere appreciation to Eng. Paulo Azevedo, my supervisor at Bluwalk, for his dedication and accompaniment during the execution of this project. He consistently motivated me to strive for excellence, provided assistance whenever needed, and devoted a significant amount of his time to this project, all with the aim of achieving the best possible results. I feel that I have learned so much from him, and I will take the lessons I have gained into my professional future.

I would like to express my gratitude to Bluwalk for providing me with this opportunity and placing their trust in me. This project has undoubtedly been a remarkable culmination of my academic journey and a stepping stone for my professional development.

Next, I would like to thank all my colleagues at Bluwalk for their warm welcome, and seamless integration, and for fostering such a pleasant environment. Their companionship has made my experience truly enjoyable.

I would also like to extend my deepest gratitude to my family, especially my mom, dad, and sister, for their unconditional love, absolute support, and belief in me during times of discouragement. Their presence has been a constant source of strength throughout this journey.

To my girlfriend Marta, I am indebted for her continuous motivation and support throughout every step of this journey. Her belief in my abilities has been an invaluable source of inspiration. I feel so lucky to have her by my side.

Last but certainly not least, I want to thank all my friends, whom I consider my second family, for their support and encouragement. They helped me navigate through adversities and made the entire journey so much better.

António Saraiva

*“When something is important enough,
you do it even if the odds aren’t in your favor”*

Elon Musk

Contents

Acronyms	xix
1 Introduction	1
1.1 Context	1
1.2 Customer success department in Bluwalk	2
1.3 Motivation	3
1.4 Methodology	4
1.5 Dissertation structure	5
2 Literature Review	7
2.1 Importance of customer satisfaction	7
2.2 Customer Journey Map	8
2.3 Measures of customer satisfaction	9
2.4 Net Promoter Score	10
2.5 Neural network models for accessing customer satisfaction	11
3 Customer Journey Map	13
3.1 Methodology followed to build the Customer Journey Map	13
3.1.1 Meet with the various departments to understand their internal processes .	14
3.1.2 Understand how each department relates to the customer	14
3.1.3 Identify the phases and stages of the customer journey	14
3.1.4 Pinpoint all the steps in the customer journey	15
3.1.5 Develop potential indicators for relevant steps	16
3.1.6 Map out the customer journey map	16
3.2 Customer Journey Map	16
3.2.1 Awareness	16
3.2.2 Acquisition	17
3.2.3 Activation	17
3.2.4 Retention	20
3.2.5 Advocacy	24
4 Defining the KPIs	25
4.1 Methodology followed to define the KPIs	25

4.1.1	Analyze the CJM and identify which steps are most relevant for customer satisfaction	26
4.1.2	Identify which factors within each step can most interfere with satisfaction	26
4.1.3	Choose the indicators that best capture the factors impacting customer satisfaction and add new ones if necessary	26
4.1.4	Assign degrees of importance and viability to the selected indicators and characterize them	27
4.1.5	Define a list of KPIs	27
4.2	KPIs	27
4.2.1	Net earnings per week	28
4.2.2	Net earnings per online hour	29
4.2.3	Number of tickets or calls - complaint	29
4.2.4	Ticket and call rating	29
4.2.5	Number of malfunctions	30
4.2.6	Vehicle damage costs	30
4.2.7	Invoice rejection rate	30
4.2.8	Number of cycles closed out of SLA	31
4.2.9	Segment	31
5	Dataset Compilation	33
5.1	Methodology	33
5.2	Inputs	34
5.2.1	Select the study population	34
5.2.2	Define the time frame and locate the information in the database	34
5.2.3	Data collection	35
5.3	Control Variable	36
5.3.1	Choose the question/s for the control variable	36
5.3.2	Select the control sample	37
5.3.3	Survey construction and launch	37
5.3.4	Data collection	38
5.4	Achieving the Dataset Milestone	38
6	Machine Learning Model	43
6.1	Methodology	43
6.1.1	Load the training dataset in Colab	44
6.1.2	Model selection	45
6.1.3	Pre-processing	45
6.2	Model building and usage	47
6.2.1	Architecture	48
6.2.2	Training	49
6.2.3	Evaluation	50
6.2.4	Model results	51

<i>CONTENTS</i>	xi
6.2.5 Usage	53
7 Conclusions and Future Work	55
7.1 Overview and main contributions	55
7.2 Further Work	57
Bibliography	59
A Customer Journey Map visualization	61
B Categorization of indicators	73
C Detailed data collection	75
D NPS collection	85
E Univariate analysis of the variables	87
F Neural Network model code	93

List of Figures

1.1	Project rationale diagram.	4
3.1	Customer journey map phase methodology map.	14
3.2	Customer journey map Phases.	15
3.3	Phase, Stage, and Steps.	15
3.4	Key to the departments responsible for each step.	16
4.1	Define KPIs phase methodology map.	25
5.1	Training Data Set phase methodology map.	33
5.2	Query for the survey responses.	38
5.3	Dynamic dataset of all indicators applied to the study population.	39
5.4	Bar chart of the NPS responses collected.	40
5.5	Overview of the document with the compiled data used to build the model.	41
6.1	Machine learning model phase methodology map.	43
6.2	Output of the best model.	51
6.3	Confusion matrix for the best model.	52
6.4	Precision and Recall for each category.	52
A.1	Awareness phase.	61
A.2	Acquisition phase.	61
A.3	Activation phase.	62
A.4	Activation phase - Shopping partner.	62
A.5	Activation phase - Food partners.	62
A.6	Activation phase - Rideshare partners (1).	63
A.7	Activation phase - Rideshare partners (2).	63
A.8	Activation phase - Rideshare partners (3).	64
A.9	Retention phase - Work stage - Shopping segment.	65
A.10	Retention phase - Work stage - Food segment.	66
A.11	Retention phase - Work stage - Rideshare segment.	66
A.12	Retention phase - Needs Help.	67
A.13	Retention phase - Rideshare - Car segment change.	67
A.14	Retention phase - Rideshare - Vehicle issues (1).	68
A.15	Retention phase - Rideshare - Vehicle issues (2).	68

A.16 Retention phase - Rideshare - Vehicle issues (3).	69
A.17 Retention phase - Cash out.	69
A.18 Retention phase - Customer with debt.	70
A.19 Retention phase - Vehicle Return.	70
A.20 Advocacy phase.	71
 B.1 Overview of the table resulting from the indicator categorization process.	 73
C.1 Query for the list of active customers per week.	75
C.2 Query for customer personal data.	75
C.3 Query for earnings within the “Rideshare” segment.	76
C.4 Query for earnings within the “Food” segment.	76
C.5 Query for earnings within the “Shopping” segment.	76
C.6 Query for the BW fee costs.	77
C.7 Query for the rental costs.	77
C.8 Query for the online hours in the rideshare segment (1).	77
C.9 Query for the online hours in the rideshare segment (2).	78
C.10 Query for the online hours in the food segment.	78
C.11 Query for the complaint type calls.	80
C.12 Query for the complaint type tickets.	80
C.13 Query for the calls rating.	81
C.14 Query for the “Zendesk” ticket rating.	81
C.15 Query for the “Odo” ticket rating.	82
C.16 Query for the malfunctions.	82
C.17 Query for the rental contracts.	82
C.18 Query for the vehicle damage costs.	83
C.19 Query for the invoices submitted.	83
C.20 Query for the cycles closed.	83
C.21 Query for the active customers per week and per segment.	84
 D.1 NPS Collection rationale.	 85
D.2 NPS Survey “pop-up”.	85
 E.1 Descriptive statistics for the “Net earnings per week” KPI.	 88
E.2 Descriptive statistics for the “Net earnings per online hour” KPI.	88
E.3 Descriptive statistics for the “Number of tickets and calls - complaint” KPI.	89
E.4 Descriptive statistics for the “Ticket and call rating” KPI.	89
E.5 Descriptive statistics for the “Number of Malfunctions” KPI.	89
E.6 Descriptive statistics for the “Vehicle Damage Costs” KPI.	90
E.7 Descriptive statistics for the “Invoice Rejection Rate” KPI.	90
E.8 Descriptive statistics for the “Number of cycles closed out of SLA” KPI.	90
E.9 Descriptive statistics for the “Rideshare” KPI.	91
E.10 Descriptive statistics for the “Food Delivery” KPI.	91

E.11	Descriptive statistics for the “Shopping” KPI.	91
E.12	Descriptive statistics for the “Courier” KPI.	92
F.1	Code developed to load the dataset and create the dataframe.	93
F.2	Code developed for the pre-processing task.	93
F.3	Code developed for the architecture of the model.	93
F.4	Code developed for the training of the model.	94
F.5	Code developed for evaluating the model.	94
F.6	Code developed for model saving.	94
F.7	Code developed for model loading.	94

List of Tables

4.1	List of the selected KPIs.	28
-----	------------------------------------	----

Acronyms

ACSI American Customer Satisfaction Index.

BW Bluwalk.

CES Customer Effort Score.

CJM Customer Journey Map.

CSAT Customer Satisfaction Score.

KPI Key Performance Indicator.

NPS Net Promoter Score.

SLA Service Level Agreement.

SQL Structured Query Language.

TVDE Transporte Individual de Passageiros em Veículo Descaracterizado.

1 Introduction

1.1 Context

This work was carried out in the context of a company operating within the gig economy. The gig economy refers to labor markets characterized by independent contracting that happens through, via, and on digital platforms.

Within the gig economy, the kind of work offered is contingent, casual, and non-permanent work. It may have variable hours and little job security, involve payment on a piece-work basis, and lack any options for career development. The “gig” in the term “gig economy” refers back to the short-term arrangements typical of a musical event. However, just like in music, there is no guarantee that these jobs will continue or become regular. Whether someone gets more gigs depends on their performance or popularity, and they might only have one opportunity to work in a particular job. There are similarities between gig work and musical gigs, but they are also quite distinct. In the gig economy, there are limited opportunities for career growth. The tasks that underpin the gig economy are typically short, temporary, and unpredictable, and gaining access to more of them depends on good performance and reputation.

The gig economy represents a new company form in which firms have an on-demand workforce with controls over the temporality of work. Workers have the freedom to choose when they work. In the context of the gig economy, a platform refers to a digital environment that provides infrastructure to intermediate between different user groups by bringing together the supply of, and demand for, labor. Platforms operate as intermediaries for work, and they offer tools that allow a client to connect with a worker, and set their own rates, and conditions.

While there is a spectrum of control, platform work is often characterized by low levels of temporality and high levels of geographic flexibility, and the workers are often classified as self-employed, which means they lose employment rights, although the protections that they afford can vary widely around the world. The gig economy represents a profound redesign of how many people work. It is designed to convenience consumers, to return a profit to platforms, and ultimately to disempower workers.

Today’s gig economy is not just enabled by technology. Particular political and social circumstances have allowed for employment relationships in which workers are atomized units competing for jobs in open markets. Work is becoming temporary, unstable, mediated, patchworked, and persistently contestable. It is an individualized pursuit with few opportunities to build a stable cohort of colleagues. The burden of training and risk is put onto the worker rather than the client, the platform, or the state (Woodcock & Graham, 2019).

The COVID-19 pandemic further accelerated the gig economy's growth as more individuals and businesses sought alternative work arrangements. Since then, there has been an increase in the number of daily tasks/jobs posted and filled on the platform-based economy (Umar et al., 2021).

The gig economy, which encompasses a range of service sectors such as parcel delivery, food delivery, transportation, and shopping, has emerged as a significant phenomenon in the contemporary labor market. Driven by a growing demand for flexibility and convenience, the gig economy is characterized by the use of digital platforms that match workers with jobs on a contingent basis. The gig economy has been lauded for providing a flexible source of income for workers, but it has also faced criticism for eroding labor protections and fostering precarious work. Recent trends in the gig economy include the growth of app-based platforms that connect workers with short-term gigs and the expansion of the gig economy to new sectors, such as healthcare and education.

This work was developed in the context of a dissertation conducted at BW. BW can be described as a gig economy aggregator service. BW's platform brings together workers and jobs in the gig economy. The company's mission is to make it quick and easy for anyone to earn money with transportation jobs. Essentially, BW mediates the connection between people looking for flexible work opportunities and companies offering them, providing support, giving tools, and eliminating all bureaucracy for the customer throughout. The company operates within four segments: food, rideshare, parcel, and shopping. Food delivery workers pick up food orders from restaurants and deliver them directly to customers, rideshare drivers provide transportation services to passengers, parcel delivery workers transport packages or mail from one location to another, and shopping delivery workers pick up groceries or other goods from supermarkets and stores, and deliver them to customers' homes. In each of these industries, workers typically use a mobile app or online platform to receive requests for delivery services, track their delivery routes, and communicate with customers.

The company was born in 2011 and maintains a start-up structure. In the last few years, the company has been growing exponentially, having been recognized two years in a row by the Financial Times in the ranking of the fastest-growing European companies in 2020 and 2021. The company is based in Porto and its operations span across more than 10 cities over the entire country of Portugal. Throughout its existence, BW has helped more than 2,700 people to increase their income.

1.2 Customer success department in Bluwalk

This project was developed in the BW's Customer Success department, a new addition to the Community Operations division of the company. The main focus of this department is to enhance customer retention by ensuring an optimal experience for each client. The author of this thesis is the sole member of the Customer Success team, imbued with the task of introducing and operationalizing the departmental objectives.

The Customer Success department's mission is to ensure that customers meet their expectations and align their needs with the company's services. With that in mind, the company decided to kick-start this mission. This project is intended to help the department identify areas that re-

quire attention and identify processes that need to be refined to ensure that each client receives the highest level of service possible. The project will also help the department better understand its customers' needs and develop strategies to meet them effectively.

The Customer Success department is grounded in customer-centricity principles, which place the customer at the forefront of every decision and action. By prioritizing the client, the department's task is to ensure that every interaction is tailored to meet the individual needs of the customer. This approach recognizes that a satisfied customer is likelier to remain loyal to the company and positively endorse its services to others. Thus, the role of the Customer Success department is vital to the company's success, and its objectives are crucial in maintaining the competitive edge of the company in the marketplace.

1.3 Motivation

The motivation for this research stemmed from BW's management recognizing the need to address the challenge of low monthly customer retention figures. As BW earns a percentage of the client's income, retaining customers was critical to the company's prosperity. In addition, BW management knew that customer retention was significantly more cost-effective than acquiring new customers.

To improve customer retention, it was crucial to understand the various factors influencing it. Customer retention is a complex phenomenon influenced by a range of factors, including both external and internal elements to the company. While factors like customer emigration, career changes, and illness fall outside of the company's control, there are factors that BW can actively influence, such as customer trust and satisfaction.

Extensive analysis and discussions within the organization led to the understanding that satisfaction plays a pivotal role in customer retention. This understanding is backed up by studies demonstrating a strong link between customer satisfaction and customer retention (Keiningham et al., 2007). Therefore, the company's perspective was that improving customer satisfaction would enhance overall retention.

With the goal of improving satisfaction and subsequently bolstering retention, it was essential to take a proactive approach. Before implementing measures to enhance satisfaction, a comprehensive study of customer satisfaction was deemed necessary. Figure 1.1 provides a visual representation of the rationale for this project.

To effectively address customer satisfaction, it was necessary to understand the underlying variables that contribute to it. Within the vast landscape of variables influencing satisfaction, some were readily identified and utilized in the analysis, while others remained undiscovered or were not incorporated in the study. Identifying and utilizing relevant variables played a pivotal role in conducting a robust analysis of customer satisfaction.

Hence, this project aimed to assess customer satisfaction within the BW context, examining its underlying variables, and identifying opportunities for improvement.

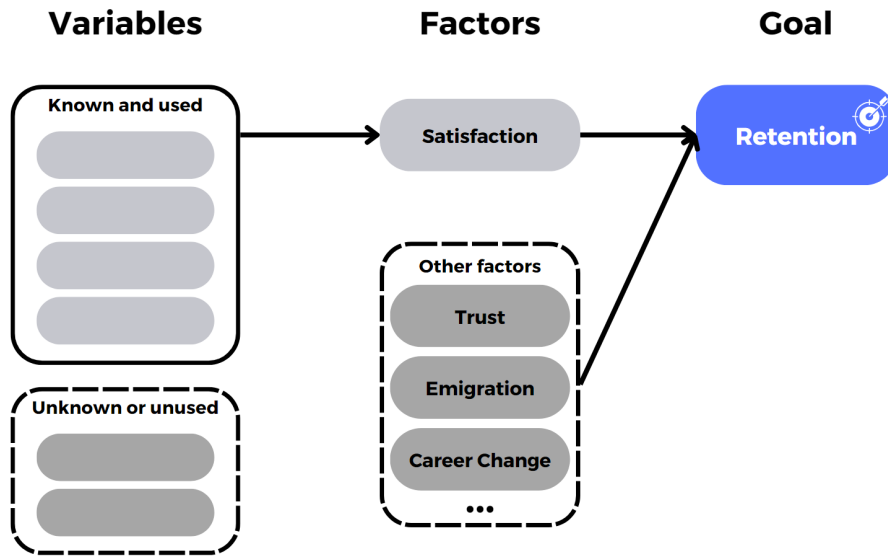


Figure 1.1: Project rationale diagram.

1.4 Methodology

The methodology adopted in this project encompassed four key phases. It started with the construction of the CJM, followed by the definition of KPIs, then the compilation of the dataset, and finally, the development of a machine learning model.

To begin, it was imperative to gain a comprehensive understanding of the factors that influence customer satisfaction. This involved acquiring in-depth knowledge about every aspect of the customer experience. To facilitate this process, a CJM was developed. The CJM provided a holistic view of the entire customer journey, encompassing points of contact with BW, customer pains, gains, and overall experiences. By analyzing the CJM, it was possible to identify the key factors that contribute to customer satisfaction.

Once the factors influencing satisfaction were identified, the next step was to define relevant KPIs that could effectively measure these factors. The selection of appropriate KPIs ensured that the evaluation process aligned with the identified satisfaction factors, enabling the organization to track and monitor them effectively.

With the defined KPIs in place, the subsequent task involved collecting data for all of them. This data collection process aimed to compile a comprehensive dataset that captured the information from the defined indicators for each active customer.

Finally, leveraging the compiled dataset, a machine learning model was developed. This model served as a powerful tool for real-time tracking of customer satisfaction. It enabled BW to monitor and analyze satisfaction levels continuously.

By following this methodology, the project aimed to deepen the understanding of customer satisfaction, establish effective measurement mechanisms through KPIs, gather relevant data, and utilize machine learning techniques for real-time tracking.

1.5 Dissertation structure

This dissertation is structured into five chapters, each addressing a specific aspect of the project's development. Chapter 3 delves into the creation of the CJM, providing an overview of the methodology employed and showcasing the visualization of the map itself. Moving on to Chapter 4, the entire process of defining the KPIs is detailed, culminating in a comprehensive list of these indicators. Chapter 5 extensively covers the meticulous data collection process and the establishment of the control variable. In Chapter 6, the complete journey of developing the machine learning model is documented, encompassing the methodology, the obtained results, and the practical applications of the model. Finally, Chapter 7 encompasses the concluding remarks derived from the completion of this project, along with the prospects for future work based on the findings and outcomes of this research endeavor.

2 Literature Review

2.1 Importance of customer satisfaction

To have a clear understanding of customer satisfaction, it is crucial to delve into the definition of the term as described in the literature. Giese and Cote (2000) define customer satisfaction as a “response (emotional or cognitive) to a particular focus (expectations, product, consumption experience, etc.) at a particular time (after consumption, after choice, based on accumulated experience, etc)”, a definition that was corroborated by the customers under study.

The ability to measure customer satisfaction in a precise and reliable manner is an essential component of any successful company. Some companies fail to understand the value of this metric and may not allocate enough effort to accurately measure and track customer satisfaction (Reichheld, 2003).

Measuring customer satisfaction is critical for businesses due to its significant impact on their long-term performance and customer purchasing behavior. In the literature, it is widely recognized that consistently providing high levels of customer satisfaction is associated with increased customer loyalty and improved reputation. Customer loyalty and retention can be influenced by various factors including personal determinism and social factors, in addition to customer satisfaction. However, customer satisfaction is still a crucial element in the formation of loyalty, as it is necessary to build strong and lasting relationships with customers (Ngo, 2015). Nevertheless, customer satisfaction effects on repeat business and customer loyalty vary from industry to industry. Loyal customers are not necessarily satisfied customers, but satisfied customers tend to be loyal customers (Fornell, 1992).

While customer satisfaction is commonly thought to result in increased profitability, the relationship between market share and customer satisfaction is not necessarily positively correlated. High levels of customer satisfaction are expected to result in positive word-of-mouth, which can enhance a company’s market share. However, if market share gains lead to an increase in the heterogeneity of the customer base without sufficient resources for servicing a larger number of customers, it may result in customer dissatisfaction. Achieving both a large market share and high average customer satisfaction is challenging, particularly if customer preferences are heterogeneous (Fornell, 1992).

Defensive strategy is a critical aspect of businesses, as it aims at reducing customer exit and switching. These goals can be achieved by ensuring high levels of customer satisfaction. When customers are highly satisfied with a company’s offerings, it becomes more costly for a competitor to attract those customers away from the company. As a result, customer satisfaction can be

an effective tool for a company to defend its market position and minimize the risk of losing customers to competitors (Fornell, 1992).

Measuring customer satisfaction is a fundamental practice for companies that wish to grow and remain competitive in today's marketplace. By understanding the level of customer satisfaction, a company can identify strengths and weaknesses in its products or services, as well as consumers' needs and wants. With this information in hand, the company can implement improvements in its strategies, which can lead to an increase in customer loyalty, customer retention, and even the acquisition of new customers through positive recommendations. In addition, measuring customer satisfaction can help a company detect problems before they become more serious, allowing for a more proactive and effective approach to dealing with these issues. Customer satisfaction is a valuable indicator of a company's success, and measuring it regularly is critical to its survival and growth in the marketplace.

2.2 Customer Journey Map

CJM has gained significant recognition as a valuable tool in strategic management for comprehending and improving the customer experience (Rosenbaum et al., 2017). CJM involves visually mapping out the sequence of events and touchpoints that customers may encounter when engaging with a service organization throughout the entire purchase process. It provides a comprehensive overview of the customer journey, highlighting all the potential interactions between customers and the organization (Rosenbaum et al., 2017).

The primary objective of CJM is to gain a deeper understanding of the user's perspective and experience in using a service or product (Marquez et al., 2015). By adopting a service design methodology, organizations can analyze the entire service ecosystem from the customer's point of view, enabling them to identify improvement areas for or create new services that better align with customer expectations. CJM can be as simple or complex as needed, allowing organizations to identify opportunities, pain points, and specific actions that can enhance the customer journey (Marquez et al., 2015).

Through the process of mapping, organizations can adopt a user-centric approach, gaining valuable insights into the customer's experience when completing a task or utilizing a service. By visualizing the user journey, organizations can better comprehend the customer's perspective, observe their interactions with various touchpoints, and identify areas where the experience may fall short or require enhancements.

Customer journey mapping offers numerous benefits. It provides organizations with a holistic view of the service experience, enabling them to identify gaps, pain points, and areas for improvement. Organizations can design and deliver services that align more closely with customer needs and expectations by gaining a user-centric perspective. CJM also facilitates cross-functional collaboration and decision-making by providing a shared understanding of the customer journey that can guide strategic initiatives and resource allocation.

2.3 Measures of customer satisfaction

To measure customer satisfaction, various methods and measures can be employed, which often depend on factors such as the industry, the type of business, and the specific goals of the company. Among the notable approaches in this regard are the American Customer Satisfaction Index (ACSI), Customer Satisfaction Score (CSAT), Customer Effort Score (CES), and NPS. These metrics have gained prominence in the field of customer satisfaction research and serve as valuable tools for assessing and understanding customer perceptions and experiences.

The ACSI is a widely used measure specifically designed to assess overall customer satisfaction. It takes into account three key antecedents: perceived quality, perceived value, and customer expectations (Anderson & Fornell, 2000; Fornell et al., 1996). The ACSI methodology takes into account these antecedents and aims to estimate the relationships between customer satisfaction and its underlying causes as perceived by the customer. Despite the complexity involved in estimating the model, the ACSI maintains a reasonable level of simplicity. It utilizes a 0 to 100 scale for calibration, where the absolute values of the index are of interest (Anderson & Fornell, 2000).

In order to operationalize the measurement of ACSI, three survey measures are employed. These include: an overall rating of satisfaction, an evaluation of the extent to which performance meets or falls short of expectations, and a rating of performance relative to the customer's ideal product or service within the given category. By incorporating these measures, the ACSI provides a comprehensive and multi-dimensional perspective on customer satisfaction enabling businesses to gain valuable insights into the drivers of customer perceptions and experiences (Fornell et al., 1996).

CSAT is a metric used to measure the level of satisfaction that customers have with a product, service, or overall experience provided by a company. CSAT is typically measured through surveys or feedback forms where customers are asked to rate their satisfaction on a scale or provide qualitative feedback. The surveys usually include questions that ask customers to rate their satisfaction on a numerical scale (e.g., from 1 to 5 or from 0 to 10) or provide qualitative feedback about their experience, consisting of a questionnaire with a Likert scale response options with extreme values and a central value (very satisfied to very dissatisfied) (Baquero, 2022).

CES have been recognized as a potential indicator of customer loyalty. By assessing the level of effort required from customers, companies can gain insights into the ease of their interactions and the impact it has on customer satisfaction and loyalty. In the research study performed by Clark and Bryan (2013), the CES was measured using a single question: "How much effort did you personally have to put forth to handle your request?" Respondents were asked to rate their level of effort on a scale ranging from 1, indicating very low effort, to 5, indicating very high effort.

One of the strengths of CES is its applicability throughout the customer experience journey. It can be used at various touchpoints to identify specific actions that need to be taken to make the customer experience easier and more streamlined. Companies have found that while CES is easily understood by both customers and employees, more accurate results were obtained by rephrasing the question as "how easy was it" rather than "how much effort was needed." This subtle change

in wording helps capture the customer's perception of ease rather than focusing solely on the effort expended. By leveraging CES as a metric and optimizing the customer experience based on the feedback received, companies can proactively address areas of high effort, enhance customer satisfaction, and foster long-term loyalty (Clark & Bryan, 2013).

A more detailed analysis was conducted for the NPS, which can be found in 2.4.

2.4 Net Promoter Score

The NPS has gained widespread adoption across various industries due to its ease of understanding and intuitive nature. Compared to other traditional customer satisfaction measures, the NPS stands out for its simplicity and ease of calculation.

Many companies invest significant time and resources in measuring customer satisfaction as they strive for unprecedented growth through the cultivation of intensely loyal customers. However, the yardsticks commonly used in these efforts tend to be complex, yielding ambiguous results that may not necessarily correlate with profits or growth (Reichheld, 2003). Companies can simply ask their customers one question: "How likely is it that you would recommend our company to a friend or colleague?".

Customers are then asked to rate their likelihood of recommending on a scale from 0 to 10. Based on their responses, customers are classified as:

- "Promoters": 9-10.
- "Passives": 7-8.
- "Detractors": 0-6.

The NPS is calculated by subtracting the percentage of detractors from the percentage of promoters, resulting in a score that ranges from -100 to +100.

The more "promoters" a company has, the greater its potential for growth (Reichheld, 2003). By asking only one question, it significantly reduces the barrier for data collection on customer satisfaction. Customers tend to feel less burdened by a single, straightforward question compared to a lengthy questionnaire (Liuqu et al., 2015).

NPS focuses on measuring word-of-mouth, which has become increasingly important with the popularization of internet usage and the influential power of online word-of-mouth for organizations (Huang & Wang, 2014). In today's business landscape, it is common for companies to include NPS in their internal dashboards, providing daily, weekly, and monthly updates, as well as featuring it in their annual reports to shareholders (Lemon & Verhoef, 2016). NPS remains one of the most commonly used metrics for measuring satisfaction and loyalty internationally, primarily due to the high correlation between referral intention and loyalty behavior established by previous research (Liuqu et al., 2015).

However, as organizations gain more experience with NPS, challenges arise regarding its predictive validity for loyalty behavior. NPS was compared with the traditional ACSI model in predicting company growth and found no superior performance with NPS (Liuqu et al., 2015). Moreover, for newly developed e-commerce businesses, relying solely on the NPS score may not provide a reliable reflection of customer satisfaction (Liuqu et al., 2015).

Huang and Wang (2014) affirm that relying solely on NPS as a predictor of customers' future loyalty behaviors may be insufficient and multiple indicators may perform significantly better in this regard. Nevertheless, when using the standard segmentation, NPS demonstrates strong predictive validity overall. In the study developed by Huang and Wang (2014), in the three months following the survey, "promoters" exhibit a significantly higher tendency to repeat purchases, increase purchase volume, and contribute higher value compared to "passives", while "passives" show higher tendencies in these aspects compared to "detractors". This highlights the usefulness of NPS as a measure for predicting customer behavior and potential business outcomes.

While this question may not explicitly inquire about customer satisfaction or loyalty, it captures customers' willingness to recommend a product or service to others, which is often a strong indicator of loyalty. By replacing the complex typical customer satisfaction surveys with a single question, companies can effectively leverage consumer survey results and focus their employees on stimulating growth (Reichheld, 2003).

Conventional customer-satisfaction measures, on the other hand, are even less reliable for gauging loyalty, as Reichheld (2003) research indicates, satisfaction lacks a consistent connection to actual customer behavior and growth. By clustering customers into three categories— "promoters", passively satisfied individuals, and "detractors" —companies can gain the simplest, most intuitive, and most accurate predictor of customer behavior (Reichheld, 2003).

Comparing NPS and customer satisfaction, Lemon and Verhoef (2016) found no significant differences, although their correlation with certain financial and customer feedback metrics is generally low. Studies examining the predictive power of these metrics for customer retention have concluded that the disparities between NPS and satisfaction are minimal (Lemon & Verhoef, 2016). Moreover, the research demonstrates that both NPS and CSAT outperform CES and suggests that combining these metrics can enhance predictive performance (Lemon & Verhoef, 2016).

2.5 Neural network models for accessing customer satisfaction

To gain a comprehensive understanding of existing models in the field of customer satisfaction, an extensive analysis was conducted. This analysis revealed a variety of approaches that have been developed, with neural network models featured.

Notably, Grnholdt and Martensen (2005) emphasized the efficacy of utilizing neural networks in customer satisfaction analyses. The research demonstrated the viability of neural networks in predicting customer satisfaction, achieving an impressive 98% accuracy rate. In this study, "perceived overall quality" was employed as the output variable to represent customer satisfaction. It is important to note that, similar to the majority of the analyzed studies, the data collected for the model was strictly collected from questionnaires (Goode et al., 2005; Hendalianpour & Razmi, 2017; Lin, 2007; Zeinalizadeh et al., 2015). Meaning that the whole model was fed with information collected directly from the customer. To the best of the knowledge of the author, there weren't found models built on indicators related to client performance.

Hendalianpour and Razmi (2017) and Lin (2007) used fuzzy neural networks while Grnholdt and Martensen (2005) and Zeinalizadeh et al. (2015) used artificial neural networks in their mod-

els. Fuzzy neural networks and artificial neural networks differ in handling uncertainty and data representation. Fuzzy neural networks use fuzzy logic to explicitly deal with uncertainty and linguistic terms, representing input and output variables as fuzzy sets. They employ rule-based inference and learning algorithms to adjust the parameters of the fuzzy rules. In contrast, artificial neural networks operate on crisp values, do not directly incorporate linguistic terms or fuzzy sets, and focus on adjusting connection weights between neurons to minimize errors. Fuzzy neural networks are advantageous in domains with uncertain data, while traditional artificial neural networks excel at learning from large datasets but assume precise input. Zeinalizadeh et al. (2015) proceeded to an exploratory factor analysis on the collected data to determine the factors that most influenced customer satisfaction. From this factor analysis, the most relevant factors were used to develop the model.

Regarding the sample size, several cases were found. Goode et al. (2005) collected a total of 232 observations, and allocated 186 for model training and 46 for validation purposes. The resulting model demonstrated an accuracy of 57% on the validation set. The study concluded that this model was deemed useful and robust for predicting customer satisfaction, and the sample size of 232 respondents was considered adequate for testing the proposed model. However, it was noted that a larger sample size might have yielded more reliable estimates. On the Lin (2007) study, only 207 observations were available, which was concluded to be a limitation on the model due to the relatively small sample size.

When considering models with larger samples, two notable examples were analyzed. Zeinalizadeh et al. (2015) model was built upon a dataset consisting of 436 survey responses, providing a reasonably sized sample for analysis and modeling. On the other hand, Lee et al. (2022) took advantage of an extensive collection of online reviews, amassing a massive dataset comprising 4,783,669 reviews.

In the Zeinalizadeh et al. (2015) study, the data was partitioned into a training set comprising 75% of the information and a validation set comprising the remaining 25%. The model training process involved iterating over 100 epochs, allowing the model to learn and adjust its parameters over multiple passes through the training data. The architecture of the model comprised an initial layer with 9 inputs, representing the features or variables under consideration. This was followed by a hidden layer consisting of 30 neurons, which processed and transformed the input data. Finally, an output layer with a single neuron was utilized to generate the desired prediction or outcome. The model exhibited proficiency in accurately forecasting overall customer satisfaction, effectively capturing the genuine trends of fluctuations and demonstrating a high level of prediction accuracy. The mean squared error for the validation dataset was 0.16, indicating the model's ability to minimize the discrepancy between predicted and actual values.

3 Customer Journey Map

This chapter provides a detailed overview of the initial phase of the project, which focused on the construction of the CJM. The primary objective of this phase was to gain comprehensive knowledge and understanding of the entire customer journey with BW. By exhaustively mapping out the customer journey, this phase played a pivotal role in laying the foundation for the project's development. This stage culminated in the creation of a visual representation of the customer journey, offering a clear and holistic view of the customer's path and serving as a fundamental tool for the development of the project. This comprehensive understanding of the customer journey became the bedrock upon which subsequent phases of the project were built, facilitating informed decision-making and providing strategic insights about the customer experience.

This chapter was structured into two main sections. The first section provides an overview of the methodology employed to execute this phase, offering detailed explanations of the tasks undertaken throughout the process. Subsections within this section delve into the intricacies of each task, providing valuable insights into the approach and methodology employed. This comprehensive breakdown of the methodology allows for a clear understanding of the systematic process followed to construct the CJM.

The second section of this chapter shifts the focus to the output of this phase, namely the CJM resulting from this phase. This section offers a comprehensive depiction of the customer journey, organized by CJM stages, starting from the initial awareness of BW and extending through the entire customer lifecycle until the point the customer no longer works with the company. Accompanying visuals of the CJM developed are also included, enabling visualization of the customer journey, and further enhancing the understanding of the process.

3.1 Methodology followed to build the Customer Journey Map

This section presents the methodology used in the development of this phase. The Figure 3.1 serves as a visual representation of the methodology applied in this phase.

Divided into six key tasks, this methodology encompassed a comprehensive exploration of the customer's interaction and experience with the company. This phase began by conducting meetings with various departments within the organization, aiming to gain a comprehensive understanding of their respective operations. Then, the next task was to understand how each department interacts with customers and contributes to their overall experience. Building upon this knowledge, the following task was to identify and map out all the phases and stages encompassing the customer journey. Next, exhaustive work was done to map all the possible steps in the cus-

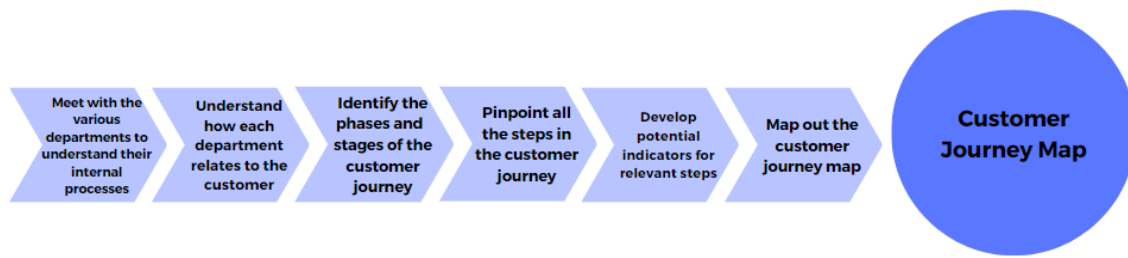


Figure 3.1: Customer journey map phase methodology map.

tomer journey. For the steps deemed significant, there were added indicators that could be useful in monitoring and evaluating the performance of those steps.

Finally, leveraging the accumulated insights and information, a visually appealing and informative board was developed, representing the complete CJM. This visualization provides a comprehensive overview of the customer’s entire journey.

3.1.1 Meet with the various departments to understand their internal processes

The first task involved conducting meetings with various departments within the organization to gain valuable insights into their internal processes. This comprehensive process spanned approximately one week and encompassed interactions with key departments including customer activation, customer service, community operations, product and technology, people, marketing, finance, and accounting. Through these collaborative sessions, a deeper understanding of each department’s operations and their respective roles in serving the customer was obtained. In addition, it was possible to obtain the perspective of each of the departments on what impacts customer satisfaction the most. Through this valuable engagement, a comprehensive understanding of the intricacies of each department’s functioning within the organization was achieved, laying a solid foundation for subsequent project activities.

3.1.2 Understand how each department relates to the customer

In the subsequent task, dedicated efforts were made to understand the specific dynamics between each department and the customer. This involved compiling a detailed list of direct interactions between the departments and the customer. The aim was to gain a comprehensive understanding of how each department directly impacted the customer experience.

3.1.3 Identify the phases and stages of the customer journey

The following task involved the identification of the distinct phases and stages within the customer journey. The phases were meticulously categorized as awareness, acquisition, activation, retention, and advocacy. The awareness phase is where customers first discover BW. The acquisition phase represented the pivotal moment when customers signed up on the website, showcasing their interest in engaging with BW. The activation phase denotes the conversion of signed-up customers into active customers, where they begin to actively work through BW’s platform. The retention phase is characterized by customers maintaining their active involvement and continued

collaboration with BW. Finally, advocacy emerged as the phase where customers, upon concluding their engagement with BW, provide valuable feedback regarding their experiences.



Figure 3.2: Customer journey map Phases.

After identifying the phases of the CJM, the next task was to delve into each phase and identify the specific stages within them. Each stage represents a significant milestone in the customer’s journey, marking a distinct point where their experience and interactions with the company shift their goal. By breaking down the customer journey into stages, it was possible to obtain a deeper understanding of the different touchpoints¹ and moments of engagement that customers encounter along their path.

3.1.4 Pinpoint all the steps in the customer journey

Following the identification of the customer journey stages, the subsequent task entailed a meticulous examination to identify all the individual steps within the customer journey. Figure 3.3 gives a visual understanding of the “phase”, “stage” and “steps” concepts.

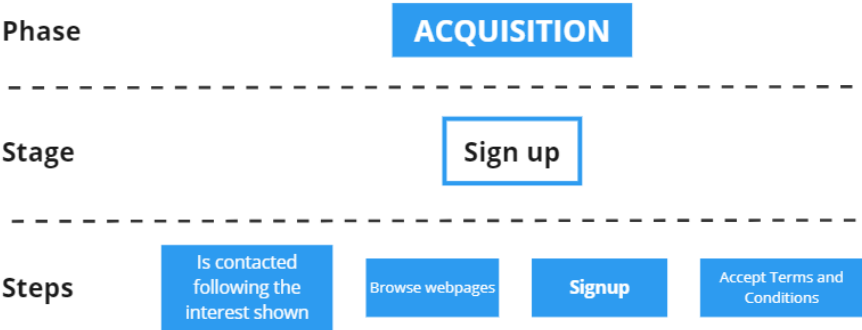


Figure 3.3: Phase, Stage, and Steps.

This process involved exhaustive research and analysis to uncover all possible interactions between customers and BW. The steps were thoughtfully grouped and aligned with the respective stages they corresponded to. Furthermore, close collaboration and regular consultations with various stakeholders within the company were conducted to ensure the comprehensive inclusion of all steps. Each step was also attributed to the specific BW department responsible for its execution, fostering a holistic understanding of the customer journey and organizational involvement at each touchpoint. Figure 3.4 shows the key used for each department in the CJM.

This process of step identification and departmental alignment guaranteed that no steps were overlooked, laying the groundwork for a comprehensive analysis of the customer journey.

¹A touchpoint in a Customer Journey Map refers to any point of contact between a customer and a business throughout their journey. It can happen through various channels such as websites, social media, phone calls, emails, physical stores, or any other platform where customer interacts with the company.

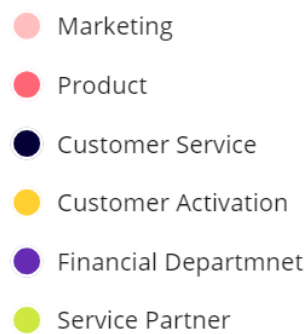


Figure 3.4: Key to the departments responsible for each step.

3.1.5 Develop potential indicators for relevant steps

Once all the steps of the customer journey were identified, the subsequent task involved developing a list of indicators that could be used to measure and evaluate the performance of steps that could potentially impact overall customer satisfaction. This was used as an initial exploratory approach. This approach involved systematically examining each step to determine its potential relevance concerning customer satisfaction and investigating, through in-depth research, delving into industry best practices and customer feedback analysis, suitable indicators to measure its performance. These indicators were incorporated into the CJM below the respective step in order to provide the company with a panoply of suggested indicators that may be adopted in the future.

3.1.6 Map out the customer journey map

The final stage of the customer journey mapping process involved visually mapping out the entire customer journey. To accomplish this, a dedicated software tool, “Miro”, was utilized to create an organized and comprehensive representation. The mapping process followed a logical and sequential approach, ensuring that each step of the customer journey was accurately depicted. By leveraging the capabilities of “Miro’s” software, the CJM was structured in a visually appealing and easily understandable format, allowing stakeholders and team members to gain a holistic view of the customer’s interactions and experiences with the organization. This visual representation served as a valuable reference point, facilitating further analysis and decision-making during the subsequent project phases.

3.2 Customer Journey Map

To fully comprehend the content of this section, it is recommended to refer to Appendix A, where all the figures of the CJM are provided.

3.2.1 Awareness

The customer journey begins in the awareness phase, where the primary goal is to make potential customers aware of the existence of BW. This phase consists of a single stage, also called “Awareness,” which focuses on creating brand awareness and capturing the attention of the target

audience. The Marketing department is primarily responsible for orchestrating this phase and implementing strategies to effectively communicate BW's value proposition.

In the awareness stage, the process of customer awareness can manifest and occur in various ways, as depicted in Figure A.1. Unlike other stages, these steps do not follow a sequential order, they emerge as different hypotheses through which customers may come to know about BW. Thus, this can happen through online research, articles read online, recommendations from colleagues or friends, or other sources. The diverse nature of these steps reflects BW's multi-channel and multi-touchpoint approach to reach and engage with potential customers.

A few indicators have been included in the steps involving advertisements because, being steps that involve the company allocating financial resources, it is advisable to evaluate their effectiveness. Additionally, special attention has been given to the step labeled "Fill out the leads form." This step holds significant importance as it represents the "hottest" point as far as the transition from the awareness phase to the subsequent acquisition phase. To gauge the effectiveness of this step and its impact on lead generation, an indicator has been incorporated to measure its performance.

3.2.2 Acquisition

The next phase in the customer journey is the acquisition phase, which aims to convert potential customers into registered users of BW's platform. This phase consists of a single stage called "Sign up" as depicted in Figure A.2. At this stage, customers proceed to sign up on BW's website, officially becoming registered users of the platform.

The first step in the acquisition stage is "Is contacted following the interest shown," which follows the completion of the leads form, applying only to customers who have filled the form in the awareness phase. This step falls under the responsibility of the customer activation department, as they are tasked with reaching out to these potential customers to foster their sign-up process.

Subsequent steps within the "Sign up" stage are performed by the customers themselves on the BW website (product). They begin by browsing webpages to gather information about the company and its offerings. Following that, they proceed to fill in their name, email, and password to create an account. Finally, customers are required to accept the terms and conditions. The responsibility for these steps lies with the product and IT department, as it develops and maintains the website and ensures a seamless user experience throughout the registration process.

To track the effectiveness of the acquisition phase, some indicators have been incorporated. In the "Browse webpages" step one indicator was included to potentially allow the company to assess the website's traffic and engagement, providing insights into the number of visitors. Furthermore, indicators have been implemented for the pivotal "Sign up" step, to enable the company to measure the conversion rate of visitors to registered users and evaluate the cost per registration.

3.2.3 Activation

The activation phase is the next phase in the customer journey, focusing on converting registered customers into active users ready to start working. The primary objective of this phase is to ensure customers are equipped with the necessary information and resources to begin their

working journey with BW.

This phase has a common part shared across all segments, encompassing the stages of “Application” and “Needs extra information” depicted in Figure A.3. Following this common part, the customer journey diverges into three distinct paths based on the rideshare (Figure A.6, Figure A.7 and Figure A.8), food (Figure A.5), and shopping (Figure A.4) segments, each tailored to the unique characteristics and needs of these segments. The Courier segment was not considered as it was inactive during the research period.

The first stage in the activation phase is the “Application”. In this stage, customers through BW website have the opportunity to select the partner or partners they wish to work with and proceed to submit their application. If a customer does not complete the application process, the customer activation department proactively reaches out to offer assistance and encouragement in finishing the application. Furthermore, if any documents submitted during the application are incorrect, customers have the option to make the necessary changes directly on the website.

Several indicators were incorporated into the “Submit Application” step as it holds significant importance within this activation phase, serving as a pivotal moment where the customer truly showcases their determination to start working. By tracking these indicators, BW can assess the effectiveness of the application process, and identify any potential bottlenecks or areas for improvement.

It’s important to note that the initial step of this stage exclusively applies to customers interested in working in the rideshare segment. To submit an application for partners in this segment, customers are required to possess a Transporte Individual de Passageiros em Veículo Descaracterizado (TVDE) license. Obtaining this license involves completing a training course, which customers can conveniently apply for directly on BW’s website.

The subsequent stage in the activation phase is called “Needs extra information.” Unlike other stages, this stage is not fixed within the customer journey, but rather it spans the entire activation phase, offering customers the opportunity to seek clarification, resolve doubts, or request additional information. To do that, customers can contact with the customer activation department through various channels, such as phone calls, submitting tickets, or accessing the help center available on the website. The “Experience Rating” indicator present in the steps “Ticket for information” and “Call for information”, was already implemented by the company, which allows customers to rate the quality of assistance received after concluding a call or obtaining a response to a ticket.

Now, the customer journey delves into the segment-specific part of the activation phase. Concerning the shopping segment, the “Training event” stage takes center stage. This stage revolves around a series of interactions and processes that culminate, expectedly, in the customer’s readiness to begin working.

It begins with the customer being contacted by the customer activation department to schedule their training event. Subsequently, the partner sends the customer an email and a message to confirm their attendance at the training event. Additionally, a reminder email is sent to the customer the day before the scheduled training event. The training event itself is the responsibility of the partner, and during this event, three potential outcomes may occur: the customer successfully

completes the training and becomes eligible to start working, the customer fails to meet the training requirements and their application is withdrawn, or the customer fails to attend the training and must reschedule. Regardless of the outcome, BW's customer activation department assumes the responsibility of communicating the result to the customer via email.

To monitor and evaluate the effectiveness of this stage, some indicators were added. These indicators provide insights into the attendance of the training events, the efficiency of the process in terms of timeliness, and the overall performance of clients during the training sessions.

Shifting the focus to the food segment, the activation process is remarkably straightforward, encompassing a single stage known as "Account creation."

During this stage, two distinct paths unfold, contingent upon the type of customer. For clients who are working or already worked in the food partner they applied to but through a company other than BW, having already an existing account, they receive an email invitation to switch fleets. Upon accepting this invitation, they are able to commence working seamlessly under BW's fleet.

Conversely, customers who have never previously worked with the food partner they applied for follow a slightly different trajectory. Upon the creation of their account, they receive an email notification confirming the successful account creation. Subsequently, another email is dispatched to inform them once their account becomes active, signifying their readiness to begin working.

All email communications are efficiently handled by BW's customer activation department. To gauge the effectiveness and efficiency of this process, a specific indicator has been implemented within the step where customers are notified that their account is active. This indicator was added to allow BW to monitor the time elapsed between the customer's application submission to a food partner and the moment they are ready to start working.

Regarding the rideshare segment, it entails a more intricate activation process, encompassing three stages. The first stage within this segment is "Rent a vehicle". During this stage, the customer is personally contacted by the customer activation department, aiming to persuade them to rent a vehicle. It is noteworthy that, during the development of this CJM, the option for customers to work with their own vehicles had not yet been implemented. Consequently, at that time, customers would proceed to the "Account creation" stage only after successfully booking a vehicle.

Subsequently, customers navigate the website to search for available cars and proceed to book a vehicle for their desired date. However, before finalizing this stage, a crucial step ensues. A phone call is made by the customer activation department to perform a booking fit, ensuring that the car the customer booked is indeed available on the selected date. In the event that the selected car is unavailable for the date selected, alternative options such as rescheduling the date or suggesting a different vehicle are proposed to the customer.

To effectively evaluate the efficiency and user-friendliness of the "Book a vehicle" step, specific indicators have been incorporated. These indicators provide valuable insights to the company, shedding light on the efficacy and ease with which customers progress to this pivotal step within the activation process.

Moving on to the next stage, "Account creation," it bears resemblance to the activation process in the food segment. For customers who are already working or have previously worked with the

rideshare partner they applied for under a fleet other than BW's, they are simply requested to accept the invitation to transition to BW's fleet. On the other hand, if the customer is new to the rideshare partner, their account is created within the partner's platform. Subsequently, the customer is promptly notified once their account becomes active.

Similarly to the food segment, a pertinent indicator has been integrated to gauge the duration between a customer's application submission and the subsequent creation of their account. This indicator serves as a valuable metric to assess the efficiency of the account creation process, enabling BW to monitor and optimize the time it takes for customers to progress from application submission to active account status.

Moving forward, the customer arrives at the final stage of the rideshare segment's activation process, the "Vehicle Pickup." Within this stage, customers are afforded the flexibility to make modifications to their existing reservation should they desire to alter the vehicle selection or adjust the pickup date. Additionally, customers have the option to cancel their reservations entirely. All these functionalities are conveniently accessible through the BW website.

Two days before the vehicle pickup date, the customer receives a notification from the fleet partner confirming the reservation and specifying the designated pickup location for the vehicle. At the pickup location, the customer retrieves the car from the fleet partner, who also provides them with a fleet card for fuel purposes. If the customer intends to utilize the fleet card, they have the choice of either directly contacting the fleet partner for immediate activation or waiting a 24-hour period for the card to become active.

Some indicators were added into the step the customer picks up the car in order to measure customer satisfaction with the car pick up process as well as the efficiency of the whole activation process.

3.2.4 Retention

Subsequent to the activation phase, the customer enters the retention phase, encompassing the entirety of the customer's active period with BW until the moment they stop working and become inactive. This phase comprises stages specific to each segment and stages applicable across all segments.

As Figure A.9 shows, the work stage for the shopping segment encompasses a series of five steps. Initially, the customer communicates their availability and specifies the desired establishment where they intend to work. This step occurs on a weekly basis, allowing for flexibility and adaptation to the customer's schedule. Once the availability is confirmed, the customer proceeds to pick up their work kit, which is a one-time event that takes place at the commencement of their activity. Subsequently, the customer receives requests for orders and is responsible for fulfilling them promptly.

Throughout this process, any questions or issues related to their deliveries or the partner platform can be addressed directly with the shopping partner. To monitor the customer's performance and availability, specific indicators have been implemented, enabling BW to track customers' earnings and work availability.

In the food segment, the work stage comprises six distinct steps as it can be seen in Fig-

ure A.10. The stage begins with the customer logging in to the food partner's platform, signaling their availability to accept delivery orders. As orders come in, the customer accepts them and proceeds to fulfill the delivery. Upon completion of the delivery, the customer has the opportunity to provide an evaluation of the receiver.

In parallel, the customer can track their earnings in real-time on the food partner's platform. Should any inquiries or challenges arise pertaining to the food partner's platform, the customer can directly contact them for assistance and resolution. In addition, several indicators have been implemented in order to monitor and assess customer performance and availability throughout the work stage in the food segment.

The work stage in the rideshare segment comprises six steps and operates on a similar principle as in the food segment as the Figure A.11 shows. To initiate the process, the customer goes online on the rideshare partner's platform and awaits trip requests. Upon receiving a trip, the customer accepts and completes it, delivering the passengers to their destination. At the end of the trip, the customer has the option to evaluate the passenger.

Real-time earnings can be monitored through the partner's platform. Any questions or issues regarding the partner's platform are promptly addressed by contacting the partner directly. To assess customer performance and availability, several indicators have been implemented, allowing for a comprehensive evaluation of their performance and overall availability.

The stage "Needs help", represented in Figure A.12, applies to all segments and accompanies the entire retention phase. If a customer has any questions or requires additional information from BW, they have the option to browse the help center, submit a ticket, or make a call.

The customer service department is responsible for handling all inquiries and support requests during this stage. To measure customer satisfaction and the effectiveness of the support provided, an "Experience Rating" indicator has been added to the "Ticket for information" and "Call for information" steps, which was already implemented by the company. Additionally, an indicator has been introduced for the "Browse the help center" step in the sense to assess the effectiveness of the articles published by the customer service department in the help center.

Next, there are a series of stages that apply only to customers operating on rideshare. These stages are related to the car they rented through BW. The first stage, depicted in Figure A.13, is the "Segment Change". This stage allows customers to switch from one car segment to another, for instance, this may involve transitioning from a fuel-powered car to an electric vehicle, switching from a manual to an automatic transmission, or upgrading from a 5-seater to a 7-seater vehicle.

The process of changing segments is designed to be straightforward and user-friendly. Initially, the customer initiates the segment change request by contacting the customer service department. The customer indicates their intention to switch segments, and the department promptly evaluates the feasibility of the requested change. Upon confirmation of the availability of the desired segment, the customer can proceed to choose and book the car of their preference within the desired segment on BW website. With the booking successfully made, the subsequent steps involve returning the current car in their possession to the designated fleet partner. Upon the return, an inspection is conducted to assess any damages, missing elements, or potential additional costs, such as a lower amount of gasoline compared to the initial pickup. Once the inspection is completed,

the customer can conveniently pick up their new car.

Following the segment change process in the rideshare segment, the subsequent stage is “Vehicle Issues”. This stage encompasses three possible scenarios: malfunctions (Figure A.14), accidents (Figure A.15), and routine maintenance (Figure A.16).

In the event of a vehicle malfunction, the customer first contacts the customer service department and reports the issue. Subsequently, he is redirected to the fleet partner line to schedule a visit to an authorized workshop for diagnosis and repair. If the malfunction is a minor issue that can be swiftly resolved, the customer retrieves the repaired car and can promptly resume their work. However, if the repair necessitates an extended duration and requires the car to remain in the workshop for several days, the customer returns the vehicle. At the moment the customer returns the car, an inspection is made of the car to check for any damages or additional costs.

The customer then proceeds to book a replacement car. Regarding the booking of vehicles, priority is given to customers that experienced vehicle issues rather than those renting a new vehicle. It is worth noting that the duration the car spends at the workshop is deducted from the rental price, ensuring a fair adjustment for the customer.

Some indicators were added in the sense to help monitor the recurrence of malfunction-related problems and assess the efficiency with which customers are provided with replacement cars following the reporting of a malfunction. Given that the car serves as the primary working tool in the rideshare segment, a prompt resolution to vehicle issues is crucial, as the customers’ ability to work directly depends on the availability of a functioning vehicle.

In the unfortunate event of an accident while operating in the rideshare segment, a specific process is in place to ensure a prompt and efficient resolution.

Firstly, the customer is required to report the accident on BW’s website and submit the friendly declaration. If assistance is needed in completing the friendly declaration, the customer can contact the fleet partner for guidance. However, if the customer can’t obtain a friendly declaration, he must leave the car for an appraisal. This enables the insurance companies to assess and determine liability for the accident.

Subsequently, for the scenario where the customer gets a friendly declaration, the customer is instructed to take the car to a workshop designated by the fleet partner. Similar to the procedure for vehicle malfunctions, if the repair is minor in nature, the customer can await the completion of the repair and resume their work with the same vehicle. However, in the case of a lengthier repair process, the customer is required to return the car, undergo an inspection to assess any damages or additional costs, and proceed to book another car. In the scenario where the customer had to drop off the car for the insurance expertise report, he has to book another vehicle as well.

To effectively monitor and address accidents, relevant indicators have been implemented. These indicators serve the purpose of tracking the percentage of accidents and measuring the time it takes for a customer to obtain a replacement car in the event of an accident.

In the case of car maintenance, the process is very simple. The customer contacts the customer service department, which forwards him to the fleet partner with whom he schedules a workshop to perform the maintenance on the car. It is important to note that the time spent performing maintenance on the car is then deducted from the rental price paid by the customer.

The “Cash out” stage plays a pivotal role in the customer journey of all clients and is presented in Figure A.17. This stage revolves around customers withdrawing their income. To initiate the cash out process, customers must access BW’s website and review their earnings, determining the available balance for withdrawal. Subsequently, they are required to submit an invoice specifying the amount for withdrawal. Following the correct invoice submission, customers can expect to receive their funds within 24 to 48 hours. The responsibility of validating the invoices and issuing the payments lies with the financial department.

Various indicators were added to assess BW’s handling of the process, the overall customer experience, and the ease with which customers can navigate through the necessary steps.

Once again, there are specific stages that cater to the rideshare segment. One such stage is the “Customer with debt” stage, depicted in Figure A.18, which solely applies to rideshare customers because, unlike other segments where customers only pay the BW fee based on a percentage of their earnings, rideshare customers can accumulate debt due to various expenses associated with the car, such as rent, fuel (if utilizing the fuel card), tolls, damages, and more.

When a rideshare customer finds themselves in debt for two consecutive weeks, it becomes the responsibility of the financial department to communicate through an e-mail, notifying them of their debt. Then, another e-mail is sent including a receipt for the debt payment and specifying the 24-hour deadline for settling the amount owed. As the payment deadline approaches, the customer service department takes action by making a direct call to inform the customer about the debt, in case they don’t already know, and understand if the customer intends to pay the debt or return the car.

At this point, the customer has three options. They can choose to pay the debt and continue working normally, schedule the return of the car, or in case the customer neglect both options, the car will be blocked, and the customer will be required to not only settle their existing debt but also cover the costs associated with towing the vehicle. If a customer fails to respond to the customer service department’s call, the car will also be blocked.

The financial department assumes the responsibility of verifying whether the customer has made the necessary payment and issues the order to block the car if required.

Some indicators were added to help track the frequency at which customers enter this stage in their journey, the percentage of customers who successfully pay off their debt, and the percentage of customers who enter into conflict with the company.

Another significant stage concerning the rideshare segment is the “Vehicle return” stage presented in Figure A.19, which occurs when a customer decides to discontinue working and wishes to return the rented vehicle.

The customer initiates the vehicle return process by submitting a request on BW’s website, specifying the desired date for the return. This request must be made 72 hours in advance.

Once the request is received, the customer service department contacts the client to confirm the return of the car and the drop-off location. If the customer intends to permanently cease working with BW, they can also request the return of their deposit through the customer service department.

The customer then drops-off the vehicle in the designated workshop and the fleet partner conducts a thorough inspection of the vehicle to assess any damages or additional costs that may be

incurred.

After determining any extra costs associated with the car, the financial department is responsible for processing the deposit return to the customer. Regarding the deposit return, the financial department has a maximum of fifteen working days from the moment the customer returns the vehicle to complete the refund process.

To assess the customer experience throughout the entire vehicle return process and to evaluate the performance of the “Deposit return” step, several indicators were implemented.

3.2.5 Advocacy

The final phase of BW’s CJM is the advocacy phase, presented in Figure A.20. This phase occurs when a client stops working with BW. BW’s primary objective is to prevent clients from reaching this phase by trying to keep the client working with BW for as long as possible. The advocacy phase consists of a single stage called “Churn”. Customers enter this stage when they have not actively worked for an entire calendar month, resulting in their classification as “churned”. During the “Churn” stage, BW’s customer service department contacts the customer to gather valuable feedback about their departure. This includes understanding the reasons behind their decision, identifying potential factors that could entice them to return, assessing their likelihood of coming back, and many others.

To assess the effectiveness of the overall customer journey, various indicators were added in the “Churn” stage. These indicators provide insights into the frequency of client departures each month, the financial contributions made by clients during their working period with BW, their earnings while working with the company, the average duration of a client’s engagement with BW, and how many customers are starting to work with the company by referral from existing ones. By measuring these indicators, BW can continuously evaluate and improve its services, aiming to enhance customer retention and satisfaction throughout the entire customer journey.

4 Defining the KPIs

This chapter presents the entire phase of defining the KPIs that best captured the factors underlying satisfaction, which were later used as inputs to the model. Following the completion of the CJM phase, this phase of the project aimed to build upon the comprehensive understanding gained regarding all customer interactions and points of contact with the company.

The structure of this chapter was divided into two main sections. The Section 4.1 provides a comprehensive overview of the methodology employed during the conclusion of this phase, offering a detailed explanation of each task performed.

Section 4.2 presents the list of identified KPIs. Each KPI is accompanied by a subsection that provides a comprehensive rationale for its selection, outlining the specific reasons why it was chosen, as well as an explanation of each one.

4.1 Methodology followed to define the KPIs

This section presents the methodology adopted to identify a set of KPIs suitable to measure the factors that can influence customer satisfaction. Through a thorough analysis and evaluation, a comprehensive list of KPIs was generated. Figure 4.1 serves as a visual representation of the methodology applied in this phase.

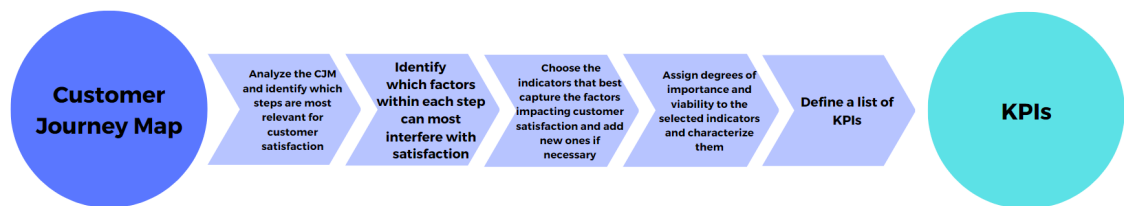


Figure 4.1: Define KPIs phase methodology map.

The methodology employed is structured into five distinct tasks, each with a specific objective. The initial task focused on analyzing the CJM to identify the key steps that significantly impact customer satisfaction.

The second task involved identifying the intrinsic factors associated with each key step of the CJM.

In order to effectively capture these factors, the third task involved choosing a combination of existing indicators from the CJM and newly developed indicators. This selection process aimed to create a comprehensive set of indicators that accurately reflected the identified factors.

In the fourth task, the selected indicators were characterized and underwent an evaluation

process, where degrees of importance and viability were assigned to them. This task helped to prioritize the indicators based on their significance and practicality.

Finally, the final list of KPIs was defined based on the outcomes of the previous tasks. These KPIs were designed to serve as the measurement tools to assess customer satisfaction.

4.1.1 Analyze the CJM and identify which steps are most relevant for customer satisfaction

In the initial task, a comprehensive analysis of the CJM was conducted to determine the steps that held the greatest significance for customer satisfaction. Given that the ultimate objective of this project was to enhance retention, the focus was directed toward examining the CJM steps that had the potential to impact customer satisfaction during the retention phase.

To identify the steps with the most substantial influence on customer satisfaction, it was deemed necessary to delve deep into the subject matter to gain a thorough understanding. The “churn feedback collection” document was meticulously analyzed, and several churn calls were listened to, extracting valuable insights about the factors that contributed to customers discontinuing their engagement with BW. This exploration provided information on what went wrong in his experience with BW, what made him stop working with BW, if he intended to work with BW again, what would BW need to change for him to come back, and his “temperature”, i.e., the perception of his degree of satisfaction/unsatisfaction with BW.

Furthermore, the customer service department, being in direct contact with active customers, was consulted to obtain knowledge on customer complaints and understand their perspective of what the “pains” of the customers are. Additionally, extensive research was conducted to gain knowledge of what other studies understood as relevant steps in customer satisfaction.

By assimilating information from these varied sources, it was possible to discern the key steps within the customer journey that significantly influence customer satisfaction.

4.1.2 Identify which factors within each step can most interfere with satisfaction

The next step involved identifying the factors within each step of the customer journey that has the greatest potential to influence satisfaction. Leveraging the knowledge and insights gained from the study conducted in the previous task, a thorough analysis was conducted to uncover the potential “pains” and “gains” associated with customer satisfaction at each relevant step of the CJM.

4.1.3 Choose the indicators that best capture the factors impacting customer satisfaction and add new ones if necessary

The subsequent step involved the selection of indicators that would effectively capture the factors influencing customer satisfaction, along with the potential addition of new indicators if deemed necessary. Building upon the indicators initially developed during the customer journey mapping phase, a thorough evaluation was conducted in light of the insights gained from the previous steps. This process entailed careful consideration of the identified factors impacting

satisfaction.

As a result, certain indicators were adjusted or refined, while new indicators were introduced to accurately capture the key elements influencing customer satisfaction, enabling a precise assessment.

4.1.4 Assign degrees of importance and viability to the selected indicators and characterize them

Next, it was necessary to assign degrees of importance and viability to the selected indicators and characterize them. Regarding viability, it was necessary to analyze the company's databases to understand what data was already being collected that could support the indicators. One of the company's CEOs was also consulted to give his opinion about the feasibility of collecting information for each of the planned indicators, as well as about the ease of collecting information from third-party companies. Moreover, the limited time frame of the project was considered, which imposed constraints on the time available for data collection. Finally, after all this analysis, the indicators were classified as "viable", "not sure" or "not viable". Regarding their degree of importance they were classified as "must-have", "should-have" and "nice-to-have". The "must-have" KPIs were considered indispensable, directly aligning with the research focus, while the "should-have" and "nice-to-have" KPIs offered additional insights and enriched the analysis. As for the characterization, following a logic from the most macro to the most micro, the indicators were categorized regarding the scope, stage, and step to which they referred to. Subsequently, they were further characterized by their type, measurement units, and a comprehensive indicator description was provided. Figure B.1 provides an overview of the table elaborated in a Google Sheets file that resulted from this task.

4.1.5 Define a list of KPIs

In the final step, the list of KPIs was established. As part of this process, any indicators categorized as "not viable" were removed from consideration. Contingency plans were devised by defining replacement KPIs in case any of the selected KPIs proved to be non-viable due to data availability or other constraints. The resulting list of KPIs represented a comprehensive and robust framework to monitor and evaluate the factors impacting customer satisfaction.

4.2 KPIS

The KPIs were divided into two macro scopes: "Experience map" and "Involvement with BW." Within the "Experience map" scope, four stages were selected: "Work", "Need help", "Vehicle issues", and "Cash out". The "Work" stage is essential for this analysis as it focuses on active customers currently working. This stage is particularly important as it directly impacts their satisfaction and success within the platform. The "Need help" stage holds significant importance as it involves direct interactions between customers and the company, particularly with the Customer Service department. Evaluating this stage provides valuable insights into the quality of customer service, responsiveness, and problem resolution, all of which contribute to customer sat-

isfaction. The “Vehicle issues” stage is particularly relevant as the company knows that problems with rented vehicles generate a lot of dissatisfaction. This stage is only dedicated to customers who rent a car with BW, which implies that they are operating in the TVDE segment since only customers working in the TVDE segment can rent a car with BW. Problems with vehicle malfunctions, breakdowns, or any other vehicle-related issues can hinder a customer’s ability to work effectively and generate income. Lastly, the “Cash out” phase is crucial as it represents the stage where customers receive their earnings, making it a pivotal point in their experience with the company. It encompasses the process of invoicing, payment processing, and the overall efficiency of the cash-out system. Customers expect a seamless and timely payment experience, as it directly affects their financial well-being and trust in the company. Table 4.1 demonstrates the output of this phase, that is, the list of the selected KPIs.

Table 4.1: List of the selected KPIs.

KPI	Units	Description	Step	Stage
Experience Map				
Net earnings per week	€/week	Average net earnings per week considering the number of weeks that the customer worked	Work	Work
Net earnings per online hour	€/hour	Average net earnings per hour considering the hours that the customer was online to work	Work	Work
Number of tickets or calls - complaint	Number of tickets or calls	Number of complaint type tickets or calls made	Leave a ticket or make a call	Need Help
Ticket and call rating	0-1; 1-4; 0-9	Average of the ratings given by the customer after his tickets or calls are answered	Leave a ticket or make a call	Need Help
Number of malfunctions	Number of malfunctions	Number of car malfunctions that the customer experienced	Report a malfunction	Vehicle Issues
Vehicle damage costs	€/week	Average cost of vehicle damages per week	Vehicle Inspection	Vehicle Issues
Invoice rejection rate	%	Percentage of invoices that are rejected due to errors or incomplete information from those that the customer submitted	Submit Invoice	Cash Out
Number of cycles closed out of SLA	Number of cycles	Number of cycles that got published out of the SLA that the customer experienced	Submit Invoice	Cash Out
Involvement with BW				
Rideshare	True/False	The customer has worked in the Rideshare segment		
Food Delivery	True/False	The customer has worked in the Food Delivery segment		
Shopping	True/False	The customer has worked in the Shopping segment		
Courier	True/False	The customer has worked in the Courier segment		

4.2.1 Net earnings per week

The inclusion of “Net earnings per week” as a KPI holds significant importance in our analysis. Firstly, this KPI enables us to gain insights into the weekly income of each client, providing a valuable measure of their financial success. Considering that our customers aim to maximize their earnings, this indicator becomes essential as it aligns with our core value proposition. Calculating

net earnings per week involves deducting the BW fee and the cost of renting a car (if applicable) from the client's earnings on the platforms, dividing it by the number of weeks they worked. Other costs such as fuel and toll expenses were not included in the analysis. These types of costs were not included because it was not possible to obtain them for all customers, it was only possible to get them for customers operating in rideshare and working with vehicles rented through BW, and even for these, fuel costs were only available for those who used the fuel card. Furthermore, the analysis revealed that the majority of individuals tended to overlook these costs when calculating their income. Instead, their primary focus was on the balance available for withdrawal on BW's website, as it directly impacted their financial gains. Therefore, considering the limitations and customer priorities, the analysis focused on capturing the most relevant aspects that influenced their earnings and overall satisfaction.

By including this KPI, we address the stage "Work" and the corresponding step, emphasizing the crucial aspect of financial performance in our assessment.

4.2.2 Net earnings per online hour

The integration of the "Net earnings per online hour" KPI allows us to accurately assess the income generated by each client for every hour they were available for work. By considering the effort dedicated by our clients, this indicator becomes essential as it provides insights into both their income and the level of commitment they invest. Solely relying on the "Net earnings per week" indicator would overlook the important aspect of evaluating the effort exerted by each client. Individuals who dedicate more time to work are expected to also anticipate higher earnings. Ultimately, all clients aim to maximize their earnings within the time they allocate for work. The calculation of net earnings per online hour involves dividing the client's net earnings (after deducting the BW fee and rental car costs, if applicable) by the number of hours the client was available to work. By incorporating this indicator, we address the stage "Work" and the corresponding step, underscoring the significance of both income and effort in our evaluation.

4.2.3 Number of tickets or calls - complaint

Including the KPI "Number of tickets or calls - complaint" allows to track and analyze the frequency of customer complaints made through tickets or calls. This indicator holds significant importance as it provides insights into the number of times customers have expressed their dissatisfaction. This indicator is specifically inserted in the stage of "Need help" and within the step of "Leave a ticket or make a call."

4.2.4 Ticket and call rating

The incorporation of the KPI "Ticket and call rating" allows to assess the average rating assigned by customers to the tickets or calls they have made. During customer interactions with BW's customer service team, after a call is made and answered, customers are given the opportunity to provide a rating based on their experience. Similarly, when a ticket is resolved and closed, customers are also given the option to rate their satisfaction.

This indicator holds significant importance as it serves as a measure of customer satisfaction with the service provided by BW's customer service department. The rating assigned by customers reflects their level of satisfaction or dissatisfaction with the support they received. Moreover, while the rating is initially associated with a specific ticket or call, for some customers, it may serve as an overall indicator of their satisfaction or dissatisfaction with the company as a whole. The units for rating tickets and calls have evolved over time. Initially, tickets were rated on a scale of 1 to 4, while calls were rated on a scale of 0 to 9. However, as of March 8, 2023, tickets were reclassified on a scale of 0 to 1, and as of March 16, 2023, calls were reclassified as either 0 or 1. This indicator is specifically inserted in the "Need help" stage and the "Leave a ticket or make a call" step.

4.2.5 Number of malfunctions

The addition of the "Number of malfunctions" KPI provides insights into the number of malfunctions experienced by customers. This indicator specifically applies to customers who rent vehicles through BW, which implies that they work in the rideshare sector, as only customers working in this sector can rent a vehicle with BW. The decision to include this KPI was based on comprehensive analysis, which revealed that the number of malfunctions significantly impacts the satisfaction of customers renting cars with BW. Given that the car serves as the working tool in the rideshare segment, experiencing a malfunction directly affects a driver's ability to work and earn income during that time. As such, monitoring the frequency of malfunctions enables the monitoring of this critical aspect of customer satisfaction. The "Number of Malfunctions" KPI is categorized within the "Vehicle issues" stage and the "Report a malfunction" step.

4.2.6 Vehicle damage costs

The integration of the "Vehicle damage costs" KPI enables to track the expenses incurred by customers due to vehicle damages. As for the "Number of malfunctions" KPI, this particular indicator applies exclusively to customers who rent vehicles through BW. The assessment of damages occurs during the vehicle inspection, which takes place upon the customer's return or exchange of the vehicle. The decision to include this KPI was based on extensive analysis, revealing that the costs associated with vehicle damages have a significant impact on the satisfaction of the customers. Such damages can result in substantial expenses and may lead to disputes regarding the amount charged and its validity. This KPI aligns with the "Vehicle issues" stage and the "Vehicle inspection" step, allowing us to comprehensively evaluate the impact of damage-related costs on our customers' experience.

4.2.7 Invoice rejection rate

The inclusion of the "Invoice rejection rate" KPI allows to monitor the number of invoices that are rejected by the finance department, divided by the total number of invoices submitted. BW's value proposition includes flexibility in payments and the absence of bureaucracy, which naturally leads customers to expect prompt payment. To receive their earnings, customers must submit an invoice accurately filled out with all the required information (detailed instructions are available

in the Help Center). If a customer fails to fill in the fields correctly and submits the invoice on the BW platform, it will be rejected, accompanied by an explanation. This rejection necessitates generating a new invoice and resubmitting it, which can be a time-consuming process, leading to delayed payments. Therefore, this indicator reflects a significant impact on customer satisfaction, as customers may feel frustrated and unsupported by BW, in addition to being dissatisfied with the extended time it takes to receive their earnings. The “Invoice Rejection Rate” KPI is categorized within the “Cash Out” stage and specifically in the “Submit Invoice” step.

4.2.8 Number of cycles closed out of SLA

The “Number of cycles closed out of Service Level Agreement (SLA)” KPI allows for monitoring the number of cycles launched after the agreed-upon timeframe experienced by the customer (within the weeks they were active). Customers rely on BW’s website to view their earnings and costs, which are calculated weekly and uploaded for their reference. The SLA between BW and customers specify that earnings and costs of a determinate week must be updated every second business day of the following week, typically on Tuesday. When cycles are closed beyond this timeframe, it can impact customer satisfaction as they can only see their net earnings, which they need to include in their invoice for payment, once the cycle has been launched. The “Number of cycles closed out of SLA” KPI is categorized within the “Cash Out” stage and specifically in the “Submit Invoice” step.

4.2.9 Segment

Within the scope “Involvement with BW” there were included four KPIs that evaluate the segments in which the customer was active. Thus, the KPIs “Rideshare”, “Food Delivery”, “Shopping” and “Courier” evaluate with “True” or “False”, whether the customer worked on that segment or not. The inclusion of these segment-based KPIs is crucial due to the significant differences observed between segments. Income levels, work types, customer expectations, and customer profiles vary across these sectors, all of which can have a considerable impact on customer satisfaction. Categorizing customers based on their respective segments allows for a more targeted analysis.

5 Dataset Compilation

This chapter delves into the comprehensive work undertaken in the compilation of the dataset. The primary objective of this phase was to construct a comprehensive dataset comprising the information gathered from the previously defined KPIs and the control variable.

To provide a clear structure and facilitate comprehension, this chapter is divided into five sections. Section 5.1 outlines the methodology adopted throughout this phase, ensuring a clear understanding of the process followed to the dataset. Section 5.2 details the process that culminated with the data collection for the KPIs, encompassing various sources and techniques to gather relevant information.

Section 5.3 focuses on the definition of the control variable and the meticulous collection of its associated data. The section provides an in-depth explanation of the steps taken to ensure accurate parameterization and comprehensive data collection for this control variable.

Moving forward, Section 5.4 outlines the comprehensive process of building the dataset. In addition, it shows all the processes until the training dataset was obtained, which was the dataset used to build the model. This involved merging, cleaning, and preprocessing the collected data to ensure consistency, accuracy, and compatibility with the subsequent modeling phase.

5.1 Methodology

This phase encompassed two distinct paths, one specifically focused on the KPIs, and the other centered around the control variable. Figure 5.1 serves as a visual representation of the methodology applied in this phase.

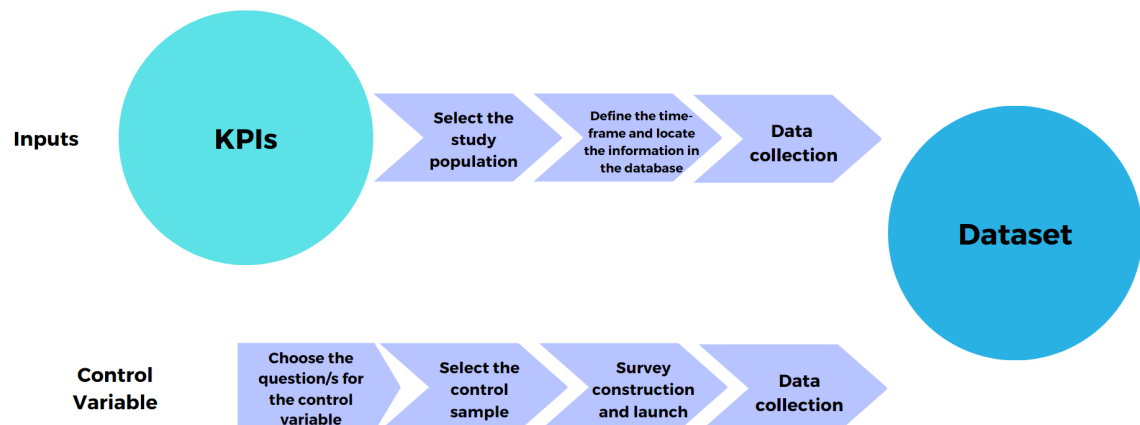


Figure 5.1: Training Data Set phase methodology map.

Concerning the inputs, the methodology followed the definition of the KPIs in the previous phase. The initial step involved defining the population under study. Once the population was determined, the next step was to define the time frame to be considered for the analysis. With the population and time frame in place, the relevant information pertaining to the identified KPIs was located within the database. Subsequently, the data for each indicator was systematically collected.

In relation to the control variable, the methodology for its incorporation consisted of four key steps. Initially, it was imperative to determine the specific variable that would serve as the representation of customer satisfaction. This involved carefully selecting the appropriate question or questions to be included in the customer survey, allowing for an effective measurement of satisfaction. Subsequently, the control sample was established, outlining the specific group or subset of customers that would be utilized for this analysis. Once these foundational elements were established, the survey was constructed and launched, enabling the collection of customer responses and feedback. Lastly, the data obtained from the customer responses were gathered, providing valuable insights into the control variable.

The completion of this phase was marked by the successful compilation of a comprehensive dataset, comprising the collected data for all the identified KPI's (inputs), as well as the collected data for the control variable.

5.2 Inputs

5.2.1 Select the study population

Regarding the "Inputs", the initial step involved selecting the study population. Given BW's dynamic nature as a company experiencing ongoing growth and maturation, it was crucial to exclude customers whose satisfaction might have been influenced by outdated factors. The focus of the analysis was then on clients who were active in the last week, that is, those who had earnings during that period. This approach ensured that the satisfaction measurements were based on the most current and relevant information available. Since the goal was to have real-time access to the satisfaction of the customer base, this population was continually updated for the last week with available data, that is, the cycle from Monday to Sunday of the previous week. This update is done automatically through formulas in the Google Sheets document where the dataset was developed and it occurs on Wednesdays, which is the day after the closing of the cycle (typically Tuesday) in which the income and costs for the previous week are calculated.

5.2.2 Define the time frame and locate the information in the database

The chosen time frame for the analysis spans the last eight weeks, including the most recent week. This decision was made after careful research and consideration. The aim was to strike a balance between capturing sufficient information that might impact current customer satisfaction and avoiding the pitfalls of an excessively wide or narrow time frame. A very wide time frame carried the risk of including outdated information that could no longer have a significant impact

on current customer satisfaction. Conversely, a very short time frame could result in inadequate coverage of factors influencing customer satisfaction. By selecting an eight-week time frame, the aim was to minimize both risks and ensure a comprehensive understanding of the client's recent activities and their potential impact on customer satisfaction.

In order to locate the necessary information in the database, an extensive exploration of the company's "BigQuery" database was conducted. "BigQuery" is a cloud-based data warehouse platform that allows for the analysis of massive datasets using Structured Query Language (SQL)-like queries. This task involved navigating through various tables to gain a comprehensive understanding of the data collected by the company. Through this analysis, it became apparent that certain critical information required for calculating the "Number of Malfunctions" and "Net earnings per online hour" indicators was missing from the database. To address this, meetings were arranged with the fleet partner to request the necessary data for calculating the "Number of Malfunctions" indicator. Additionally, meetings and email exchanges were held with partners in the food and shopping segments to obtain the missing data on the number of hours the customer was online, essential for calculating the "Net earnings per online hour" indicator. The whole process of communicating with the partners involved several meetings and many e-mail exchanges in order to explain clearly what was intended. This process was very time-consuming because for these partners the task of sharing data with BW was not seen as a priority and besides having to find and send the information intended, it was necessary on their part to analyze the information they were going to share so as not to share confidential information.

5.2.3 Data collection

The data collection step proved to be one of the most challenging and time-consuming stages of the project. Initially, it necessitated acquiring proficiency in navigating and working with "BigQuery", as well as improving the knowledge in SQL to effectively query the database. The SQL language is commonly used for managing and querying relational databases, making it an ideal choice for working with the data in this project. Resorting to SQL, the data was filtered, sorted, and transformed into a format that was suitable for analysis.

The process of locating and retrieving information from the company's database required substantial effort and autonomy, as many of the tables had never been worked on and contained duplicated entries, errors, and missing values. The overall goal was to ensure data quality, accuracy, and consistency throughout the analysis process. It required a combination of data exploration, data cleansing techniques, and critical thinking to handle tables with missing data, duplicate rows, and errors effectively.

Integration and connecting tables through foreign keys demanded extensive work to ensure data accuracy and completeness. In addition to this, changes in the way the company collected some information and changes in the software during the information collection process also made the task more difficult.

Obtaining the requested information from partner companies also proved to be a lengthy and persistence-driven endeavor as some of the companies were taking too long to send the data or even answer the requests. The data received from them in most cases was not what had been

asked, was not in the required formats, had missing values and extra effort was needed to interpret it. Overcoming these challenges required meticulous attention to detail, problem-solving skills, and perseverance in order to gather the necessary data for the indicators accurately. To manage the collected data, a Google Sheets document was utilized as a central repository. The data was extracted from the database by implementing queries that fetched the relevant information. These queries allowed for the retrieval of specific datasets based on the defined criteria.

Once the data was retrieved, it was inserted into the Google Sheets document for further analysis. A challenge encountered in this process was the 25,000 line limit imposed by Google Sheets, which necessitated careful consideration of queries to avoid losing crucial information while staying within the line limit. The raw data required processing and transformation to derive meaningful insights. This involved the application of numerous formulas and functions within the Google Sheets document. These formulas were utilized to clean, manipulate, and format the data, ensuring that it was in the desired format. The combination of query-based extraction from the database and subsequent formula-based treatment within the Google Sheets facilitated the efficient handling and manipulation of the collected data for analysis and interpretation. This entire data collection process for the KPIs can be seen in detail in Appendix C.

5.3 Control Variable

The second path focused on selecting the control variable. The control variable represents the target variable, which served as the dependent variable in the model. To achieve the goal of this project, the control variable had to capture customer satisfaction, which was the ultimate objective of the analysis.

Given the abstract and subjective nature of customer satisfaction, it was determined early on in this phase of the project that a survey would be essential to gather data directly from the customers themselves. This approach was chosen to ensure the collection of information in its purest form, in an attempt to capture customers' perceptions of their own satisfaction accurately.

As a result, all of the steps in this phase required a great deal of thought and consideration given that the control variable was critical to the project's success.

5.3.1 Choose the question/s for the control variable

The selection of the control variable, which aimed at representing customer satisfaction, was a critical step in this research project. Extensive research and study were conducted to identify the most suitable metric for assessing customer satisfaction. Among the various metrics analyzed, three key metrics stood out: CSAT, ACSI, and NPS.

To make an informed decision, several meetings involving the CEO and the head of Community Operations were held to discuss the merits of each metric. After careful consideration and thoughtful deliberation, it was ultimately decided to select the NPS as the control variable for this project.

The decision to choose NPS was influenced by several factors. Firstly, there had been a long-standing desire within the company to collect this particular indicator, even for purposes beyond

the scope of this research. Furthermore, it was believed that NPS would be the most appropriate metric for evaluating customer satisfaction within our specific customer base. Moreover, one significant advantage of NPS is its simplicity and ease of understanding. The metric revolves around a single question, making it straightforward and user-friendly for customers to provide their feedback. Additionally, NPS has gained substantial recognition and widespread adoption in the business world, making it a reliable and widely accepted metric.

Therefore, the question chosen to be launched in the customer survey was “How likely are you to recommend BW to a friend or colleague?” and the response range was between “0” and “10”.

5.3.2 Select the control sample

After determining the control variable, the next crucial step was to select the control sample, which involved identifying the specific customers who would be targeted for the survey. Considering the small size of the study population, which consisted of active users per week ranging from 240 to 280, it was decided to launch the survey to the entire active population in the 14 days leading up to the survey launch.

By surveying the entire active population, the aim was to maximize the number of responses in an attempt to get a robust and representative sample for the analysis.

5.3.3 Survey construction and launch

The construction and launch of the survey played a pivotal role in the overall process. However, launching a survey presents its own set of challenges, particularly in ensuring a high response rate which is crucial to obtain a substantial sample size for training the model. While trying to maximize the response rate, it was essential to avert being bothersome to the customers and to avoid biases introduced by incentives to responses.

To discuss and analyze the best approach for launching the survey, a series of meetings involving the CEO (who is also responsible for the IT department), the head of Community Operations, and the head of the Marketing department were held. After careful deliberation, it was determined that the survey would be strategically launched directly on the website, specifically on the dashboard page, which is the first page customers see upon logging in. Therefore, as soon as the customer logged into the site, a “pop-up” with the survey would appear, thus ensuring that the customer would not “miss” the survey. To mitigate any potential inconvenience to customers, a “Not now” button was implemented, giving customers the option to defer their response if they wished.

This ensured maximum visibility and accessibility for customers without compromising the site’s functionality or user experience. Additionally, to enrich the company’s understanding, a text box was also incorporated, allowing customers to provide justifications for their assigned scores.

Having defined the structure of the survey it only remained to decide when the survey would be launched. Determining the ideal launch time for the survey was another critical consideration. Once again, the decision was focused on the goal of ensuring a high response rate. Since the survey would be launched directly on the website, it made sense to launch the survey at the time most customers go to the website which is at the launch of the weekly cycle when customers log in

to check their income. Therefore, it was defined that the survey would be launched on a Tuesday. In addition, as there are customers who only receive their income on a monthly basis, many do not bother to check their balance every week and therefore do not go to the site. Customers who receive their income monthly can withdraw their income on the Tuesday following the last Sunday of each month. Thus, it was necessary to ensure that the survey launch date also coincided with a week in which these customers would be receiving their earnings. The date found that served all these purposes and gave enough margin for the development of the “pop-up” was May 2. Figure D.1 demonstrates all the rationale behind the NPS collection process.

The following task entailed overseeing the implementation process and conducting thorough follow-up. This involved explaining the intended design and functionality to the IT technician, ensuring clear communication and understanding of the project’s objectives. The progress was actively monitored, and any bugs or errors encountered during the implementation phase were promptly alerted to the IT technician. Through rigorous testing and multiple iterations, the “pop-up” design was iteratively refined, addressing any issues that arose. This collaborative effort and meticulous attention to detail ultimately led to the successful creation of the final “pop-up” survey, depicted in Figure D.2, which was deemed ready for launch.

On May 2, the survey went live, and the results were collected until the end of the 4th to ensure the purity of the results so that they were not influenced by events of the weeks following the ones under analysis.

5.3.4 Data collection

The next step involved collecting the responses from the survey, which were stored in a dedicated database table. To retrieve this information, a query was developed. It was necessary to ensure that only responses within the specified time period, from May 2nd to May 4th, were included. Additionally, it was required to join two tables to identify the corresponding customers who had provided the responses. The query developed is presented in Figure 5.2.

```
SELECT a.context_campaign_name,a.nps_score,a.loaded_at,a.sent_at, a.score_reason,a.user_id,c.id,c.name
FROM `bluwalk-data-warehouse.bluwalk_website_prod.nps_response_submitted_view` a
left join `odoo_realtime.res_users` b on a.user_id=cast(b.id as string)
left join `odoo_realtime.res_partner` c on b.partner_id=c.id
where sent_at > '2023-05-01'and sent_at < '2023-05-05'
order by a.sent_at desc
```

Figure 5.2: Query for the survey responses.

After having the information imported into Google Sheets it was necessary to filter it through formulas because there were cases of repeated lines and null values in the scores.

5.4 Achieving the Dataset Milestone

After successfully traversing both the Inputs and Control Variable paths, a comprehensive dataset was constructed, encompassing the data collected for both the Inputs and Control Variable pertaining to all active customers during the analyzed week. To enhance the dataset’s usability, visual treatments were applied, ensuring its intuitiveness and facilitating a better understanding of the information it contained. This visual treatment aimed to present the data in a visually appealing

and organized manner, enabling stakeholders to easily interpret and extract valuable insights from the dataset.

The dataset obtained was meticulously designed to ensure its automatic functionality and continuous data refreshing. This approach allowed for the seamless updating of information over time. All the queries and formulas were implemented so that the dataset remained dynamic, accommodating any changes or updates in the underlying data sources. The only indicator that did not get this automatic refresh feature was the "Net earnings per online hour" indicator due to the previously mentioned reasons. Despite this, the indicator was retained in the dataset due to its fundamental importance, with the anticipation that in the future, the necessary information for regular and automated collection would become available. One of the key aspects of the dataset was its ability to adapt to the weekly updates in the list of active customers. As the list is refreshed on a weekly basis, the dataset was specifically structured to incorporate this update frequency.

To enhance the visibility of the collected dataset, a visual representation of the Google Sheets document used for its development is presented in Figure 5.3. In order to prioritize client data protection, the names of clients have been anonymized, and all corresponding values have been altered.

Active users of week:		202317																
Time frame:		8 weeks																
ID	Name	1. Segment				Work		Need Help		Vehicle Issues		Cash Out		NPS collected				
		1.1 Rideshare	1.2 Food Delivery	1.3 Shopping	1.4 Courier	2. Net earnings	3. Net earnings	4. Number of tickets	5. Ticket and cost	6. Number of miles	7. Vehicle damage	8. Invoice rejected	9. Number of complaints	NPS Value				
12345	Client 1	TRUE	FALSE	FALSE	FALSE	7.43	449.29	2	0.00	3	0	0%	2	2				
12345	Client 2	FALSE	FALSE	TRUE	FALSE	4.27	114.50	0	NA	Unrelated	Unrelated	0%	2	10				
12345	Client 3	FALSE	FALSE	TRUE	FALSE	6.08	105.43	0	NA	Unrelated	Unrelated	0%	2	10				
12345	Client 4	FALSE	FALSE	TRUE	FALSE	4.45	120.15	0	NA	Unrelated	Unrelated	0%	2	NA				
12345	Client 5	FALSE	FALSE	TRUE	FALSE	4.92	107.67	0	NA	Unrelated	Unrelated	0%	2	8				
12345	Client 6	FALSE	TRUE	FALSE	FALSE	3.14	128.65	0	NA	Unrelated	Unrelated	0%	2	NA				
12345	Client 7	FALSE	TRUE	FALSE	FALSE	3.05	30.64	0	NA	Unrelated	Unrelated	0%	1	NA				
12345	Client 8	FALSE	TRUE	FALSE	FALSE	1.09	9.02	0	1.00	Unrelated	Unrelated	0%	1	10				
12345	Client 9	FALSE	TRUE	FALSE	FALSE	3.01	92.66	0	NA	Unrelated	Unrelated	0%	2	NA				
12345	Client 10	FALSE	TRUE	FALSE	FALSE	4.75	69.81	0	NA	Unrelated	Unrelated	0%	2	10				
12345	Client 11	FALSE	TRUE	FALSE	FALSE	1.10	21.83	0	NA	Unrelated	Unrelated	0%	2	10				
12345	Client 12	FALSE	FALSE	TRUE	FALSE	3.17	70.07	0	NA	Unrelated	Unrelated	0%	2	8				
12345	Client 13	FALSE	FALSE	TRUE	FALSE	5.23	143.35	0	NA	Unrelated	Unrelated	0%	2	10				
12345	Client 14	FALSE	FALSE	TRUE	FALSE	4.86	140.66	0	NA	Unrelated	Unrelated	0%	2	10				
12345	Client 15	FALSE	FALSE	TRUE	FALSE	1.36	31.68	0	NA	Unrelated	Unrelated	0%	1	9				
12345	Client 16	TRUE	FALSE	FALSE	FALSE	9.70	195.59	1	NA	0	0	0%	2	NA				
12345	Client 17	TRUE	FALSE	FALSE	FALSE	3.43	89.30	0	1.00	0	0	NA	2	NA				
12345	Client 18	TRUE	FALSE	FALSE	FALSE	8.59	367.96	3	1.00	0	0	0%	1	10				
12345	Client 19	TRUE	FALSE	FALSE	FALSE	2.06	74.22	3	1.00	1	0	NA	1	6				
12345	Client 20	TRUE	FALSE	FALSE	FALSE	12.65	295.75	0	NA	1	0	0%	2	NA				
12345	Client 21	TRUE	FALSE	FALSE	FALSE	19.13	209.96	0	NA	Unrelated	Unrelated	0%	2	10				
18445	Client 22	TRUE	FALSE	FALSE	FALSE	5.46	111.53	0	NA	0	-425.52	0%	2	NA				
36919	Client 23	TRUE	FALSE	FALSE	FALSE	3.97	121.89	1	NA	0	0	NA	2	8				

Figure 5.3: Dynamic dataset of all indicators applied to the study population.

In order to create the training dataset for building the model, a specific week needed to be chosen to collect the data. As the control variable was collected in week 18, the target population for the training dataset consisted of the active customers from the preceding week, week 17. This population consisted of 252 customers. Given that the goal was to provide data to train the model, only the customers who responded to the survey were included in the training dataset. This resulted in a total of 129 customers who formed the training dataset with 129 data points. Figure 5.4 shows the distribution of responses collected by the NPS values.

Additionally, in order to prepare the training dataset for input into the model, certain variables required treatment and decisions had to be made regarding missing values. Several steps were taken to address these considerations.

Firstly, the segment variables, originally represented as "True" and "False," were converted to numeric values of "1" and "0" respectively. This conversion enabled a standardized representation and facilitated further analysis and modeling.

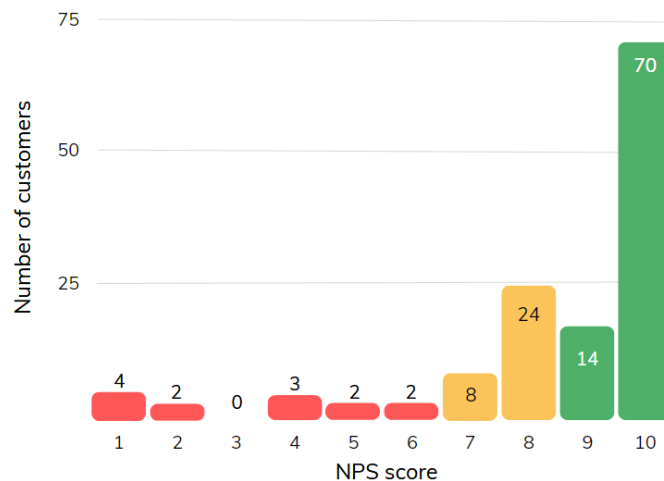


Figure 5.4: Bar chart of the NPS responses collected.

Furthermore, the variables “Number of Malfunctions” and “Vehicle Damage Costs” were applicable only to customers operating in the rideshare segment who rented vehicles through BW. Therefore, it was necessary to define what values to set for these variables for the other customer types. Thus, it was decided to assign a value of “0” so that the impact of these variables on these customers was mitigated.

The variable “Invoice Rejection Rate” posed a challenge due to some customers having a value of “NA” as they had not yet issued any invoices. To handle this, a decision was made to assign a value of “0” to these cases. This approach aimed to minimize the impact of the indicator on these customers.

The variable “Ticket and Call Rating” presented another challenge, as some customers had a value of “NA” since they had never rated a ticket or call. Extensive discussion and deliberation led to the conclusion that a value of “0.9” would be appropriate for these cases. The reasoning behind this decision stemmed from the understanding that customers who had never rated a ticket or call were likely satisfied with the responses they received. Studies also supported the notion that individuals are more inclined to express their opinions when dissatisfied. However, it was important to differentiate them from customers whose average rating was 1, indicating a high level of satisfaction. Thus, “0.9” was deemed suitable to represent the absence of rating while still accounting for a potential elevated level of satisfaction.

After undergoing this comprehensive process of filtering, cleaning, and data treatment, a well-prepared training dataset was obtained, ready to be worked on, and interpreted by the model. This robust training dataset served as the foundation for training the model.

Figure 5.5 depicts the Google Sheets document with the compiled data, providing transparency and insight into the data used for building the model.

It is important to note that all numbers displayed in the figure have been altered to ensure the privacy and confidentiality of customer data.

A comprehensive univariate analysis was conducted for each KPI. The univariate analysis involved examining the characteristics, distributions, and patterns of each individual input variable, enabling a deeper understanding of their individual behaviors and impacts on the outcome of in-

ID	Rideshare	Food_Delivery	Shopping	Courier	ratings_per_online	earnings_per_week	tickets_and_calls	ket_and_call	rather_of_mall	functionality	damage_cost	choice_rejection	rejection_rate	cycles_closed	NPS Value
12345	0	0	1	0	4.23	143.98	0	0.9	0	0	0	0.50	0.00	2	10
12345	0	0	1	0	4.27	114.50	0	0.9	0	0	0	0.00	0.00	2	10
12345	0	0	1	0	6.08	105.43	0	0.9	0	0	0	0.00	0.00	2	10
12345	0	0	1	0	7.93	294.37	0	1.00	0	0	0	0.00	0.00	2	10
12345	0	0	1	0	4.92	107.67	0	0.9	0	0	0	0.00	0.00	2	8
12345	0	1	0	0	1.09	9.02	0	1.00	0	0	0	0.00	0.00	1	10
12345	0	1	0	0	4.75	69.81	0	0.9	0	0	0	0.00	0.00	2	10
12345	0	1	0	0	1.10	21.83	0	0.9	0	0	0	0.00	0.00	2	10
12345	0	0	1	0	3.17	70.07	0	0.9	0	0	0	0.00	0.00	2	8
12345	0	0	1	0	5.23	143.35	0	0.9	0	0	0	0.00	0.00	2	10
12345	0	0	1	0	4.86	140.66	0	0.9	0	0	0	0.00	0.00	2	10
12345	0	0	1	0	1.36	31.68	0	0.9	0	0	0	0.00	0.00	1	9
12345	1	0	0	0	8.59	367.96	3	1.00	0	0	0	0.00	0.00	1	10
12345	1	0	0	0	2.06	74.22	3	1.00	1	0	0	0.00	0.00	1	6
12345	1	0	0	0	19.13	209.96	0	0.9	0	0	0	0.00	0.00	2	10
12345	1	0	0	0	3.97	121.89	1	0.9	0	0	0	0.00	0.00	2	8
12345	1	0	0	0	8.81	193.36	1	0.9	0	0	0	0.00	0.00	2	9
12345	1	0	0	0	7.05	292.87	0	0.9	0	0	0	0.00	0.00	2	8
12345	1	0	0	0	8.13	316.98	0	0.9	0	0	0	0.00	0.00	1	9
12345	1	0	0	0	5.29	295.71	0	0.9	0	0	0	0.00	0.00	2	10
12345	1	0	0	0	10.41	637.48	1	1.00	0	0	0	0.67	0.00	2	5
12345	1	0	0	0	7.43	449.29	2	0.00	3	0	0	0.00	0.00	2	2
12345	1	0	0	0	7.59	403.30	0	0.9	0	0	0	0.00	0.00	1	10
12345	1	0	0	0	3.82	182.63	2	0.9	0	0	0	0.00	0.00	2	8
12345	1	0	0	0	4.82	293.14	0	0.9	0	0	0	0.00	0.00	2	7
12345	1	0	0	0	7.92	530.84	3	0.9	1	0	0	0.00	0.00	2	10
12345	1	0	0	0	6.56	379.04	0	0.9	0	0	0	0.67	0.00	2	10
12345	1	0	0	0	7.57	494.10	2	1.00	2	0	0	0.57	0.00	1	10
12345	1	0	0	0	7.84	525.04	1	1.00	1	0	0	0.00	0.00	1	10
22334	1	0	0	0	8.35	381.29	1	0.9	0	0	-605	0.00	0.00	2	4

Figure 5.5: Overview of the document with the compiled data used to build the model.

terest. All this analysis can be found in Appendix E.

6 Machine Learning Model

The project's final phase focused on constructing the machine learning model. With the training dataset carefully defined, the objective in this phase was to create a mathematical model capable of classifying the degree of satisfaction for each customer based on the data collected from the indicators.

This chapter is structured into two main sections. Section 6.1 presents the methodology employed throughout this phase, providing a clear and detailed explanation of all the tasks performed. This section provides a comprehensive guide to the entire model construction process, facilitating a thorough understanding of the methodology.

Section 6.2 delves into the intricacies of model development and its practical application. It explains the various decisions involved in building the model. Furthermore, this section demonstrates the utilization of the constructed model. It elucidates on how the model was used to predict and classify the satisfaction level of each customer based on their relevant data. The section also provides insights into the performance metrics used to evaluate the model's accuracy and effectiveness in making predictions.

6.1 Methodology

This section provides an overview of the methodology employed from the completion of the training dataset until achieving the machine learning model. The methodology consisted of four tasks, each playing a crucial role in the successful development of this phase. Figure 6.1 serves as a visual representation of the methodology followed.

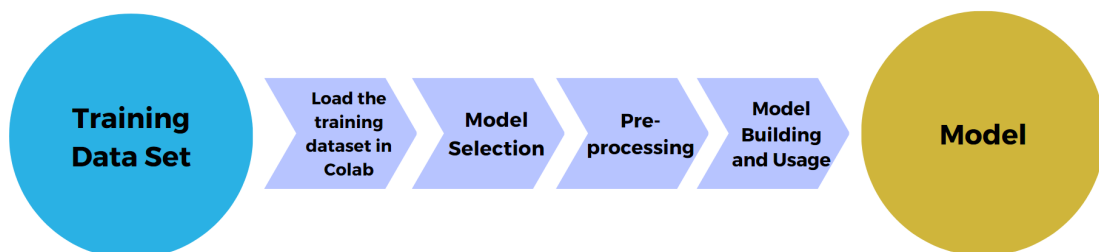


Figure 6.1: Machine learning model phase methodology map.

The first task involved loading the training dataset into a Google Colab¹ file, which served as

¹Google Colab, short for Google Colaboratory, is a cloud-based development environment that enables users to write, run, and share Python code collaboratively. Google Colab offers a convenient and accessible platform for coding, experimenting with data, and running machine learning models, making it popular among developers and researchers in the Python ecosystem.

the development environment for the machine learning model. This step ensured the dataset was readily available for further analysis and model construction.

The second task held significant importance in this phase, as it involved selecting the most suitable modeling approach for the given problem. This task required careful consideration of the dataset characteristics, the nature of the satisfaction classification problem, and the available machine learning algorithms.

The third task revolved around data pre-processing, encompassing various actions to prepare the dataset for model training. By performing these pre-processing actions, the dataset was effectively cleaned and standardized, and ready to be worked on.

The fourth task encompassed the actual construction and utilization of the machine learning model. Given the complexity and significance of this task, Section 6.2 was created to provide a comprehensive understanding of the model-building process. It showcases the steps taken to optimize the model's performance and ensure its ability to accurately classify the satisfaction degree of each customer.

It is crucial to acknowledge that throughout the tasks of pre-processing and building the model, it was not a linear and straightforward path. Instead, it involved numerous iterations and experiments to refine the final result. In Section 6.1.3, it is demonstrated the various techniques and approaches that were explored, tested, and evaluated. Each experiment provided valuable insights and contributed to the final pre-processing pipeline. Similarly, in the Section 6.2, the multiple iterations to the architecture, training, and forms of evaluating the model are presented. These iterations allowed for learning from both successes and failures, leading to an informed decision-making process. Ultimately, the experiments conducted throughout the pre-processing and model building tasks highlight the journey and the thought process involved in arriving at the final result.

6.1.1 Load the training dataset in Colab

The first task involved loading the training dataset into a software program that would allow the creation of the machine learning model. However, before proceeding, it was needed to carefully choose the program that would meet the requirements. Several factors had to be taken into consideration during this decision-making process.

One crucial aspect was the ability of the chosen program to integrate seamlessly with Google Sheets. The program chosen would have to allow an integration with Google Sheets so that it would be possible to receive the data to be generated weekly in the Google Sheets document with the dataset. This would ensure a smooth and efficient workflow, enabling the utilization of the latest dataset without any manual data transfers.

Additionally, it was required a program equipped with up-to-date tools and libraries that would enable building a machine learning model using the latest technologies. Staying current with the advancements in the field was vital to ensure that our model would incorporate state-of-the-art techniques and achieve optimal performance.

After conducting extensive research and evaluation, it was concluded that Google Colab was the ideal tool for the requirements. As a product developed by Google itself, it was deduced that the integration with Google Sheets would be simple.

Moreover, the research developed indicated that Google Colab was widely recognized as a state-of-the-art tool, recommended and utilized by numerous top universities and researchers in the field of machine learning. This further validated the choice and assured us that Google Colab was a cutting-edge platform with the necessary tools and libraries to create the machine learning model.

After the program selection, it was necessary to determine the process for loading the dataset into the Colab file. Extensive research was conducted to understand the integration procedure and the required steps involved.

Initially, permissions were requested from the IT department to grant the file access permissions to the company's Google Drive. This ensured secure access to the dataset within the Colab file. Furthermore, it was key to acquire knowledge in Python² programming language (the language used for all file development) to write the requisite code for integrating and converting the Google Sheets document into a dataframe. This allowed for efficient handling of the dataset within the machine learning phase. The Figure F.1 presents the code generated in the Google Colab file as a result of this task.

6.1.2 Model selection

The following task involved selecting the appropriate model for the classification problem at hand. Several factors were considered during the model selection process. Firstly, the chosen model needed to be compatible with Google Colab, the platform being used for model development. Additionally, it was important for the model to be capable of capturing non-linear relationships between the variables, as such relationships were expected to exist in the dataset.

After evaluating various options, a neural network model was chosen as the most suitable choice. This model satisfied all the aforementioned requirements and possessed several advantages. Neural networks are widely used in the field of Artificial Intelligence and have a wealth of information and studies surrounding them. They excel at learning complex patterns and relationships within data, making them ideal for capturing non-linear dependencies.

During the analysis, one potential drawback to using a neural network model was identified: the limited amount of data available for training. Neural networks typically require large amounts of data to achieve optimal performance. However, the intention of the company was to continually feed the model with more data over time. Therefore, the limited dataset size was not deemed a significant hindrance to selecting the neural network model.

6.1.3 Pre-processing

The subsequent task involved pre-processing the data to prepare it for model training. Part of this task had already been executed directly on the Google Sheets dataset file during the last task of the previous phase. As outlined in Section 5.4, the encoding of binary variables and handling of missing values had been performed.

²Python is a popular high-level programming language known for its simplicity, readability, and versatility. Python finds application in various domains, including web development, scientific computing, data analysis, artificial intelligence, machine learning, automation, and scripting. Its versatility, readability, and extensive ecosystem make it a preferred choice for both beginners and experienced developers.

The next step in pre-processing was to identify and remove outliers from the dataset. One customer was identified as working in outsourced services, and as such, was using BW's services only to rent the car. Therefore, despite having negative income the customer gave an NPS response score of 8. This was indeed an outlier and was therefore removed.

Given that the variables within the dataset had different scales, it was necessary to normalize the quantitative variables. To achieve this, a min-max normalization technique was applied. This normalization approach helps enhance the performance and convergence speed of machine learning models by ensuring all variables are on a similar scale. The Equation (6.1) shows the formula of a min-max normalization.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (6.1)$$

The variable "Courier" had a value of 0 for all data points. This occurred because there were no customers operating in this particular segment during the observed period. As a result, it was determined that the "Courier" variable did not provide any meaningful information for the model. Therefore, it was decided to remove this variable from the analysis. However, it is important to note that the "Courier" variable was still retained in the Google Sheets dataset document. The rationale behind this decision was to future-proof the document, as the company anticipated the possibility of having customers from this segment in the future. By keeping the variable in the document, it allowed for the potential inclusion of data for this segment when it becomes relevant, ensuring the dataset remains adaptable.

Finally, the input and output dataframes needed to be defined. To define the input variables for the model, a feature selection process was conducted. The initial selection of features involved analyzing the relationship between each variable and the output variable through the development of box plots. This analysis revealed that several variables had a significant impact on the output. The most relevant variables identified were "Food", "Shopping", "Number of tickets and calls - complaint", "Ticket and Call Rating", and "Number of cycles closed out of SLA."

Subsequently, an iterative process was employed to refine the feature selection. Starting with these five base variables, additional variables were added one by one, and the model's performance was evaluated at each iteration. Only those variables that contributed to improving the model's performance were retained. This iterative process was always tested for two different network architectures.

However, despite these efforts, the results of the feature selection process were inconclusive in determining the optimal set of variables. None of the iterations produced superior results compared to a model that included all the variables as inputs. Therefore, it was concluded that including all the variables in the model yielded the best performance, and no subset of variables demonstrated a clear advantage.

Regarding the output variable, the variable used initially, as planned, was the "NPS Value". However, the model's performance with this variable was found to be consistently poor. Several factors contributed to this outcome. Firstly, there were very few data points for certain scores, and some scores were not even present in the dataset. For instance, there were no customers who assigned a score of 3 in the NPS survey. Moreover, expecting the model to accurately classify

among 11 different scores (ranging from 0 to 10) with only 128 data points was overly demanding.

In light of these challenges, a reevaluation of the output variable was necessary. A new column was created in the dataset to represent NPS categories. The NPS categories are the following: “Promoter” for scores of 9 or 10, “Passive” for scores of 8 or 7, and “Detractor” for scores ranging from 6 to 0. The “Promoter” category was encoded as 2, the “Passive” category was encoded as 1 and the “Detractor” category was encoded as 0. This transformation reduced the number of categories from 11 to 3. Consequently, the model’s accuracy improved significantly without compromising the overall objective of classifying customer satisfaction. This solution was logical because, ultimately, it was more important to determine the satisfaction category a customer belonged to rather than the exact numerical score. Thus, the revised approach aligned with the project’s purpose and the company’s goals.

As a result, for the output variable, ultimately, an array was constructed using the values from the “NPS Category” variable. This served as the target variable for the machine learning model. As for the input dataframe, the variables “ID” and “NPS Value” and “NPS Category” were removed and the remaining variables constituted the input features of the model.

By performing these pre-processing steps, including outlier removal, normalization of quantitative variables, and defining the input and output variables, the data was transformed into a suitable format for training the machine learning model. These pre-processing actions ensured that the data was cleansed, scaled appropriately, and organized in a manner conducive to effective model training and classification.

Figure F.2 shows the code developed in this pre-processing task.

6.2 Model building and usage

In this section, the whole process of building the model is presented. During the construction of the model, “Tensorflow”, a free and open-source software library for machine learning and artificial intelligence was used, significantly simplifying the modeling process.

Initially, it was necessary to define the architecture of the model, which involved defining aspects such as the number of layers in the network, the number of neurons, the activation functions, and others.

Then it was necessary to define how the model would be trained. This involved dividing the dataset into training and test sets, selecting an optimization algorithm, and tuning hyperparameters.

Next, the model’s performance was evaluated to assess its ability to predict customer satisfaction categories. The evaluation results provided insights into the model’s strengths and weaknesses.

Finally, code was developed to save the trained model and enable its future usage. The model was serialized into a file format and stored for later retrieval. This allowed the model to be used for predictions on new data, ensuring its continued utility for the future.

Throughout the entire model building process, it became clear that the tasks involved were not fixed or unchangeable. As a result, multiple iterations were undertaken, necessitating changes to various aspects of the architecture, training procedure, evaluation metrics, and even pre-processing

techniques. These iterative steps allowed for continuous refinement and improvement of the model, ensuring that it adapted to the unique characteristics and requirements of the dataset.

It is important to mention that all decisions taken were always in favor of obtaining the model with the best possible performance, which, in the final analysis, was what the company ultimately desired. Within each subsection, the entire process until reaching the final version of the model is presented.

6.2.1 Architecture

The first task in developing the model was to define the network architecture. Extensive research was conducted to determine the optimal configuration for this specific problem. Since the dataset was small, consisting of only 128 data points after removing outliers, careful consideration was given to designing a network that could effectively learn from the available data.

The initial decision was to limit the network to one or two hidden layers, in addition to the input and output layers. This choice was based on the understanding that a more complex architecture with multiple hidden layers may require a larger training dataset to avoid overfitting. By keeping the network relatively simple, the aim was to strike a balance between model complexity and the limited availability of training data.

The next crucial aspect was to determine the number of neurons in each layer. Neurons in artificial neural networks are mathematical units that receive inputs, perform calculations, and produce outputs. They mimic the behavior of neurons in the human brain. Essentially, they are the building blocks of neural networks and play a vital role in information processing and learning within the network.

Given the small size of our dataset, it was essential to avoid an excessively high number of neurons, which could potentially lead to overfitting. Conversely, using too few neurons could result in the model underfitting and being unable to capture important patterns in the data. Determining the optimal number of neurons in a network is a topic that lacks a definitive rule in the literature. Therefore, in order to identify an appropriate number of neurons, multiple iterations were conducted. Different configurations were tested and evaluated, considering both the model's ability to learn from the available data and the risk of overfitting or underfitting.

Finally, the configuration that gave the best performance to the model was: one initial layer with 11 neurons (inputs), two hidden layers each with 64 neurons, and an output layer with 3 neurons (the 3 NPS categories). Despite being a configuration with an apparently high number of neurons, it was indeed this configuration that brought the best results to the model.

Another step in the process was to choose the appropriate activation functions for the neural network. The purpose of activation functions is to introduce non-linear transformations to the weighted sum of inputs in each neuron. This allows the network to learn and model complex patterns in the data.

Several iterations were carried out to experiment with different activation functions and evaluate their impact on the model's performance. Extensive research was conducted to explore and identify the recommended activation functions for this network. There were experimented activation functions such as "Sigmoid", "ReLU" (Rectified Linear Unit), "Tanh" (Hyperbolic Tangent),

“Softmax”, and others. After all the iterations, the combination of activation functions that gave the best results for the model was with the “Tanh” function for the hidden layers and the “Softmax” function for the output layer.

Figure F.3 shows the code developed for the architecture of the model.

6.2.2 Training

Firstly, it was necessary to define the model compilation process which configures the necessary components for training the model. Within these components, there are the loss function, the optimizer algorithm, and the evaluation metrics.

The loss function measures the discrepancy between the predicted output of the model and the true output. It quantifies how well the model is performing during training by comparing its predictions to the ground truth. The choice of a specific loss function depends on the problem type and the nature of the target variable. Within all the loss functions studied, the “Sparse Categorical Cross-Entropy” loss function was selected. This loss function was considered appropriate for this model because it is used for multi-class classification with integer-encoded labels. It is suitable when the class labels are provided as integers instead of one-hot encoded vectors which is the case. The goal during training is to minimize this loss, improving the model’s ability to make accurate predictions.

The optimizer algorithm determines how the model’s parameters should be updated based on the calculated loss. It aims to find the optimal set of parameter values that minimize the difference between the predicted outputs and the true values. Its primary purpose is to minimize the loss function by adjusting the model’s parameters, such as weights and biases, during the training process. Within the analyzed optimizers, there were two that were widely used and recommended: the “Stochastic Gradient Descent” (SGD), which is a basic and widely used optimizer that updates the parameters based on the gradients of a randomly selected subset of training examples at each iteration and the “Adam” (Adaptive Moment Estimation). It combines ideas from both momentum-based optimization and root mean square propagation. “Adam” has emerged as one of the most popular choices in recent machine learning models. It has been widely adopted due to its effectiveness in achieving good results and efficient training. “Adam’s” adaptive learning rate, which adjusts based on the gradients and previous updates, enables it to navigate the parameter space effectively. After careful evaluation and experimentation, “Adam” was the one that offered the best results for the model and as such was selected.

The evaluation metric is used to assess the performance of the trained model on a separate validation or test dataset. It provides a summary measure that indicates how well the model is performing in terms of the desired outcome. In this case, it made sense to choose the “accuracy” metric as it calculates the proportion of correctly classified samples. Maximizing the evaluation metric, in this case, indicates the model’s ability to correctly classify data points.

Then it was necessary to split the dataset into two sets: one for training and another for testing. To determine an appropriate split, after some research it was concluded that an 80% training and 20% testing split would be suitable. This split ensured a reasonable number of datapoints for the model to train on while also providing a separate set to effectively assess the model’s performance.

Considering the dataset's imbalance, with 84 "Promoters", 31 "Passives", and 13 "Detractors", it was crucial to stratify the output variable during the split. This ensured that the output variable was evenly distributed between the training and testing sets, helping to maintain the same class distribution in both sets. To guarantee reproducibility and obtain the same train-test split each time the code is executed, a random seed was set. This random seed ensured consistent results and facilitated comparability in subsequent model evaluations.

The next step in the model development process was to define the training procedure. This involved specifying the training set, the number of epochs, and the batch size. The number of epochs determines how many times the model will iterate over the training dataset during the training process. Each epoch consists of processing the input data in batches, with the model updating its weights and biases based on the calculated loss and the chosen optimization algorithm. Selecting the appropriate number of epochs is crucial to achieving optimal model performance. Too few epochs may result in an underfit model that fails to capture the underlying patterns in the data, while too many epochs can lead to overfitting, causing the model to overly adapt to the training data and perform poorly on new, unseen data. After conducting several iterations and evaluating the model's performance, it was determined that training the model for 500 epochs yielded the best results.

Regarding the batch size, it determines the number of training examples processed in each iteration or batch during the training process. In this case, since the training dataset was relatively small, the batch size was set to the total number of training examples. Using the entire training set as a batch allows the model to update its weights and biases based on a more comprehensive view of the data at each iteration.

Figure F.4 shows the code developed for the training of the model.

6.2.3 Evaluation

In order to evaluate the performance of the model, it was necessary to define a suitable evaluation approach. The accuracy of the model was chosen as the metric for evaluation, and it was assessed on both the training set and the test set. Evaluating performance on the training dataset provided valuable insights into how effectively the model learned from the training data. It allowed for assessing the model's ability to fit the training data and detecting signs of underfitting or overfitting. However, it's important to acknowledge that relying solely on the training dataset for evaluation may not provide a reliable indication of how the model will perform on unseen data. Hence, evaluating the model's performance on the test dataset was crucial to assess its generalization capabilities. The test dataset represented real-world scenarios, presenting the model with unseen data points. By evaluating the model on the test dataset, a more accurate estimate of its performance in real-world applications could be obtained, providing insights into its ability to generalize to new instances.

Then it was necessary to predict the output values for the test input data using the trained model. The predict function applies the trained model to the input data and returns the predicted values. Next it was required to convert the predicted values to their corresponding class labels. The "argmax" function was used to find the index of the maximum value in each predicted output.

This index corresponds to the predicted class label. The list comprehension iterates over each predicted output value and replaces it with the index of the maximum value, resulting in a list of predicted class labels.

Considering the imbalance of the dataset, where the distribution of classes was uneven, evaluating the model's performance solely based on accuracy may not have provided an accurate representation of its effectiveness. This is because accuracy can be misleading in the presence of class imbalance, as a high accuracy score can be achieved by a model that simply predicts the majority class for all instances, ignoring the minority class. This situation happened in several iterations where the model predicted all "Promoters", disregarding all the other classes.

With this in consideration, it became crucial to consider evaluation metrics that take into account the class imbalance and provided a more comprehensive assessment of the model's performance. Therefore, after plenty of research, it was decided to also include the weighted "F1 score". The weighted "F1 score" is one metric that considers both precision and recall for each class and provides an overall performance measure that considers the imbalance in class distribution.

The weighted "F1 score" calculates the "F1 score" for each class individually, taking into account both false positives and false negatives, and then computes a weighted average of the "F1 score"s based on the support (number of instances) for each class. This ensures that the performance of the model on each class is appropriately considered and weighted according to the class distribution. By using the weighted "F1 score", we can evaluate how well the model performs not only on the majority class but also on the minority class, providing a more balanced evaluation of its effectiveness in handling class imbalance.

Finally, lines of code were developed to make the values of the training accuracy, test accuracy, and weighted "F1 score" visible at each iteration of the model, as well as the values predicted by the model compared to the real values.

The code developed for evaluating the model is depicted in Figure F.5.

6.2.4 Model results

This subsection showcases the results of the model that achieved the highest performance in terms of accuracy and "F1 score". It provides a comprehensive overview of the model's outcomes, highlighting its effectiveness.

The output of the best model is depicted in the Figure 6.2, showcasing its performance and predictions. The model presented 80% training accuracy, 76% test accuracy, and a weighted "F1 score" of 71%. The top row of the figure displays the satisfaction categories predicted by the model for the test set, while the bottom row represents the real/true values.

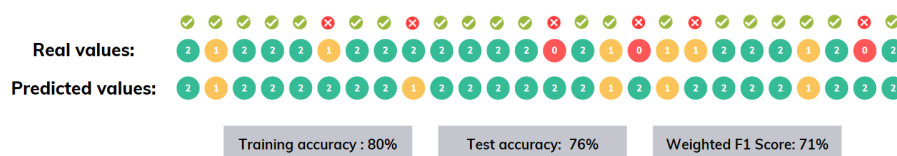


Figure 6.2: Output of the best model.

These results surpassed the initial expectations and can be considered quite good. However,

they also indicate that there is still potential for further improvement.

The close proximity of the training accuracy to the test accuracy suggests that overfitting didn't occur. This implies that the model has successfully generalized its learned patterns to unseen data.

Regarding the values predicted by the model, a confusion matrix was developed to better interpret them. Figure 6.3 shows the confusion matrix that takes into account the predicted values and the true/actual values.

		True/Actual		
		Detractor (0)	Passive (1)	Promoter (2)
Predicted	Detractor (0)	0	0	0
	Passive (1)	0	4	1
	Promoter (2)	3	2	16

Figure 6.3: Confusion matrix for the best model.

The evaluation of the model's confusion matrix reveals interesting findings. Among the 17 instances identified as "Promoters", the model accurately predicted 16 but misclassified 1 as "Passive". In the case of the 6 instances labeled as "Passives", the model correctly classified 4, but mistakenly categorized 2 as "Promoters". For the 3 instances categorized as "Detractors", the model incorrectly predicted all of them as "Promoters". Out of the 21 predictions classified as "Promoters", the model correctly predicted 16. Similarly, out of the 5 predictions classified as "Passives", 4 were correctly identified and there were no predictions made for "Detractors". The table from Figure 6.4 shows the precision, recall, and "F1 score" for each of the categories.

	Precision	Recall	F1 Score
Detractor (0)	0.00%	0.00%	0.00%
Passive (1)	80.00%	66.67%	72.73%
Promoter (2)	76.19%	94.12%	84.21%

Figure 6.4: Precision and Recall for each category.

The obtained results align with the initial expectations considering the imbalanced nature of the dataset. With a significantly larger number of datapoints in the "Promoters" category compared to the other categories, the model tends to exhibit a bias towards predicting "Promoters" more frequently, while making fewer predictions for "Passives" and none for "Detractors". Consequently, the model achieved a high recall and an acceptable precision for the "Promoters" category, indicating that it accurately captures the majority of actual "Promoters" but may misclassify some instances. Conversely, the model demonstrated high precision and a reasonable recall for the "Passives" category, suggesting that it correctly identifies most "Passives" but may overlook some instances. However, due to the scarcity of data for the "Detractors" category, the model struggled to make predictions in this category. These observations highlight the impact of dataset imbalance on the model's performance and emphasize the need for further data collection.

6.2.5 Usage

To enable the saving of the created models, code was implemented to allow for their preservation, incorporating the test accuracy and “F1 score” into the model’s name for identification. Figure F.6 shows the code developed for this purpose.

Subsequently, additional code was implemented to enable the loading of the desired model. The code developed for this specific functionality is depicted in Figure F.7.

7 Conclusions and Future Work

Customer satisfaction has become a paramount consideration for companies in today's business landscape, prompting them to invest resources in evaluating and enhancing it. This work aimed to analyze and assess customer satisfaction considering the real-world case of a company operating in the gig economy, BW.

This work started with a literature review overviewing leading practices to measure and evaluate customer satisfaction. It continued with the development of its main phases, including a comprehensive CJM, identifying KPIs, collecting data, and constructing a machine learning model.

This chapter is structured into two main sections. Section 7.1 provides an overview of the main findings and lessons learned from this project, and Section 7.2 outlines potential steps for future research.

7.1 Overview and main contributions

From this project, three major deliverables for the company were constructed. The CJM stands as a lasting asset, providing a crucial foundation for future decision-making endeavors. Moreover, it grants the company a comprehensive understanding of the customer's entire path, enabling informed assessments on which processes should be optimized, eliminated, or introduced. Furthermore, it facilitates the identification of customer pain points that necessitate resolution.

Furthermore, the dataset document created in Google Sheets serves as an invaluable deliverable for the company. Through this document, the company gains the ability to track the performance of not only its entire customer base but also its partners, as well as its own performance on a weekly basis. Most of the indicators collected during this project were previously not being tracked and provided the company with highly valuable information. This document holds the potential for various analyses that were not conducted within the scope of this project. This wealth of information supports future decision-making processes and grants the company a deeper understanding of its customers' experiences.

Additionally, the queries built within the dataset enable the easy construction of other performance indicators. These indicators encompass metrics such as the number of hours worked by each client per week, the revenue obtained by each client within each partner, and the duration of the client's engagement with BW. Such supplementary indicators contribute to a comprehensive assessment of the company's performance and facilitate strategic insights for future growth and improvement.

Finally, the machine learning model represents an invaluable asset in the project's deliverables.

This tool plays a pivotal role in shaping actions aimed at enhancing customer satisfaction, as it enables BW to effectively evaluate the success of these initiatives. With the model in place, the company can access the satisfaction levels of its customer base on a weekly basis, eliminating the need to repeatedly solicit feedback through surveys. This not only alleviates the burden on customers but also provides real-time insights into customer satisfaction without disrupting their experience. The model empowers the company to make data-driven decisions and swiftly identify the impact of implemented measures on customer satisfaction, allowing for proactive adjustments and continuous improvement.

Regarding the machine learning model, it is important to highlight its innovative character. Extensive research conducted prior to its development revealed a lack of similar models in the field. Most neural network models used to predict satisfaction relied on customer questionnaires for data collection, collecting all the data directly from the customer whereas this model incorporated performance indicators, relying only on data collected from the customer experience. The absence of comparable models initially posed a risk to the viability of the developed model.

It is essential to acknowledge that predicting satisfaction differs significantly from predicting other variables. Satisfaction is a deeply personal experience, subject to individual expectations, experiences, and even personality traits. Attempting to mathematically predict satisfaction inherently involves a certain degree of error as a person who has exactly the same experience as another may be very satisfied and the other unsatisfied. These inherent complexities added to the model's challenge of achieving high performance.

Moreover, it is crucial to recognize that the model is designed to continuously evolve and improve with ongoing data input. Given the limited dataset available for training, it was apparent from the start that training a neural network model with such a small dataset would be exceptionally demanding.

Considering these factors, the achievement of a model with a 76% test accuracy and 71% "F1 score" was viewed as highly positive. This model lays the foundation for the company to continue feeding and enhancing its performance. Moving forward, the model's iterative improvement will be crucial for attaining more accurate predictions and gaining deeper insights into customer satisfaction.

Reflecting on the time and effort allocated to each phase, it became evident that data collection consumed more time and effort than anticipated, primarily due to the challenges faced in obtaining data from partners. This time could have been utilized for further statistical analyses with the collected data or for exploring alternative models.

This project marked the beginning of the customer success department, a vital addition to the company's structure that was previously absent. The project served as the cornerstone, laying the foundation for the future development and growth of this department. Its success has paved the way for further advancements and initiatives to enhance customer satisfaction and retention. Notably, the company expressed immense satisfaction with the outcomes achieved and the deliverables obtained, surpassing initial expectations. The project's impact has been profound, solidifying its value and setting a promising trajectory for the company's customer-centric endeavors.

7.2 Further Work

In terms of future work, there are several aspects that can be pursued to further enhance the project's effectiveness. Firstly, the CJM should be regularly updated to accommodate any changes that may occur in the customer journey. This ensures that the map remains relevant and provides accurate insights into customer experiences.

Regarding the dataset document developed in Google Sheets, there is room for collecting additional indicators that can provide valuable information to the company. It would be beneficial to create a dashboard that presents the information from the document, facilitating the analysis of the indicators. Such a dashboard can serve as a powerful tool to support decision-making within the company.

As for the machine learning model, continuous improvement and data enrichment should be prioritized. As planned, collecting the NPS through surveys at least every six months will provide new data to train and refine the model. Additionally, conducting a sensitivity analysis on the model's indicators would be valuable to identify the factors that are impacting customer satisfaction the most. This analysis can guide the implementation of targeted actions aimed at boosting satisfaction levels.

By focusing on these future endeavors, the project can remain adaptive, ensuring that it keeps pace with evolving customer journey, utilizes comprehensive and up-to-date datasets, and refines the machine learning model to deliver even more accurate predictions and actionable insights.

Bibliography

- Anderson, E. W., & Fornell, C. (2000). Foundations of the american customer satisfaction index. *Total quality management*, 11(7), 869–882.
- Baquero, A. (2022). Net promoter score (nps) and customer satisfaction: Relationship and efficient management. *Sustainability*, 14(4), 2011.
- Clark, M., & Bryan, A. (2013). Customer effort: Help or hype? *Henley Business school*.
- Fornell, C. (1992). A national customer satisfaction barometer: The swedish experience. *Journal of marketing*, 56(1), 6–21.
- Fornell, C., Johnson, M. D., Anderson, E. W., Cha, J., & Bryant, B. E. (1996). The american customer satisfaction index: Nature, purpose, and findings. *Journal of marketing*, 60(4), 7–18.
- Giese, J. L., & Cote, J. A. (2000). Defining consumer satisfaction. *Academy of marketing science review*, 1(1), 1–22.
- Goode, M. M., Davies, F., Moutinho, L., & Jamal, A. (2005). Determining customer satisfaction from mobile phones: A neural network approach. *Journal of Marketing Management*, 21(7-8), 755–778.
- Grnholdt, L., & Martensen, A. (2005). Analysing customer satisfaction data: A comparison of regression and artificial neural networks. *International Journal of Market Research*, 47(2), 121–130.
- Hendalianpour, A., & Razmi, J. (2017). Customer satisfaction measurement using fuzzy neural network. *Decision Science Letters*, 6(2), 193–206.
- Huang, G., & Wang, H.-l. (2014). Improving the predictive validity of nps in customer satisfaction surveys. *Cross-Cultural Design: 6th International Conference, CCD 2014, Held as Part of HCI International 2014, Heraklion, Crete, Greece, June 22-27, 2014. Proceedings 6*, 458–469.
- Keiningham, T. L., Cooil, B., Aksoy, L., Andreassen, T. W., & Weiner, J. (2007). The value of different customer satisfaction and loyalty metrics in predicting customer retention, recommendation, and share-of-wallet. *Managing service quality: An international Journal*, 17(4), 361–384.
- Lee, S. H., Lee, H., & Kim, J. H. (2022). Enhancing the prediction of user satisfaction with meta-verse service through machine learning. *Computers, Materials & Continua*, 72(3).
- Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of marketing*, 80(6), 69–96.

- Lin, W.-B. (2007). The exploration of customer satisfaction model from a comprehensive perspective. *Expert Systems with Applications*, 33(1), 110–121.
- Liuqu, Y., Fan, X., & Fu, P. L. (2015). From customer satisfaction to customer experience: Online customer satisfaction practice in international e-commerce. *Cross-Cultural Design Applications in Mobile Interaction, Education, Health, Transport and Cultural Heritage: 7th International Conference, CCD 2015, Held as Part of HCI International 2015, Los Angeles, CA, USA, August 2-7, 2015, Proceedings, Part II* 7, 80–89.
- Marquez, J. J., Downey, A., & Clement, R. (2015). Walking a mile in the user's shoes: Customer journey mapping as a method to understanding the user experience. *Internet Reference Services Quarterly*, 20(3-4), 135–150.
- Ngo, V. M. (2015). Measuring customer satisfaction: A literature review. *Proceedings of the 7th International Scientific Conference Finance and Performance of Firms in Science, Education and Practice*, 7, 1637–1654.
- Reichheld, F. F. (2003). The one number you need to grow. *Harvard business review*, 81(12), 46–55.
- Rosenbaum, M. S., Otalora, M. L., & Ramírez, G. C. (2017). How to create a realistic customer journey map. *Business horizons*, 60(1), 143–150.
- Umar, M., Xu, Y., & Mirza, S. S. (2021). The impact of covid-19 on gig economy. *Economic Research-Ekonomska Istraživanja*, 34(1), 2284–2296.
- Woodcock, J., & Graham, M. (2019). The gig economy. *A critical introduction*. Cambridge: Polity.
- Zeinalizadeh, N., Shojaie, A. A., & Shariatmadari, M. (2015). Modeling and analysis of bank customer satisfaction using neural networks approach. *International Journal of Bank Marketing*.

A Customer Journey Map visualization

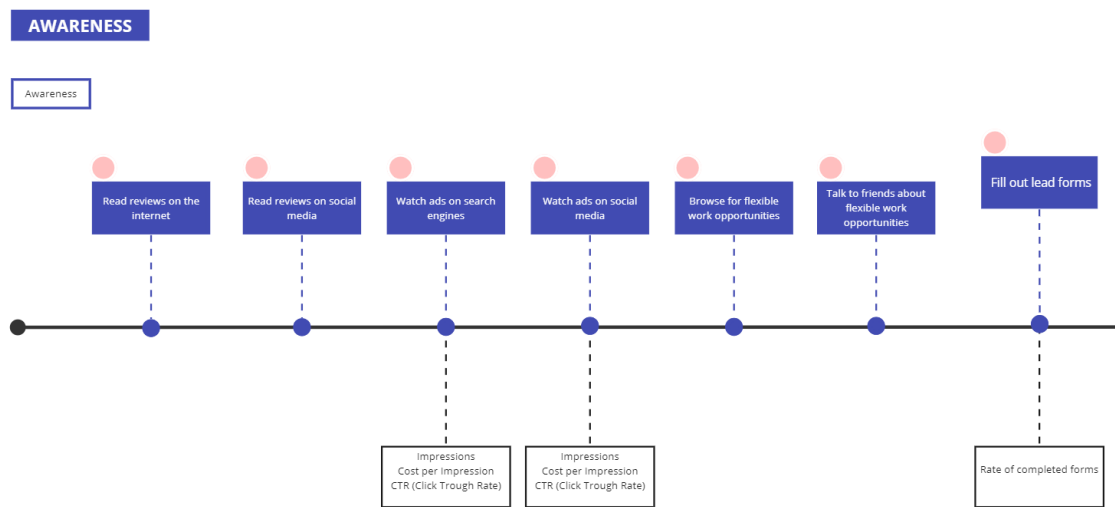


Figure A.1: Awareness phase.

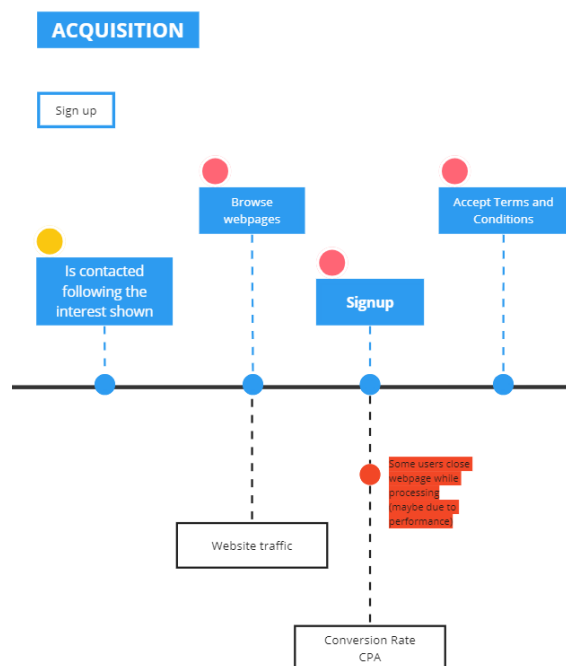


Figure A.2: Acquisition phase.

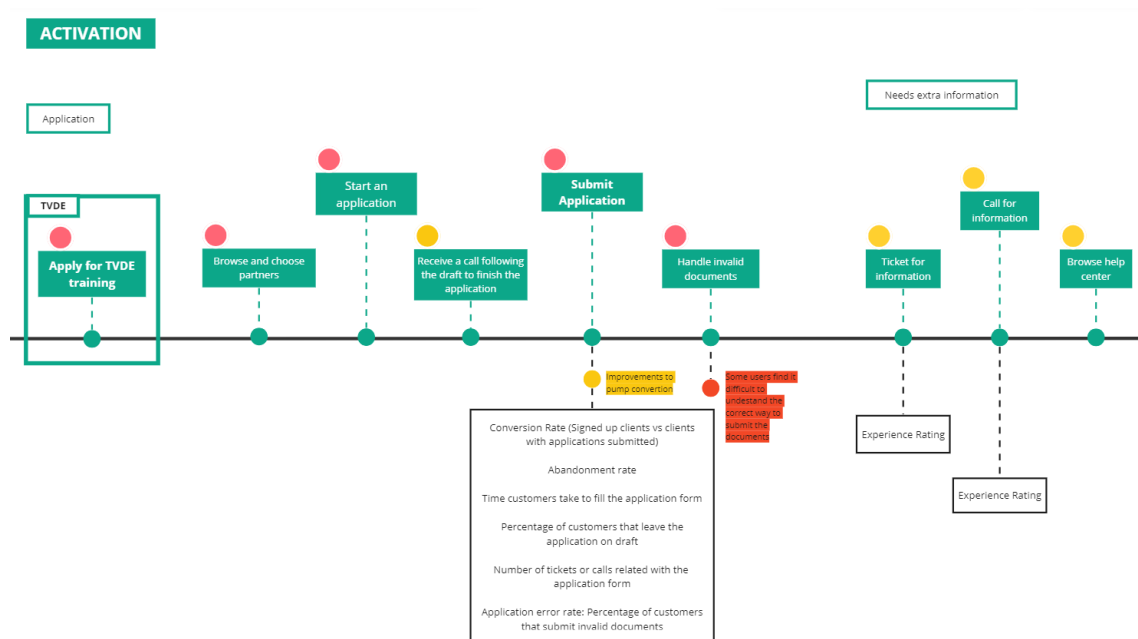


Figure A.3: Activation phase.

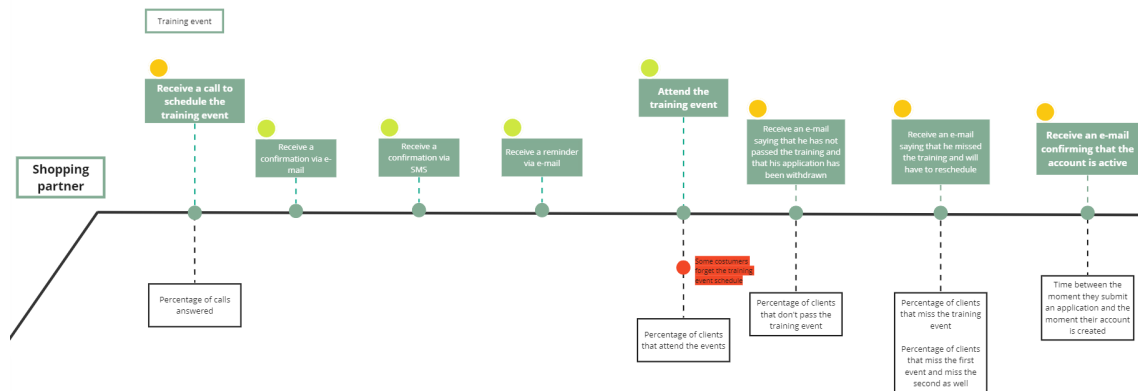


Figure A.4: Activation phase - Shopping partner.

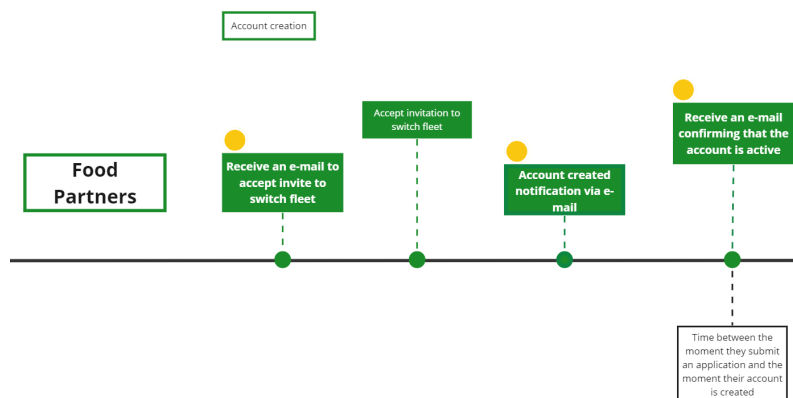


Figure A.5: Activation phase - Food partners.

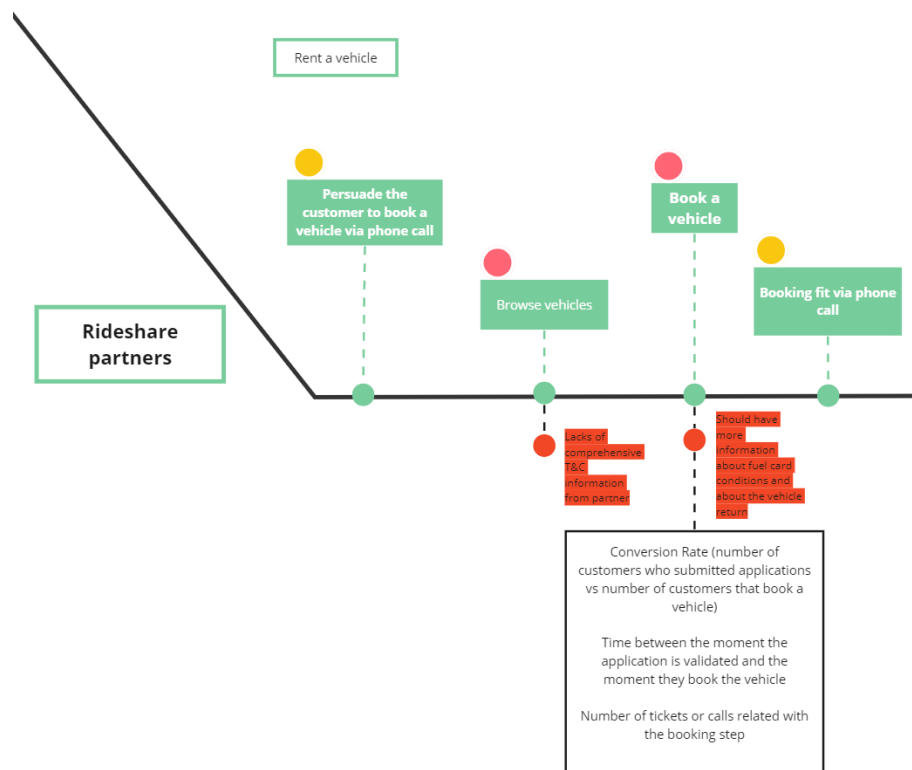


Figure A.6: Activation phase - Rideshare partners (1).

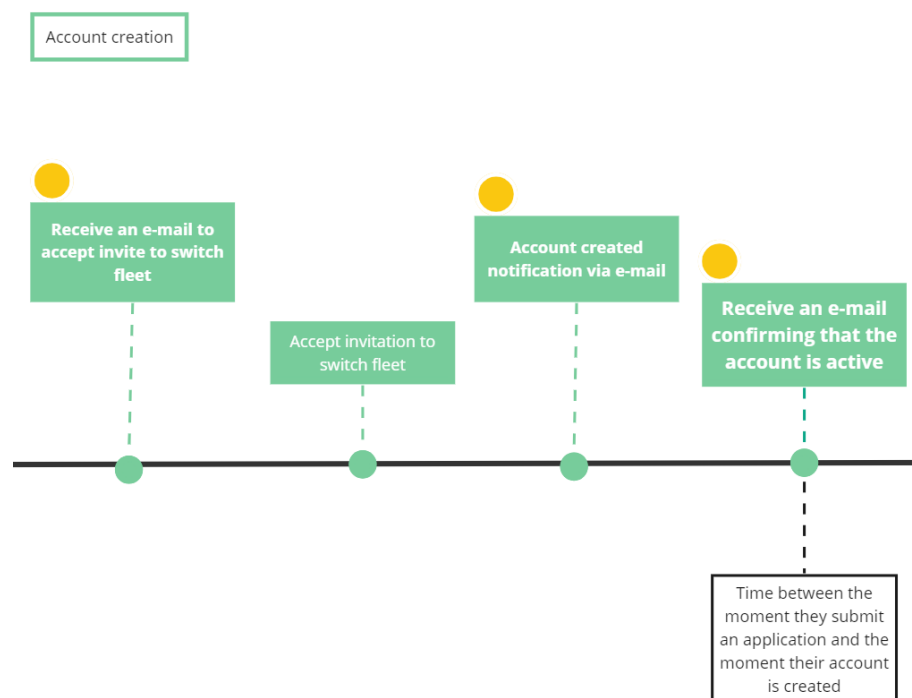


Figure A.7: Activation phase - Rideshare partners (2).

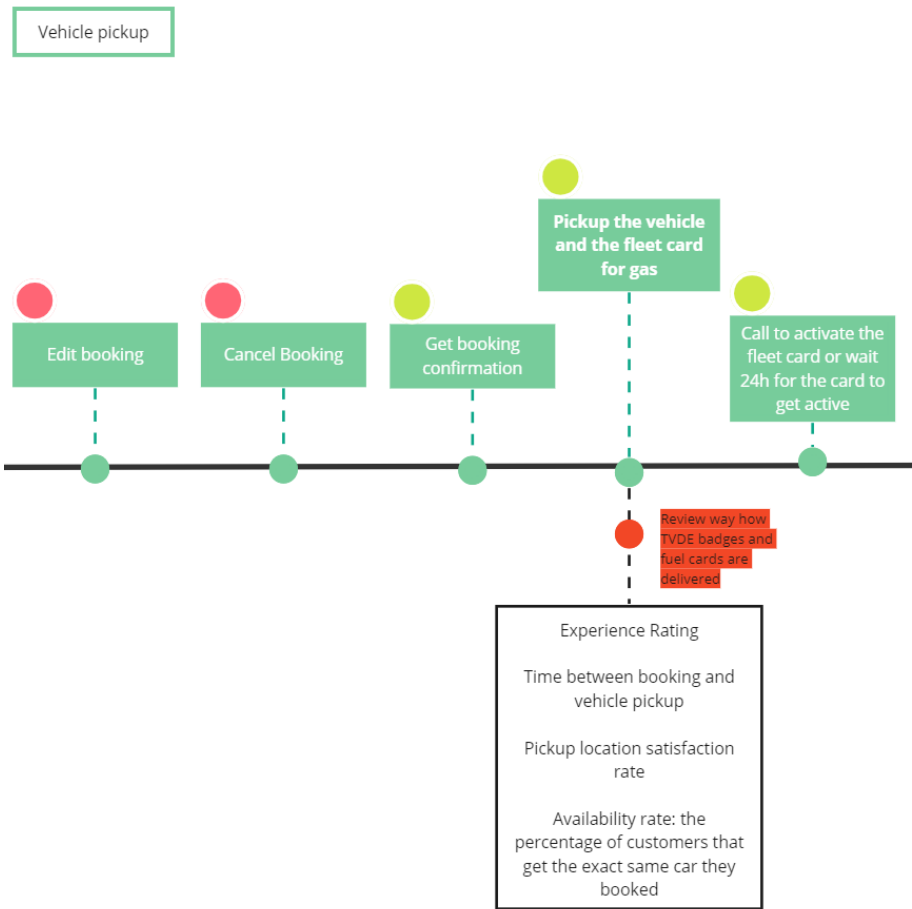


Figure A.8: Activation phase - Rideshare partners (3).

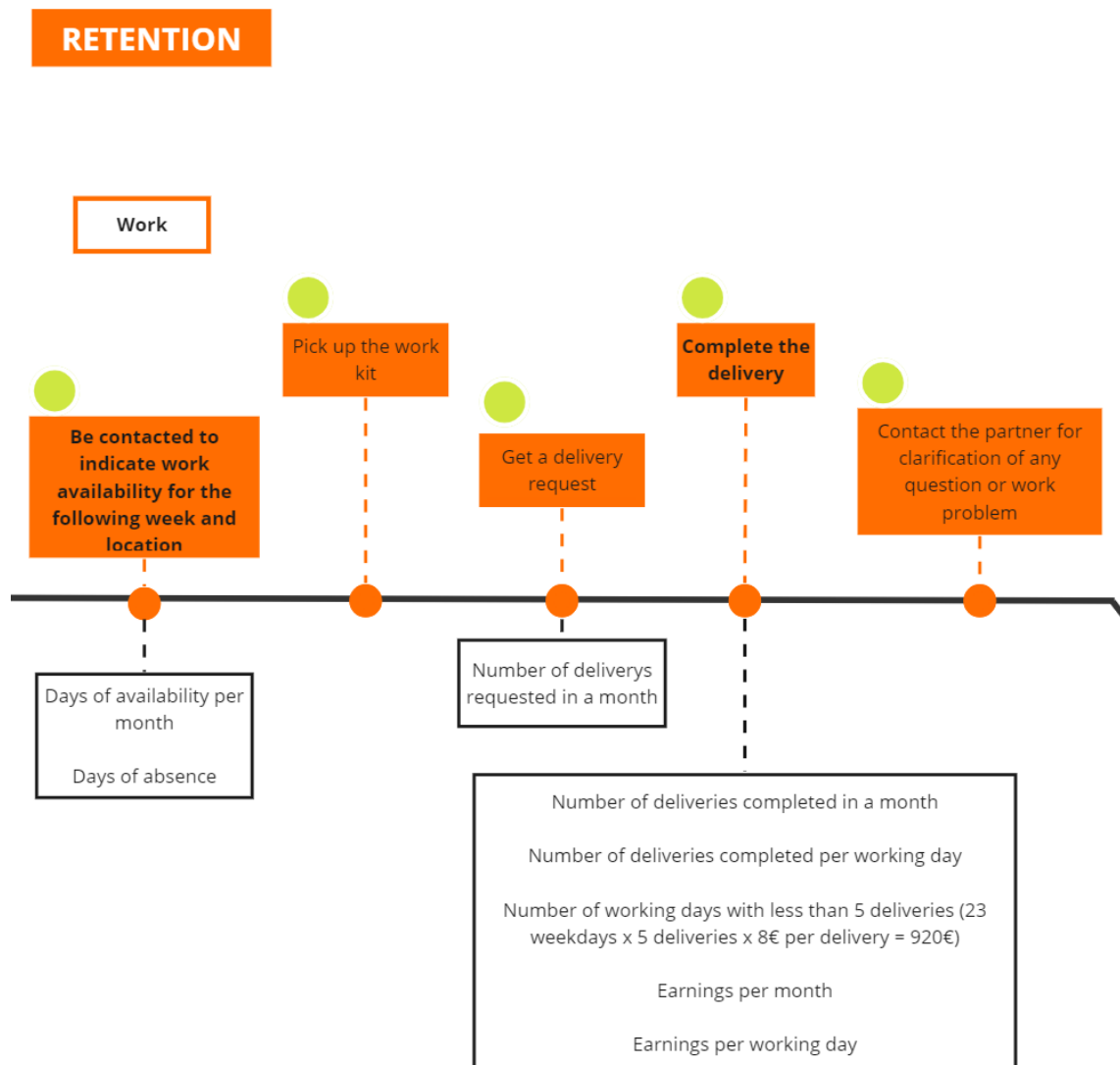


Figure A.9: Retention phase - Work stage - Shopping segment.

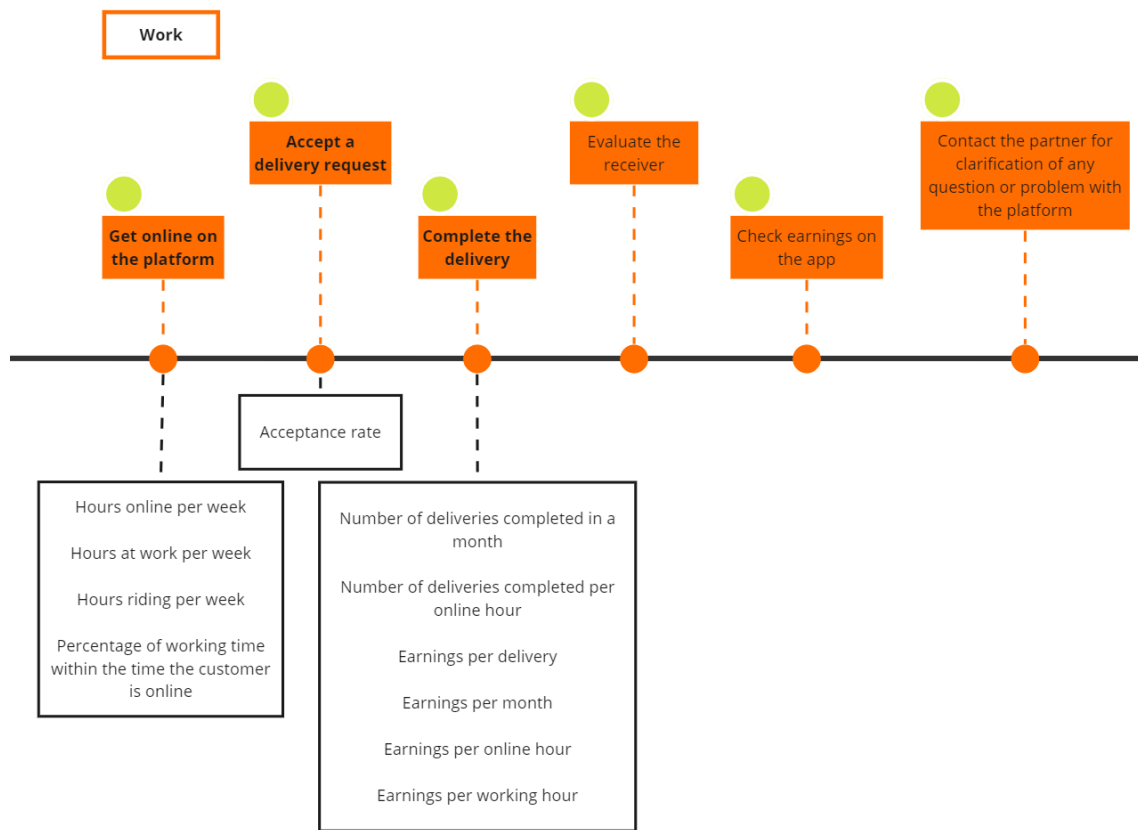


Figure A.10: Retention phase - Work stage - Food segment.

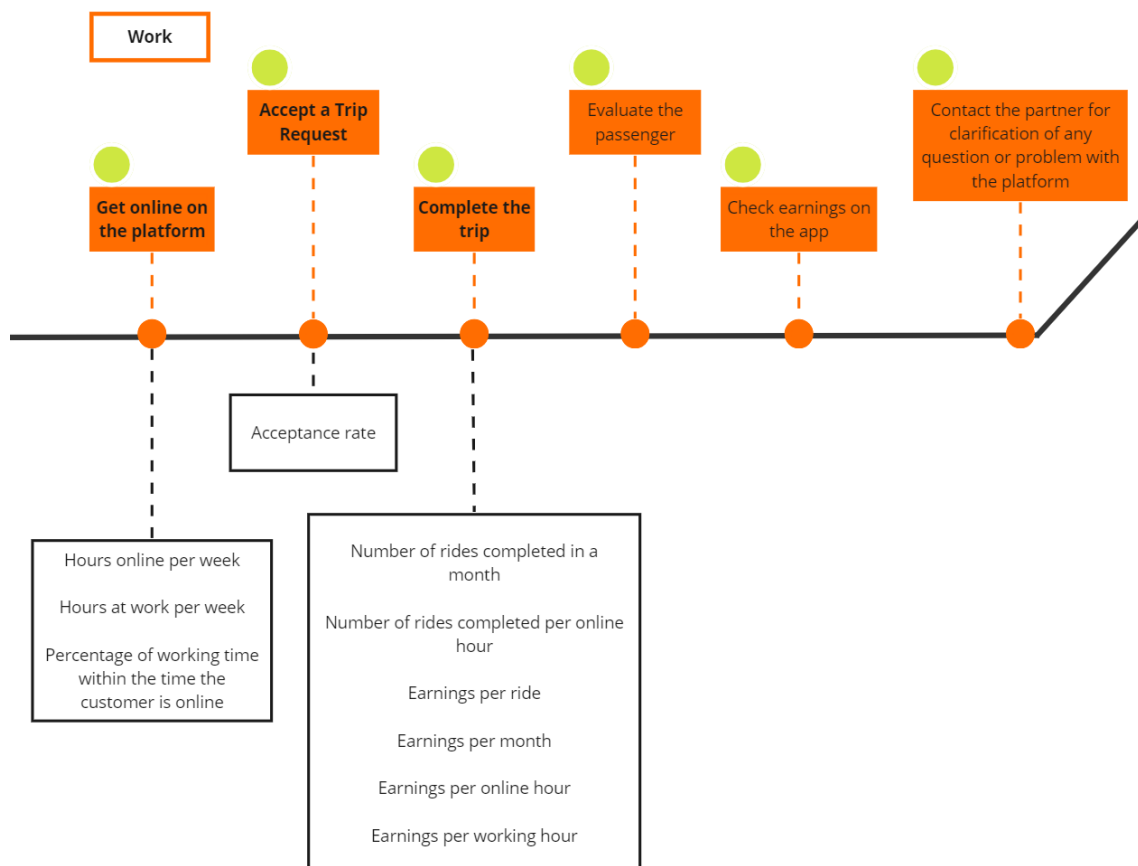


Figure A.11: Retention phase - Work stage - Rideshare segment.

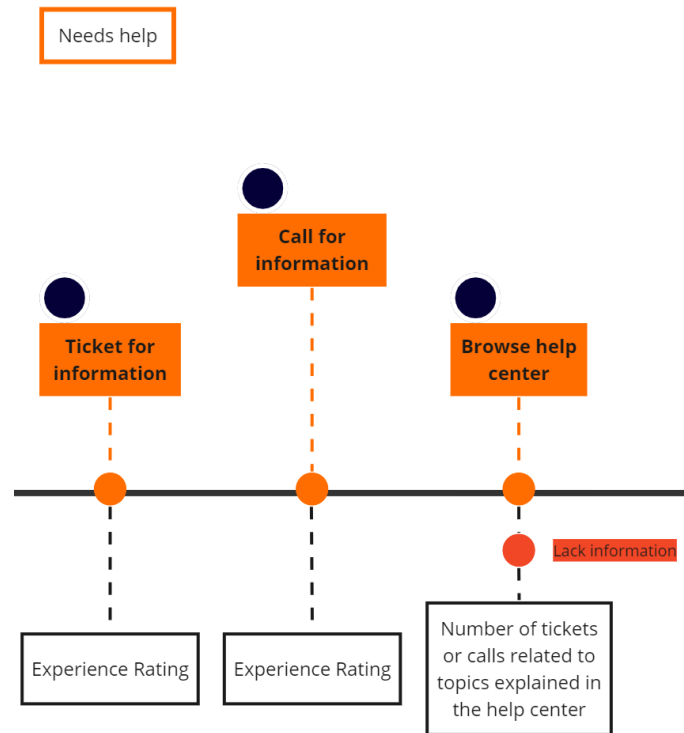


Figure A.12: Retention phase - Needs Help.

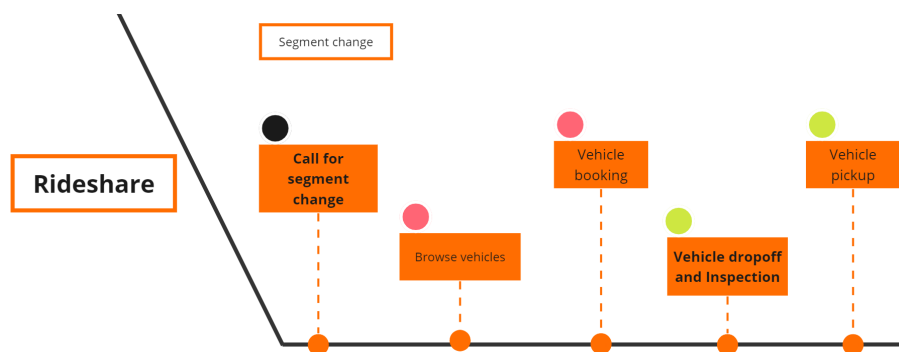


Figure A.13: Retention phase - Rideshare - Car segment change.

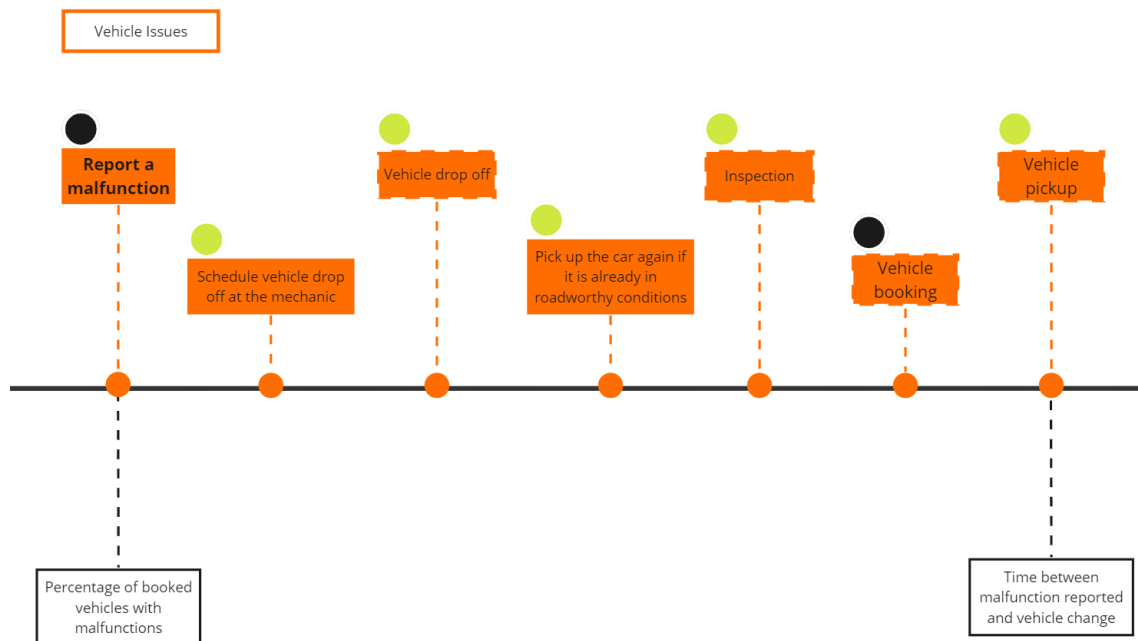


Figure A.14: Retention phase - Rideshare - Vehicle issues (1).

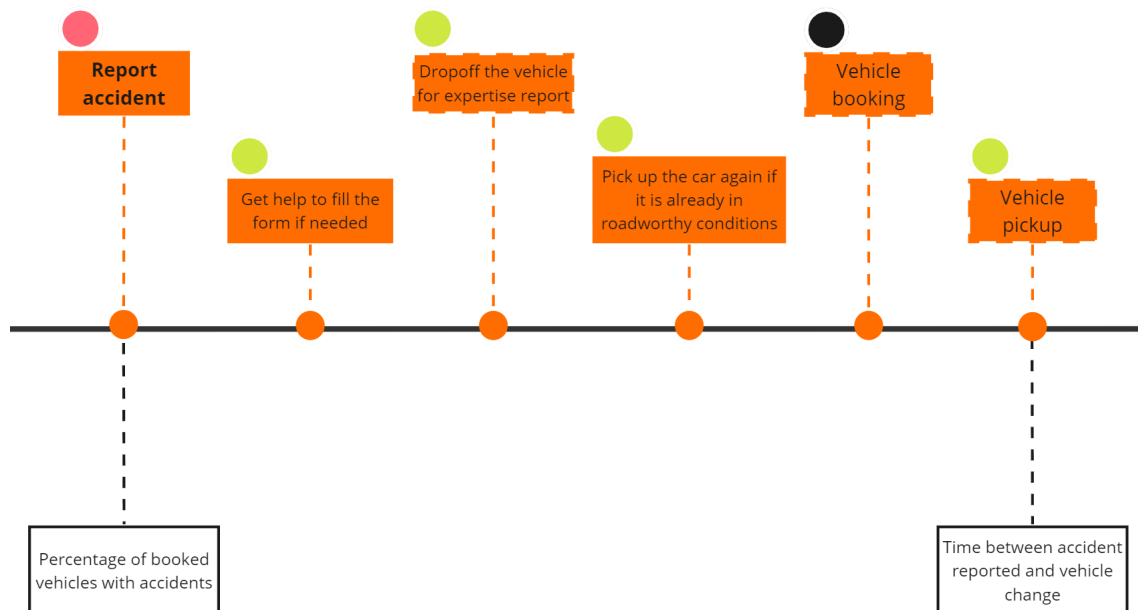


Figure A.15: Retention phase - Rideshare - Vehicle issues (2).

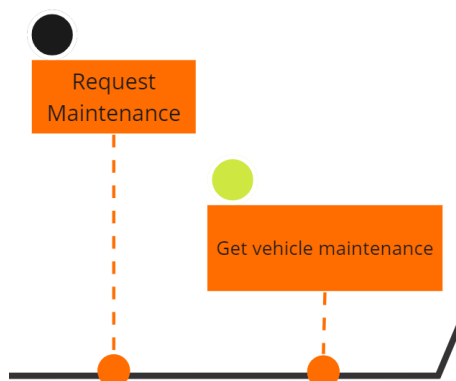


Figure A.16: Retention phase - Rideshare - Vehicle issues (3).

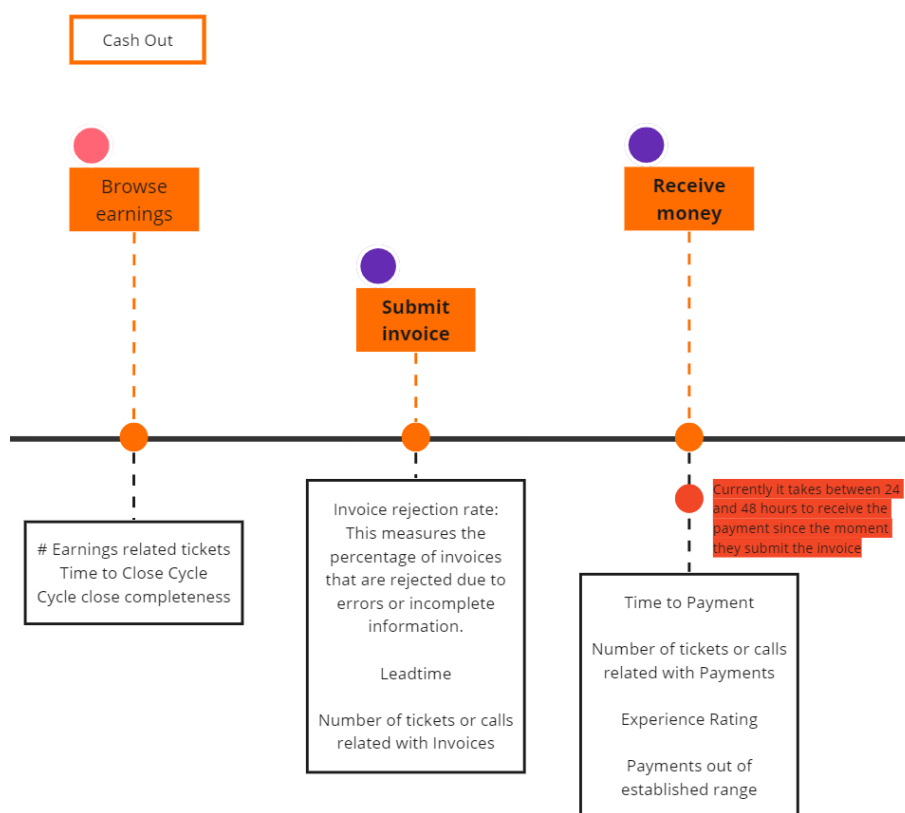


Figure A.17: Retention phase - Cash out.

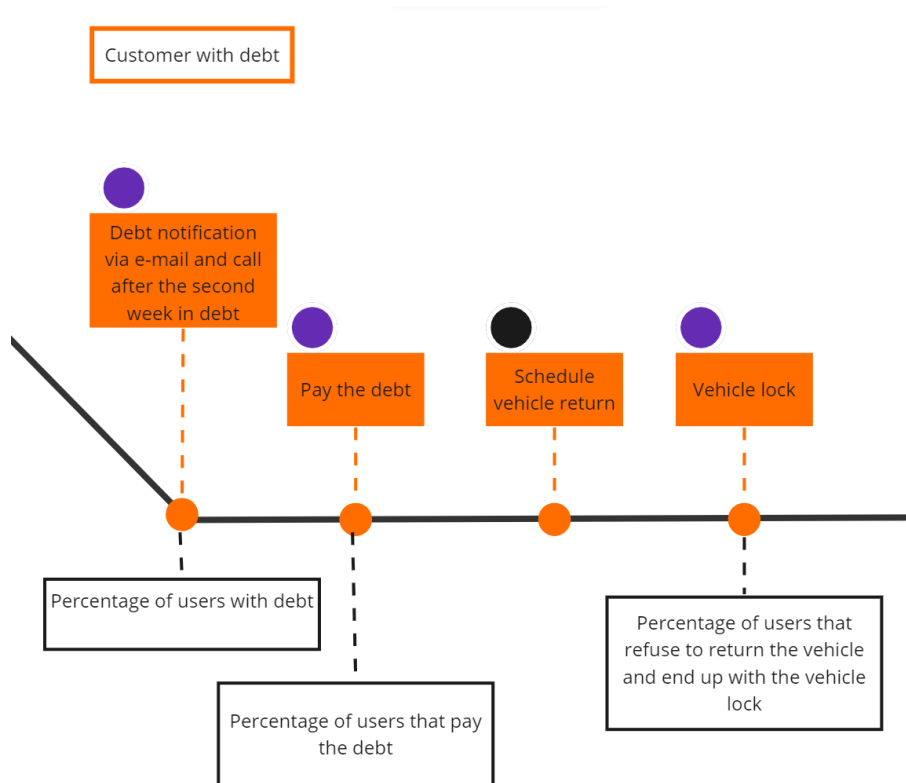


Figure A.18: Retention phase - Customer with debt.

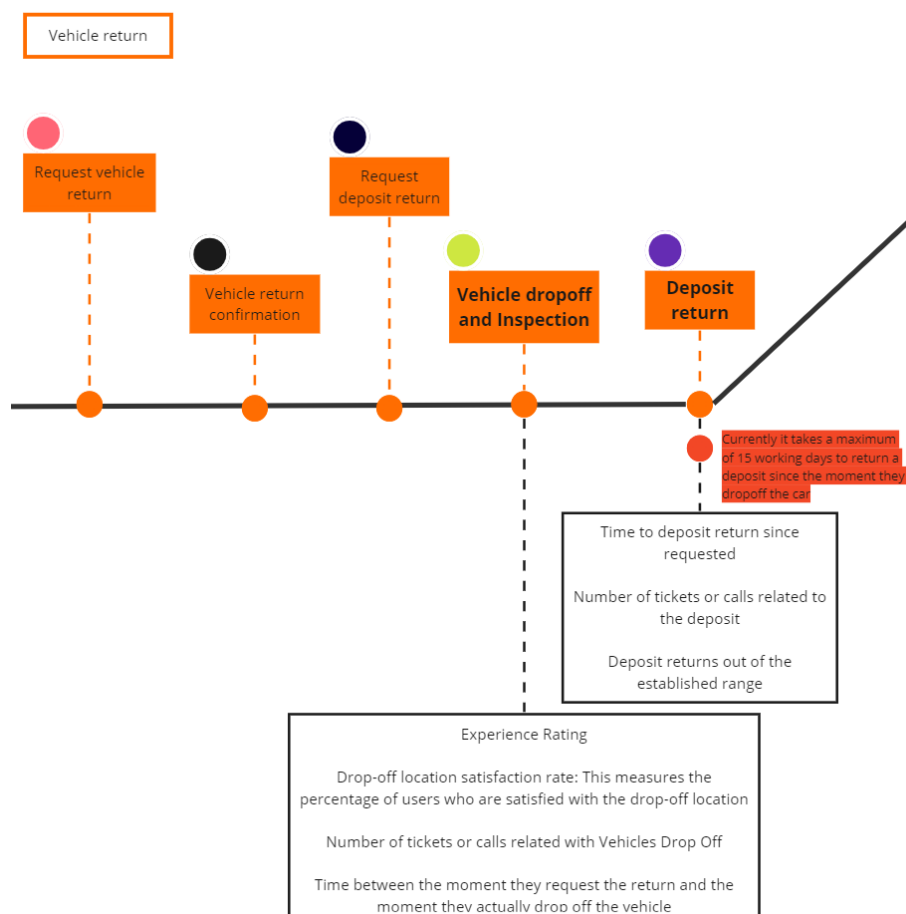


Figure A.19: Retention phase - Vehicle Return.

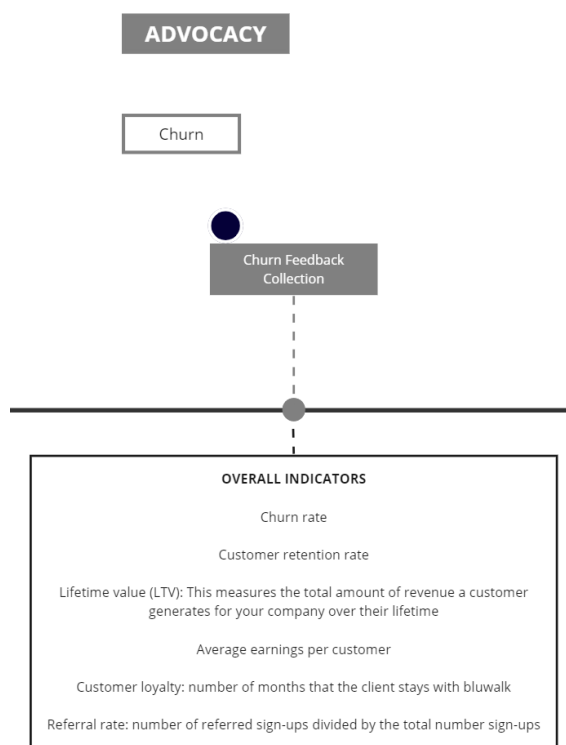


Figure A.20: Advocacy phase.

B Categorization of indicators

Scope	Stage	Step	Indicator	Viability	Priority
Experience map	<i>multiple*</i>	Vehicle Pickup*	Vehicle Pickup Rating	✓Viable	Should have
	Work	<i>multiple</i>	Net earnings per online hour	✗Not sure	Must have
			Net earnings per week	✓Viable	Must have
	Need help	Contact Customer Service	Number of tickets - complaint	✓Viable	Must have
			Number of tickets - information	✓Viable	Nice to have
			Number of tickets - request	✓Viable	Nice to have
			Time to written ticket resolution	✗Not sure	Should have
			Time to written ticket response	✗Not sure	Should have
			Number of abandoned calls	✗Not sure	Should have
			Ticket Rating	✓Viable	Must have
			Number of tickets related to topics explained in the help center	✗Not sure	Should have
		Browse Help Center	Number of tickets related to topics explained in the help center	✗Not sure	Should have
	Vehicle issues*	Report a malfunction/accident	Number of malfunctions	✓Viable	Must have
			Time between malfunction/accident reported and vehicle change	✗Not viable	Should have
		Vehicle Inspection	Missing documents or items costs in a week	✗Not sure	Nice to have
			Vehicle fuel match costs in a week	✓Viable	Should have
			Vehicle cleaning costs in a week	✓Viable	Should have
			Vehicle damage costs	✓Viable	Must have
	Cash Out	Submit Invoice	Invoice rejection rate	✓Viable	Must have
			Number of cycles closed out of SLA	✓Viable	Must have
			Number of tickets or calls related with Invoices	✗Not sure	Should have
		Receive Money	Time to Payment	✗Not sure	Nice to have
			Number of tickets or calls related with Payments	✓Viable	Nice to have
			Payments out of SLA	✓Viable	Should have

Figure B.1: Overview of the table resulting from the indicator categorization process.

C Detailed data collection

List of active customers

To extract the list of active clients per week, it was utilized a pre-existing table in the database, which specifically captured clients who had generated income during that particular week. To retrieve this information, a query depicted on Figure C.1 was executed.

```
SELECT * FROM `bluwalk-data-warehouse.marts.fct_listActiveUsersWK` limit 2000
```

Figure C.1: Query for the list of active customers per week.

By leveraging the existing table, it was possible to efficiently obtain the list of active clients IDs and proceed with further analysis and computations related to other performance metrics.

To retrieve the names of each customer from the list of active clients per week, an additional table containing the personal data of each customer was required. Due to the size of this table, which exceeded the 25,000 row limit imposed by Google Sheets, a left join operation was performed. This allowed for the connection between the table of active clients per week and the customer personal data table, ensuring that the desired information could be collected for the active customers without exceeding the row limit. The query for this purpose is presented in Figure C.2.

```
SELECT * FROM `bluwalk-data-warehouse.marts.fct_listActiveUsersWK` a  
left join `bluwalk-data-warehouse.odoo_realtime.res_partner` b on a.userPartnerID = b.id  
ORDER BY yearWeek desc
```

Figure C.2: Query for customer personal data.

By executing this query, it was possible to obtain a comprehensive dataset that combined active user information with corresponding personal data.

Net earnings per week

To get the data for this indicator there were 3 things that were needed. The earnings, the costs, and the number of weeks worked within the time frame for each customer. To gather the necessary data for these three components, multiple steps were involved. Firstly, it was necessary to locate tables containing earnings and cost information for each partner and customer, recorded on a daily or weekly basis. To gain a deeper understanding of which tables to look for and their contents, the financial department, responsible for importing partner information into the database, was consulted. The table used in this task was the table with the analytical rows, where all the earnings and costs for each client are recorded. To ensure the line limit in Google Sheets was

not exceeded, there were implemented three separate queries. The first query focused on earnings within the rideshare segment, and it is depicted in Figure C.3.

```
SELECT a.id, a.name, a.date, a.amount, a.unit_amount, a.partner_id, a.create_date, a.product_id, a.categ_id, a.ref,a.payment_cycle,
b.name partner_name
FROM `bluwalk-data-warehouse.odoo_realtime.account_analytic_line` a
left join `odoo_realtime.res_partner` b on a.partner_id=b.id
Where a.date >= '2023-01-01' and product_id IN(25, 26)
order by date desc
```

Figure C.3: Query for earnings within the “Rideshare” segment.

For the other segments similar queries were used with the difference being in the “product ID”, in order to select different partners. To obtain the earnings within the food segment the query used is displayed in Figure C.4.

```
SELECT a.id, a.name, a.date, a.amount, a.unit_amount, a.partner_id, a.create_date, a.product_id, a.categ_id, a.ref,a.payment_cycle,
b.name partner_name
FROM `bluwalk-data-warehouse.odoo_realtime.account_analytic_line` a
left join `odoo_realtime.res_partner` b on a.partner_id=b.id
Where a.date >= '2023-01-01' and product_id IN(16,15)
order by date desc
```

Figure C.4: Query for earnings within the “Food” segment.

The query applied to extract the earnings of the shopping segment is presented in Figure C.5.

```
SELECT a.id, a.name, a.date, a.amount, a.unit_amount, a.partner_id, a.create_date, a.product_id, a.categ_id, a.ref,a.payment_cycle,
b.name partner_name
FROM `bluwalk-data-warehouse.odoo_realtime.account_analytic_line` a
left join `odoo_realtime.res_partner` b on a.partner_id=b.id
Where a.date >= '2023-01-01' and product_id IN(22)
order by date desc
```

Figure C.5: Query for earnings within the “Shopping” segment.

With all this information collected, it was then necessary to treat it using Google Sheets formulas until we reached the point where each active customer had the value of their earnings within the time frame. For the “Courier” segment, no query was made because, at the time this project was developed, there was no customer working in this segment.

When analyzing costs for the indicator, two types of costs were taken into account. Firstly, the BWs fee and secondly the rental costs for clients who opted to rent a car through BW.

The query used to obtain the BW fee costs is displayed in Figure C.6 and the query to get the costs of the car rental the following query is presented in Figure C.7.

To calculate the number of weeks worked by each customer, additional queries were not required. Instead, Google Sheets formulas were utilized to identify the days on which the customer had income, indicating their active status. By determining the corresponding week for each active day, a cross-reference was performed with the weeks falling within the specified time frame. This approach allowed for the determination of the number of weeks worked by each customer without the need for additional queries or data retrieval processes.

In the final step, a formula was developed to calculate this indicator by subtracting the costs from the earnings and dividing the result by the number of weeks worked.

Net earnings per online hour

To collect the data for the indicator “Net earnings per online hour”, several data sources were required, including each client’s earnings, costs, and the number of hours they were available for work (online) within the specified time frame. In terms of earnings and costs, this information

```
SELECT a.id, a.name, a.date, a.amount, a.unit_amount, a.partner_id, a.create_date, a.product_id, a.categ_id, a.ref,a.payment_cycle,
b.name partner_name
FROM `bluwalk-data-warehouse.odoo_realtime.account_analytic_line` a
left join `odoo_realtime.res_partner` b on a.partner_id=b.id
Where a.date >= '2023-01-01' and product_id IN(136)
order by date desc
```

Figure C.6: Query for the BW fee costs.

```
SELECT a.id, a.name, a.date, a.amount, a.unit_amount, a.partner_id, a.create_date, a.product_id, a.categ_id, a.ref,a.payment_cycle,
b.name partner_name
FROM `bluwalk-data-warehouse.odoo_realtime.account_analytic_line` a
left join `odoo_realtime.res_partner` b on a.partner_id=b.id
Where a.date >= '2023-01-01' and product_id IN(32)
order by date desc
```

Figure C.7: Query for the rental costs.

had already been collected in previous queries, making their utilization relatively straightforward. However, obtaining the data for online hours proved to be more challenging and time-consuming, making this the most difficult indicator to obtain and the last one acquired.

Regarding the rideshare segment, a thorough search of the database was conducted to identify the most suitable table for each partner, from which the online hours for each client could be extracted. Understanding and interpreting the columns within these tables was crucial, along with determining how often data was being loaded into these tables to ensure that the data was being updated.

Two queries were ultimately employed to retrieve the online hours data from the rideshare partners. The first query utilized is shown in Figure C.8 and the second query employed is presented in Figure C.9.

```
SELECT distinct a.driverUUID, a.firstName, a.lastName, a.nrTrips, a.onlineMinutes, a.tripMinutes, a.date, b.partner_id, b.account_user
FROM `bluwalk-data-warehouse.████████.driver_activity` a
left join odoo_realtime.res_sales_partner_account b on a.driverUUID=b.account_unique_id
where date >= "2023-01-01"
ORDER BY date desc
```

Figure C.8: Query for the online hours in the rideshare segment (1).

Both queries required joining a table to obtain the unique ID of each customer, enabling the retrieval of accurate online hour data for analysis and calculation of the indicator.

After collecting the necessary data, the focus shifted to determining the optimal approach for handling online hours within the rideshare segment. A significant challenge arose due to the fact that many clients work through multiple partners, allowing them to be simultaneously online on multiple platforms. However, this situation typically occurs when the customer is waiting for a trip since being online on both platforms during a trip may lead to trip request refusals, potentially resulting in negative consequences such as platform restrictions.

Thus, the dilemma was how to accurately account for online hours without double-counting or neglecting hours when the client was actively working on one of the platforms. A careful analysis revealed three key findings. Firstly, customers tend to spend more time waiting for trips than actually traveling. Secondly, it was observed that many drivers have a clear preference for one particular platform. Additionally, on days with a high volume of trips, drivers often do not have sufficient time to switch between platforms.

Considering these insights, it was concluded that the best approximation for a customer's available hours would be to select the maximum online hours per day across the rideshare partners for each individual client. To facilitate this process, formulas were developed in Google Sheets to

```
SELECT a.partner_id, a.driver_name driver_name, a.period_date, a.online_h, a.finished_orders, a.utilisation, a.rides_per_hour, b.name name_odoo
FROM 'bluwalk-data-warehouse' driver_performance' a
left join 'odoo_realtime.res_partner' b on b.id=a.partner_id
Where a.period_date >= '2023-01-01'
ORDER BY a.period_date desc
```

Figure C.9: Query for the online hours in the rideshare segment (2).

automate the calculation of the maximum online hours for each day based on the available data. This approach ensured a more accurate representation of the time customers were available to work within the rideshare segment.

Similarly to the rideshare segment, an examination of the available tables in the database was conducted to identify a table that could provide insights into the online time of each customer within the food segment. For one of the partners, a suitable table containing the desired information was found. The next step involved comprehending the structure of the table and determining the frequency of updates to ensure data accuracy. Once this was accomplished, the query, depicted in Figure C.10 was formulated.

```
SELECT a.driverUUID, a.firstName, a.lastName, a.nrTrips, a.onlineMinutes, a.tripMinutes, a.date, b.partner_id, b.account_user
FROM 'bluwalk-data-warehouse' driver_activity' a
left join odoo_realtime.res_sales_partner_account b on a.driverUUID=b.account_unique_id
where date >= "2023-01-01"
ORDER BY date desc
```

Figure C.10: Query for the online hours in the food segment.

To retrieve the customer IDs, another table was joined in the query. Subsequently, formulas were developed within the Google Sheets document to calculate the online hours for each customer within this particular partner of the food segment.

Obtaining the online hours' data for the other partner within the food segment proved to be a more challenging task. To initiate the process, a meeting was arranged with the individuals responsible for the partner, and a detailed explanation of the requirements intended was given. Specifically, it was requested a document containing the online hours' data of BW clients, including unique client IDs. Ideally, the aim was for a shared document that would grant regular access to the data, either on a daily or weekly basis, with a historical record dating back to the beginning of 2023. Regrettably, despite multiple requests, the desired document was never received, casting doubt on the feasibility of this indicator.

Ultimately, the best that was obtained was a document containing weekly online hours data for all customers within the period of February 27 to April 24. However, unlike the other sources of information used in the data collection, this document lacked regular updates and remained static over time. Moreover, it did not include any client ID that could be used for unique identification. Consequently, it was necessary to cross-reference the phone numbers present in the partner's document with the phone numbers available in our database for each customer. This task was accomplished using Google Sheets formulas, but it resulted in unidentified customers. To address this issue, a manual effort was undertaken to identify and associate these customers with their respective data.

Obtaining online hours data for the shopping segment presented its own set of challenges. Similar to one of the food partners, our database did not contain any information regarding the online hours of customers associated with the shopping partner. As a result, several meetings and extensive email communication were conducted in an attempt to secure a shared document that

would be updated weekly. This document was intended to provide the availability to work offered by BW's customers, encompassing a historical record since the beginning of 2023, along with unique customer IDs for identification purposes. Unfortunately, despite these efforts, it was not possible to obtain such a document.

The best that was possible to obtain was a document that contained customer availability data from December to May. However, this document presented three significant issues. Firstly, it was not updated regularly, which, once again, contradicted the desired weekly update characteristic of the dataset. Secondly, it lacked any form of unique identification or key to identify individual clients. Lastly, it only included information for active clients as of the end of May.

Regarding the first problem, there was nothing that could be done to rectify the lack of regular updates. However, for the second problem, Google Sheets formulas were employed to attempt customer identification based on their names within the document provided by the partner. For those customers who could not be identified by name, manual efforts were required to determine their identities. Regarding the last problem, for the clients necessary to complete the training dataset who were not included in the document provided by the partner, it was necessary to make use of a previous document shared by the partner. This document contained the historical records of these clients, allowing us to analyze their typical weekly working hours and approximate the number of hours worked within the time frame of our training dataset.

Number of tickets or calls - complaint

In order to gather data for the "Number of tickets or calls - complaint" indicator, the collection process involved obtaining information on customer complaints made through both tickets and calls. The complaint typification is done by the customer service department after answering a call or opening a ticket.

Starting with the calls, a comprehensive query was executed, involving the joining of four tables. On March 3 of 2023, the company started using "Zendesk", a customer service software, instead of "Odoo", a suite of business management software tools, to handle the tickets and calls. From this point on, each incoming call generated a ticket. To identify complaint type calls in "Zendesk", the ticket table was utilized, along with the "Zendesk" user table to determine the user responsible for the call. Additionally, other two tables were involved, one to match "Zendesk" users to "Odoo" users, this had to be done because it is in the "Odoo" tables that the customer IDs are stored, and another to verify their names for data consistency. However, several challenges were encountered during this process. Duplicate "Zendesk" users without corresponding matches in "Odoo", users without accounts in either system and cases where the phone number in "Odoo" was not associated with the "Zendesk" account required extra effort to minimize missing values. Duplicate accounts were merged, and accounts created solely with a phone number were linked to the respective user accounts. Furthermore, determining the correct keys for cross-referencing the tables added complexity to the task. The query performed to obtain the complaint calls is presented in Figure C.11.

The performed query included filtering conditions to retrieve complaint type calls. Afterwards, through custom formulas developed in Google Sheets, it was possible to successfully obtain the

```
SELECT a.id id_ticket_tabela_tickets, a.created_at ticket_creation_date_tabela_tickets, a.subject subject_ticket_tabela_tickets,
a.topic topic_ticket_tabela_tickets, a.requester_id user_id_tabela_tickets,
b.id ZD_user_id_table_users_ZD, b.name ZD_user_name_tabela_users_ZD, b.external_id Odoo_user_id_table_users_ZD,
c.id Odoo_user_id_table_users_Odoo, c.partner_id Odoo_partner_id_table_users_Odoo,
d.id Odoo_partner_id_table_partners_Odoo, d.name Odoo_user_name_table_partners_Odoo
FROM 'bluwalk-data-warehouse.zendesk.tickets_view' a
left join 'zendesk.users_view' b on cast(a.requester_id as string)=b.id
left join 'odoo_realtime.res_users' c on b.external_id=cast(c.id as string)
left join 'odoo_realtime.res_partner' d on c.partner_id=d.id
where a.subject like 'Inbound call%' and a.created_at >= '2023-03-08' and a.type= "incident"
order by a.created_at desc
```

Figure C.11: Query for the complaint type calls.

count of complaint type calls for each active customer.

To gather data on tickets of the complaint type, a process similar to that of complaint calls was followed. The query utilized for this purpose closely resembled the one used for complaint calls but with a few adjustments. The “incident” type, specifically associated with complaints, was retained, while the “inbound call” type tickets, representing calls, were excluded. Additionally, the customer account named “Rodrigo Miguel” was removed from the results as it served as a test account for the company. So, the query performed to get the complaint tickets is depicted in Figure C.12. By applying suitable conditions in the query, only relevant complaint tickets were retrieved.

```
SELECT a.id id_ticket_tabela_tickets, a.requester_id requester_id_tabela_tickets,a.created_at created_at_tabela_tickets,
a.topic topic_ticket_tabela_tickets,
b.id ZD_user_id_table_users_ZD, b.name ZD_user_name_tabela_users_ZD, b.external_id Odoo_user_id_table_users_ZD,
c.id Odoo_user_id_table_users_Odoo, c.partner_id Odoo_partner_id_table_users_Odoo,
d.id Odoo_partner_id_table_partners_Odoo, d.name Odoo_user_name_table_partners_Odoo
FROM 'bluwalk-data-warehouse.zendesk.tickets_view' a
left join 'zendesk.users_view' b on cast(a.requester_id as string)=b.id
left join 'odoo_realtime.res_users' c on b.external_id=cast(c.id as string)
left join 'odoo_realtime.res_partner' d on c.partner_id=d.id
WHERE a.type like 'incident' and a.subject not like 'Inbound call'and b.name not like 'Rodrigo Miguel'
order by a.created_at desc
```

Figure C.12: Query for the complaint type tickets.

Ticket and call rating

The ticket and call rating indicator presented its own set of challenges, demanding considerable effort to collect and analyze the data. The data collection process involved gathering information for tickets and calls separately. Moreover, an additional layer of complexity arose due to the changes in the rating scales at a certain point in time. This transition necessitated careful handling of the data, as the rating scales for both tickets and calls were modified. These factors required careful consideration and meticulous data handling to ensure accurate and meaningful results.

Beginning with the call rating, obtaining the name and ID of each customer who provided a rating for a call involved a complex process that required joining six tables. BW utilizes the “Talkdesk” platform, a cloud-based call center solution, for handling calls. To construct the query, various left joins were employed to connect the six tables. The “calls” table from “Talkdesk”, which holds essential call information like start time, customer’s phone number, and answering agent, was connected to the “flows” table from “Talkdesk”, where the assigned ratings are stored. Additionally, connections were made to the “Zendesk” tables, first to access the ticket associated with each call and then to retrieve the “Zendesk” user responsible for the call. Finally, the query connected to the “Odoo” tables to obtain the customer’s user ID and Partner ID, which serves as the internal customer ID. This entire process required significant effort to comprehend the information

contained within each table, what filters had to be applied and understand the interrelationships of foreign keys. So, the query used to complete this task is shown in Figure C.13.

```
select a.interaction_id, a.call_start_time, a.customer_phone, a.agent_name, a.talk_time, a.disposition, a.recording_link,
b.exit as score,
c.id id_tabela_tickets, c.subject subject_tabela_tickets, c.description description_tabela_tickets, c.requester_id requester_id_tabela_tickets,
d.id ZD_user_id_table_users_ZD, d.name ZD_user_name_tabela_users_ZD, d.external_id Odoo_user_id_table_users_ZD,
e.id Odoo_user_id_table_users_Odoo, e.partner_id Odoo_partner_id_table_users_Odoo,
f.id Odoo_partner_id_table_partners_Odoo, f.name Odoo_user_name_table_partners_Odoo
from `talkdesk.calls` a
left join `talkdesk.flows` b on a.interaction_id = b.interaction_id
left join `zendesk.tickets_view` c on a.interaction_id=c.external_id
left join `zendesk.users_view` d on cast(c.requester_id as string)=d.id
left join `odoo_realtime.res_users` e on d.external_id=cast(e.id as string)
left join `odoo_realtime.res_partner` f on e.partner_id=f.id
where b.flow_name="Bluwalk 29/4" and b.step_name like "survey%" and b.exit != "timeout"
and b.exit != "room_finished" and a.call_start_time >= '2023-01-01' and b.exit not like "error" and b.exit not like "invalid"
order by call_start_time desc
```

Figure C.13: Query for the calls rating.

The rating system for calls underwent a significant change, transitioning from a scale of 0 to 9 to a binary scale of 0 to 1 starting on March 16th. To accommodate this change and ensure consistency in the data, additional steps were taken after importing the query information into a Google Sheets file. Formulas were implemented to normalize the calls with the previous rating system (ranging from 0 to 9) to conform to the new scale between 0 and 1. This normalization process was crucial to align the ratings across all calls and enable meaningful comparisons and analysis.

To handle the ticket rating, two separate queries were utilized. The first query was designed to retrieve tickets with the new rating scale (0-1) present in “Zendesk”, while the second query targeted tickets with the old rating scale (1-4) stored in “Odoo”.

The process of obtaining the ticket ratings in Zendesk was similar to that of the calls, although with some variations in the query. In this case, the “Talkdesk” tables were not required. Consequently, a modified query was utilized to retrieve the required data. The query excluded tickets that had not been offered or where the satisfaction rating had not been provided. By executing this query, the necessary information could be retrieved. Therefore, the query that resulted is represented in Figure C.14.

```
SELECT a.id id_ticket_tabela_tickets, a.requester_id requester_id_tabela_tickets, a.created_at, a.satisfaction_rating_score satisfaction_rating_tabela_tickets,
b.id ZD_user_id_table_users_ZD, b.name ZD_user_name_tabela_users_ZD, b.external_id Odoo_user_id_table_users_ZD,
c.id Odoo_user_id_table_users_Odoo, c.partner_id Odoo_partner_id_table_users_Odoo,
d.id Odoo_partner_id_table_partners_Odoo, d.name Odoo_user_name_table_partners_Odoo
FROM `bluwalk-data-warehouse.zendesk.tickets_view` a
left join `zendesk.users_view` b on cast(a.requester_id as string)=b.id
left join `odoo_realtime.res_users` c on b.external_id=cast(c.id as string)
left join `odoo_realtime.res_partner` d on c.partner_id=d.id
where a.satisfaction_rating_score not like 'unoffered' and a.satisfaction_rating_score not like 'offered'
order by a.created_at desc
```

Figure C.14: Query for the “Zendesk” ticket rating.

The query used to collect the tickets with “Odoo’s” rating involved joining the table that gathered the ticket information with the customer personal data table to obtain the relevant information and identify who rated the ticket. By filtering out any null customer ratings and selecting tickets created on or after January 1, 2023, the query ensured the retrieval of the desired data. So the query used to collect the tickets with “Odoo’s” rating is presented in Figure C.15.

Additionally, resorting to Google Sheets formulas, it was necessary to convert these tickets with the old rating system to a standardized scale ranging from 0 to 1.

Finally, to conclude this indicator for each customer, using formulas elaborated in Google Sheets, an average of the ratings attributed by each customer to calls and tickets within the time frame was calculated.

```
SELECT a.partner_id, a.id, a.date_create, a.customer_rating, a.category, a.ticket_category_id,
b.name
FROM `bluwalk-data-warehouse.odoo_realtime.support_ticket` a
left join `odoo_realtime.res_partner` b on b.id=a.partner_id
where a.customer_rating not like 'null' and date_create >= '2023-01-01'
order by date_create desc
```

Figure C.15: Query for the “Odo” ticket rating.

Number of malfunctions

To measure the “Number of malfunctions” indicator, collaboration with our fleet partner was crucial. Since our fleet partner shares the same ownership as BW, there is a higher level of cooperation, granting BW real-time access to relevant data from the partner’s database. To begin this process, there were arranged meetings with the fleet partner to identify the location of the table containing malfunctions information within their database and to gain a comprehensive understanding of how the data should be interpreted. Armed with this knowledge, the query constructed to retrieve the required information is displayed in Figure C.16.

```
select * from `drivfit-data-warehouse.dataxchg.drivfit_services`
where start_date > "2023-01-01"
order by start_date desc
```

Figure C.16: Query for the malfunctions.

During the analysis of the malfunctions table, it became apparent that there was no specific identifier to determine who was using the car at the time of the malfunction. To address this, it was necessary to turn to another table within BW’s database, which was the responsibility of our fleet partner, to gather rental contract information. Additionally, two other tables were joined to obtain the vehicle license plate and the customer’s name. The query used to retrieve rental contract information with the vehicle license plate and customer’s name is presented in Figure C.17.

```
SELECT a.id, a.name contract_name, a.driver_id, a.vehicle_id, a.start_date, a.end_date, a.write_uid,
b.license_plate,
c.name driver_name
FROM `bluwalk-data-warehouse.odoo_realtime.rental_contract` a
left join odoo_realtime.fleet_vehicle b on a.vehicle_id=b.id
left join `odoo_realtime.res_partner` c on a.driver_id=c.id
Where a.start_date >= "2023-01-01"
order by a.start_date desc
```

Figure C.17: Query for the rental contracts.

Challenges arose during this process as the rental contract table contained inconsistent entries, including contracts with hours of duration, end dates earlier than start dates, and other anomalies. To address these issues, discussions were held with a responsible representative from the fleet partner, aiming to understand the reasons behind these cases. Furthermore, it was determined that no direct key could link the malfunctions table with the rental contract table. However, since each time a car enters the workshop, the rental contract is terminated to avoid charging the customer during this period, formulas within Google Sheets were employed to match the license plate of the vehicle and the date it entered the workshop, to the license plate of the vehicle in the customer contract and the date the contract finished. Thus, it was possible to associate each customer with the number of breakdowns experienced within the time frame.

Vehicle damage costs

To calculate the “Vehicle Damage Costs” indicator, a query was performed on the analytical lines table, similar to the approach taken for the “net earnings per week” indicator. The query aimed to retrieve essential information related to vehicle damage costs. Filters were applied to limit to a specific “product ID” related to vehicle damage costs. Additionally, a “join” operation was conducted with another table to obtain the customer’s name, providing a sanity check for the data. The resultant query is displayed in Figure C.18.

```
SELECT a.id, a.name, a.date, a.amount, a.unit_amount, a.partner_id, a.create_date, a.product_id, a.categ_id, a.ref,a.payment_cycle,
b.name partner_name
FROM `bluwalk-data-warehouse.odoo_realtime.account_analytic_line` a
left join `odoo_realtime.res_partner` b on a.partner_id=b.id
Where a.date >= '2023-01-01' and product_id IN(44)
order by date desc
```

Figure C.18: Query for the vehicle damage costs.

Invoice rejection rate

To calculate the “Invoice Rejection Rate” indicator, collaboration with the financial department was necessary to determine the source of information related to invoices. After identifying the relevant table, a detailed analysis of its columns was conducted to understand the data contained within. This analysis aimed to identify the specific filters required to extract only the invoices issued by customers. The query elaborated is presented in Figure C.19.

```
SELECT id, name, date, ref, state, type, journal_id, partner_id, amount_untaxed, amount_total, amount_residual,
invoice_payment_state, invoice_date, invoice_date_due, invoice_partner_display_name, justify, deposit_partner_display_name
FROM `bluwalk-data-warehouse.odoo_realtime.account_move`
where partner_id is not null and date >= '2023-01-01' and journal_id = 60
order by date desc
```

Figure C.19: Query for the invoices submitted.

After importing the invoice data into the Google Sheets document, formulas were implemented to calculate the number of rejected invoices for each customer, as well as the total number of invoices issued. With this data in hand, the final step was to compute the ratio of rejected invoices per customer.

Number of cycles closed out of SLA

To calculate the “Number of cycles closed out of SLA” indicator, it was necessary to meet with the financial department to gain a clear understanding of how this metric should be treated and which table would provide the necessary information. After gathering this information, the query presented in Figure C.20 was formulated to extract the cycle release dates from the appropriate table.

```
SELECT * FROM `bluwalk-data-warehouse.tracker_logs.close_period_log`
where date >= '2023-01-01'
order by date desc
```

Figure C.20: Query for the cycles closed.

After importing the information about cycle release dates into the Google Sheets file, formulas were utilized to identify which cycles were posted outside the SLA. This involved comparing

the cycle release dates with the agreed-upon SLA time frame to determine if the cycles were completed within the specified time frame. Next, with the information previously collected about which weeks each client worked, through formulas, a cross-check was done to determine how many cycles outside the SLA each client experienced.

Segment

To gather information about the segments in which each client worked, a query was performed on the table that stored data for each week and for each client about the specific segment in which they were active. However, due to the limitations of Google Sheets and to ensure the analysis remained within the platform’s capacity, a limit of 10,000 records was imposed on the query results. This allowed for a sufficient amount of relevant data to be retrieved while avoiding exceeding the limitations of Google Sheets. Hence, the query performed is presented in Figure C.21.

```
SELECT *  
FROM `bluwalk-data-warehouse.marts.fct_listActiveUsersWK_stream` limit 10000
```

Figure C.21: Query for the active customers per week and per segment.

Afterward, in the Google Sheets document, it was necessary to apply formulas to evaluate only the weeks within the time frame and store as “True” or “False” whether or not the customer worked in each of the “Rideshare”, “Food”, “Shopping” or “Courier” segments.

D NPS collection

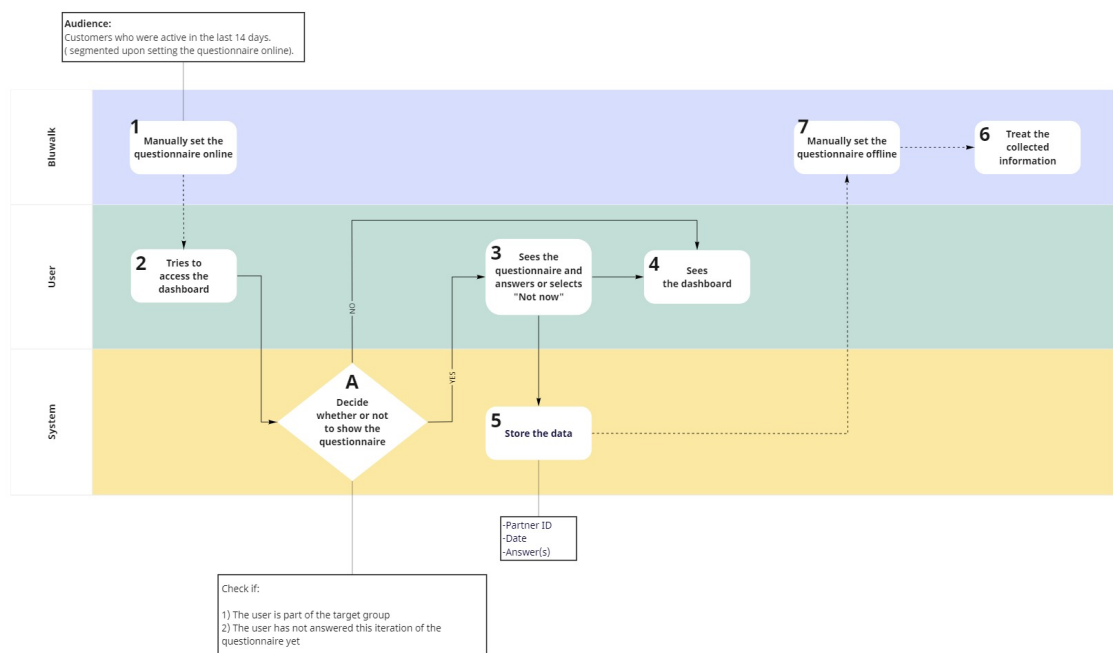


Figure D.1: NPS Collection rationale.

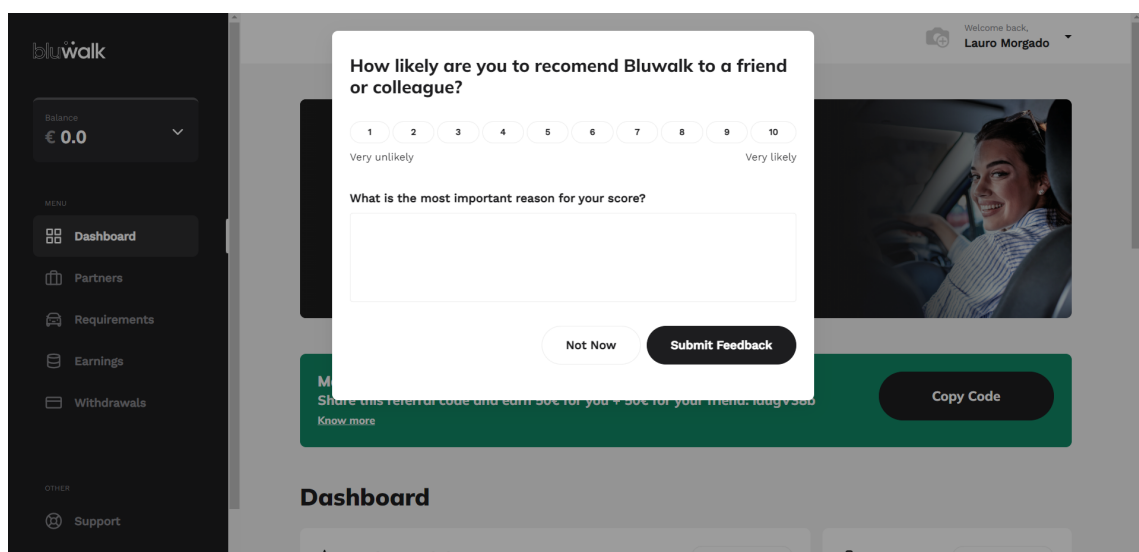


Figure D.2: NPS Survey “pop-up”.

E Univariate analysis of the variables

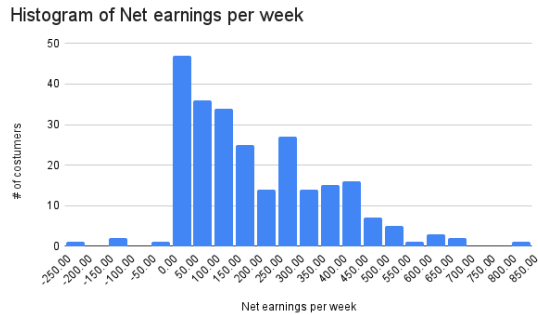
This appendix outlines a univariate statistical analysis conducted on each KPI. This analysis included measures for location, dispersion, skewness, and tailedness, alongside visualizing main descriptive statistics.

The total number of customers across all columns for the “Ticket and call rating” KPI amounts to only 47, not 252, as not all of them provided evaluations for tickets or calls.

The total number of customers across all columns for “Number of Malfunctions” KPI amounts to only 123, not 252, as this indicator specifically pertains only to customers in the rideshare segment who rent a car through BW.

The total number of customers across all columns for the “Vehicle Damage Costs” KPI amounts to only 123, not 252, as this indicator specifically pertains only to customers in the rideshare segment who rent a car through BW.

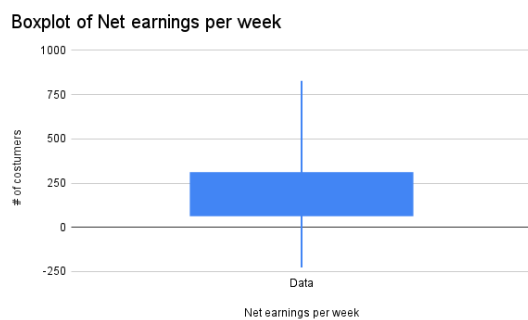
The total count of customers in all columns for the “Invoice Rejection Rate” KPI is 171, not 252, as some customers have not submitted any invoices. This can be attributed to various reasons, such as being new customers or choosing to accumulate their balance on the platform and withdraw it at their convenience.



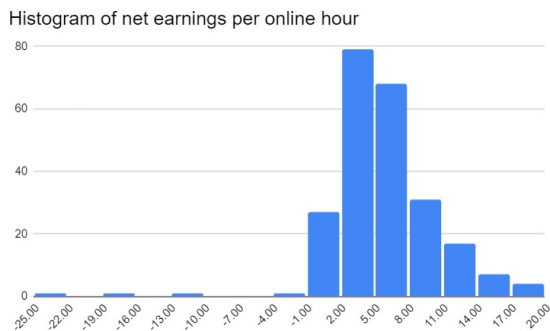
(a) Histogram.

Location Measures	Mean	199.34
	Min	-226.94
	Q1	68.17
	Q2	161.95
	Q3	306.75
Dispersion Measures	Max	828.00
	Amplitude	1054.93
	Amplitude interquartiles	238.58
	Variance	27908.85
Skewness Measure	Standard deviation	167.06
	Pearson's moment coefficient of skewness	0.76
Tailedness Measure	Kurtosis	0.35

(b) Descriptive statistics.



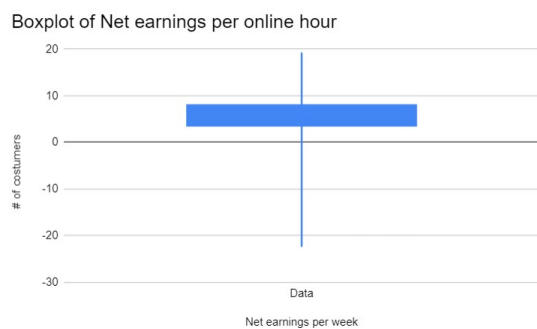
(c) Boxplot.

Figure E.1: Descriptive statistics for the “Net earnings per week” KPI.

(a) Histogram.

Location Measures	Mean	5.90
	Min	-22.39
	Q1	3.59
	Q2	5.33
	Q3	7.98
Dispersion Measures	Max	19.26
	Amplitude	41.65
	Amplitude interquartiles	4.39
	Variance	21.21
Skewness Measure	Standard deviation	4.61
	Pearson's moment coefficient of skewness	-1.03
Tailedness Measure	Kurtosis	8.26

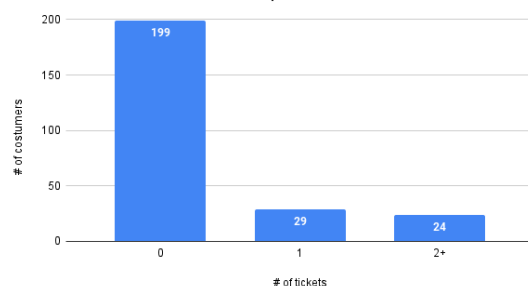
(b) Descriptive statistics.



(c) Boxplot.

Figure E.2: Descriptive statistics for the “Net earnings per online hour” KPI.

Number of tickets or calls - complaint



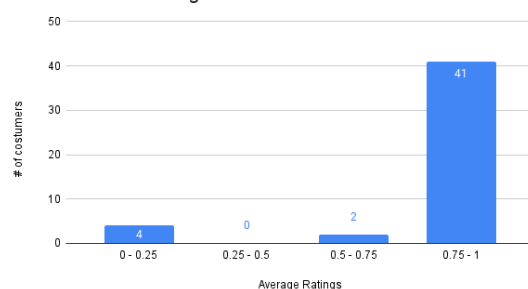
(a) Bar chart.

Number of tickets - complaint	Ordinal Scale	No.	%	
0	1	199	78.97%	
1	2	29	11.51%	
2+	3	24	9.52%	
Median	0			
Total			252	100.00%

(b) Descriptive statistics.

Figure E.3: Descriptive statistics for the “Number of tickets and calls - complaint” KPI.

Ticket and Calls Rating



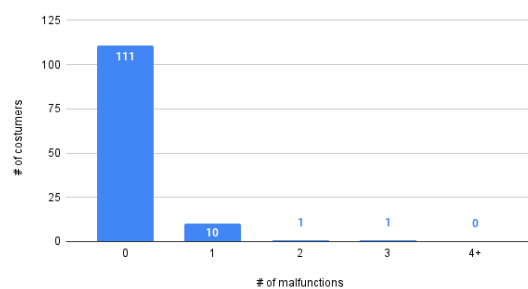
(a) Bar chart.

Location Measures	Mean	0.90
	Min	0.00
	Q1	1.00
	Q2	1.00
	Q3	1.00
	Max	1.00
Dispersion Measures	Amplitude	1.00
	Amplitude interquartiles	0.00
	Variance	0.08
	Standard deviation	0.29
Skewness Measure	Pearson's moment coefficient of skewness	-2.76
Tailedness Measure	Kurtosis	6.31

(b) Descriptive statistics.

Figure E.4: Descriptive statistics for the “Ticket and call rating” KPI.

Number of malfunctions

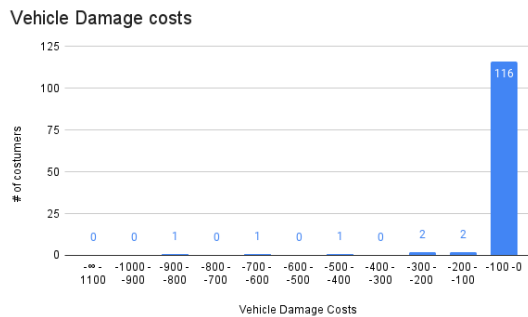


(a) Bar chart.

Number of calls - complaint	Ordinal Scale	No.	%	
0	1	111	90.24%	
1	2	10	8.13%	
2	3	1	0.81%	
3	4	1	0.81%	
4+	5	0	0.00%	
Median	0			
Total			123	100.00%

(b) Descriptive statistics.

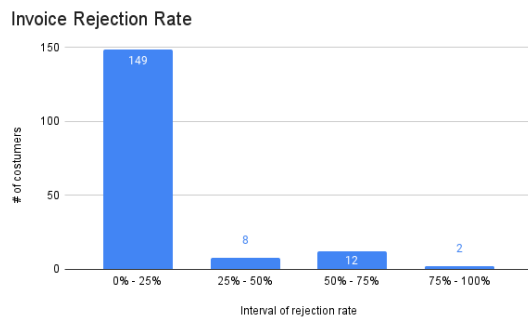
Figure E.5: Descriptive statistics for the “Number of Malfunctions” KPI.



(a) Bar chart.

Location Measures	Mean	-21.94
	Min	-868.00
	Q1	0.00
	Q2	0.00
	Q3	0.00
	Max	0.00
Dispersion Measures	Amplitude	868.00
	Amplitude interquartiles	0.00
	Variance	11547.50
	Standard deviation	107.46
Skewness Measure	Pearson's moment coefficient of skewness	-6.01
Tailedness Measure	Kurtosis	39.54

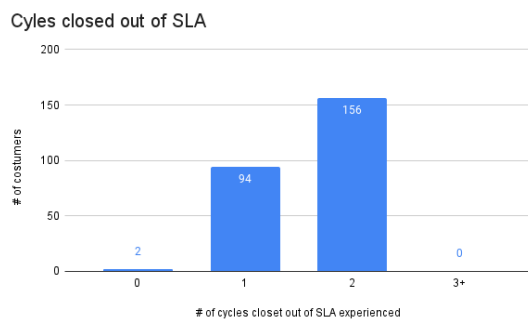
(b) Descriptive statistics.

Figure E.6: Descriptive statistics for the “Vehicle Damage Costs” KPI.

(a) Bar chart.

Location Measures	Mean	0.07
	Min	0.00
	Q1	0.00
	Q2	0.00
	Q3	0.00
	Max	0.80
Dispersion Measures	Amplitude	0.80
	Amplitude interquartiles	0.00
	Variance	0.03
	Standard deviation	0.18
Skewness Measure	Pearson's moment coefficient of skewness	2.62
Tailedness Measure	Kurtosis	5.87

(b) Descriptive statistics.

Figure E.7: Descriptive statistics for the “Invoice Rejection Rate” KPI.

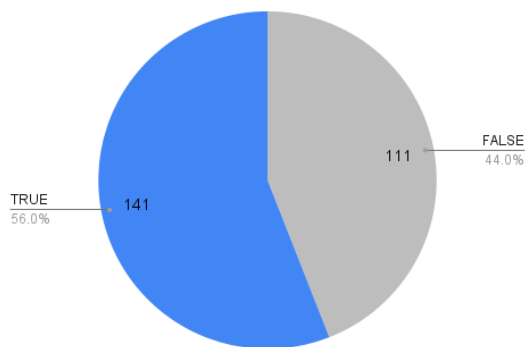
(a) Bar chart.

Cycles closed out of SLA	Ordinal Scale	No.	%
0	1	2	0.79%
1	2	94	37.30%
2	3	156	61.90%
3+	4	0	0.00%
Median	2		
Total	252		
	100.00%		

(b) Descriptive statistics.

Figure E.8: Descriptive statistics for the “Number of cycles closed out of SLA” KPI.

Rideshare



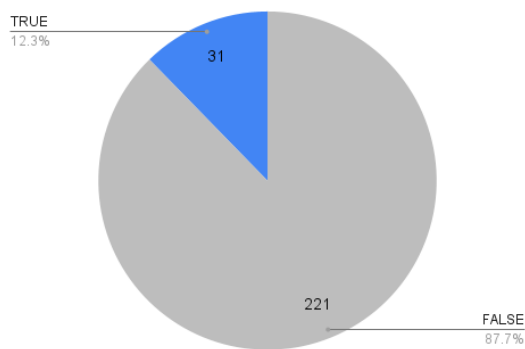
Rideshare Drivers	Nominal Scale	No.	%
TRUE	1	141	55.95%
FALSE	2	111	44.05%
Total		252	100.00%

(a) Pie chart.

(b) Descriptive statistics.

Figure E.9: Descriptive statistics for the “Rideshare” KPI.

Food Delivery



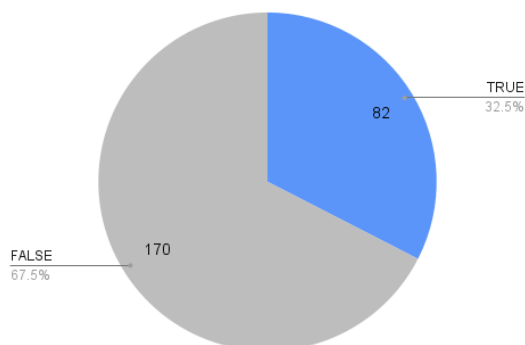
Food Delivery drivers	Nominal Scale	No.	%
TRUE	1	31	12.30%
FALSE	2	221	87.70%
Total		252	100.00%

(a) Pie chart.

(b) Descriptive statistics.

Figure E.10: Descriptive statistics for the “Food Delivery” KPI.

Shopping



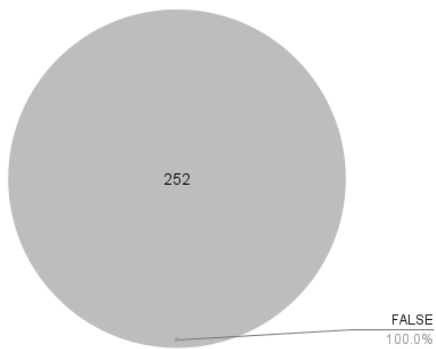
Shopping drivers	Nominal Scale	No.	%
TRUE	1	82	32.54%
FALSE	2	170	67.46%
Total		252	100.00%

(a) Pie chart.

(b) Descriptive statistics.

Figure E.11: Descriptive statistics for the “Shopping” KPI.

Courier



Courier drivers	Nominal Scale	No.	%
TRUE	1	0	0.00%
FALSE	2	252	100.00%
Total		252	100.00%

(a) Pie chart.

(b) Descriptive statistics.

Figure E.12: Descriptive statistics for the “Courier” KPI.

F Neural Network model code

```
# Authenticate in google drive
auth.authenticate_user()
creds, _ = default()
gc = gspread.authorize(creds)

# Mount drive for potential model saving/loading
drive.mount('/content/drive')

# Load data
spreadsheet=gc.open('DataSetTeste')
page=spreadsheet.get_worksheet(0)
dataset = pd.DataFrame(page.get_all_records())
```

Figure F.1: Code developed to load the dataset and create the dataframe.

```
# Pre-process data

# Remove outlier
dataset = dataset[dataset['ID'] != 11333]

# Normalize quantitative variables
scaler = MinMaxScaler()
quantitative_vars = ['Net_earnings_per_week', 'Ticket_and_call_rating', 'Vehicle_damage_costs', 'Invoice_rejection_rate', 'Net_earnings_per_online_hour']
dataset[quantitative_vars] = scaler.fit_transform(dataset[quantitative_vars])

# Split the dataset into input and output
x = dataset.drop(['ID', 'NPS Value', 'NPS Category', 'Courier'], axis=1)
y = dataset['NPS Category'].apply(lambda x: int(x)).values
```

Figure F.2: Code developed for the pre-processing task.

```
# Model definition
created_model = tf.keras.models.Sequential()
created_model.add(tf.keras.layers.Dense(units=64, activation='tanh', input_dim=len(x.columns)))
created_model.add(tf.keras.layers.Dense(units=64, activation='tanh'))
created_model.add(tf.keras.layers.Dense(units=3, activation='softmax'))
```

Figure F.3: Code developed for the architecture of the model.

```
#Training

#Model Compilation
created_model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

#Split the dataset into training and testing
seed=42
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=.2,stratify=y, random_state=seed)

# Train the model
created_model.fit(x_train, y_train, epochs=500, batch_size=len(x_train), verbose=0)
```

Figure F.4: Code developed for the training of the model.

```
#Evaluate the model's precision
train_loss, train_acc = created_model.evaluate(x_train, y_train, verbose=0)
test_loss, test_acc = created_model.evaluate(x_test, y_test, verbose=0)

# Use model to predict test's real values
y_test_hat = created_model.predict(x_test)
y_test_hat = [np.argmax(val) for val in y_test_hat]

# Calculate F1 score
f1 = f1_score(y_test, y_test_hat, average='weighted')

# Print the evaluation metrics
print(f"\nTraining accuracy: {int(train_acc*100)}%, Test accuracy: {int(test_acc*100)}%, F1 score: {int(f1*100)}%")

# Print test's predicted and real values
print(np.array(y_test_hat))
print(y_test)
```

Figure F.5: Code developed for evaluating the model.

```
#Model Saving

path = '/content/drive/Shareddrives/Community Operations/Customer Success/Tese António Saraiva/4. Tensorflow code/Modelos guardados/Model with '
+str(int(round(test_acc*100,0)))+ ' test accuracy and '+str(int(round(f1*100,0)))+ ' f1 score.hdf5'
user_input=input('Are you sure you want to save? Enter Y if so, or anything else if not ')
if (user_input.upper()=='Y'):
    created_model.save(path)
```

Figure F.6: Code developed for model saving.

```
# Load model
loaded_model = tf.keras.models.load_model('/content/drive/Shareddrives/Community Operations/Customer Success/Tese António Saraiva/4.
Tensorflow code/Modelos guardados/Model with '+str(77)+' test accuracy and '+str(72)+' f1 score.hdf5')
```

Figure F.7: Code developed for model loading.