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Service Failures, Recovery, and Repurchase Intent: Understanding Customer Satisfaction Dynamics

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Declaration of Independent Work

I hereby declare that this thesis entitled 'Service Failures, Recovery, and Repurchase Intent: Understanding Customer Satisfaction Dynamics' is the result of my own independent research work, conducted under the supervision of Prof. Faußer and Mr. Knapp. All sources of information used in the preparation of this thesis have been duly acknowledged. No part of this thesis has been submitted for any other degree or qualification.

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Abstract

This paper aims to perform analysis on service failures impact on three components of customer satisfaction. Thesis concentrate of three major service failure i.e. severity of failure, repeated failure, and unresolved failure in Heavy machinery industry. It also seeks to evaluate how effectively service recovery can address dissatisfaction resulting from these failures. Additionally, study extended the analysis on predicting customer repurchase intention based on prior customer satisfaction of product, dealer and brand experience. It delves into predictive modeling using decision trees to identify key influencers, including product, brand, and dealer experiences. The findings provide valuable insights into service management theory and practical approach by highlighting the vital role of service recovery strategies in maintaining customer satisfaction and encouraging repurchase intention. The study employs a mixed sequential method, incorporating qualitative and quantitative analyses. Quantitative data are collected through customer survey responses, while qualitative insights are derived from interviews. The thesis concludes that while service failure directly impacts customer satisfaction in the heavy machinery manufacturing industry, while more than fast service recovery may be required for long-term satisfaction. Brand experience significantly influences customer repurchase intention, with dealer engagement also being crucial. The findings emphasize the necessity of ongoing service improvement initiatives and the role of dealer involvement in building customer repurchase intention in heavy machinery.

Keywords: service failures, service recovery, customer satisfaction, repurchase intention, heavy machinery manufacturing

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1 Introduction

The first chapter introduces the thesis subject, providing the background information of failure to recovery and further background of customer satisfaction and future intention of buying the same brand The objectives and motivation of the thesis are then discussed in greater detail in the following problem discussion. The chapter also covers the research questions and introduces the Company.

1.1 Theoretical Background

Customer service is a significant concern for all industries, regardless of their business (Liao, 2007). Previous studies have explored the concern of failures to provide acceptable recovery in different industries and also paid attention to the value of a satisfied customers by Liao, 2007; Riscinto-Kozub, 2008; Hess Jr., Ganesan and Klein, 2003; Sousa and Christopher A. Voss, 2009.

After carefully going over these academics and presenting a range of views and research findings from earlier projects, this study attempts to synthesize and critically examine various research by carefully reviewing these academic contributions. By doing so, it aims to explain how these factors interact in the current evaluation context. Identifying the variables impacting consumer satisfaction and repurchase intention has thus received increasing focus in the study. Prioritizing the reasons for customer dissatisfaction is necessary to achieve customer satisfaction. Service failure is among the most common causes, regardless of the industry. These failures comprise three distinct variables: severity of failure, repeated failure, and unresolved failure. Such failures can range from minor nuisances to substantial interruptions in service delivery, with repercussions extending far beyond the initial interaction. Unsatisfactory service poses a severe problem, potentially causing consumer dissatisfaction and damaging lasting brand relationships. Understanding the major concern of failure, recovery after failure and customer experience is essential. Particularly, where immediate feedback, such as heavy machinery manufacturing, may not be readily available.

1.2 Motivation

In today's competitive business world, companies in every industry, including heavy machinery manufacturing, understand the importance of keeping customers satisfied for lifetime. However, it is more crucial to have in Heavy machinery sector. Even though companies focus more on customers, they still need help fixing problems and making customers satisfied again. This thesis is driven by the urgent need to address these issues and better understand the dynamics between failure, service recovery, customer happiness, and repurchase intention within the heavy machinery manufacturing industry. Effectively managing service failures and providing outstanding customer experiences has become crucial. This motivation came from recognizing significant gaps in the current literature regarding service management practices in heavy machinery manufacturing. Heavy machinery has received less attention in service difficulties studies than other sectors. This gap offers an opportunity to provide extended perspectives and bridge the knowledge gap. Furthermore, manufacturing heavy machinery necessitates reevaluating traditional service management techniques due to the rapid advancements in technology and the evolving demands of customers. This thesis explores the variables affecting customer satisfaction and repurchasing the product, offers actionable insights to guide strategic decision-making, and enhances organizational performance in this highly competitive market. This thesis is motivated by the need to fill crucial gaps in understanding service issues, recovery, customer satisfaction, and repeat purchases within heavy machinery manufacturing. The study's geographic focus will be mainly on a particular area or market segment within the heavy machinery manufacturing sector, ensuring a targeted and detailed analysis of relevant factors and dynamics. Through thorough research and analysis, this study aims to reveal practical insights to improve service management, build better customer connections, and sustain growth in today's competitive business environment.

1.3 Problem definition

In today's ever-changing business environment, organizations across different sectors must prioritize maintaining high customer satisfaction levels to ensure long-term success. However, despite the increasing focus on customer-centric strategies, businesses need help managing service failures and recoveries, particularly in sectors characterized by complex service processes and longer product lifecycles. This section outlines the major problems and areas that require further investigation, which makes the current study essential. Despite the increasing number of studies on service issues and customer happiness, a notable gap exists in how these things work in the heavy machinery business. While traditional service recovery strategies have been extensively studied in various service sectors, their applicability and effectiveness in addressing service failures in industries characterized by longer product lifecycles and complex service processes still need to be explored. Furthermore, the study needs to explore more into on the how customer repurchasing intention getting influence by level of customer satisfaction in past experience. Particularly regarding the unique components of customer satisfaction, such as dealer experience, product experience, and brand experience. Therefore, this study explores the gap, how service problems, fixing those problems, and keeping customers happy affect whether they will buy again in the heavy machinery industry. It also looks into how quickly fixing problems can make customers happier and help businesses succeed in the long run.

1.4 Research Question

The following research questions provide a structured framework for examining how service failure, fixing those failures, and keeping customers satisfied impact whether they will buy again in the heavy machinery manufacturing industry:

1. How do service failures over three years impact customer satisfaction in heavy machinery manufacturing, considering dealer interactions, product usage, and brand experiences?
   1.1 To what extent does service recovery mitigate the negative impact of service failures?
2. How does customer satisfaction (dealer, product, and brand experiences) influence customer repurchase intention in heavy machinery manufacturing?

1.5 About Company

John Deere, formally known as Deere & Company, is an American corporation founded in 1837 by blacksmith John Deere. The Company is heavily involved in the construction and agricultural industries and specializes in manufacturing power systems, forestry, construction, and agricultural machines. John Deere transformed agriculture by developing the self-scouring Steel Plow, which set the stage for the Company's ongoing achievement and innovation. The Company continues to be among the foremost agricultural equipment manufacturers worldwide, offering top-notch products and services to customers in several nations. The agricultural equipment offered by John Deere is designed according to the demands of modern farming. John Deere assures that farmers have access to the equipment required for effective crop production, ranging from versatile tractors - which includes compact utility tractors and high-horsepower row-crop tractors - to a wide range of harvesting tools, such as combines, grain and cotton headers, and for- age harvesting machinery. The equipment used for planting and seeding, which includes air seeding systems, planters, and seed drills, emphasizes the Company's dedication to improving agricultural practices by offering further assistance in improving the planting process. Some key milestones in the Company's history include the introduction of tractors, combines, sprayers, and other machinery. John Deere, Inc.'s extensive range of products is committed to providing farmers and agribusinesses with cutting-edge machinery, precision agriculture technology, and integrated solutions covering the whole production cycle. These products, which reflect the business's long history and continuous commitment to quality, are still essential to the development and productivity of the forestry, construction, agricultural, and turf care sectors. The business's commitment to growth is illustrated by its ongoing developments in automation and precision agriculture technologies, such as satellite-guided navigation, remote management software, and data analytics.

Having recognized the importance of customer support in agriculture, John Deere established John Deere customer support. As a business division within Deere & Company, John Deere customer supports a wide range of service solutions to customers, from asking for survey feedback to helping dealers solve failures. Its vision is to provide the best customer experience and make customers satisfied. The customer support team maintains a proactive stance to understand and adapt to customer requirements for the duration of products, starting the journey after the sale. The top focus is recognizing the value of first-hand customer feedback regarding their experiences with products. To do this, conduct the surveys at two crucial points: six and thirty-six months after the purchase. These surveys are essential points of contact to know how satisfied customers are, what needs to be improved, and how best to provide help regarding product, dealer, and brand experience. After gathering customer feedback, use an integrated approach and communicate with them directly through mail and the postal service to ensure their opinions are heard. In addition, the support team works closely with a network of dealers, who act as crucial intermediaries between customer and brand. Utilizing dealer insights and promoting open communication provides a better understanding of consumer preferences and issues. When service failures arise, a quick response support system comes in. Minor issues are swiftly addressed by dealers, who possess the expertise to rectify concerns promptly. Concurrently, facilitate the resolution process by providing dealers with the necessary support and resources. For more complex technical challenges, a specialized technical team steps in to diagnose and solve the situation expediently. Furthermore, prioritizing the distribution of information through focused dealer training programs would ensure that experts are prepared to manage unforeseen circumstances correctly in the future. The core objective has consistently been cultivating exceptional customer retention and satisfaction throughout this endeavor. The Department of Customer Support is working to strengthen the John Deere brand.

1.6 Methodology: Sequential Mix-Method

When developing the sequential mixed methods methodology, Inspiration was drawn from notable scholars such as (Cameron, 2009; Lopez-Fernandez and Molina-Azorin, 2011; Desjarlais, 2023). This methodology represents the QUAN (quantitative) and QUAL (qualitative) analysis. Mixed methods design offers a comprehensive data collection and analysis approach by incorporating quantitative and qualitative techniques within a single research framework. Scholars such as (Cameron, 2009) have proposed various typologies within mixed methods research, demonstrating the versatility and applicability of this methodology. The sequential mixed methods approach aligns with a more in-depth examination of the study issue, as it bases the research questions for later stages on the conclusions of earlier ones. This methodology typically involves an initial phase characterized by analysis of quantitative data.

Phase 1

Quantitative Analysis

Utilizing data from each variable, we aim to assess how service failures affect customer satisfaction, Moderating effect of recovery of speed and customer willingness to buy again same brand. We also looked into how service failure affects customer satisfaction. We collected quantitative data through customer surveys and claims data using SQL and Databricks. The survey items were scaled from 1 to 10 and focused on three composite variables: product, dealer, and brand experience. Service failure data from customer claims included three distinct variables: severity of failure, Repeated failure, and Unresolved failure. Quantitative Analysis was performed in two stages:

Stage 1: Direct Impact Analysis:

- Hypothesis Formulation and testing for direct impact analysis

Stage 1: Repurchase Intention Analysis and Prediction:

- Using logistic regression and decision tree models

Phase 2

Qualitative Analysis

In the qualitative phase, we utilized interviews to gain insights into the significance of certain external and
internal factors tested in the initial phase. This was aimed at enhancing the solidity of the quantitative results and obtaining perspectives from individuals closely involved with these variables. The phase involved in-depth data collection from multiple sources through interviews with various individuals, enriching our understanding through diverse perspectives.

Implementation**:** In quantitative phase, perform the statistical analysis to get insight about the collected information and answered the research questions. The study's goal and the research questions guide deciding whether to proceed in this order, especially when looking for contextual explanations for statistical data. The requirement for contextual explanations rooted in the field for the results observed during the quantitative phase influences the sequencing decision.

Integration: On this stage of research, result have analyzed in both phase of analysis. Reviewing both result and performing analysis on the more insightful information about finding and providing disparity and similarity of both analyses. The integration allows for a comprehensive and connected approach to analyzing quantitative and qualitative findings.

Conclusion: To conclude, the sequential mixed methods research methodology typically demonstrates areas of integration through integrating data from qualitative and quantitative studies, strengthening core ideas acquired from diverse perspectives. Combining qualitative and quantitative data validates common findings and promotes a more profound comprehension of the intricacies of the study field. To provide a more detailed view of the sequential mixed methods research design, shown in Figure 1.

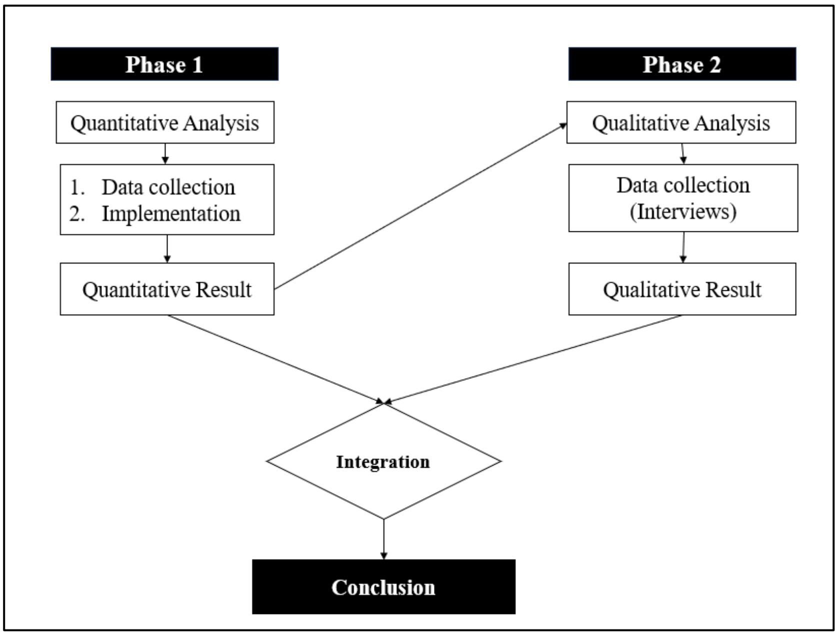

Figure 1: Sequential Mix-Method Diagram

2 Literature Review

The literature thoroughly investigates customer satisfaction, re-purchase intention, service failure, and recovery in a variety of businesses, offering diverse perspectives and insights. We have gathered insights from various researchers who have explored similar topics. The analysis of how service failures and their subsequent recovery efforts affect customer satisfaction is conducted by Hess Jr., Ganesan and Klein, 2003. The psychological factors influencing these expectations are also explored by Amy K Smith, Bolton and Wagner, 1999. Customer experiences are significantly impacted by recovery initiatives, recovery as the level of expectation has noticeable effect on customer experience (Liao, 2007). Sousa and Christopher A Voss, 2009 purposed the relationship value between satisfied customer and service recovery, who proposed theories demonstrating how customer loyalty intentions are negatively impacted by poor service, failure resolution, recovery, and satisfaction. Moreover, customers' actions in response to recovery initiatives, as shown by Wirtz and Mattila, 2004. *Service recovery* is an effort made by a service provider to fix the issue that caused with failure Sheth, Sisodia and Sharma, 2000. Furthermore, satisfaction with service recovery, which includes aspects like compensation, speed of recovery, and apologies, is the only component that mediates repurchase intentions and other behavioral intents (Sousa and Christopher A. Voss, 2009).

Comprehensive Overview

The importance of providing continuous and personalized services to customers has been recognized in the manufacturing industry (Gebauer *et al.*, 2010), leading to the addition of new services such as after-sale contact and committed customer support to improve long-term customer advantages (Baines et al., 2013; Gebauer et al., 2010). When customers attribute service failures to the service provider rather than themselves, their satisfaction ratings notably decrease (Mattila, 1999). This suggests that customers hold the service provider responsible for shortcomings, leading to a detrimental effect on their overall satisfaction.

Furthermore, it has been acknowledged that effective service recovery strategies are critical to improve customer satisfaction and establishing lasting relationships in the heavy machinery industry (Nunes, Abi-Saab and Ralisch, 2017). It significantly enhances a firm's performance and customer satisfaction (Calma *et al.*, 2020). Previous study also explored how service quality influences customer loyalty following such failures. Similar efforts have been made in the service marketing industry, spanning business-to-business (B2B) and business-to-consumer (B2C) sectors. Regardless of the industry, customer satisfaction has become intricately linked to service recovery (Kau and Wan-Yiun Loh, 2006). Customers suffer financial, energy, time, physical, and psychological consequences when services fail in the ever-changing field of service marketing (Hoffman and Kelley, 2000). The outcome varied from recovery strategies such as replacements, cash reimbursements, speedy recovery, and apology. When customers receive compensation for a service failure, regardless of the type, they are typically more satisfied than when receiving replacements (Amy K Smith, Bolton and Wagner, 1999). Extending this narrative, Lee et al., 2016 emphasized that a firm's willingness to recover from a failure and prevent recurrence can significantly enhance customer satisfaction. This positive approach often results in favorable word-of-mouth, loyalty, and high customer trust whereas unsuccessful recovery may trigger harmful behavioral intentions, including negative word-of-mouth and discontinued purchases or subscriptions to the service (Kau and Wan-Yiun Loh, 2006). Conversely, unsuccessful recovery may trigger harmful behavioral intentions, including negative word-of-mouth and discontinued purchases or subscriptions to the service (Oliver, 1999). To gain deeper insights into customer experiences, it becomes crucial to understand the timeline of surveys and when customers may offer precise experience feedback (Lemon and Verhoef, 2016). Oliver, 1999 introduced the four forms of loyalty: cognitive, emotional, conative, and action. Cognitive loyalty, rooted in prior experiences and information available to consumers, built the higher expectations to the service quality (Cadotte, Woodruff and Jenkins, 1987). Thus, understanding of detrimental effect of service failure, providing expected recovery, and level of satisfaction with experience becomes significant for businesses that foster customer loyalty and trust.

2.1 Service Failure

Service failure is an inevitable concern within enterprise services, which cannot be entirely avoided (Bailey, 1994;Smith, Bolton and Wagner, 1999). Despite firm aims to provide flawless service, the specific nature of service makes it nearly impossible to eliminate failures (Michel and Meuter, 2008). The interaction between firms and customers based on encountered service failures has been studied in past research. When customer's expectations is higher than what they receiving in service, it is also come up as service failure (Hoffman and Kelley, 2000). It is an incident during service delivery that results in customers experiencing loss and dissatisfaction (Amy K. Smith, Bolton and Wagner, 1999; Maxham, 2001b). Customer interactions with businesses and their service providers inherently include service failure, described as a direct, unpleasant experience with a brand (Amy K Smith, Bolton and Wagner, 1999). These failures can take various forms, influencing customer satisfaction and shaping their overall perception of the brand. The significant impact of improper responses to a service failure increases negative customers experience (Weun, Beatty and Jones, 2004a). Customers' perception of the seriousness of service failures is crucial; when an evident and unacceptable service failure arises, customers anticipate prompt corrective action (Chang, Fang and Huang, 2016). Service failure is viewed as a major memory that might eventually cause a relationship to end (Aaker, Fournier and Brasel, 2004; Sajtos, Brodie and Whittome, 2010). An unsatisfactory level of service affects not just the customer's satisfaction but also the established value evaluation of the entire relationship. When customers and service providers interact, the results of a service failure become crucial in forming their ongoing relationship (Homburg and Fürst, 2005). As a result, service failure is a significant factor leading to customers considering a switch in their service provide (McCullough, 2000). Service failures categorized into two main types: outcome and process failure (Bitner, 1992). Outcome failure involves issues like service unavailability or not meeting basic customer expectations. In contrast, process failure relates to a drop in the quality-of-service delivery, leading to a perception of lower service quality (Bitner, 1992). This simple categorization aids in our comprehension of service failure as a breakdown in service, regardless of whether it is the result of failing to meet expectations or a decline in the quality of service provided.

2.1.1 Impact of Service Failure

Direct Impact of Service Failure

Service failure impact is explored through numerous research, offering comprehensive insights into it is influence on customer behavior and the overall success of organizations. This intricate scenario involves multiple aspects such as attributions, behavioral intentions, deterioration of trust, disconfirmation, recovery, and customer retention. Each element is shaped by the complex dynamics of how customers perceive and interact with a service provider. Research has consistently demonstrated that customers' attributions about encountered failures significantly influence their attitudes and behavioral intentions toward the firm (Folkes, Koletsky and Graham, 1987; Bitner, 1992). Building on this basis, these explanations are formed by the quantity of most recent interactions with the company and the quality of previous service delivery (Bitner, 1992). Consequently, these attributions have a significant effect on customer (Hess, Ganesan and Klein, 2003). The disconfirmation of service expectations occurs when trust a critical primary factor between the customer and dealer, is compromised (Colgate and Norris, 2001). Loyalty and retention tend to be higher when there are no significant negative incidents with the service provider (Smith and Colgate, 2007). This realization changes the narrative by emphasizing how sensitive consumers are to the nuances of service delivery. Even after a positive Service recovery experience, service failure can cause a decline in trust, which is a sign of a reduction in customers(Ranaweera and Prabhu, 2003). The threat of failure might upset the balance between customers and service providers (Hess, Ganesan and Klein, 2003). In service Failure, where trust is at stake and customer satisfaction depends on attribution, the impact of each type of failure is central, shaping the complex dynamics of customer behavior and company success (Sivakumar, Li and Dong, 2014).

Across Industries

Customers perceive Service failures differently based on their characteristics and intensity (Liao, 2007). The heavy machinery industry (HMI) has been highlighted by Gebauer et al., 2010, within the broader domain of service failures. Study revealed that challenges such as delayed maintenance or insufficient after-sales support in the HMI have far-reaching effects beyond immediate customer dissatisfaction. According to their research, an unexpected effect occurs, impacting financial and customer-supplier relationships and causing negative impacts on overall customer satisfaction (Gebauer *et al.*, 2010). Further emphasized financial insights specific to HMI, consequences beyond the cost of repairs, such as indirect expenses incurred due to machine downtimes, which contribute significantly to heightened dissatisfaction among heavy machinery consumers (Karatepe and Ekiz, 2004). Adding a relational perspective, the service failures affect the bond between customer-supplier relationships and the broader stakeholder ecosystem in the industry (Oly Ndubisi, 2007). Adding a psychological layer to the discussion, the study emphasizes how long-lasting service disruptions may be. Severe failures can lead to long-lasting negative perceptions and attitudes (Harris et al., 2006; Kristen et al., 2014). After recognizing these difficulties, creating recovery strategies becomes essential, mainly when dealing with the particular with HMI experiences. From an industry-to-industry perspective, the impacts of service failures take on distinct forms. Across businesses, each has its unique traits and customers' expectations. Factors like magnitude of failure, prompt recovery, unresolved failure, and repeated failures significantly impact customer responses.

Additionally, customer reactions to a service failure, including their expectations of justice and fairness, forgiveness, and recovery satisfaction, significantly affect overall satisfaction and future behavior (Kazi and Prabhu, 2016). In retail banking, dissatisfaction with a service or service provider is considered the significance of service failure on consumer experience with all factors (Lewis and Spyrakopoulos, 2001;Meuter et al., 2000. Service failures in the commercial banking sector are illuminated by the research of PAI, KO and SANTOS, 2019. They categorize these failures into two categories: core service failure and policy-related issues, resulting in consequences ranging from customer dissatisfaction to encompassing financial losses, increased costs, and negative WOM. Similar concepts are applied across industries by the study of Amy K. Smith, Bolton and Wagner, 1999, distinguishing between outcome-related failures, where basic needs or core services are unmet, and process-related failures, characterized by flawed service delivery. Egyptian hotels also examined service failure (Taleb and Kamar, 2013), identifying common problems such as product or service defects, low or unavailable service, and employee behavior issues. Notably, improper employee responses to service delivery systems significantly cause service failures. The Airline Industry, where customer reaction rise immediately in that scenario, handling issue with respect and providing quick recovery as soon as possible actions can have high value of customer experience and touching the emotional level of customer behaviour, therefore it assures the reliability, high trust factor and significant customer feedback (Xu, Liu and Gursoy, 2019). Satisfying customers is the most critical element in any industry, whether retail, banking, hotels, airlines, telecoms, or heavy machinery. Effective recovery tactics is vital to keep strong customers relation as well as benefit the business. Service failures have unique and significant implications across various industries, with distinctive challenges in heavy machinery manufacturing. In heavy machinery, service failures extend beyond immediate customer dissatisfaction, disrupting interconnected supply chains, collaborative projects, and stakeholder relationships. Delays in maintenance or insufficient after-sales support contribute to broader repercussions, intensifying the negative impact on overall customer satisfaction. Comparatively, in the broader context, industries like commercial banking, restaurants, hotels, airlines, and telecom face diverse consequences of service failures.

2.2 Service Recovery

Service recovery refers to the compensation of service breakdown or interruption which the service provider avail to mitigate the adverse effect on the brand or service. (Seawright *et al.*, 2008). It is considered a comprehensive approach to rectifying mistakes and regaining the customer trust (Battaglia et al., 2012). Service recovery aims to address issues at the service interaction point before customers become dissatisfied or decide to terminate the service encounter (Van Vaerenbergh, Larivière and Vermeir, 2012). Service recovery is setting up measures to ensure that customers receive a suitable level of care if standard service is disrupted. It includes many different things, such as level of effect communication with customer, at first initial service is unsatisfactory, the supplier's reaction to the insufficient service, and the objective of turning dissatisfied customers into satisfied ones (C. Colin Armistead, 1995). A well-functioning service recovery system should identify and resolve issues, mitigate dissatisfaction, and be structured to facilitate the lodging of complaints (Devaraj, Matta and Conlon, 2001a). Service failure and recovery are popular topics in service management, with companies attempting to regain customer trust through various mean of recovery (Amy K. Smith, Bolton and Wagner, 1999). Strategized recovery action the need for a methodical approach to address customer complaints and dissatisfaction. It is a meticulously planned strategy to win back satisfied consumers following a service or product dissatisfaction (Seawright *et al.*, 2008). Additionally, service recovery facilitates tracking failures, contributing to databases that offer insights for dealing with and preventing future failures (Kuo *et al.*, 2013). However, it is crucial to recognize that service recovery may not be a universal solution in every situation, as long recovery times can lead to negative consequences (Van Vaerenbergh *et al.*, 2019). Satisfaction with the recovery effort is crucial for customer attitudes and behavior and effective service recovery results in heightened customer satisfaction and positive behaviors (Duffy, Miller and Bexley, 2006). Service recovery is recognized as essential for maintaining customer-firm relationships and as a proactive response to service failure (Weun, Beatty and Jones, 2004a; Homburg and Fürst, 2005). Service providers' exceptional service performance requires particular provider behavior and shows the action taken by service provider while delivering service (Wirtz and Mattila, 2004; Battaglia *et al.*, 2012). The actions and communication of service providers in addressing customer complaints, which is the foundation of service recovery performance, have a direct influence on customer satisfaction and repurchase intent (Liao, 2007).

2.2.1 Impact of Effective Service Recovery

Across all industries, the speed of recovery actions is vital. Swift responses to service failures and continuous communication are vital for mitigating the negative effects of problems, prompt recognition and resolution positively influence customers' impressions (Smith, Karwan and Markland, 2012)**.** Service recovery commonly include payback and apology, while an apology plays a role in social and psychological healing, compensation, such as discounts or refunds, addresses financial service shortcomings (Weun, Beatty and Jones, 2004b; Battaglia *et al.*, 2012). service recovery behaviors directly impact customer perceptions, communication, empathy, and apology facilitate a practical service recovery experience; building databases and learning from service failures can help prevent future failures (Hoffman and Kelley, 2000).

Service Recovery Across Industries

In the heavy machinery industry, Service recovery has favourable effect and mitigating unfavorable outcomes, such as negative word of mouth and reduced recovery satisfaction levels (Van Vaerenbergh *et al.*, 2019). Effective service recovery positively influences customer trust and loyalty, with quick and efficient recovery procedures capable of minimizing the detrimental effects of service failures (Hogreve *et al.*, 2017) . The critical importance of prompt and timely recovery actions is acknowledged, particularly concerning the financial implications of downtime and operational disruptions in heavy machinery (Hays and Hill, 2001). The significance of understanding customer expectations suggests that aligning recovery strategies with these expectations is essential for effective service recovery (Hogreve *et al.*, 2017). Meeting customer expectations through recovery efforts significantly enhances satisfaction (Xu, Liu and Gursoy, 2019). The crucial role of prompt and satisfactory service recovery actions is consistently highlighted in various industries, as research conducted by (Amy K Smith, Bolton and Wagner, 1999; Xu, Liu and Gursoy, 2019). Positive employee attitude and quick recovery efforts in the airline industry contribute to more positive customer, while efficient issue resolution significantly impacts customer loyalty and satisfaction in the hotel industry(Smith and Colgate, 2007; Xu, Liu and Gursoy, 2019). Furthermore, various contexts, including continuous communication and satisfactory compensation as part of recovery procedures, positively influence customer perceptions of quality of service and future consumption behavior (Van Vaerenbergh *et al.*, 2019). The collective findings of this research highlight the widespread significance of efficient service recovery tactics in improving customer experiences and establishing lasting relationships.

2.3 Customer Satisfaction

Customer satisfaction with service recovery directly impacts whether service providers are suggested and repurchased (Lewis and McCann, 2004). Customer satisfaction after recovery, defined as the emotional and psychological reaction of the customer, is determined by their subjective assessment of the overall service performance after the efforts made by the organization to rectify the situation (Bitner and Hubbert, 1994; Oliver, 1999). Service providers give service recovery much attention because loyal customers can boost revenues through increased sales and word-of-mouth referrals (Cranage, 2004). Service quality has been positioned within the larger context of customer satisfaction that includes cognitive and affective evaluations (Zeithaml, 1988; Bowden, 2009). Customer satisfaction is determined by customers magnitude of satisfaction with the product or service and depends on whether the purchaser's desires were fulfilled or exceeded (Oliver, 1999). Future purchase intention is significantly predicted by customer satisfaction, attained when the expected quality standard is met or exceeded (Mittal and Kamakura, 2001). High (low) levels of repurchasing intention are typically correlated with high (high) levels of customer satisfaction (Hellier *et al.*, 2003a; Chang, Fang and Huang, 2016). Organizations need to understand the nuances of consumer perceptions to ensure satisfaction (Tešić and Bogetić, 2022). customer satisfaction greatly influences behavior, partially based on prior experiences (Cadotte, Woodruff and Jenkins, 1987). According to perspective theory, these experiences significantly impact customers during service failures (Kahneman and Tversky, 1979). Customer satisfaction has a nuanced effect on behavior; while it is essential to businesses, it also has a positive financial impact when associated with loyalty (Oliver, 1999). Satisfied customers are highlighted as having high satisfaction levels, which is associated with a greater chance of repeat business and a closer bond with company and service provider (Boll, 2010).

Customer loyalty with satisfaction

Customer loyalty is determined by factors such as customer happiness (Fornell, 1992). Previous studies by Zeithaml, 1988; Cronin and Taylor, 1992; Taylor and Baker, 1994 evidently shown the deeper connection between loyalty and consumer satisfaction. However, researchers like Szymanski and Henard, 2001 raised doubt about this correlation. The challenges highlight that loyalty may only sometimes be determined by customer satisfaction. This is demonstrated by the fact that happy customers may decide to transfer providers, while unhappy customers may, on the other hand, show loyalty in certain situations. Furthermore, Bowen and Chen, 2001 illustrated the asymmetric and nonlinear link between customer happiness and loyalty. According to their argument, loyalty can be exhibited even in the face of dissatisfaction, especially when few options are available. Despite this, there is a greater likelihood that satisfied customers will eventually become loyal, even if they delay showing loyalty or making additional purchases. Loyalty analysis explores attitudinal and behavioral aspects of loyalty (Chiu *et al.*, 2009). Exploring the domain of customer loyalty, it is clarified that two essential components are behavioral loyalty, demonstrated by recurring transactions, and attitudinal loyalty, which reflects intentions regarding future behavior (Kuo *et al.*, 2013) . Additionally, experience positively affects users' views and as a result their level of fulfillment. Customers with more experience shop online with a positive attitude and appreciate it more than those with less expertise (Endo, Yang and Park, 2012).

2.4 Repurchase Intention

Consistent brand purchases are the outcome, even with the possible influence of situational factors and promotions brand switching (Giovanis, Athanasopoulou and Tsoukatos, 2015). There are two types of customer loyalty: attitudinal and behavioral (Chiu *et al.*, 2013). Attitude-based and behavior-based loyalty are the two categories (Chiu *et al.*, 2013). Intentional loyalty mostly shows behavioral loyalty because it is impossible to observe behavior in qualitative research (Jones and Taylor, 2007). Conversely, attitudinal loyalty expresses consumers' attitudes toward specific products or service (Bennett and Rundle-Thiele, 2002). This study explored behavioral loyalty more to understand customer repurchase intention. Repurchase intention is a person's choice to use a specific service again or buy a product from the same brand again (Hellier *et al.*, 2003b). Building and maintaining customer loyalty requires organizations to be able to deliver exceptional value to their customers and be committed to maintaining strong connections with them (Varga, Dlačić and Vujičić, 2014). Consequently, Firms should encourage dedication and favorable reviews of the product to increase consumers' propensity to buy (Varga, Dlačić and Vujičić, 2014). They acknowledge that customers' intentions to repurchase help to create more effective business strategies, and heavy machinery manufacturers must set the foundation by defining customer loyalty by recommending the business to others and making repeat purchases (Heskett, Sasser and Schlesinger, 2003). From a psychological perspective, *customer loyalty* is defined as a way of thinking characterized by positive attitudes toward a business, a desire to use the company's goods or services again, and a propensity to refer them to others (Pearson, 1996). consumer loyalty is the strong desire to continue purchasing a favored good or service; it is also the tendency of the consumer to regularly select a certain good or service for a specific need (Oliver, 1999).

Cross-Industry Analysis: Customer Satisfaction and Repurchase Intent

Customer experiences have a significant and extensive connection with repurchase intention across various industries, indicating the impact of these encounters on behavior (Meriç and Yıldırım, 2021). In sectors like heavy machinery, customer satisfaction is critical in fostering loyalty and encouraging repeat purchases (Delgado-Ballester and Luis Munuera-Alemán, 2001). Studies consistently show that higher satisfaction levels correlate with increased customer loyalty (Yi 1991; (Anderson and Sullivan, 1993; Zeithaml *et al.*, 1993). The role of emotional responses in satisfaction, influencing word-of-mouth communication and repurchase intention (Zhang, Deng and Xu, 2017). Customer satisfaction ratings are reliable predictors of future expectations and intentions (Zhang, Deng and Xu, 2017). Repurchase intention is crucial for maintaining profitable customer relationships (Lai and Chou, 2015). Customer satisfaction is fundamental across diverse industries, emphasizing its role in fulfilling consumer needs (Oliver, 1999). Past customer experiences also impact satisfaction and repurchase intention (Pappas *et al.*, 2014). Service thresholds influence consumer behavior, with satisfied customers more likely to repurchase, and have positive relationships across industries (Oliva, Oliver and MacMillan, 1992). According to ECT and earlier research, customer happiness is positively influenced by their intention to make additional online purchases (Lee and Lin, 2005). Customer satisfaction positively affects their propensity to make additional online transactions (Olorunniwo, Hsu and Udo, 2006). Experience also has a favorable impact on users' attitudes and, consequently, their satisfaction. Customers with more experience shop online with a positive attitude and appreciate it more than those with less expertise (Endo, Yang and Park, 2012). Combining pragmatic and psychological recovery efforts can increase customer satisfaction (Liao, 2007).

2.5 Research Gap

The field of research across the industry is vast and varied, covering complex aspects like service failures, recovery methods, customer happiness, and repeat purchases across different fields, including heavy machinery. Notably, previous studies, like the one by Chang, 2006, have carefully studied the connection between service problems, ways to fix them, and how customers feel afterward. They looked into what customers prefer when solving problems, distinguishing between issues with the process and those with the outcome. Despite these valuable discussions, there is a need for more in our understanding. In heavy machinery, when things go wrong with service, it only notes that it immediately affects customers as it does in businesses like hotels or online stores. This creates a gap in our knowledge. Unlike those industries where quickly fixing a problem makes customers happy right away, in heavy machinery, it takes time to see the effects. Customers' experiences with heavy machinery unfold over time, so we must understand how problems like machine downtime, repeated issues, and unresolved problems affect them in the long run. Surprisingly, very few studies in the heavy machinery sector have looked at these important factors. While many believe quickly fixing service issues is the best way to make customers happy again, this idea can be studied less in heavy machinery. Heavy machinery is different, unlike industries where fast service immediately makes customers happy. Here, other things besides speed matter more in keeping customers satisfied. This gap in our knowledge shows that we need to look deeper into how service problems are handled in heavy machinery to determine what satisfies customers in the long term.

3 Variable Definition & Hypothesis Development

Before formulating hypotheses, it is essential to establish clear definitions for the key terms and variables used throughout the research. This foundational step ensures a shared understanding of the concepts, under research and sets the stage for hypothesis development. Defining terms related to service; failure, recovery, satisfaction of customers, and repurchase intent is pivotal to aligning the research methodology and theories in the field. The subsequent hypotheses can be grounded in a robust and well-defined framework by providing detailed and comprehensive conceptualizations of these variables. This study determines the three independent variables regarding the impact of service failure, three dependent variables regarding customer satisfaction, and one moderate variable in favor of service recovery. The dependent variable, repurchase intention, is the final objective; all three customer satisfaction variables act as the independent variables for Repurchase Intention.

3.1 Variable Definition

3.1.1 Independent Variables: Service Failure

The severity of failure

The severity of failure has been described as the magnitude of the impact on customers, reflecting the level of loss customers experience due to the severity of failure (Hess, Ganesan and Klein, 2003). Understanding how severe a failure is to customers is crucial because it directly affects their experience. Customers' feeling align with the failures' magnitude (Hess, Ganesan and Klein, 2003). In such a scenario, losses can be two types: either can be a consequence of Tangible, such as monetary loss or could be intangible effects, such as frustration and anger (Hess, Ganesan and Klein, 2003). The level of the failure vary from industry to industry and to what extent customers tolerate the failures; some industry has severe failures on tangible losses and some on intangible. Moreover, the measurement of the severity of failure also differs according to the industry type. Hess, 2008 measured the severity of failure by its type. The study considers failures severe when they happen to the core (Hess, 2008). The core service refers to the fundamental benefit that customers anticipate from the service. In a restaurant scenario, when customers order food, and the waiter fails to serve the correct dish they requested, it disrupts the expected core service (Hess, 2008). Likewise, when the machine is inactive in the heavy machinery industry, it hinders all activity. It can cause severe issues for customers. In this study, after examining the several types of failures that customers encounter throughout the three years of their journey with the industry and while using the same product, some types of failures were more severe than others when they happened in the core service value-related to machine uptime/downtime, and not necessarily all failures will have machine downtime. We considered only those failures severe when the machine is inactive, which is Machine downtime. In recorded customers' journeys, they have encountered machine downtime several times. To measure the machine downtime correctly, take each of the downtime customers experience with related failures, and the more severe the issue, the more downtime for the failure.

Repeated Failure

Customers' prior experience with the brand significantly influences the customer's overall satisfaction (Hess Jr., Ganesan and Klein, 2003). The effect of these experiences becomes more inevitable when customers encounter failures. Each such failure contributes to negative feedback, influencing not just specific aspect that failed but also their perception of the entire product, service, and brand. Furthermore, the quality of past service and the frequency of failures experienced over time also influence the bond between dealer and customer (Liao, 2007). However, if these failures occur more than once, a shift in perception occurs (Liao, 2007). Customers begin to believe these issues are not isolated incidents but indicative of broader, persistent problems related to product quality, dealer service, and brand attributes (Maxham and Netemeyer, 2002). Additionally, they begin to evaluate their experience based on the claims that the performance of specific service providers can fluctuate across different instances or that the same product has several failures on different occasions. It becomes straightforward for them to determine whether to continue their relationship with the organization. Customers who understand that service quality can vary from one occasion to another may hesitate to base their decision to continue a relationship solely on the quality of a single service experience (Hess, Ganesan and Klein, 2003). This shift in perception has significant consequences. As customers experience failures repeatedly, their expectations regarding the brand, product, and service quality start to decline (Maxham and Netemeyer, 2002; Liao, 2007). It also shows the efficiency of service provider performance in achieving favourable customer outcomes (Liao, 2007). The cumulative effect is a reduced level of confidence and trust in the overall reliability and quality of the brand and its offerings. Handling service failures is a dynamic process that begins with the occurrence of a failure, involves specific procedures being initiated, and culminates in interactions between the customer and the organization (Amy K. Smith, Bolton and Wagner, 1999). It is anticipated that failures with stable (enduring) causes would occur more frequently than failures with non-stable causes (Hess, Ganesan and Klein, 2003). Building on insights from prior research, this study characterizes repeated failure as occurrences that persist throughout a customer's three-year engagement with the organization leading up to the survey. The focus is specifically directed toward customers who have encountered multiple instances of failure during their interaction with the organization. We delve into the experiences of those. Customers who have faced more than one failure throughout their three-year journey with the organization measure this variable based on the total number of claims they raised.

Unresolved Failure

*C*ustomers tend to express more negative impressions when the service failure experience persists negatively (Hess Jr., Ganesan and Klein, 2003; Garnefeld and Steinhoff, 2013; Sivakumar, Li and Dong, 2014). There is a substantially greater decline between ordinary and bad recovery performance than there is between exceptional and average recovery performance (Hess Jr., Ganesan and Klein, 2003). Adding to the contextual component, the recency effect suggests that current consumer contacts with a service provider significantly impact customer rating more than favorable prior interactions (Garnefeld and Steinhoff, 2013). However, a serious caution is shown for customers who are still having issues at the time of the survey. They see the brand more negatively than their competitors (Sivakumar, Li and Dong, 2014). Based on past research, this study categorizes unresolved failures as customers whose most recent experience is negative due to a service failure. To evaluate this variable, we rely on responses to the survey question, "Do you have any unresolved product problems?" Customers indicate the presence or absence of unresolved failures in their accounts by providing a binary answer. The survey question is added in Appendix Table 1.

3.1.2 Moderate Variable: Service Recovery

Service recovery is the sense of satisfaction when customers recover from failure, and it shows the experience with service to firms; it moderates the negative impact (Seiders and Berry, 1998). Providing the desirable recovery to customers according to their needs highly influences customers' satisfaction (Goodwin and Ross, 1992). In contrast, it added that if the recovery service is not provided according to the customer's requirements, it can also have negative repercussions (Alexandra, 2020). Keeping the customers in the loop of information strengthens the relationship, and putting their requirements first will lead to repurchase intention in the future and to keep customers for the long term (van Doorn and Verhoef, 2008). In service recovery, companies make several different recoveries to cover the failure. It also depends on the mode of industry. While dealing with service failure, dealers are more successful in recovering from service failure. They actively work on service failure and have detected quick failure measurements or even diagnosed the failure problem. Customers are more likely to feel satisfied and having a positive experience, when they are kept informed about the status of a failure, compared to when they are left uninformed (Hübner, Wagner and Kurpjuweit, 2018).

Recovery of Speed: Moderate Variable

Customers' feedback is influenced by how quickly they get into service while performing procedural recovery. One of the attributes of procedural recovery is Recovery Speed, which is defined as the speed of recovery time in dealing with all the procedures of service failure and providing solutions to the customers (Crisafulli and Singh, 2017). For the service provider, it is initially challenging to encounter service failure and provide recovery at the speed (Crisafulli and Singh, 2017). This attribute has significant role in evaluating the customer's service experience and product experience, which take over the brand experience (Blodgett, Hill and Tax, 1997). In past research, much research has been discussed and suggested that there is a negative impact if recovery speed has taken more extended time; it can directly influence the brand reputation through adverse word-of-mouth and overall customer contentment (Hogreve *et al.*, 2017; Babin, Zhuang and Borges, 2021). In the Business Process, if the service provider, the dealer, acts proactively in providing a quick response or solution to the customers that could help to mitigate the negative impact, and the speed of recovery moderates the effect of the negative impact of failure (Hübner, Wagner and Kurpjuweit, 2018). In addition, to speed up recovery, service providers have a specialized team who are masters in their job, like processing the failure, investigation, quick diagnosis, and providing the level of recovery that customers are expecting, which would help to reduce the negative impact (Hübner, Wagner and Kurpjuweit, 2018). It would help them to deliver quick responses because, especially in a b2b (Business to Business) situation, it is not easy to deliver prompt responses. However, it has quite an impressive impression on customers' emotions and eliminates negative thoughts from saying and referring to any of the customers.

This study focuses on the Dealer's Speed in dealing with service failures as a recovery attribute. Recovery speed is measured by the number of days from the day the customer encounters the failure (i.e., failure date) to the day the dealer delivers the solution to the failure (i.e., failure completion date). The difference between these dates represents the recovery speed, indicating the duration the dealer takes throughout the entire failure process.

3.1.3 Dependent Variable: Customer Satisfaction

Product Experience

Product Experience is defined as the focus on how well a product meets the unique needs of consumers. Three essential elements comprise the framework's definition of product quality: performance, dependability, and consistency throughout time (Ulaga, 2003). In parallel with this, Product experience is the sum of a product's characteristics that enable it to fulfill the required standards (Alex and Thomas, 2011). According to Ulaga, 2003; Alex and Thomas, 2011 and others viewpoint, *product Experience* is defined as the functional characteristics of a product that meet the user's basic needs and guarantee its continued functionality over time (Garvin, 1987). Additionally, product experience should consider aspects including performance, features, compliance, durability, serviceability, aesthetics, customer perception of quality, and technical and perceived quality viewpoints. Within this comprehensive framework, these diverse viewpoints collectively establish the product's value and are essential to fulfilling consumer expectations about efficiency and uptime (Garvin, 1987). This study defined the product experience as fulfilling customer expectations with product quality, performance, reliability, and consistency. Additionally, we incorporate the overall evaluation of product value into this construct. To measure the overall product experience and give varying importance to each aspect based on participant responses, we calculate a weighted average of all product experiences. This provides a comprehensive view, summarizing the total overall product experience.

Dealer Experience

In examining the relationship quality between customers and service providers, perceived service value (Dealer experience) is crucial (Rauyruen and Miller, 2007). Two essential components were identified by Ulaga, 2003, in their analysis of the aspects of this service value: personal interaction and service support. The constant interaction between dealers and customers brings these elements to life, serving as the core component of the customer-service provider relationship (Ulaga and Eggert, 2006). Dealer experience is the dedication to providing consumers with correct information and product-related help (Ulaga, 2003). Proactively responding to customer requests and ensuring that customers receive a product and an extensive range of support services indicate satisfactory support. However, personal interaction represents a relationship exchange beyond transactional limits (Ulaga, 2003). With the help of this framework for continuous commitment, customers can communicate their issues, share their experiences, and work together to establish goals with the service provider. It is a cooperative effort to build a mutually beneficial connection rather than just a transaction (Ulaga, 2003). This study defines *dealer experience* as evaluating the service dealers provide during interactions related to failures and fulfilling customer requirements throughout their overall experience. It includes situations in which dealer services meet or exceed consumer expectations. The services offered include attending to the client's demands, making sure that parts are available on schedule, fixing problems as soon as they arise, and showing them respect. This build additionally summarizes the dealer experience as a whole.

Brand Experience

Brand experience holds a unique position as an intangible asset; it is sometimes considered a company's equity and is seen to be the most critical factor in economic success (Oke *et al.*, 2016). Academics like Murphy, 1987; Aaker, 1991stressed how vital branding is in setting products and services apart from competitors. On the other hand, this apparent difference becomes necessary when a brand is presented as the primary source of information when making decisions about purchases or repurchases (Oke et al., 2016). Perceived quality and values significantly impact consumer purchasing decisions, leading to consumer loyalty behaviors. Interestingly, demographic traits and sales promotions have minimal influence on customers' purchasing decisions, showing the significance of quality and perceived values in building brand loyalty (Oke *et al.*, 2016). Furthermore, there is a perception that people who purchase higher-quality machines naturally anticipate receiving services of a similar quality (Devaraj, Matta and Conlon, 2001a). Customers who choose higher-rated machinery are more likely to use dealer facilities for repair (Devaraj, Matta and Conlon, 2001b). Based on the idea and evaluation of Net Promoter Score (NPS), this research defines *Brand Experience* as the overall interaction that consumers have with a brand throughout their relationship with the company. It includes the general perception consumers form of the brand and the tendency to recommend it to others. We use survey questionnaire results to measure this variable, evaluating them using a weighted average method. This guarantees an in-depth understanding of the customer's overall brand experience.

3.1.4 Dependent Variable: Repurchase Intention

The quality of previous service performance is a critical component in determining the probability of future contacts (Hess, Ganesan and Klein, 2003). Interestingly, depending on the customers' history of interactions with the organization, the influence of past service performance quality on the customers' expectations of relationship continuation varies. Furthermore, a significant finding is that following a service failure, consumers who expect an ongoing relationship tend to have lower expectations for recovery (Hess, Ganesan and Klein, 2003). This is explained by the theory that recovery becomes less significant when consumers are more likely to repurchase or maintain their brand loyalty. These customers do not only need less intensive because they have a strong relationship with the brand and confidence in it. Repurchase Intention, supported by prior research, measures a customer's brand loyalty. In this study, we define Repurchase Intention by dividing consumers into two categories: Those who pose a threat to the company intend to explore alternative brands. In contrast, those who exhibit brand loyalty intend to remain faithful to the brand. To evaluate this variable, we rely on survey answers to the question "At risk: Are they inclined to repurchase the same brand, or are they considering switching to another brand? It has been reduced to binary categories to make this measurement easier to understand. Survey questions are attached in Appendix Table 1.

3.2 Hypothesis Development

Focusing on service failure model, this study analyses the hypothesis; direct effect of failure on PE, DE, and B. perform a thorough analysis to learn more about customer behavior in the sample of manufacturing firm after than analysis expand the regression model by adding the moderating effect of recovery speed and at the end goal to predict customer repurchase intention on the basis on customer satisfaction. All three steps and required variable is demonstrated in the conceptual framework in Figure 2.

3.2.1 Service Failure Impact on Customer Satisfaction

Service failures, whether perceived or actual, represent a breakdown in the delivery of services, include both outcome and process aspects (Duffy, Miller and Bexley, 2006). Service failures have a detrimental effect on customer loyalty, the ultimate goal for businesses aiming to retain customers and foster sustained growth (Sousa and Christopher A. Voss, 2009). This shows the importance of effective delivery, as SF not only compromise immediate customer satisfaction but also pose a threat to long-term customer loyalty (Sousa and Christopher A. Voss, 2009). On the basis of past research, in order to better understand the moderating role that service recovery has in these dynamics, we first analyzed the direct impact that service failure on customer satisfaction.

3.2.1.1 Moderating Effect of Recovery Speed on Severity of Failure

Numerous studies have been conducted in a range of industries, including food service, automotive, e-commerce, and retail, to better understand the linkages between customer satisfaction, brand experience, and the impact of severity failure on these domains. In B2C scenario even after the implementation of recovery actions, customers who experienced more severe failures tended to express lower satisfaction (Hess, 2008). Customers who encounter substantial losses or perceive such losses are likely to remain dissatisfied with the brand, even after the issue has been resolved. However, it's intriguing to note that recovery efforts have the potential to positively influence customers' negative perceptions, especially in the case of minor failures. (McCollough, Berry and Yadav, 2000). However, when significant failures are involved, the dynamics shift. Consumers who endure such setbacks not only maintain a negative stance toward the brand but also exhibit a diminished perceived product value that is not entirely recoverable (McCollough, Berry and Yadav, 2000). Dealing with severe failure is more significant, it causes the sense of disloyalty and also losses the gained trust which earned through high recovery (Weun, Beatty and Jones, 2004b). Moreover, B2C company service recovery has significant role as a moderator in the effects of failures. When a problem is significant and the customer receives prompt resolution, they tend to be content with the brand. Delivering timely service recovery that aligns with customer expectations has the capacity to mitigate the negative effects of failures (Zeithaml, Berry and Parasuraman, 1996). Research from the past has shown that customers' perceptions of failure impact are significantly impacted negatively by major failures. More severe failures can cause a perceived loss greater than the objective loss (Kahneman and Tversky, 1979; Sivakumar, Li and Dong, 2014). Customers may, therefore, evaluate perceived value differently based on the severity of the failure. Before assuming that recovery speed lessens the detrimental effect of the severity of failure (SOF), we intended to conduct a detailed investigation to gain insights into customer behavior. Finding out which experience of the customer - product, dealer, or brand has been impacted by the severity of the failure and then the recovery speed has a mitigating the impact of severity failure.

H1.0a-c: Severity of failure has no significant impact on (H1.0a) product experience, (H1.0b) dealer experience, and (H1.0c) brand experience.

H1.a-c: Severity of failure has negative impact on (H1a) product experience, (H1b) dealer experience, and (H1c) brand experience.

H2.0.a-c: Severity of failure has no significant impact on (H2.0a) product experience, (H2.0b) dealer experience, and (H2.0c) brand experience with recovery of speed act as moderate variable.

H2.a-c: Severity of failure has positive impact on (H2a) product experience, (H2b) dealer experience, and (H2c) brand experience with Recovery of speed act as moderate variable.

3.2.1.2 Moderating Effect of Recovery Speed on Repeated Failure

In past research Hess Jr., Ganesan and Klein, 2003 emphasized that the number of prior interactions influences customers' expectations of relationship continuity in a positive way and it is important to recognize the negative effects of repeated service failures in this framework. Repeated failures in customer contacts negatively impact their satisfaction and experience, in contrast to the expected positive correlation. As customers engage with an organization over time, the quality of each interaction becomes paramount. Customers have more service encounters; they become familiar with the provider. However, it is crucial to highlight that the quality of these encounters is as significant as their quantity (Solomon et al., 1985). However, the important factor in building these expectations lies in the number of interactions and, crucially, in the nature of these encounters. Persistent service failures weaken the foundation of trust and fulfillment built by positive interactions. Businesses must understand that customer happiness depends on the quality of each encounter rather than just the quantity of previous interactions. Maintaining the positive momentum of the customer relationship becomes dependent upon quick diagnosis and restoration of service failures (Hess Jr., Ganesan and Klein, 2003). Attribution theory further suggests that repeated failures lead customers to attribute issues to stable, inherent problems within the service company, making them less receptive to recovery efforts. Building on prior research, this study assesses the repeated failures' effect on customer satisfaction with the product, dealer, and brand experience. Furthermore, the study explores how the exceptional speed of recovery impacts the occurrence of repeated failures.

H3.0.a-c: Repeated Failure has no significant impact on (H3.0a) product experience, (H3.0b) dealer experience, and (H3.0c) brand experience.

H3.a-c: Repeated Failure has negative impact on (H3a) product experience, (H3b) dealer experience, and (H3c) brand experience.

H4.0.a-c: Repeated Failure has no significance impact on (H4.0a) product experience, (H4.0b) dealer experience, and (H4.0c) brand experience and recovery speed act as moderator.

H4.a-c: Repeated Failure has positive Impact on (H4a) product experience, (H4b) dealer experience, and (H4c) brand experience and recovery speed act as moderator.

3.2.1.3 Moderating Effect of Recovery Speed on Unresolved Failure

Resolving problems quickly becomes essential to maintaining customer satisfaction is the critical step after the service failures (Liao, 2007). Customers tend to give more weight to the failure when they are left unresolved (Lockshin and McDougall, 1998). Moreover, being aware of unresolved problems causes increased customer dissatisfaction, which delivers an unfavorable signal to customers and can lower their satisfaction with and trust in the product, brand, and dealer experience (Lockshin and McDougall, 1998). The increasing customer satisfaction levels require a successful recovery from a negative occurrence (Sivakumar, Li and Dong, 2014). On the other hand, if a service failure is not rectified during the evaluation stage, the customer may feel that they have lost more than they did (Sivakumar, Li and Dong, 2014). Customers' most recent interactions with a brand significantly impact their impressions (Maxham and Netemeyer, 2002; Garnefeld and Steinhoff, 2013). When customers are still dealing with an unsolved issue, their last experience with the company develops a bad memory and the significance of unfavorable incidents that happen towards the conclusion of the customer experience, increasing unfavorable impressions (Garnefeld and Steinhoff, 2013). This is consistent with more extensive studies that indicate a customer's perception of a brand can be significantly impacted by the date and proximity of a negative incident (Kahneman & Tversky, 1979). Based on the past research by Garnefeld and Steinhoff, 2013; Sivakumar, Li and Dong, 2014, unresolved failure harms the perceived value of product, service and brand.

H5.0a-c: Unresolved failure has no significant impact on (H5.0a) product experience, (H5.0b) dealer experience, and (H5.0c) brand experience.

H5.a-c: Unresolved failure has negative impact on (H5a) product experience, (H5b) dealer experience, and (H5c) brand experience.

H6.a-c: Unresolved failure has no significance impact on (H6.0a) product experience, (H6.0b) dealer experience, and (H6.0c) brand experience and recovery speed act as moderator.

H6.a-c: Unresolved failure has positive impact on (H6a) product experience, (H6b) dealer experience, and (H6c) brand experience and recovery speed act as moderator.

3.2.2 Impact of Customer Satisfaction

Researchers' perspectives on consumer satisfaction have varied in previous studies. As per (Sousa and Christopher A. Voss, 2009), Customers who are satisfied with the service quality and product received tend to express an intention to make more purchases and consider future commercial relationships with the customers. The Results on behavioral intention, trust, loyalty, customer complaints and recoveries in business-to-consumer transactions and the importance of justice in influencing consumer views (Kau and Wan-

Yiun Loh, 2006). Customer satisfaction does not always lead to loyalty, and the connection between satisfaction and loyalty is weakest in the service economic chain (Reichheld and Teal, 1996; Oliver, 1999). Furthermore, c Furthermore, customer happiness with all aspects of the goods and services received emphasizes that customer fulfillment alone does not guarantee loyalty (Oliver, 1999). There is evidence from recent studies that a customer's level of loyalty and their continued satisfaction are positively correlated. Loyalty to an organization strongly influences attitudes and intentions for future action. This relationship becomes more pertinent when considering the magnitude of service failures because prior research has shown that it significantly affects consumers' perceptions of the weight and negativity of service failures. Based on past studies, this research predicts that customer's decision to repurchase is influenced by their level of happiness with the brand, product, and service.

3.2.2.1 Influence Product, Dealer, and Brand Experience on Repurchase Intention

Product experience has significant value in building customer behavior. Customers' willingness to repurchase and their level of loyalty is directly impacted by their product experience (Devaraj, Matta and Conlon, 2001b). Customer loyalty is positively correlated with the customer's sense of product quality. Customers are more loyal to a brand or product when they believe it to be of greater quality (Devaraj, Matta and Conlon, 2001b). Customers' loyalty to quality is directly impacted by their perceptions of the value of high-quality products in their purchases. Perceived quality plays a crucial part in forming customer loyalty, as evidenced by the belief that it greatly influences customers' intention to repurchase. Consumers' expectations of a long-term connection with their dealer depend on their participation, prior transactions, the quality of previous service delivery, and the level of balance in the customer-service provider dynamic (Hess Jr., Ganesan and Klein, 2003). However, customer stability would result if the service provider had the service recovery on the expectation and satisfied customers (Hess Jr., Ganesan and Klein, 2003). Customer loyalty is significantly impacted by dealer facility service satisfaction, which is positively influenced by the quality of service received. Increased customer retention and repurchase intent are correlated with dealer service experience (Devaraj, Matta and Conlon, 2001b). This study examined how positively perceived dealer facilities and service quality affect customers' intentions to make additional purchases, based on research by Devaraj, Matta and Conlon, 2001b; Hess Jr., Ganesan and Klein, 2003. In order to make sure the brand fulfills its functional promises, brand performance is an essential part of the brand experience. It concerns the inherent characteristics of the good or service, trying to fulfill or transcend the attributes that customers have in mind. Brand understanding and total brand value are greatly influenced by favorable encounters with products and services (Keller, 2012). A brand's positive reputation positively impacts customer satisfaction. The focus on customer satisfaction implies that a favorable brand image will influence the desire to make another purchase by adding to a positive brand experience (Devaraj, Matta and Conlon, 2001b).

H7.0a-c: a) Product experience, b) dealer experience, and c) brand experience have no influence on customer repurchase intention.

H7.a-c: a) Product experience, b) dealer experience, and c) brand experience have influence on customer repurchase intention.

Based on the formulated hypothesis, the conceptual framework depicted in Figure 2.

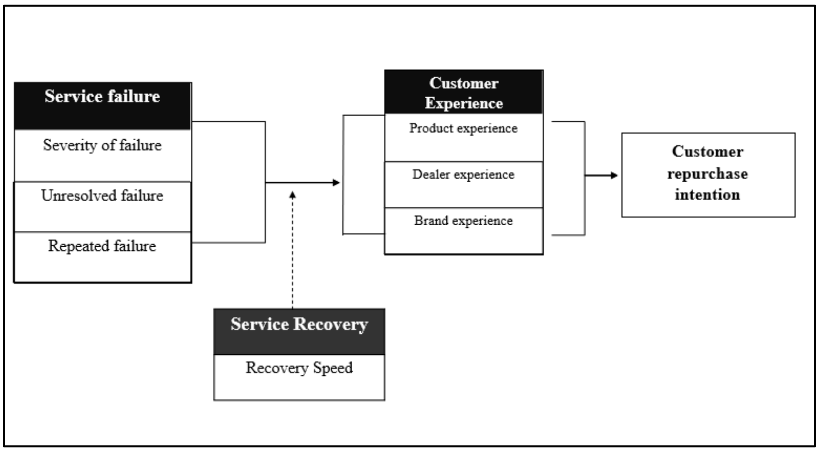

Figure 2: Conceptual Framework

Source: Self-provided

4 Methodology

4.1 Research Design

This study conducted a sequential mixed-methods approach, perform analysis of customer satisfaction and service-related failures as well as customer re-buying intention. It focuses on product, dealer, and brand experiences. It has two phase analysis. In quantitative analysis first validate the dependent variable of customer satisfaction using Confirmatory Factor Analysis (CFA) and Cronbach's alpha. It assesses the construct fit of dependent variables through model validity tests. The study also looks at the moderating role of recovery speed and the effects of service failure aspects as independent factors on customer satisfaction. An additional quantitative study is then conducted to investigate repurchase intention based on customer satisfaction with dealer, product, and brand experiences. During the qualitative stage, interview methods are developed using the knowledge gathered from the quantitative analysis. With a more thorough and nuanced viewpoint, these interviews seek to understand the quantitative data better. In the qualitative stage, interview methods are developed using the knowledge gathered from the quantitative analysis. With a more thorough and nuanced viewpoint, these interviews seek to understand the quantitative data better. This study thoroughly examines the intricate interactions between service failure, consumer satisfaction, and repurchase intention by integrating quantitative information with qualitative insights.

4.1.1 Quantitative Analysis: Data Collection

This research gathered data from a well-known international machinery manufacturer, focusing on the European region and the corresponding product types manufactured within that locale. Our analysis was built upon meticulously integrating two distinct data sets: warranty claim records and customer survey responses. The primary data source, warranty claim data, came from when customers reported service failures during their entire customer journey. Dealer involvement was essential to this procedure as they promptly addressed reported issues and recorded them in the system. Although many service failures can arise in the heavy machinery business, including problems with data security, financial conflicts, logistics, and adaptability. Our study purposefully focused on core service failures. This strategic focus from earlier research Anderson, Baggett and Widener, 2007, which suggests that failures in core services are critical and could have significant adverse effects on customers. According to earlier research (Xu, Liu and Gursoy, 2019), core service failures are crucial and could significantly impact customers. Importantly, essential service failures were selected because they were considered severe and might dramatically impact customers. The variables that were collected included machine downtime indicators, which indicate the severity of service failures, the total number of customer claims that were filed over three years (Claims), and the date on which the customer initiated the failure report (Failure Report Date) and the dealer's subsequent completion of the service (Repair Completion Date)—only those claims from customers whose repair completion date falls before their survey return date were collected. The difference between the date of the failure report and the repair completion date is recovery speed, which acts as a moderator. The second data source is customer survey data collected from direct buyers.

Six months and thirty-six months after the product purchase, respectively, passed between the first and second surveys. We gathered the 36-month survey data for our research to give comprehensive customer feedback. Respondents scored their responses on a range of 1 to 10. The Net Promoter Score (NPS) is the foundation of this grading scheme. Consumers rank the Score as promoters (9 to 10), neutral (7 to 8), and detractors (1 to 6). This numeric scale allows us to quantify customer opinions, preferences, and satisfaction levels. The study utilizes collected data from customer survey responses spanning January 2018 to October 2023, 5416 survey data for service failure. Among these, 5416 customers submitted a total of 27556 claims, all of which were subsequently resolved. This gathered data forms the foundation for analysis, enabling us to derive meaningful patterns and trends. Ultimately, this information guides strategic decision-making and enhances our understanding of customer sentiments. This thorough method provides insightful information about the complex dynamics of service failures and their impact on customer satisfaction. In the survey results, questionnaires related to product experience, dealer experience, and brand experience are listed. In Product Experience, six questions are mapped, covering each aspect of product satisfaction, such as productivity, performance, reliability, and more. We collected all the responses related to product experience. Following this, in Dealer Experience, four listed questions are related to dealer service satisfaction, ranging from how the dealer treats customers to the services provided. We collected all the responses associated with dealer satisfaction. One questionnaire is designed to measure the variable of brand recommendation intention. This includes inquiries regarding customers' overall satisfaction with the brand experience throughout their interaction. Lastly, a follow-up question inquiry about any unresolved failures: if customers still have any unresolved problems, the existence of these problems is measured at the end of the survey with an open comment.

4.1.2 Model Evaluation

Before measuring variables in this research, the constructs were comprehensively evaluated to ensure their reliability and validity. To be more precise, the dependent variables - Product Experience, Dealer Experience, and Brand Experience were carefully examined to see whether or not they were appropriate for the study. In-order to do this, it was necessary to thoroughly review the questionnaires relevant to these factors and evaluate the validity and reliability of the responses. CFA & Cronbach's alpha validate the reliability and validity. By ensuring the quality and robustness of the study's fundamental constructs, these procedures established a solid methodological basis for ensuing studies.

Reliability Analysis

The reliability indicates the consistency of the obtained results. In this study, we tested the reliability of the proposed constructs to see how consistent the scales were, following the methods outlined by Lee et al., 2016. The measure of internal consistency reliability, known as Cronbach's alpha, is utilized to evaluate the degree to which each scale's items reflect the same underlying concept. Significantly, Cronbach's alpha improves with the number of scale items; generally, three to four items are needed to obtain a valid alpha estimate. Cronbach's alpha values lie from 0 to 1, where higher values shows that variables are more internally corelated with each other. The value of Cronbach's alpha is 0.91 which obtained for the product experience questionnaires (P1 to P6), signifying a higher consistency within this construct. Likewise, a Cronbach's alpha value is 0.89 for the dealer experience construct (D1 to D4), further indicating high reliability and the acceptance of the questionnaires for both constructs. Furthermore, internal consistency and dependability are indicated by a composite reliability value closer to 1, with values above 0.70 often regarded as acceptable. The study provides composite reliability values that align with the acceptable dependability threshold: 0.65 for the product experience construct and 0.69 for the dealer experience construct. The study's questionnaires were accepted as Cronbach's alpha, and composite reliability analyses showed high internal consistency and reliability levels for the product experience and dealer experience constructs.

Validity Analysis

Convergent and discriminant validity evaluations are necessary to demonstrate concept validity in the context of validation analysis. Convergent validity is indicated when the factor loading of each indicator exceeds a value of 0.5; higher factor loading values signify a strong relationship between the latent construct and the indicator. This suggests that the indicator effectively represents the underlying construct. Furthermore, each factor's association with other factors should be less significant than the square root of its AVE. A model-data fit where RMSEA value is below 0.05, a strong match; values between 0.05 and 0.08 present an adequate fit, and values between 0.08 and 0.1 imply the fit is acceptable. A Comparative Fit Index (CFI) and Non-Normed Fit Index (NNFI) more than 0.90 suggest that model has good fit, with values more than 0.80 indicating adequate fit. Additionally, the ration of x2/df below three has acceptance chance. These standards use to evaluate the model's fit to the observed data and its convergent and discriminant validity. These extensive validation procedures are essential to guarantee the correctness and reliability of the study's findings. Table (1-2) shows that the model is appropriate for research based on the CFA and validity checks. Table 2. evaluation of model fitness.

Table 1:Reliability analysis and convergent validity

Construct	Measurement Item	Factor loading/Coeff.	Composite Reliability	AVE	Cronbach's α
Product Experience (PE)	PE1	0.85	0.65	0.65	0.91
	PE2	0.83			
	PE3	0.85			
	PE4	0.76			
	PE5	0.66			
	PE6	0.86			
Dealer Experience (DE)	DE1	0.74	0.69	0.69	0.899
	DE2	0.88			
	DE3	0.81			
	DE4	0.88			
Brand Experience (BE)	BE	1	1	1	1

Table 2:Evaluation of Model fitness

Indexes	Standard	Fitness Value	Result
Comparative Fit Index (CFI)	≥ 0.9	0.985	Good
Non-Normed Fit Index (NNFI)	≥ 0.9	0.976	Good
Root Mean Square Error of Approximation (RMSEA)	< 0.10	0.081	Good
SMAR	≤ 0.08	0.016	Good

4.1.3 Data Manipulation

Variable Measurement: Each variable is prepared for the correct measurement, the limitations is established, and the variables were defined for further analysis. We focused on a three-year customer journey, which we determined by calculating the duration between the product purchase date and the survey completion date. This approach enabled us to identify customers within the three-year journey period. Subsequently, we gathered and analyzed service failures and satisfaction data to perform variable measurements. Firstly, we obtained Net Promoter Scores (NPS) for each variable listed in the questionnaires, i.e., Product Experience (PE), Dealer Experience (DE), and Brand Experience (BE). Then, to determine factor scores, we performed a confirmatory factor analysis, which made it easier to determine the overall level of satisfaction for each element while providing each questionnaire with a suitable value. Secondly, we calculated the recovery speed, indicating the duration between the service failure and completion dates. The severity of failure and recovery speed were multiplied for each customer, and the weighted average is calculated. This approach enabled us to compare the weighted values of failure and recovery speed over time. The theory suggested that the timing of failure and recovery type impact customer satisfaction differently, with more weight assigned to the latest failure due to its lasting impact on customer satisfaction. Thirdly, we addressed unresolved failures by directly asking customers if they had any unresolved failures and then categorized the responses into binary groups (Yes=1, No=0). In the fourth step, we focused on repeated failures, considering only those customers who had experienced failures more than once, and measured this using integer values. Lastly, we examined customer repurchase intention, where we directly inquired whether customers in- tended to repurchase the same brand or opt for a different brand from the survey response and then categorized the responses into binary groups (Same brand=1, Other brand=0). The details and summary of each variable extracted are presented in Table 3. With these defined values, we conducted our analysis.

Table 3:Description of Variables

Independent Variables		
Variable	Measure	Description
Severity of Failure	Weighted Avg.	More weight on recent records
Repeated Failure	Integer Value	More than one failure
Unresolved Failure	Binary Value	1: Yes | 0: No
Moderate Variable Recovery Speed	Weighted Average	More weight on recent records
Dependent Variables		
Variable	Measure	Description
Product Experience	Factor Score	Based on the CFA factor Score
Dealer Experience	Factor Score	Based on the CFA factor Score
Brand Experience	Factor Score	Based on the CFA factor Score
Repurchase Intention	Binary	1: Same Brand | 0: Other Brand

4.1.4 Direct Impact Analysis of Service Failure

Hypothesis Testing

In this model, we first examined the hypothesis that the independent variable, service failure, directly impacts the dependent variable, customer satisfaction. Furthermore, we investigated possible interactions between recovery speed and the independent variable, which acts as a moderator. Regression analysis evaluates this hypothesis by analyzing the main and interaction effects.

Severity of Failure

The model investigated the direct impact of the severity of failure on product experience, dealer experience, and brand experience while also considering the moderating variable of recovery speed as a component of satisfaction. The study included a sample size of 4099, with 1317 missing values. The hypothesized results suggested a negative impact of the severity of failure on product experience (β*-beta* $= -0.0007$, $t = -4.055$, $p < 0.01$), dealer experience (β*-beta* $= -0.00059$, $t = -2.595$, $p < 0.01$), and brand experience (β*-beta* $= -0.00025$, $t = -1.149$, $p < 0.01$), resulting in the rejection of the null hypothesis, H1.0.a-c. As a result, the study finds support for the direct impact of the severity of failure on product experience, dealer experience, and brand experience (H1a-c). Furthermore, the research investigates the interaction effect of recovery speed, serving as a moderating variable aimed at influencing the severity of failure's impact on product experience, dealer experience, and brand experience. However, recovery speed on product experience (β*-beta* $= -0.0000004$, $t = -4.055$, $p = 0.767$), dealer experience (β*-beta* $= -0.00000127$, $t = -0.936$, $p = 0.349$), and brand experience (β*-beta* $= -0.000000479$, $t = -0.319$, $p = 0.75$) shown no interaction effect and the null hypothesis, H2.0.a-c, fails to be rejected, indicating that H2a-c is not supported. Table 4 displays the comprehensive results.

Table 4: Regression Analysis result related to Severity Failure (H1a-c) and (H2a-c)

	H1a	H1b	H1c	H2a	H2b	H2a
		Main Effect			Interaction	
	PE	DE	BE	PE	DE	BE
Severity of Failure	-0.0008*** t = -4.772	-0.000486** t = -2.99	-0.000727*** t = -4.055	-0.00059** t = -2.6	-0.00025** t = -1.149	-0.00055* t = -2.244
Recovery Speed				-0.00067** t = -2.88	-0.00029 t = -1.308	-0.00050 t = -2.04
Severity of Failure * Recovery Speed				-0.00000042 t = -0.295	-0.00000127 t = -0.916	-0.00000047 t = -0.35
Observation	4099	4099	4099	4099	4099	4099
R-Square	0.0052	0.001941	0.0037	0.00825	0.00029	0.005
F-Statistics	22.77** (d f ; 1, 4088)	8.95** (d f ; 1, 4088)	16.44*** (d f ; 1, 4088)	12.34** (d f ; 3, 4086)	5.014 (d f ; 3, 4086)	8.034 (d f ; 3, 4086)

Note: P-value is less that 0.05, where rejecting null hypothesis

Initially, regression-analysis examined the direct effect of repeated failure on customer satisfaction variables of product experience, dealer experience, and brand experience. Repeated failure is measured with a sample size of 5,416. The results of the primary effect analysis revealed compelling evidence, which showed that recurrent failure had a substantial direct influence on product experience (β*-beta* $= -0.029$, $t = -9.455$, $p < 0.01$), dealer experience (β*-beta* $= -0.014$, $t = -4.477$, $p < 0.01$), and brand experience (β*-beta* $= -0.024$, $= -7.454$, $p < 0.01$). The findings indicate rejection of the null hypothesis, thereby supporting H3a-c. Furthermore, after analyzing the direct impact, the analysis evaluated the moderating role of recovery speed. The following analysis produced some interesting findings, showing that dealer experience (*β-beta* = .000045, t = 2.532, $p < 0.01$), brand experience (*β-beta* = .00047, t = 2.560, $p < 0.01$), and product experience (*β-beta* = 0.00007, t = 4.029, $p < 0.01$) are all significantly impacted by the moderating variable's interaction effect. Consequently, the null hypothesis was categorically rejected, and hypothesis H4a-c is supported. For a thorough outcomes analysis, see Table 5 for the specific findings.

Table 5: Regression Analysis result related to Repeated Failure(H3a-c) and (H4a-c)

	H3a	H3b	H3c	H4a	H4b	H4c
		Main Effect			Interaction	
	PE	DE	BE	PE	DE	BE
Repeated Failure	-0.02931*** t = -9.455	-0.013715 *** t = -4.477	-0.0235*** t= -7.454	-0.0343*** t = -8.552	-0.01631*** t = -4.107	-0.026*** t = -6.492
Recovery Speed				-0.00107*** t = -4.536	-.0007299** t = -3.128	-.000719** t = 0.0002405
Repeated failure Recovery Speed				0.0000726*** t = 4.029	0 .00004519* t = 2.532	0.0004709* t = 2.560
Observation	5416	5416	5416	5416	5416	5416
R-Square	0.0160	0.0035	0.009	0.0198	0.00501	0.011
F Statistic	89.4 *** (df:1 ; 5404)	20.04 *** (df:1 ; 5404)	55.56*** (df:1 ; 5404)	37.39*** (df:3 ; 5402)	10.08 *** (df:3 ; 5402)	21.72*** (df:3 ; 5402)

Note: P-value is less that 0.05, where rejecting null hypothesis

Unresolved Failure

Unresolved failure involved a sample size of 5096, with 320 missing values. The results revealed a significant negative impact of unresolved failure on product experience ($\beta = -0.94, t = -28.62, p < 0.01$), dealer experience ($\beta = -0.825, t = -24.95, p < 0.01$), and brand experience ($\beta = -0.64, t = -18.23, p < 0.01$). Consequently, hypothesis H5a-c is supported, leading to rejecting the null hypothesis, H5.0.a-c. Subsequently, when the analysis included the moderating variable to examine the interaction effect, the subsequent results indicated that the moderate effect had no significant impact on product experience ($\beta = -0.00028, t = -0.723, p = 0.47$), dealer experience ($\beta = 0.0003, = 0.811, p = 0.41$), and brand experience ($\beta = -0.0006, t = -1.394, p = 0.16$). Consequently, the null hypothesis, H6.0.a-c, is rejected and hypothesis H6a-c regarding the moderating effect of recovery speed was not supported. The detailed findings are presented in Table 6 so the results can be understood comprehensively.

Table 6. Regression Analysis result related to Unresolved Failure(H5a-c) and (H6a-c)

Table 6: Regression Analysis result related to Unresolved Failure(H5a-c) and (H6a-c)

	H5a	H5b	H5c	H6a	H6b	H6c
		Main Effect			Interaction	
	PE	DE	BE	PE	DE	BE
Unresolved Failure	-0.9435*** t = -28.62	-0.825*** t = -24.95	-0.646*** t= -18.23	-0.92000*** t= -23.916	-0.83745*** t= -21.643	-0.6097*** t= -14.718
Recovery Speed				-0.000748*** t=-4.403	-0.000444** t = -2.596	-0.00050** t = -2.769
Unresolved failure Recovery Speed				-0.0002804 t =- 0.723	0.0003 t = 0.811	-0.00058 t = -1.394
Observation	5096	5096	5096	5096	5096	5096
R-Square	0.1383	0.1087	0.061	0.1427	0.1095	0.06367
F Statistic	818.9*** (df:1 ; 5094)	622.3*** (df:1 ; 5094)	332.4*** (df:1 ; 5094)	283.7*** (df:3 ; 5092)	209.9** (df:3 ; 5092)	116.5* (df:3 ; 5092)

Note: P-value is less that 0.05, where rejecting null hypothesis

4.1.5 Repurchase Intention Prediction

Logistic regression and decision tree are conducted to evaluate the influence of product experience, dealer experience, and brand experience on repurchase intent (RI). Imbalance response of RI question in survey response provided the data imbalance, where 4216 for respond same-brand repurchase and 753 for repurchase of other brands – the oversampling method is used to provide equitable representation in the dataset due to the uneven number of answers in the Repurchase Intention categories (4216 for same-brand repurchase and 753 for repurchase of other brands). As a result, there were a total of 4969 responses. Determining the relevance of each independent variable in predicting repurchase intention is the aim of the logistic regression model. Two separate models are created to investigate the best method for RI prediction. First, the data is fitted with a logistic regression model. Next, a decision tree analysis is performed to determine which model fits the data the best and provides complementing insights.

Correlation Analysis of Independent Variable

Correlation coefficient is providing a thorough understanding of the independent variables. The outcome shows how strongly PE (product experience), DE (dealer experience), and BE (brand experience) are linearly correlated and in which direction. The correlation study results show a significant positive link between dealer experience (r = 0.76), brand experience (r = 0.73), and product experience. Furthermore, dealer and brand experiences have a modest association with one another, with r = 0.54) and r = 0.54), but they show a positive correlation with product experiences (r = 0.75) and with (r = 0.73). This result suggests that customers who express more pleasure with one component also typically express greater satisfaction with the others. The specific outcomes are elaborated in Table 7.

Table 7: Correlation Matrix

	PE	DE	BE
PE	1	0.755	0.731
DE	0.75	1	0.54
BE	0.73	0.54	1

4.1.5.1 Logistic Regression Analysis

Using logistic regression analysis, estimates of the odds ratios associated with each predictor variable are generated. These odds ratios indicate the probability of repurchasing intention in response to changes in the independent variables.

Model Fitting

Estimation of Coefficients: These coefficients describe the log odds of consumer intention to repurchase in response to variations in dealer, brand, and product experiences. These coefficients represent the log odds of customer repurchase intention with changes in these experiences. The aim is to forecast the likelihood of a customer making a repeat purchase, depending on their satisfaction levels, using the three independent variables: brand experience (BE), dealer experience (DE), and product experience (PE). The binary values of repurchase intention are 1 (yes) and 0 (no). There have been 3545 responses to the repurchase; 2987 responded with "yes," and 556 responded with "no," for a ratio of 85:15.

Hypothesis Testing and Significance

Product experience positively correlates with repurchase intention (ß= 1.46, std. error = 0.05, $p < 0.01$). Dealer and brand experience are also positively and significantly correlated with customer repurchase intention (ß= 1.049, std. error = 0.044, $p < 0.01$) and (ß=1.63, std. error = 0.059, $p < 0.01$). Product experience, dealer experience, and brand experience are hypothesized to have no significant impact on the log odds of customer repurchase intention. However, the alternative hypothesis suggests that these factors exert a substantial positive influence on the log odds of customer repurchase intention. Table 8. presents the specific results, which has significant influence of all three experience, H7a-c is supported and rejected null hypothesis H7.0a-c.

Table 8: Logistic Regression result related to Product, Dealer, and Brand Experience (H7a-c)

		Repurchase Intention				
		β	Std. Error	AIC	Residual Deviation	
Product Experience	H7a	1.46***	0.05	4261.1	4257.1	df:4180
Dealer Experience	H7b	1.049***	0.044	4857.8	4853.8	df:4180
Brand Experience	H7c	1.63***	0.059	4425.1	4421.1	df:4180

Model performance and evaluation

Confusion matrix: The Confusion Matrix illustrates the accuracy of the logistic regression model in predicting customer repurchase intention. The following provides an overview of the matrix: Recall (37.2%) depicts the model ability to capture true repurchase intentions. Overall accuracy (77%) indicates the model capacity to accurately categorize precision (71%), which provides the percentage of anticipated repurchase intentions that are true positives. The F1 score (49.2) indicates the balancing recall & accuracy. The detailed result is displayed in Table 9.

Table 9:Confusion Matrix and Statistics

Metrix	Value
Accuracy	0.7754
Sensitivity	0.7200
Specificity	0.7853
Pos Pred Value	0.3737
Neg Pred Value	0.9403

ROC Curve: The ROC curve is derived from a logistic regression model predicting customer repurchase intention based on product, dealer, and brand experience. Starting at (0,0), the curve rises until it reaches (1,0) in the right corner. The model's first prediction scenario, where both sensitivity and specificity are at their lowest, ranging from (0,0) on the ROC curve. The curve that falls below the diagonal line indicates that the model could initially give specificity a higher priority than sensitivity. This would imply a higher bar for categorizing positive cases. After reaching the right corner at (1,0), the ROC curve indicates that the model has perfect specificity. However, sensitivity may suffer as a result. The diagonal line that crosses the y-axis (1,0) and the extreme right axis suggests a period in which the model operates randomly, indicating that the trade-off between sensitivity and specificity is not well-balanced at that point in the curve. The AUC of (0.83) underscores the model's [STRONG] ability to discriminate between customers intending to repurchase and those who do not. The ROC curve the compromise between sensitivity and specificity derived from logistic regression analysis in Figure.

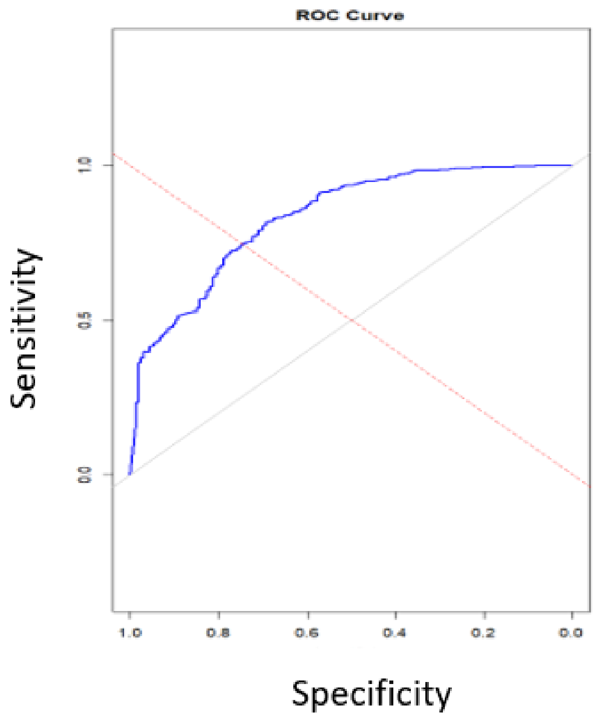

Figure 3: ROC Curve: Sensitivity vs Specificity

Logistic Regression Results

A logistic regression model predict customer repurchase intention based on product, dealer, and brand experience has yielded valuable insights. Coefficients and odd ratios provided a nuanced understanding of the relationship between experience and the likelihood of repurchase. The model showed a good fit. The Logistic regression model tailored to predict customer repurchase intention based on product, dealer, and brand experience has yielded valuable insights. A stratified sampling approach was used to validate the model, demonstrating a high fit and significant predictive influence with an AUC of (0.83). The 77 % accuracy of logistic regression illustrates how well it can classify repurchase intention. Moreover, coefficients and odds ratios revealed the correlation between experiences and the chance of a repurchase.

4.1.5.2 Decision Tree Analysis

Data collection and processing

These are the same data we collected to forecast customer repurchase intention, measured independent variable in weightage average and the categorical variable is the repurchase intention. Here, the stratified method of validation is employed due to dataset imbalance. The dataset is then divided into train and test groups, 70:30. A decision tree with several splits that each improved the model's predictive capacity was produced throughout the model-fitting process. The quality of fit and tree complexity is balanced, as shown by the complexity parameter (Cp). A variable significance analysis shows the contribution of each feature to the model's predicted accuracy.

Model Fitting

We analyzed a dataset comprising n = 3494 observations to predict the customer repurchase intention based on product, dealer, and brand experience. Nodes and terminal leaves within the trees provide a granular view of the decision-making process, offering predictions, expected loss metrics, and probabilities for each class. The primary splits, defined by variables at split value, serve as the foundation decision point guiding subsequent nodes. The Decision Tree provides a straightforward decision-making process based on the thresholds of product experience (PE), brand experience (BE), and dealer experience (DE). The percent- ages represent each class's chance (probability) result in the terminal nodes. The model iterates across the tree, making predictions following the parameters provided at each node. *Note: CP stands for Complexity Parameter.*

Table 10: Model Fitting Results for Decision Tree Analysis

CP	***Nsplit***	***Relative Error***	***Cross Validation Error***	***Cross Validation Std. Dev.***
0.16098485	0	1.0000000	1.0000000	0.04008220
0.05871212	1	0.8390152	0.8428030	0.03731091
0.02462121	2	0.7803030	0.7935606	0.03635927
0.01136364	3	0.7556818	0.7973485	0.03643403
0.01000000	5	0.7329545	0.7916667	0.03632179

Prediction of Repurchase Intention

The decision tree model reveals critical insights into customer decision-making regarding repurchase intention, primarily driven by the customer's sense. After using the complete dataset in the study, an overall outcome probability of 85% is obtained for a positive repurchase intention (class 1). In the model analysis of the customer brand experiences, positive brand experiences are those with a CFA factor score higher than -0.66 and a high 92% chance of repurchase intention. Subsequent analysis is initiated when the brand experience drops below -0.66, indicating a disparity in the following decision path. The model adds extra criteria when predicting the outcome for customers with a low brand rating (less than - 0.66). According to the model, a further drop in the brand experience score to less than -1.3 indicates a 21% chance of no repurchase intention. Customers who score their brand experience higher than -1.3 are 56% more likely to intend to repurchase. Further evaluation is to get a more positive outcome and refine the predictions based on other features such as dealer experience and product experience with the condition DE < -1.8 and product experience PE < -0.85. The most probable prediction is a negative outcome (class 0: No) if both the dealer experience (DE) and the product experience (PE) requirements are satisfied. In this scenario, customers will not consider another experience; however, after evaluating dealer experience and customers have an experience score of more than < -0.85, the model shows the subsequent consideration of another feature, which is Brand experience, with an experience score ≥ -0.83, the model predicted 62% chance to have no repurchase intention. The model predicts a 26% chance of no repurchase intention if the DE condition is met and the Product experience score is below –0.85.

Positive Scenario (Class 1 - Yes):

- Brand Rating ≥ -1.3 (higher Brand Rating)
- Product Experience < -0.85
- Dealer Experience < -1.8
- Predicted Outcome: Class 1 (Yes - repurchase intention)

Negative Scenario (Class 0 - No):

- Brand Rating < -1.3 (very low Brand Rating)
- Product Experience >= -2
- Predicted Outcome: Class 0 (No - no repurchase intention)

To display the decision tree mapping in Fig. 4 in greater depth. Note: This model shows us the customer's decision-making regarding repurchase intention. It starts by looking at customers experience, here (BE = BR).

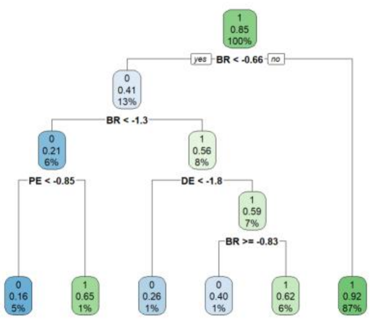

Figure 4:Prediction model of Repurchase Intention based on PE, DE, and BE

Pruning Analysis

The output of the pruned decision tree model, which involves removing specific nodes to reduce overfitting and enhance the model's generalization abilities, shows the tree's structure and offers insightful information about the variables impacting customer behavior and decision-making. The pruned decision tree model shows 3480 observations with 313 missing with a predicted class distribution of 15.17% for class 0 and 84.83% for class 1, presenting a simplified and refined structure to enhance predictive performance and interpretability. The decision tree delves deeper into customer repurchase intention, focusing on the rating of brand experience. For customers with a brand rating below -0.66, the model signifies a subsequent split based on the brand rating, leading to refined predictions based on the brand experience. The decision tree shows the terminal nodes where the decision routes terminate by specifying certain thresholds and parameters. Based on the modified factors, these terminal nodes make precise predictions that give helpful information about the preferences and behavior of the customers.

Pruning Visualization:

The pruned decision tree visual representation can help clarify the model's predictions and direct essential business decisions. Figure 5. illustrates it.

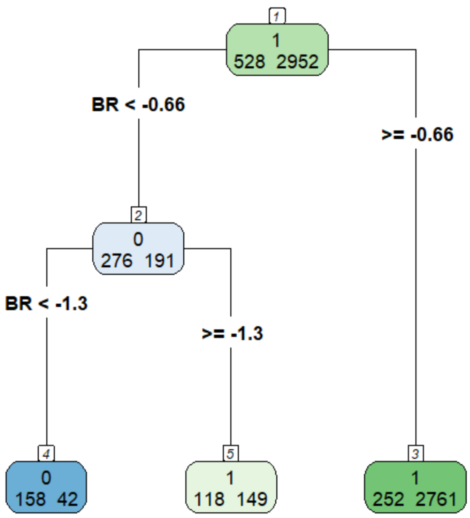

Figure 5: Pruned Model for Customer Repurchase Intention

Model Evaluation: Confusion Matrix

The model prediction performance showing the number of true positives (NP), true negatives (TN), false positives (FP), and false negatives (FN). In this instance, the confusion matrix shows 1246 true positives, 149 false negatives, 76 true negatives, and 18 false positives. 88.78% is the computed accuracy of the model, with a 95% confidence range that spans from 87.07% to 90.34%. This measure shows the precision of the model's predictions overall. The model's positive rate (sensitivity) is 33.78%, while the negative rate (specificity) is 98.57%. These measures show how well the model distinguishes between excellent and negative occurrences. It is computed that the negative predictive value is 89.32%, while the positive predictive value (precision) is 80.85%. The balanced accuracy measure shows an average sensitivity and specificity of 66.18%. These indicators show the model's advantages and possible errors, providing essential data for future model optimization and decision-making.

Table 11:Decision Tree: Confusion Matrix and Statistic

Matrix	Value
Accuracy	0.88
Sensitivity	0.33
Specificity	0.98
Pos Pred Value	0.81
Neg Pred Value	0.89

ROC Curve: The model's performance is represented by the ROC curve. It starts at (0, 0), which represents a sensitivity and specificity of 0, and it increases when the classification threshold of the model is adjusted. The intense reach in the curve indicates that the model can attain a high sensitivity with a low false positive rate. The curve moves closer to the point (1, 1) as it advances, showing a sensitivity and specificity of 1, denoting ideal categorization. The AUC-ROC assesses the model's overall discriminative ability, which is calculated at 66%. It summarized the performance across various threshold settings. A greater AUC provides valuable information about how well the model can differentiate between the positive and negative classifications. The ROC curve, depicting specificity versus sensitivity, is illustrated in Figure 6.

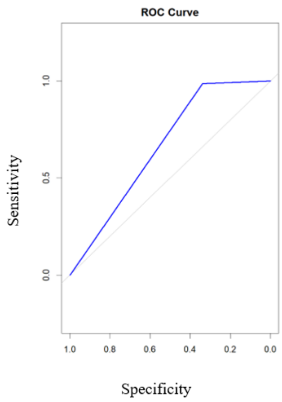

Figure 6: Decision Tree: ROC curve; Specificity vs Sensitivity

Decision tree analysis Result

The decision tree analysis concludes that customer repurchase intention is significantly influenced by their brand experience, product experience, and dealer experience. The decision tree model effectively segments the customer base based on these key factors, providing actionable insights for strategic decision-making. The decision tree model skillfully combines these aspects to understand the elements impacting a consumer's purchase decision fully, providing insightful advice for improving customer experiences, strengthening brand loyalty, and stimulating business growth. Based on brand, product, and dealer experiences, this scenario demonstrates how the tree captures several paths leading to predictions of repurchase intention or no repurchase intention. Businesses may use this data to customize tactics for various client segments, focusing on specific elements that affect the chance of repurchasing.

4.1.6 Model Comparison and Selection

The research section on model selection and comparison presents an integrated comparison of the logistic-regression and decision-tree models. Decision-tree model performed more significant prediction. With precision and recall metrics of 37% and 72%, respectively, the logistic regression model shows an overall accuracy of 77% and an F1 score of 49%. By comparison, the decision tree model has an impressive F1 score of 93% and an overall accuracy of 88%, with precision and recall scores at 98% and 89%, respectively. In addition, error rate of decision-tree model is 0.11, which indicates a lower ratio of incorrect predictions to total cases. Overall, the decision tree model's higher accuracy percentage of model and with a smaller error-rate, emphasize its effectiveness in predictive modeling and its capability to distinguish between positive and negative instances.

4.1.7 Quantitative Analysis Result

Firstly, the study revealed that service failure brought the most substantial impact on product experience, leading to customer dissatisfaction, followed by its influence on brand and dealer experience. Secondly, the research shows three critical implications of service failure: its impact on customer negativity toward product quality, service support, and brand value, all of which contribute to customer relationship value. The study employed Two main models; in the first model, service failure is considered the independent variable, while all three variables of satisfaction serves as the dependent variable, and the extended first model introduces recovery speed as a moderate variable, which depicts the interaction effect between all listed service failures like (Severity of failure* Recovery speed, Repeated failure* Recovery Speed, and Unresolved failure * Recovery speed) and in the second model, customer satisfaction act as independent variable of RI (dependent variable), the analysis emphasized the paramount influence of customer satisfaction on repurchase intention, with particular significance attributed to brand and product quality, as well as dealer service support, in shaping repurchase decisions.

In the first model of hypothesized direct and interaction impact. The study provided findings of severity failures' impact on all three customer satisfactions' variables, rejecting the null hypothesis and supporting the research hypotheses. In the interaction between service failure and recovery speed, recovery speed only moderates the effect of repeated failure, severity of failure, and unresolved failure. The initial hypothesis aims to investigate how the severity of failure influences product, dealer, and brand experience. The findings presented in the table reveal that the severe failure has a notable adverse impact on product experience, dealer experience, and brand experience. The statistical analysis showed a substantial negative impact of severity failure, supported by a significant R^2 value of 0.0052 and a significant F-statistic of 22.77 (df = 1; 4088) at 0.01 significance level. Similarly, dealer and brand experiences also showed statistically significant impacts of severity failure. Additionally, the study explored the interaction effect of severity failure with recovery speed. The hypothesis proposes that Recovery speed moderates the impact of the severity of failure on product, dealer, and brand experience. However, the analysis did not support the hypothesis, indicating that recovery speed did not mitigate the negative impact of severe failure. The R^2 values for product, dealer, and brand experiences fell below the 0.05 threshold. The F-statistics for the interactions between severity failure and recovery speed are insignificant, further indicating the lack of support for the hypothesis and failure to reject the null hypothesis. These results were derived from a total of 4099 observations.

The results also substantiated the second hypothesis, indicating a direct negative effect of repeated failure on product, dealer, and brand experience, as supported by the statistical analysis. This is further included by significant R-square values of all three experience are

(0.016, 0.003, and 0.009) and significant F-statistics of 89.4, 20.4, and 55.56 (df = 1;5404) at a * significance level. In the sub, the hypothesis proposes that Recovery speed moderates the effect of Repeated failure on product, dealer, and brand experience. With R^2 values of 0.0198, 0.00501, and 0.011 at $p < 0.05$, a significant F-statistic of 37.39, 10.08, and 21.72 (df= 3; 5402) at a * significance level, the result indicates recovery speed significantly moderates the effect of occurrence of failures on customer satisfaction. The interaction between the two constructs is directly related to customer satisfaction, which means that when customers encounter several failures and get prompt service, they will be less satisfied with their experience, which can have a positive impression. Hence, the hypothesis supported and rejected the null hypothesis. The third hypothesis, analysis of the hypothesized model (see Table 3), showed that the result supported the direct negative impact of unresolved failure on product, dealer, and brand experience. Table 3 indicates that if a customer has unresolved failures in their account, it will lead to higher customer dissatisfaction. The standardized (β value) of -0.94 means that unresolved failure can contribute about 94% to product experience, 82% to dealer experience, and 64% to brand experience, which shows that unresolved failures have the biggest impact on product experience, which is quite significant with $p < 0.05$, and (df = 1; 5094) at a * significance level. Whereas in the interaction hypothesis, recovery speed moderates the effect of unresolved failure on product, dealer, and brand experience has not been supported. The hypothesized model shows that recovery speed does not mitigate the negative effect of unresolved failure on customer each experience. Therefore, the null hypothesis is not rejected.

The second model utilizes dealer (DE), brand (BE), and product (PE) experiences as predictors of customer repurchase intention. A sample of 3480 data was collected for the study; 313 observations were excluded because of missing values. The first model indicated that the CFA factor score would predict the total experience, while Figure 4 suggests that the primary factor influencing the decision to repurchase is brand experience. Following that are dealer and product experiences. To provide a more accurate and clear understanding of customers' purchasing decision-making process. Many additional factors related to product experience and dealer experience come into consideration when aiming to understand the specific information in the manufacturing industry in greater detail. Here, we have taken into consideration a few points from the customer survey, where the question we included is about the product experience: P1: Productivity in the market P2: Product in Active state, that is, machine uptime; P3: Operating Cost; P4: Engine Satisfies Requirements; P5: Equipment Usability; and P6: Total Product Experience Score.

Furthermore, together with relevant dealer experience, D1 is for parts availability, D2 is for timely issue handling, D3 is for treating with respect, D4 is for the total dealer experience score, and BE stands for the entire brand experience. The outcome model demonstrates that a customer's brand experience is the most critical factor when deciding whether to repurchase since it influences their choice to buy any product. An eight or higher brand experience increases the likelihood that a customer will repurchase 92 % of the time. There is a 42 % probability that there will only be a purchase if the criteria are met with an eight score. Overall product experience: customers want an overall dealer experience that is more significant than a score of six out of ten, which indicates a 57 % chance of repurchase. In a service failure, they also want to know if the dealer has parts available, which can help maintain product uptime. If the dealer receives a score of at least five, this indicates a 61 % chance of repurchase. For a more comprehensive detail of customer repurchase intent, Figures 7-8 explicate the product and dealer experience factors that have the most significant impact. Detail abbreviation of questionnaires P1-P6 and D1-D4 mentioned in Appendix Table 1.

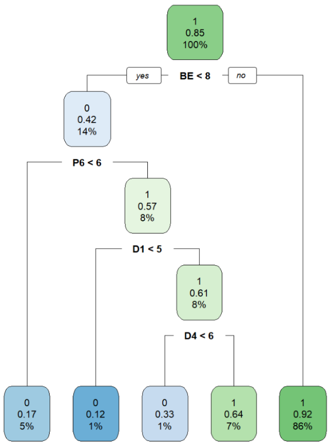

Figure 7: Prediction model with BE, P1-P6 and D1-D4

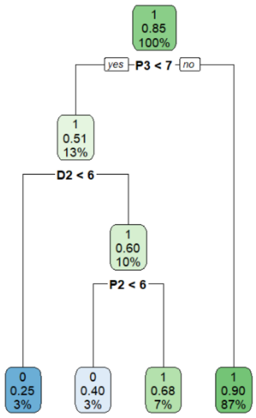

Figure 8: Prediction Model with P1-P6 and D1-D4

4.1.8 Qualitative Analysis: Data Collection & Processing

The data collection involved interviews with 13 individuals closely engaged in customer experience and post-sales service provision across various departments. Eleven participants were successfully interviewed, providing valuable insights into the customer journey and experience enhancement initiatives. The interviews were structured around ten open-ended questions designed to provide comprehensive perspectives and experiences related to customer service and product improvement processes. The interview questionnaire comprised five questions tailored to align with the thesis findings, seeking the participants' views on specific aspects identified in the study. Additionally, five questions delved into the participants' experiences throughout the customer journey, encompassing their involvement in addressing service failures, dealer training, and product enhancement initiatives. The interview format encouraged in-depth discussions, allowing participants to share their insights and feedback, contributing to a richer understanding of customer service and improvement strategies. Interviews were conducted through both live presentations and online meetings, catering to the convenience of the interviewees. Responses were noted in real-time during live interviews, whereas online interviews were recorded and transcribed for subsequent analysis. All transcribed interviews were meticulously converted into comprehensive notes to ensure to get key observation. A unified file was created for the listed questions, and the corresponding answers were attributed to each employee's name and area of specialization. This approach facilitated a structured and organized compilation of interview data, ensuring accessibility and coherence for subsequent analysis and interpretation of the thesis. The interview process served as a vital source of qualitative data, providing firsthand perspectives and experiences from department specialists and offering valuable qualitative insights that contributed to the comprehensive analysis of customer experience and service enhancement strategies.

As interviewees come from diverse backgrounds and hold various roles across different departments, we aimed to gather insights from multiple perspectives to ensure a comprehensive understanding. Consequently, not all 11 interviewees responded to every question, as some queries may not have been directly relevant to their area of expertise or experience. This approach was taken to prevent the dissemination of inaccurate information and to maintain the integrity of the data collected.

4.1.8.1 Listed Questionnaires and Summarized Responses from Interviews

the complete set of responses from all eleven interviewees and set of questionnaires are demonstrated in Table 12.

Table 12: Interview Questions and Response

1. What unexpected or surprising results did the three-year customer experience research reveal regarding customer satisfaction and service failure with recovery speed?

Response	Interviewee: Role and Main Project
The most surprising result from our three-year customer experience research was that recovery speed has a minor impact than expected on long-term customer satisfaction despite providing fast recovery. Over the longer term, recovery may have a smaller influence, and customer satisfaction could be impacted regardless.	Interviewee 1: Product Problem Resolution, Supervisor
It was surprising to observe that recovery speed had a significant impact in the early stages of the product life cycle but became less impactful as the three-year survey progressed. This unexpected finding has provided valuable insights into the evolving relationship between recovery speed, customer satisfaction, and service failure.	Interviewee 2: After Market customer Support, Supervisor

Surprising for us is that the recovery speed in the three-year survey is less impactful than in the six-month experience survey. Surprising at the beginning, and for the rest, this may confirm what we have been thinking and what seeing in the past 25 years of experience and looking at the perspective of not as an employee but as a customer in general.	Interviewee 3: Machine Health Specialist
Unsurprisingly, when discussing customer satisfaction, they could be happier. we see in my daily work that dealer experience, brand experience, and product experience are much higher in a smaller time frame than in the long term, and of course, 36 months is a long time. It is good to have improved.	Interviewee 4: Dealer Territory Customer Support, Manager
Surprisingly, service speed or service recovery speed has less influence on customer experience compared to early ownership.	Interviewee 5: Customer Experience, Data Sciencetist
The most surprising thing for me was that we only looked at more recent data in the three-year survey, so the customers provided more recent feedback on the experience. Also, the first experience and first impressions we had were still high. It is surprising that even if the dealer does its best to repeat failures to keep the customer going by doing the same repairs and replacing the same components to keep them running, the customer still had a relatively high impact on the 3-year survey.	Interviewee 6: Dealer Service & Development, Service Advisory
One surprising finding was the notable difference between responses at six-month and 36-month intervals, indicating potential memory lapses in customers. Additionally, the investigation revealed a gray-zone between unresolved and repeated issues, suggesting persistent concerns that may require further attention.	Interviewee 7: Customer experience and Part sales
It is nothing necessarily unexpected or surprising; it is a confirmation of things that we thought but are not related to statistical evidence yet.	Interviewee 8: Product Improvement, Director
The hypothesis was somewhat surprising, yet the findings confirmed its validity. Initially, customers expected no failures within the first six months. However, subsequent failures shifted their focus toward the speed of resolution.	Interviewee 9: Dealer strategies and Service, Supervisor

2. Can the thesis findings guide improvements in customer satisfaction or dealer interaction?

Response	**Interviewee: Role and Main Project**
Indeed, the thesis findings could guide customer satisfaction and dealer interaction improvements by emphasizing the need for effective and meaningful dealer interactions. This includes strong communication and relationships with customers and educating them about the impact	Interviewee 1: Product Problem Resolution, Supervisor

of customer treatment on their overall satisfaction. Ultimately, these efforts can create a positive and fulfilling customer experience, leading to happy and satisfied customers.	
The thesis findings provide valuable insights that can improve customer satisfaction and dealer interaction. We can proactively detect potential issues and offer timely solutions by using predictive alert systems powered by advanced algorithms and artificial intelligence. For instance, these systems can notify customers when their machines require maintenance or updates, ensuring proactive actions and smoother operations. We aim to improve overall satisfaction and strengthen customer and dealer relationships by prioritizing clear communication and proactive support.	Interviewee 2: Customer Experience and Dealer training, Supervisor
This information could be helpful when we talk to dealer managers and those in charge of customer experience. It shows them exactly why we are suggesting changes to the survey process. When they see that real data backs our ideas, it is easier to get them on board with making these improvements.	Interviewee 3: After Market Customer Support, Supervisor
The results show us how important it is to communicate well, especially with customers. They need to understand why things go wrong sometimes and how things like how often they use the machine can affect its reliability. For example, we had this situation where clutches kept failing because people were not using the machines properly. This shows that we must ensure customers know how to use our equipment properly.	Interviewee 4: Warranty Claim, Analyst
Implementing CRM and features like predictive alerts can positively impact customer experience by reducing diagnostic times and enabling proactive maintenance. Highlighting the advantages of these technologies to dealers can enhance their capacity to deliver efficient and timely service, thereby leading to enhanced customer satisfaction.	Interviewee 5: Dealer Territory Customer Support, Manager
The findings from the thesis, especially about parts availability and how it affects customer satisfaction, offer helpful insights for improving things. Addressing specific customer concerns, such as dissatisfaction with parts availability despite positive feedback, can guide targeted improvements and enhance customer satisfaction.	Interviewee 6: Machine Health Specialist
The thesis findings, especially regarding parts availability and its impact on customer satisfaction, provide valuable insights for improvement. Addressing specific customer concerns, such as dissatisfaction with parts availability despite positive feedback, can guide targeted improvements and enhance customer satisfaction.	Interviewee 7: Dealer Service & Development, Service Advisory

Understanding repurchase intent is identified as a key takeaway. The importance of conducting more regular surveys and using CRM tools to capture insights over a longer period is emphasized. The power of data is acknowledged as a driving force for uncovering unresolved issues and making informed decisions.	Interviewee 8. Customer Experience and Part Sales, Service Advisory
The importance of identifying the most impactful areas for improvement is highlighted. Strategic decisions can be made to address particular concerns and boost overall customer satisfaction by prioritizing areas according to their importance and anticipated impact.	Interviewee 9. Product Improvement Department, Director
Introducing digital surveys is a positive change, enabling more frequent touchpoints with customers. Staying connected with customers through advanced tools and solutions can provide insights into customer satisfaction and open issues, preventing potential customer attrition.	Interviewee 10. Dealer strategies and Service Department, Supervisor

3. How do the results regarding repurchase intentions align with observations in the role, and are there any notable discrepancies or insights identified between the predictions and actual experiences?

Response	Interviewee: Role & Main Project
The results regarding repurchase intentions align with observations. We have witnessed that repurchase intent is our goal and a key objective for dealers. So, it is essential to talk to customers often to ensure their experience matches their expectations. If any problems arise, we must fix them immediately to keep them wanting to buy from us again.	Interviewee 1: Product Problem Resolution, Supervisor
we have seen strong brand loyalty among customers. A past analysis showed that some customers were at risk of switching brands, but only a small percentage did. Surprisingly, we had yet to confirm if customers planned to repurchase our brands' products in three-year surveys before. From our experience, it takes a lot for customers to leave our brand, and convincing them to switch is challenging. This suggests loyalty and satisfaction with our brand.	Interviewee 2: After Market Customer Support, Supervisor
We have noticed a different attitude towards failures in Europe compared to the US. While there is strong loyalty to our brand in the US, customers are less tolerant of failures in Europe. They are quick to switch brands if issues persist. For example, customers from Germany, France, and the UK are demanding and expect high quality. Even though New Holland might be cheaper, customers still hold us to a higher standard. They expect more from us, so we need to be cautious	Interviewee 3: Machine Health Specialist

and attentive to their needs.	
It aligns with expectations, but sometimes, performance issues vary from the wrong machine model being recommended initially. Clear communication during sales and thorough training for customers can prevent such issues, improving overall customer experience.	Interviewee 4: Customer Experience and Dealer training, Supervisor
It is aligned with expectations. If the customer has already bought the product from us, it is more likely that he will try it with us first before he goes to the competition.	Interviewee 5: Warranty Claim Analyst
Customers' satisfaction with our brands' products may sometimes translate into immediate repurchases. Factors like significant price increases and competition from other brands can influence their decisions. Additionally, the timeframe between expressing interest in a new machine and purchasing plays a crucial role. Therefore, while customers may intend to repurchase the same brands' products, various external factors can affect their final decision.	Interviewee 6: Dealer Territory Customer Support, Manager
It is aligned, but the tricky thing is that it is not only one thing consider when making a business decision so that it might be more complex. In general, the concept is aligned.	Interviewee 7: Data Scientist, Customer Experience
From what we have seen customers care most about the quality of the product, then what they think about the brand, and finally, their experience with the dealer. Many customers emphasize that the dealer's role is less crucial than the product or brand reputation. During my interactions with customers, particularly those with larger machines, they often praise the quality of our products.	Interviewee 8: Dealer Service Development, Service Advisory
We ensure customer feedback reaches dealers promptly for resolution. Ultimately, customers prioritize cost, convenience, and dealer support. Dealerships that understand and support their needs become preferred partners.	Interviewee 9: Customer Experience and Part Sales, Service Advisory
While there may not be statistically solid evidence, various factors can contribute to a disconnect between repurchase intentions and survey responses. These factors include timing, changes in dealer partnerships, product evolution, and customer perceptions. It emphasizes the importance of considering broader trends rather than relying solely on survey results for insights into customer behavior.	Interviewee 10: Product Improvement Department, Director
Its aligned. However, other factors come while making buying decision. Emotions can sometimes drive decisions, even though price, product quality, and service matter considerably. Nevertheless, what is most important for our customers is how well our machines work and how they affect their business. They think carefully about what makes the most sense financially and practically.	Interviewee 11. Dealer strategies and Service Department, Supervisor

4. Are there any strategies, a) CRM Implementation b) Predictive Alert c) Precautionary Check already implemented into our existing processes? How feasible is it?

Response	Interviewee: Role & Main Project
The predictive alert and precautionary checks strategies have yet to be implemented in existing processes. However, we are in the phase of implementing the CRM system. Moreover, we have implemented the precautionary check only for customers with extended warranties. Predictive analytics are similar to Expert alerts but lack real-time data access. In an ideal scenario, the expert lead should be directed to a dealer rather than a customer.	Interviewee 1: Product Problem Resolution, Supervisor
CRM implementation is currently in progress, and efforts are being made towards implementing precautionary checks. Additionally, a process called NCCA is being prioritized from both a factorized perspective and a customer and warranty perspective. The aim is to efficiently resolve the most impactful service failures with priority and speed, aiming to ensure that 85% of the spare parts requirements of customers are readily available in the shops. This focus on directly ensuring spare parts availability in the shops is designed to minimize wait times and provide customers with a more efficient service experience. Furthermore, there is a strong emphasis on training and qualifying the technical personnel in the field, indicating a significant strategy for continuous improvement in product quality and preventing service failures.	Interviewee 2: After Market Customer Support, Supervisor
We are working on predictive notifications based on customer feedback, but progress could be faster due to data and sensor limitations. Efforts are also underway for precautionary checks, like expert or winter inspections, for preventive maintenance. However, we lack a CRM system crucial for real-time customer relationship tracking and data accessibility.	Interviewee 3: Machine health specialist
We have had precautionary checks like winter inspections for seasonal machines for many years, and they are popular among customers. However, we have yet to see the same success with tractors. Productive alerts have been limited lately, but expert alerts on machines are working well. As for CRM implementation, we are implementing it in Italy, focusing on customer data such as addresses, fleet machines, and business types. CRM is mainly used in sales to handle customer deals, but it must still be fully implemented for marketing materials or digital surveys.	Interviewee 4: Customer Experience and Dealer training, Supervisor
CRM helps us find solutions better suited for customers, offering better options than they anticipate. However, this relies heavily on interpersonal interactions. Precautionary checks are challenging due to technicians' workload. Implementing a system for customers to track machine data could serve as a solution, allowing for proactive	Interviewee 5: Warranty Claim, Analyst

notifications and replacing traditional precautionary checks	
Combination dealers have initiated CRM implementation, with some dealers already having 70% customer consent. Predictive alerts are in progress but require substantial effort. Precautionary checks face workshop capacity limitations. However, many customers still bring machines for winter checks, especially for warranty purposes. Workshop efficiency remains a challenge.	Interviewee 6: Dealer Territory Customer Support, Manager
All three strategies—precautionary checks, predictive alerts, and CRM implementation—are currently in place. Precautionary checks, conducted through expert inspections, have been ongoing for many years, ensuring longer service life. Predictive maintenance, facilitated by maintenance alerts, helps prevent costly downtime by scheduling maintenance tasks proactively. The CRM tool combines warranty incidents and customer feedback for enhanced service delivery. While implementing CRM initially required significant effort, customers and dealers have recognized its value in reducing downtime and improving workshop efficiency.	Interviewee 7: Customer Experience and Part Sales, Service Advisor
The CRM implementation is still pending, although we use a SWAB system to track after-sales contacts. While the system is functional, we have yet to integrate CRM with customer experience processes. CRM is used primarily to collect consent for digital surveys, accounting for about 99% of its usage. However, we have achieved high completion rates for predictive maintenance or protective repairs, with around 96% completion in my area of responsibility. Despite this success, it must be integrated with the existing customer experience. Expert or precautionary checks have successfully ensured machine reliability during the season. However, we need to assess customer satisfaction within the CRM system.	Interviewee 8. Dealer Service Development, Service Advisory
We utilize expert alerts, providing interactive solutions to assist dealers in resolving issues promptly and reducing diagnostic time. Additionally, we offer Power Guard as a corrective measure, which helps manage the customer's financial implications. Implementing expert alerts can be challenging due to their complexity and technical requirements.	Interviewee 9: Product Improvement Department, Director
We need CRM implementation for digital surveys to work effectively. Predictive alerts, similar to expert alerts but more advanced, show promise for the future with potential AI integration. Precautionary checks are essential to prevent downtime and ensure a positive customer experience, highlighting our strategic focus on expert checks.	Interviewee 10: Dealer strategies and Service Department, Supervisor

5. On a scale of 1 to 5, how likely do you think it is that the suggested strategies can be integrated into existing processes?
   a) CRM Implementation
   b) Predictive Alert
   c) Precautionary Check

5: Very Easy 4: Easy 3: Moderate 2: Difficult 1: Very Difficult

Response	Name, Role, Main Project
a) CRM Implementation - 5 (*Very Easy*) b) Predictive Alert - 1 (*Very Difficult*) c) Precautionary Check - 2 (*Difficult*)	Interviewee 1: Product Problem Resolution, Supervisor
a) CRM Implementation: Likelihood - 5 *(Very easy)* b) Predictive Alert: Likelihood – 4 *(Easy)* c) Precautionary Check: Likelihood – 4 *(Easy)*	Interviewee 2: After Market Customer Support, Supervisor
a) CRM Implementation: Likelihood - 2 (*Difficult*) b) Predictive Alert: Likelihood - 1 (*Very difficult*) c) Precautionary Check: Likelihood - 1 or 2 (Difficult)	Interviewee 3: Machine health specialist
a) CRM Implementation - 3 (*Moderate*) b) Predictive Alert - 4 (*Easy*) c) Precautionary Check - 2 (*Difficult*)	Interviewee 4: Customer Experience and Dealer Training, Supervisor
a) CRM Implementation - 4 (Easy) b) Predictive Alert - 5 (Very e*asy*) c) Precautionary Check - 2 (*Difficult*)	Interviewee 5: Warranty Claim, Analyst
a) CRM Implementation - 3 (*Moderate*) b) Predictive Alert - 5 (*Easy*) c) Precautionary Check - 2 (*Difficult*)	Interviewee 6: Dealer Territory Customer Support, Manager
a) CRM Implementation - 2 (*Difficult)* b) Predictive Alert - 3 (*Moderate*) c) Precautionary Check - 2 (*Difficult*)	Interviewee 7: Customer Experience, Data Sciencetist
a) CRM Implementation – 3 (*Moderate)* b) Predictive Alert - 4 (*Easy*) c) Precautionary Check – 1 (*Very difficult*)	Interviewee 8: Dealer Service Development, Service Advisory
a) CRM Implementation – 4 (*Easy)* b) Predictive Alert - 1 (*Very difficult*) c) Precautionary Check – 2 (D*ifficult*)	Interviewee 9: Customer Experience and Part Sales, Service Advisory

a) CRM Implementation – 3 (*Moderate)* b) Predictive Alert - 5 (*Very easy*) c) Precautionary Check – 2 (D*ifficult*)	Interviewee 10: Product Improvement Department, Director
a) CRM Implementation – 3 (*Moderate)* b) Predictive Alert - 3 (*Moderate*) c) Precautionary Check – 1 (Very d*ifficult*)	Interviewee 11. Dealer strategies and Service Department, Supervisor

6. Can you share insights on the specific types of failures that result in more extended machine downtime based on observations or experiences?

Response	Interviewee: Role & Main Project
Based on observations and experiences, the specific types of failures that lead to more extended machine downtime are primarily related to engine and transmission issues. When the engine or transmission fails, it significantly impacts the machine's operability, resulting in more extended downtime. While smaller software-related issues may require an extended period to resolve, they generally do not result in the machine being inoperable. Therefore, the most significant and impactful failures that lead to extended machine downtime are those related to the engine and transmission.	Interviewee 1: Product Problem Resolution, Supervisor
The failures that result in longer machine downtime include transmission issues, engine malfunctions, hydraulic problems, and other complex mechanical failures. To address these challenges efficiently, we implemented strategies such as component remanufacturing, specific overhaul processes, and facilitating component exchanges for customers and dealers. These measures helped minimize downtime and effectively manage machine failures.	Interviewee 2: After Market Customer Support, Supervisor
The most time-consuming type of failure causing extended machine downtime is associated with the drivetrain, particularly broken shafts and other major components. This issue consistently leads to downtime exceeding ten days, resulting in significant customer dissatisfaction. Engine-related issues, specifically with turbochargers in mid tractors, also contribute to challenges in minimizing downtime and maintaining operational efficiency."	Interviewee 3: Machine health specialist
The type of failure that significantly leads to more extended machine downtime, in terms of severity, is associated with engine malfunctions or breakdowns.	Interviewee 4: Customer Experience and Dealer Training, Supervisor
Extended machine downtime is often attributed to specific failures, such as transmission overheating. This issue, along with track failures, can result in prolonged downtime. Challenges with track parts	Interviewee 5: Warranty Claim, Analyst

availability and the need for engineering engagement in diagnosing transmission problems contribute to the extended duration of machine unavailability.	
Particularly with transmission issues. In significant transmission failures, the unavailability of necessary parts exacerbates the situation. If the dealer encounters challenges in identifying the problem, resorting to diagnostic cases and the subsequent analytical process may extend the downtime to approximately a week before a conclusive resolution is reached.	Interviewee 6: Dealer Territory Customer Support, Manager
When the product, specifically the engine, requires intricate inspection involving the removal of various components for a thorough examination, it can result in more extended downtime. Challenges arise when the diagnostic process is not swift.	Interviewee 7: Customer Experience, Data Sciencetist
Long periods of machine downtime are mostly caused by major problems like engine or transmission failures. Even when we have the right parts, fixing issues like transmissions can take days. We reduce downtime by offering programs like the Harvest Promise for combines and SPFH. If a machine has not worked for less than a day, we quickly provide the needed parts. However, sometimes, delays happen because of factors like the type of machine or where it is from, especially if the dealer needs the parts we need.	Interviewee 8: Dealer Service Development, Service Advisory
The potential for longer machine downtime is associated with various factors, mainly when there is a complete failure in critical components like the engine. While some failures, such as malfunctioning alternators or fuel pumps, might not entail additional engine issues, they can still lead to extended downtime due to factors like the availability of parts. The complexity arises when specific components are unavailable, prompting discussions on alternative repair approaches. Apart from traditional components, newer technologies introduce electrical failures, adding another layer to potential causes of downtime.	Interviewee 9: Customer Experience and Part Sales, Service Advisory
The main reason for longer recovery times is dealing with intermittent issues, which do not always cause immediate downtime but still slow things down. These issues are often about performance rather than complete failure and take longer to fix because they are harder to diagnose and may come back even after repairing a component. Plus, getting the right parts, especially in remote areas, can take time and add to the overall delay.	Interviewee 10: Product Improvement Department, Director
Sporadic failures occur randomly, appearing and disappearing without a consistent pattern. Unlike immediate failures that stop the machine right away, these issues pop up after some time or usage. While they are not always severe, they are still annoying and challenging. Customers get frustrated because the problems keep coming and going, making it hard for technicians to fix them.	Interviewee 11. Dealer strategies and Service Department, Supervisor

7. Which aspect of customer satisfaction, whether it is product experience (PE), dealer experience (DE), or brand experience (BE), do you think is most impacted by service failures, and why?

Response	Interviewee: Role and Main Project
When things go wrong with our service, the product experience (PE) hits the hardest for our customers. If they have a terrible time with a particular machine or equipment, it taints their view of the product and our whole brand. Even though dealers play a role, if they manage to exceed expectations, it helps soften the blow. So, improving the product and brand experience in situations like these is super important.	Interviewee 1: Product Problem Resolution, Supervisor
The aspect of our customers' satisfaction most significantly affected by service failures is the dealer experience (DE). Our research has shown that over 50% of a customer's purchase decision depends on the dealer and their service, while the machine's brand influences less than half. This underscores the critical role of the dealer in shaping customer satisfaction and loyalty.	Interviewee 2: After Market Customer Support, Supervisor
Service failures directly affect how customers view the product, dealer, and brand. The dealer's role is crucial in keeping machines running smoothly, especially during the warranty period. Unresolved issues or frequent service needs can significantly impact customer satisfaction and brand perception. Thus, the quality of dealer service significantly influences the overall customer experience.	Interviewee 3: Dealer strategies and Service Department, Supervisor
Most impacted by service failures is the Product Experience (PE). When crucial parts like the drivetrain fail, it reflects poorly on the product's design and quality, directly affecting how customers perceive the machine. While the Dealer Experience (DE) and Brand Experience (BE) also matter, service failures primarily influence how customers feel about their purchased product.	Interviewee 4: Machine health specialist
The most affected part of customer satisfaction due to service failures is the Product Experience (PE). When the machine breaks down, it directly impacts how customers feel about the product, leading to dissatisfaction. Next comes the Dealer Experience (DE). If the dealer cannot effectively fix the issue, it frustrates the customer. Lastly, there is the Brand Experience (BE). If the problem persists or needs to be addressed better, it reflects poorly on the brand. This could make customers reluctant to purchase from the brand in the future.	Interviewee 5: Customer Experience and Dealer Training, Supervisor
The most crucial aspects of customer satisfaction are the product's reliability and performance, along with the effectiveness of the dealer's experience in handling repairs and maintenance. Reliable product design and performance and proactive and capable dealer support significantly impact overall customer satisfaction.	Interviewee 6: Customer Experience and Dealer Training, Supervisor
The customer's perception can shift based on how the dealer communicates the issue. If the dealer is seen as the problem, it is a dealer issue. However, if the dealer transparently communicates that the problem is familiar with our brands' products, it becomes more about the product and brand perception.	Interviewee 7: Customer Experience and Dealer Training, Supervisor

Service failures primarily impact the product experience. When something goes wrong, it directly affects how customers view the product's quality and functionality. While the dealer's role is crucial in addressing issues, the focus remains on maintaining high product quality to ensure customer satisfaction. A smooth product experience is critical, but dealers step in to handle any possible hiccups.	Interviewee 8: Customer Experience, Data Sciencetist
Service failures primarily impact the product experience. When machines frequently malfunction, this directly affects how customers perceive the product's reliability and quality, influencing their overall impression of the brand.	Interviewee 9: Dealer Service Development, Service Advisory
The customer indicates that the predominant concern is the Brand Experience (BE) when confronted with recurrent product failures. They assert that consistent product failures harm their overall perception of the brand, resulting in a negative brand experience. The customer underscores the paramount importance of brand reputation, ranking it as their primary consideration followed by the Product Experience (PE) as the second most crucial factor. Additionally, the role of the dealer is acknowledged, with the expectation that effective communication and support from the dealer are essential in addressing repeat failures. This perspective positions brand experience as a critical factor influencing the customer's satisfaction and loyalty.	Interviewee 10: Customer Experience and Part Sales, Service Advisory
Service failures affect all aspects of customer experience - Product (PE), Dealer (DE), and Brand (BE). While there is a slight tilt towards DE and BE, efficient dealer support can positively influence overall satisfaction. DE may surpass PE in regions with proactive dealerships, underscoring their crucial role.	Interviewee 11: Product Improvement Department, Director

Moderation by Recovery Speed

8. After reviewing the recovery speed results from the 36-month and 6-month experiences, do you find the outcomes aligned with expectations or anticipating different results? Please share your thoughts.

Response	Interviewee: Role & Main Project
Outcomes did not align with expectations. Initially, anticipated similar impacts on service failures in both periods. However, the results revealed a disparity between the two-time frames. Moreover, the unexpected discovery that unresolved failures had a positive impact in the long term was intriguing. Further investigation into this finding would be valuable.	Interviewee 1: Product Problem Resolution, Supervisor
The results were surprising because we had observation that recovery speed would stay the same over time. When someone is new, they might need time to get used to the service. However, after three years, expect the service level to be consistent, especially if they had a good experience at the start. The first interactions might make them happy, but keeping that satisfaction is crucial.	Interviewee 2: After Market Customer Support, Supervisor
It is aligned. When recovery speed increases, Dealer Experience (DE)	Interviewee 3:

improves, and Product Experience (PE) gets a boost, too. We rely on our dealers to handle any issues from the factory. Premium brands like ours should have a few early failures. Customers expect consistent recovery speed throughout the product's life, without significant problems in the early stages.	Machine health specialist
Initially, it was surprising that the recovery speed did not have a lasting impact after 36 months compared to the first six months. Nevertheless, after understanding it better, it makes sense. It is logical to have a more significant impact in the initial six months and then less over time.	Interviewee 4: Customer Experience and Dealer Training, Supervisor
It is aligned. It depends on how recent their bad experiences were. If they have had a lot, they might not be happy. However, if things have been mostly good lately, it is similar to what finding showed with lifetime promoters and new owners being happy, too.	Interviewee 5: Warranty Claim, Analyst
Upon reviewing the recovery speed results from the 36-month and 6-month experiences, outcomes aligned with expectations. Initially, it was anticipated a consistent impact on service failures over time. However, the findings revealed a noticeable difference between the two periods. The unexpected discovery that unresolved failures positively impacted the long term was particularly intriguing and warrants further investigation.	Interviewee 6: Dealer Territory Customer Support, Manager
It is aligned. Customers may forgive early mistakes as they are still learning about the machine. However, as time goes on, they expect things to get better, not worse. It is like when one starts a relationship that might overlook minor annoyances at first, but they become more bothersome over time. So, it is not just about quick fixes but about consistently improving things.	I Interviewee 7: Dealer Service Development, Service Advisory
The outcomes from the 36-month and 6-month experiences did not align with my expectations. It was surprising to see how unresolved issues over three years could shift a customer's perception from promoter to detractor. Additionally, the mismatch in the number of customers responding to the initial and three-year surveys added complexity to the findings.	Interviewee 8: Product Improvement Department, Director

Repurchase Intention with Customer Satisfaction

9. In the respective roles of professionals, which do you believe matters most to customers when they decide to repurchase: the product experience, dealer experience, or overall brand experience?

Response	Interviewee: Role and Main Project
Interaction with the dealer influence whether customers decide to buy again. Quality interactions with dealers create loyal customers, while	Interviewee 1: Product Problem

positive product experiences and brand trust also contribute. Overall, dealer interactions are pivotal in shaping repurchase intent, followed closely by product experience and brand trust.	Resolution, Supervisor
The key factor influencing customer repurchase intention is the product's reliable performance. Customers prioritize having a dependable machine, regardless of any issues that may arise. Additionally, the dealer's role in providing quality service post-purchase is crucial. Customers value the service department's support, which heavily influences their decision to repurchase.	Interviewee 2: After Market Customer Support, Supervisor
Over time, we have observed a shift in customer loyalty from brands to dealerships. A notable example is a national dealer in my country who transitioned between brands for various reasons. Despite changing brands multiple times, most customers remained loyal to the dealer rather than the brand. This demonstrates the growing importance of dealer relationships in customer retention. While product quality remains crucial, having reliable dealer support is equally vital. Even the best product may only meet customer expectations with adequate dealer support.	Interviewee 3: Machine health specialist
Customer loyalty is influenced by the brand's promises, product performance, and dealer responsiveness. Initial recommendations may be based on brand reputation and word-of-mouth, but subsequent experiences with the product and dealer determine long-term loyalty.	Interviewee 4: Customer Experience and Dealer Training, Supervisor
The customer's evolving needs and experiences with different models influence their loyalty. If customers have a negative experience with one model, they may switch to another model better suited to their changing needs. Therefore, the product experience is critical in shaping their repurchase intention.	Interviewee 5: Warranty Claim, Analyst
The customer's preference between product, dealer, and brand experience varies. Generally, the product and brand experience influence the initial purchase decision, while the dealer's performance impacts long-term loyalty. However, some customers prioritize dealer support and parts availability over brand reputation. Overall, the dealer's service quality and support play a crucial role in retaining customers, although brand reputation and product features also contribute to repurchase decisions.	Interviewee 6: Dealer Territory Customer Support, Manager
Overall, the brand has the most significant impact on influencing customers' decisions to repurchase. Brand reputation symbolizes product quality and fosters strong customer relationships. While individual experiences matter, the overall brand perception remains paramount in driving customer loyalty and repurchase intentions.	Interviewee 7: Customer Experience, Data Sciencetist
The most critical factor influencing customer repurchase is the effectiveness of dealer support. While product quality and brand loyalty are important, customers heavily rely on dealer support for issues like sprayer functionality or combined performance. If dealers cannot offer adequate support, it hampers equipment functionality and satisfies customers, impacting repurchase decisions. Thus, robust dealer support is important for customer satisfaction and loyalty.	Interviewee 8: Dealer Service Development, Service Advisory
The primary factor driving customer repurchase intention is the	Interviewee 9:

product itself, particularly its impact on operational costs and overall performance. A reliable product directly influences productivity and financial outcomes, making it a key motivator for repurchase decisions. Dealer support, backed by effective problem-solving and product improvement programs from the brand, is essential for ensuring customers are happy, and building lasting relationships is significant.	Customer Experience and Part Sales, Service Advisory
The primary factor influencing customer repurchase intention is the dealer experience. Customers are inclined to remain loyal if they believe dealers can effectively address their concerns, outweighing the impact of product quality or brand perception. Direct interaction with the brand has the least influence on repurchase intention.	Interviewee 10: Product Improvement Department, Director
We prioritize customer orientation and place a high value on our customer relationships. Our commitment extends to providing special allowances during visits, particularly for key accounts with multiple machines. However, we recognize that the real game-changer is the dealer. Dealers play a vital role in shaping our customer interactions and are the daily face of our brand. As such, we heavily invest in enhancing their efficiency, advancing their capabilities, and aligning them with our strategic goals. We understand that dealers have a lasting impact on customer satisfaction, even more so than our occasional visits.	Interviewee 11. Dealer strategies and Service Department, Supervisor

10. In considering the allocation of 100 points among product, dealer interactions, and brand experiences regarding their impact on repurchase intention, how would one distribute them?

Response	**Interviewee: Role and Main Project**
40 points for the dealer experience, 40 points for the brand experience, and 20 points for the product experience.	Interviewee 1: Product Problem Resolution, Supervisor
Forty points for the product and brand and 60 points for the dealer experience.	Interviewee 2: After Market Customer Support, Supervisor
Fifty points for dealer interactions, 40 points for the product, and 10 points for the brand.	Interviewee 3: Customer Experience and Dealer Training, Supervisor
Forty points for the product, 40 points for dealer interactions, and 20 points for the brand. The product and dealer interactions have a more immediate and direct impact on the customer's decision to repurchase, whereas the brand contributes less since the customer has already established trust and familiarity with it.	Interviewee 4: Warranty Claim, Analyst
Fifty points for the product, 30 points for dealer interactions, and 20 points for the brand. The quality and performance of the product are the primary drivers of repurchase intention, followed by the customer's experience with the dealer and, finally, the brand's reputation and perception.	Interviewee 5: Machine Health Specialist

Forty points for the dealer, 30 points for the product, and 30 points for the brand.	Interviewee 6: Dealer Territory Customer Support, Manager
Thirty points for PE, 30 points for DE, and 40 points for BE.	Interviewee 7: Customer Experience, Data Sciencetist
Forty points for dealer interactions, 30 points for product experience, and 30 points for brand experience.	Interviewee 8: Dealer Service Development, Service Advisory
Fifty points for the product, 25 points for dealer interactions, and 25 points for brand experiences.	Interviewee 9: Customer Experience and Part Sales, Service Advisory
Fifty points to the dealer, 40 points to the product, and 10 points to the brand.	Interviewee 10: Product Improvement Department, Director
Sixty points for the dealer, 20 points for the product, and 20 points for the brand.	Interviewee 11. Dealer strategies and Service Department, Supervisor

4.1.8.2 Key Observation & Theme

To provide a comprehensive overview of the interview, it is essential to identify significant key observations and key themes. This process aims to enhance understanding, clarifying the key issues the interviewee touched up in response to different questions. Applying a systematic approach makes it possible to extract the main points of the conversation and identify recurring themes or patterns, thus facilitating a more nuanced comprehension of the interviewee's responses.

1. *What unexpected or surprising results did the three-year customer experience research reveal regarding customer satisfaction and service failure with recovery speed?*

Key Observation: The most important finding from the responses of the 11 participants in the study is the unexpected conclusion about the reducing effect of recovery speed on long-term customer satisfaction, even though it was anticipated that a rapid recovery would significantly impact satisfaction levels. This surprising outcome reflects doubt on the initial theory and emphasizes how the link between recovery speed, customer satisfaction, and service failure changes over time.

Key Theme: The contrast between the short- and long-term effects of recovery speed on customer experience emerges as a primary subject. Fast recovery may significantly impact the first few years of ownership or in a shorter amount of time. However, throughout a three-year survey period, its impact decreases. This implies that additional elements - like dealer relationships, product reliability, and overall brand experience become increasingly essential predictors of client satisfaction and ability to repurchase over time.

2. *Please share any specific instances where you believe the thesis findings could guide improvements in our customer satisfaction or Dealer interaction.*

Key Observation: The most important takeaway from the responses highlights how the thesis results have the potential to significantly increase dealer involvement and customer pleasure. Using cutting-edge technology, improving lines of communication, prioritizing strategic adjustments, and utilizing data-driven insights.

Key Theme: Proactive steps and thoughtful adjustments are prioritized to im- prove dealer engagement and customer happiness. This involves utilizing cutting- edge technology like CRM installation and predictive alert systems, enhancing customer communication, ranking areas for development according to importance, and using data-driven insights to guide decision-making processes.

3. *How do the results regarding repurchase intentions align with your observations in your role? Are there any notable discrepancies or insights you have identified between the predictions and your actual experiences?*

Key Observation: Repurchase intentions often align with expectations; a significant finding from the responses suggests that consumers strongly feel brand loyalty. Regional variations exist in consumer behavior, though, with European consumers being less tolerant of setbacks and more likely to move brands than American consumers. Pricing, dealer relationships, and product performance can also influence repurchase intentions.

Key Theme: The primary idea is to keep customers satisfied and loyal; it is critical to recognize the variables that affect their intentions to make more purchases and address them successfully. To maintain positive, repurchase intent, engaging with customers frequently is necessary to ensure their experience meets their expectations. Acknowledging the impact of dealer interactions, pricing, and product performance on customer decisions is also essential. Furthermore, the emotional component of consumer decisions is acknowledged, highlighting the necessity of considering both emotional and rational aspects when examining repurchase intentions.

4. Are any strategies, a) CRM Implementation, b) Predictive Alert, or c) Precautionary Check, already implemented into our existing processes? How feasible is it?
5. On a scale of 1 to 5, how likely do you think it is that the suggested strategies can be integrated into existing processes?
a) CRM Implementation
b) Predictive Alert
c) Precautionary Check
Key Observation: The key observation is that while CRM implementation is in progress, precautionary checks and predictive alerts are not fully implemented in existing processes. However, efforts and strategies are underway to incorporate these elements gradually. Challenges include the need for data collection, advanced analytics, and integration with existing systems.
Key Theme: Predictive Alert emerges as the easiest to implement, with a majority of respondents rating it as easy or very easy. CRM Implementation also favorable ratings, with a significant portion of respondents considering it easy or very easy. In contrast, Precautionary Check poses the greatest challenge, as most respondents rate it as difficult or very difficult. Despite some variability in perceptions, the overall trend suggests that Predictive Alert is the most feasible strategy for integration, followed by CRM Implementation, while Precautionary Check presents the highest level of difficulty.
The overall subject recognizes the value of preventive measures like predictive alarms and preventative inspections in improving customer satisfaction and reducing downtime. Notwithstanding obstacles, there is general agreement over the potential advantages of these tactics in raising customer satisfaction levels, cutting maintenance expenses, and optimizing service effectiveness.

6. *Can you share insights on the specific types of failures that result in more extended machine downtime based on observations or experiences?*

Key Observation: A thorough understanding of the particular kinds of failures that lead to extended machine downtime is necessary to manage it, as the main finding indicates. Even while the engine and gearbox are the two leading causes of failure, other problems, such as irregular or sporadic ones, contribute significantly. Effective diagnostic procedures are required to meet these obstacles, in addition to preemptive steps that guarantee part availability and lessen the impact of reoccurring problems.
Key Theme: The main idea is that certain kinds of failures, especially those involving essential heavy machinery product parts like the engine, gearbox, drive train, and hydraulic system, are mostly to blame for extended machine downtime. These malfunctions necessitate protracted diagnostic and remedial procedures, which frequently entail disassembling and examining several components. Problems with diagnostic complexity and component availability can also cause prolonged downtime. Furthermore,

irregular or sporadic failures present particular difficulties as they cannot instantly render the equipment unusable, but instead, they result in recurrent problems that complicate diagnosis and repair.

7. *Which aspect of customer satisfaction, whether it is product experience (PE), dealer experience (DE), or brand experience (BE), do you think is most impacted by service failures, and why?*

Key Observation: Service failures considerably impact each aspect of customer satisfaction, but opinions differ on which component is most severely impacted. This is an important finding. Some underline the significance of the product experience, emphasizing that the product's functioning and quality are immediately impacted by its successes. Others put the dealer experience first, stressing how important it is for dealers to handle and resolve servicing issues to reduce customer dissatisfaction. There is also recognition of the broader consequences for how consumers perceive a business, as poor service may damage a company’s reputation and overall experience. The replies, as a whole, highlight how difficult it is to handle service outages and how different elements influence customer satisfaction in various ways.

Key Theme: Customer satisfaction, such as Product Experience (PE), Dealer Experience (DE), and Brand Experience (BE), according to the recurrent topic in the responses. Opinions differ, although, as to which element is more impacted. While some stress how breakdowns in crucial components directly affect the product experience, others emphasize how vital the dealer is in determining total happiness. Furthermore, acknowledging the cascading impact of service failures on brand image emphasizes how these elements are interrelated in the customer satisfaction process.

8. *After reviewing the recovery speed results from the 36-month and 6-month experiences, do you find the outcomes aligned with expectations or anticipating different results? Please share your thoughts.*

Key Observation: Customer expectations and responses show a changing trend over time, as seen by examining recovery speed over both 36-month and 6-month experiences. First and foremost, quick recovery times are critical in creating favorable customer impressions and emphasize the value of timely resolution in the initial phases of ownership. The results also show that, over 36 months, consumers become less tolerant of service problems and have higher expectations, even though quick recovery is still crucial. This progression implies that while first encounters determine a customer’s level of pleasure, sustained loyalty and favorable brand impressions depend on long-term consistency and improvements in recovery speed.

Key Theme: This highlights how consumer expectations for recovery speed are dynamic and significantly influence loyalty and customer satisfaction. It highlights how crucial it is to control the recovery pace throughout the whole owner-ship lifespan, not just in the near term. Although quick recovery times create an excellent first impression, ongoing efforts to preserve and enhance recovery procedures are essential for satisfying higher standards and keeping customers loyal in the long run. Therefore, the subject emphasizes the need to continuously review and improve recovery tactics to align with changing customer needs and maintain long-term satisfaction.

9. *In the respective roles of professionals, which do you believe matters most to customers when they decide to repurchase: the product experience, dealer experience, or overall brand experience?*

Key Theme: Dealerships has big role in whether customers intend to repurchase or no. Even though having a good product and a strong brand is important, what really matters is how well dealers take care of customers. So, focusing on training dealers, improving their services, and making sure they can solve problems effectively is key to keeping customers happy and wanting to come back.
Key Observation: The responses emphasize three key factors impacting customer repurchase intentions: product reliability, dealer support, and brand reputation. Customers prioritize reliable machine performance, value positive dealer interactions, and consider brand reputation, although dealer support often outweighs brand perception in driving long-term loyalty.

10. *In considering the allocation of 100 points among product, dealer interactions, and brand experiences regarding their impact on repurchase intention, how would one distribute them?*

Key Observation: Diverse viewpoints on the distribution of points across products, dealer interactions, and brand experiences about their influence on repurchase intention are recorded in the response. Some give more weight on the dealer experience, while others stress the significance of product satisfaction and brand loyalty. The distribution of points is also inconsistent, with some respondents giving equal weight to each component while others give particular characteristics a more considerable weight based on their perceived importance in influencing repurchase intention. The findings demonstrate how difficult it is to determine which aspects affect a consumer's desire to repurchase and how subjectively points are assigned to different product, dealer, and brand experiences.
Key Theme: The main subject that emerges from the responses is the range of viewpoints on the relative significance of the product, dealer contacts, and brand experiences in influencing the intention to repurchase. Although there is an overall agreement about the importance of each of the three elements, there are significant differences in the distribution of points, which correspond to different interpretations of each factor's contribution. The subject also emphasizes how complex and multifaceted customers' decision-making processes may be, with many different elements and considerations

playing a role. Thus, the subject underscores the necessity for developing customized tactics and gaining a thorough grasp of consumer preferences to successfully manage the variety of factors on repurchase intention.

Overall points:

- Experience with Dealers: 40 points
- Experience with Products: 30 points
- Experience with Brand: 20 points

4.1.9 Integration and Discussion

Integrating our study's quantitative and qualitative findings provides a comprehensive understanding of how unsatisfactory service influences the consumer satisfaction and repurchase intent within the heavy-machinery-industry. The quantitative analysis and qualitative interviews revealed consistent themes regarding the detrimental effects of service failures on customer perceptions and behaviors. More extended machine downtime significantly reduced dealer and brand trust and the perception of more severe product quality within both analyses. The quantitative and qualitative findings followed this, although there were significant discrepancies regarding the recovery speed's long-term implications for customer satisfaction. While qualitative responses provided more nuanced insights into the changing nature of customer demands and the corresponding importance of recovery speed, the quantitative research revealed that quick recovery may only work for a short time. Along with fast recovery, it is essential to have continuous improvement. Findings about the negative effects of service failures are converging, emphasizing how crucial quick and thorough resolution techniques are to preserving customer loyalty and satisfaction. Customer perceptions, brand loyalty, and service quality are interdependent dynamics emphasized by qualitative narratives and quantitative statistics. The differences in the long-term consequences of recovery speed can be explained by the complexity of client experiences and the changing environment in which service interactions occur. While qualitative interviews give rich situational information that strengthens and supports our understanding of customer behaviors and repurchase intentions, quantitative studies offer insights into broad trends. Heavy machinery requires proactive tactics to improve customer satisfaction and rectify service failures. These findings align with this observation. Recommendations to consistently enhance service quality and responsiveness include implementing predictive maintenance technologies, improving dealer training programs, and utilizing customer feedback.

While making the repurchase intention, qualitative and quantitative analyses involve navigating the disparity between numerical data and qualitative insights. While quantitative analysis may suggest that brand experience holds the most weight in customer repurchase intentions, qualitative findings from professionals emphasize the critical role of dealer interactions. Despite this discrepancy, qualitative insights discussed specific factors within product and dealer experiences that profoundly influence customer decisions, such as product performance and service quality. Contextualizing these insights reveals the direct impact of dealer support on customer satisfaction, which shows that positive measures may not fully capture. By synthesizing these diverse perspectives, organizations can develop more nuanced strategies that address the complex relationship between brand perception, product experience, and dealer interactions, ultimately enhancing customer satisfaction and loyalty.

In the future, maintaining corporate performance and building long-term customer connections will require an inclusive and seamless approach to customer service management.

5 Conclusion

This study analyzed customer repurchase intentions, service failure impact, and dealer critical role in improving service recovery in the heavy machinery sector. Research primarily concentrated on the influence of failure, dealer service role in rapid speed of recovery, and its implications for customer satisfaction. The foundation for our study was first established by using a mixed sequential methodology and carrying out a thorough literature review. Using ML algorithms and regression approaches, quantitative analysis was conducted using a thorough survey covering the first 36 months of the customer journey. Our research showed that customer satisfaction is negatively impacted by each of the three categories of service failures: severity of failure, repeated failure, and unresolved failure.

Additionally, dealer recovery initiatives might lessen the negative effects of service failures. Regression research showed that long-term consumer satisfaction, especially in the industrial sector, requires ongoing improvement rather than quick recovery. In the same way, after-sales services are essential indicators of customer needs and desires in the manufacturing machinery sector, and they are also crucial in many other service industries, including retail, e-commerce, banking, hotels, and restaurants. These services function as effective marketing channels in addition to building solid customer-brand relationships. Moreover, our study's results indicated that customer satisfaction variables - product, dealer, and brand experience impact customer repurchase intention. Decision tree and logistic regression analysis revealed that satisfied customers tend to repurchase on all three variables. Among customers with rich brand awareness, brand experience is a significant consideration.

Furthermore, qualitative analysis supported quantitative results, providing insights. In the heavy-machinery-industry, quick recovery helps lessen the negative consequences of repeated failures, but it cannot maintain long-term customer relationships. Interviewees' perceptions of repurchase intentions varied; some stressed dealer and brand experiences, while others placed more importance on the product experience. However, the general agreement pointed to the critical impact that dealer contacts have on influencing repurchase choices, highlighting the importance of dealer involvement in customer retention efforts. The study comprehensively understood customer satisfaction dynamics in the heavy machinery industry by integrating quantitative and qualitative analyses. Our study thoroughly grasped customer satisfaction trends in the heavy machinery sector by mixing quantitative and qualitative analysis. It emphasized how crucial continuous after-sale service is to building solid customer-brand relationships and guaranteeing long-term business growth.

6 Limitation and Future Research Suggestion

The survey data collected provided a comprehensive view of 36 months of customer experience with a single product. However, customers may have interacted with other products during this period, leading to different experiences with the product, brand, and dealer. Furthermore, there is a chance of losing track of customers' actual experiences because of the delay between the time a product was purchased and the survey was completed, recording just the most recent interactions around the survey return date. While the study found that fast recovery speed alone is insufficient in mitigating the negative impacts of service failures over the long term, other factors or strategies, such as continuous improvement initiatives, could help reduce these negative impacts throughout the product ownership journey. Exploring the interaction of these additional factors with recovery speed has shown valuable insights for enhancing customer satisfaction and loyalty. The survey only captured the number of customer claims over 36 months without distinguishing whether these claims were for the same failure repeatedly or for different failures of the same product. Further study into the technical causes of recurring failures may be necessary to see whether timely fixing of such issues lessens the negative impact on customer satisfaction. Furthermore, considering differences in customer behavior between various geographic locations may offer a greater understanding of customers' requirements and preferences.

Future studies could look into other transactional purchases besides customers' intention to repurchase a particular product. Whether customers purchase various models or goods within the same brand based on brand trust or repurchase the same product because of favorable experiences with the brand or dealer is part of this. Furthermore, examining customer transactional histories could identify patterns in repurchasing behavior for specific products. Future studies could extend the scope by incorporating additional variables, such as the product warranties effect on customer whole journey with brand.

In acknowledging and addressing these limitations and exploring the suggested future research, scholars can further enrich their understanding of customer satisfaction, loyalty, and brand perception within the heavy machinery industry and beyond.

7 Recommendation

Through the thesis findings and exploration of diverse industries, several recommendations have emerged to address service failures and enhance customer satisfaction for long-term retention and increased repurchase in the heavy machinery industry.

Firstly, implementing predictive alert systems is crucial to mitigate the *severity of failure* (machine downtime), which significantly impacts customer satisfaction and future repurchases. These systems provide real-time information about machine health status and forecast potential failures, enabling customers to take preventive measures and minimize downtime. Additionally, conducting precautionary checks before machine operation can ensure optimal performance.

Secondly, the findings show that *repeated failure* has an interaction effect with recovery speed. It indicates that addressing repeated failures requires efficient communication that directly connects customers with technical experts to minimize diagnosis time and enable fast recovery.

Thirdly, when consumers sense ignorance, they are more likely to provide negative feedback about a brand. Maintaining *unresolved issues* in customer accounts shows a lack of seriousness about the brand and service, and unresolved failures reflect negatively on the brand and service. Establishing escalation procedures ensures that unresolved issues receive adequate attention and follow-up until satisfactorily resolved, fostering transparency and trust with customers.

Fourthly, Increasing the intention to repurchase is the ultimate objective for any organization looking to retain customers and grow their business. It involves implementing customer satisfaction with product, dealer, and brand experiences. Implementing CRM systems allows businesses to better understand customer preferences and behaviors, offers to meet individual needs, and increases repurchase intention. Integrating CRM data with predictive analytics enables businesses to anticipate customer needs, enhancing personalized engagement strategies.

Lastly, our research found that the most important component in obtaining customer experience feedback is the length of the survey timeframe. In our study, we took into account a 36-month survey to provide a thorough understanding of the customer experience journey throughout time. To capture more accurate and timely customer feedback, reducing the survey time frame is essential. Conducting surveys six months after purchase and then directly at 36 months results in a significant gap that may not capture real-time reactions effectively. Optimizing survey time frames is crucial for capturing accurate customer feedback. Shortening survey intervals allows for real-time feedback collection, providing more accurate measurements of service impact, recovery, and customer satisfaction across experiences.

These recommendations aim to address specific challenges and opportunities in the heavy machinery industry. They focus on strategic adjustments in communication, technology utilization, and feedback collection processes to enhance customer satisfaction, deal with service failure, and drive repurchase intention.

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9 Appendix:

Survey Questions: Table 1

NPS score 1-10

10 being extremely likely and 0 being not at all likely.

Construct	Question
Product Experience	
PE1	Productivity: Product has efficient productivity. **- P1**
PE2	Uptime: This product is ready for work when I am. **-P2**
PE3	Cost of operation: This product helps me work more efficiently. **– P3**
PE4	The engine associated with this product meets my needs. **– P4**
PE5	Equipment performance: This product helps me increase productivity. **– P5**
PE6	Lifetime Survey Product Experience Score; scale of 0-10. **– P6**
Dealer Experience	
DE1	In-stock parts availability. **– D1**
DE2	Resolving problem in timely way. **- D2**
DE3	Treating me with respect. **– D3**
DE4	Lifetime Survey Dealer Experience Score; scale of 1-10. **– D4**
Brand Experience	
BE1	Overall Brand Experience Score; scale of 1-10
Independent Variable	
Unresolved Failure: Do you have any unresolved product problems?	
Dependent Variable	
Repurchase Intention: When it comes to replace this product. What brand do you expect to purchase?	

Stage 1: **Import data set and data wrangling**

```
> View(Srvy_Data)
>
> ##################Data Cleaning and manipulation############################################
>
> ################################################################################
>
> # Count non-NA values in column 'b'
> non_na_count <- sum(!is.na(Srvy_Data$Downtime_Hrs))
>
> # Print the result
> cat("Number of non-NA values in column 'Downtime_Hrs':", non_na_count, "\n")
Number of non-NA values in column 'Downtime_Hrs': 27556
>
> #Step 2. Data cleaning and manipulation
> # Convert 'Machine_downtime' to numeric, and date columns to date type
> Srvy_Data$Downtime_Hrs <- as.integer(ifelse(Srvy_Data$Downtime_Hrs == "null", NA, Srvy_Data$Downtime_Hrs))
> Srvy_Data$claim_received_dt <- as.Date(Srvy_Data$claim_received_dt)
>
> Srvy_Data$repair_cmpl_dt <- as.Date(Srvy_Data$repair_cmpl_dt)
> Srvy_Data$SRVY_RTRN_DT <- as.Date(Srvy_Data$SRVY_RTRN_DT)
> Srvy_Data$recovery_speed_Days <-  as.integer(ifelse(Srvy_Data$recovery_speed_Days == "null", NA, Srvy_Data$recovery_speed_Days))
>
> View(Srvy_Data)
>
> ##---add repeated failure column Claim_count
>
> library(dplyr)

Attache Paket: ‘dplyr’

Die folgenden Objekte sind maskiert von ‘package:stats’:

    filter, lag

Die folgenden Objekte sind maskiert von ‘package:base’:

    intersect, setdiff, setequal, union

> result_count <- Srvy_Data %>%
+   group_by(ntv_pin) %>%
+   summarise(Claim_Count = n_distinct(claim_name))
>
> # Left join the result_count back to the original table
> data_with_count <- left_join(Srvy_Data, result_count, by = "ntv_pin")
>
> # View the result
> View(data_with_count)
> #drop the Claims name
> data_with_count <- select(data_with_count, -claim_name)
> View(data_with_count)
> CX_data <- data.frame(data_with_count)
> # Unresolved Failure
> CX_data <- CX_data %>%
+   mutate(Unresolved_Failure = case_when(
+     Unresolved_Failure == "Yes" ~ 1,
+     Unresolved_Failure == "No" ~ 0,
+     TRUE ~ NA_real_
+   ))
```

```
>
> CX_data <- CX_data %>%
+   mutate(RI = case_when(
+     RI == "John Deere" ~ 1,
+     RI == "Others Brand" ~ 0,
+     TRUE ~ NA_real_
+   ))
> View(CX_data)
>
> ##Calculate weightage average of machine downtime and recovery speed
>
> Service_Failure <- data.frame(Survey_Id = CX_data$SURVEY_ID,
+                               Claims = CX_data$Claim_Count,
+                               Severity_Failure = CX_data$Downtime_Hrs,
+                               Recovery_Speed = CX_data$recovery_speed_Days,
+                               Unresolved_Failure = CX_data$Unresolved_Failure,
+                               Repaired_Date = CX_data$repair_cmpl_dt,
+                               Claim_date = CX_data$claim_received_dt
+
+ )
> View(Service_Failure)
```

Stage 2: Data cleaning and Manipulation

2.1 Calculation of Weightage Average

```
> ###weighted average calcuation for recovery speed & severity of failure####
>
> ordered_data <- Service_Failure[order(Service_Failure[,1], Service_Failure[,6]),]
> #check NA value in primary column
> if (anyNA(ordered_data$Survey_Id)) {
+   stop("Survey_Id column contains NA/NaN values. Please clean the data before proceeding.")
+ }
>
> View(ordered_data)
> vw <- matrix(ncol = 3)
> colnames(vw) <- c("Survey_Id", "Severity_Failure_weighted","Recovery_Speed_weighted")
> i <- 1
> repeat {
+   vw <- rbind(vw,cbind((ordered_data[i,1]),
+                        mean(ordered_data[(i):((i-1)+ordered_data[i,2]),3]*(1:ordered_data[i,2]),na.rm=T),
+                        mean(ordered_data[(i):((i-1)+ordered_data[i,2]),4]*(1:ordered_data[i,2]),na.rm=T)))
+   i <- i+ordered_data[i,2]
+   if (i >nrow(ordered_data)) {
+     break
+   }
+ }
>
> vw <- vw[(-1),]
> View(vw)
> #merge the vw(Weightage metrix  to Service failure table)
> Service_Failure <- Service_Failure[!duplicated(Service_Failure[, 1]), ]
> Service_Failure <- merge(x=Service_Failure, y=vw, by = "Survey_Id", all.y = TRUE)
> Service_Failure <- Service_Failure[, -c(3,4,6,7)]
> View(Service_Failure)
> #drop duplicates
>
> CX_data <- CX_data[!duplicated(CX_data[, 1]), ]
> View(CX_data)
> names(Service_Failure)[1] <- "SURVEY_ID"
> #merge weightage average table to orginal table
> CX_data  <- merge(x=CX_data, y=Service_Failure, by = "SURVEY_ID", all.y = TRUE)
> View(CX_data)
> # Group by 'id' and find the row with the latest completion date
> CX_data <- CX_data %>%
+   group_by(SURVEY_ID) %>%
+   slice(which.max(repair_cmpl_dt)) %>%
+   ungroup()
> # Calculate the difference between the latest completion date and survey date
> CX_data$date_difference <- as.numeric(difftime(CX_data$repair_cmpl_dt, CX_data$SRVY_RTRN_DT, units = "days"))
> View(CX_data)
> #drop unnecessary columns
> CX_data <- CX_data[, -c(3,4,5, 6, 7, 8, 10, 11, 12, 13, 14, 15, 16, 17, 18)]
```

2.2 Calculate CFA factor : Check reliability

```
> #Step4 check variable reliability
> ##convert in int
>
> CX_data$P1 <-  as.integer(ifelse(CX_data$P1 == "null", NA, CX_data$P1))
> CX_data$P2 <-  as.integer(ifelse(CX_data$P2 == "null", NA, CX_data$P2))
> CX_data$P3 <-  as.integer(ifelse(CX_data$P3 == "null", NA, CX_data$P3))
> CX_data$P4 <-  as.integer(ifelse(CX_data$P4 == "null", NA, CX_data$P4))
> CX_data$P5 <-  as.integer(ifelse(CX_data$P5 == "null", NA, CX_data$P5))
> CX_data$P6 <-  as.integer(ifelse(CX_data$P6 == "null", NA, CX_data$P6))
> CX_data$D1 <-  as.integer(ifelse(CX_data$D1 == "null", NA, CX_data$D1))
> CX_data$D2 <-  as.integer(ifelse(CX_data$D2 == "null", NA, CX_data$D2))
> CX_data$D3 <-  as.integer(ifelse(CX_data$D3 == "null", NA, CX_data$D3))
> CX_data$D4 <-  as.integer(ifelse(CX_data$D4 == "null", NA, CX_data$D4))
> CX_data$BE <-  as.integer(ifelse(CX_data$BE == "null", NA, CX_data$BE))
> library(lavaan)
> model <- 'PE =~ P1 + P2 + P3 + P4 + P5 + P6
+          DE =~ D1 + D2 + D3 + D4
+          BR =~ BE
+ '
> fit <- cfa(model, data = CX_data)
> #fit the cfa model
> fit <- cfa(model, data = CX_data)
> #get factor loading
> factor_loading <- lavInspect(fit, "std")
> #####calulate latent factor corelation
>
> factor_loadings_matrix <- as.matrix(factor_loading)
> latent_factor_correlation <- cor(factor_loadings_matrix)
Error in cor(factor_loadings_matrix) : 'x' muss numerisch sein
> # Extract the factor loadings matrix
> lambda_matrix <- as.matrix(factor_loadings_matrix[[1]])
> # Compute the correlation matrix
> latent_factor_correlation <- cor(lambda_matrix)
> # Print the latent factor correlation matrix
```

2.3 Calculate Cronbach alpha:

```
> # Calculate Cronbach's alpha
> library(psych)
> # Remove rows with missing values
> cleaned_data <- na.omit(CX_data[, c("P1", "P2", "P3", "P4", "P5", "P6", "D1", "D2", "D3", "D4", "BE")])
> alpha_result <- alpha(cleaned_data[, c("P1", "P2", "P3", "P4", "P5", "P6", "D1", "D2", "D3", "D4", "BE")])
```

```
> alpha_result

Reliability analysis
Call: alpha(x = cleaned_data[, c("P1", "P2", "P3", "P4", "P5", "P6",
    "D1", "D2", "D3", "D4", "BE")])

  raw_alpha std.alpha G6(smc) average_r S/N    ase mean  sd median_r
      0.93      0.93    0.94      0.56  14 0.0015  8.8 1.4     0.53

    95% confidence boundaries
         lower alpha upper
Feldt     0.93  0.93  0.93
Duhachek  0.93  0.93  0.93

 Reliability if an item is dropped:
   raw_alpha std.alpha G6(smc) average_r S/N alpha se var.r med.r
P1      0.92      0.93    0.94      0.56  13   0.0016 0.013  0.53
P2      0.92      0.93    0.94      0.56  13   0.0017 0.014  0.53
P3      0.92      0.93    0.94      0.55  12   0.0017 0.013  0.53
P4      0.93      0.93    0.94      0.57  13   0.0016 0.014  0.55
P5      0.92      0.93    0.94      0.56  12   0.0017 0.015  0.51
P6      0.92      0.92    0.94      0.55  12   0.0017 0.014  0.51
D1      0.93      0.93    0.94      0.57  13   0.0016 0.013  0.55
D2      0.93      0.93    0.94      0.56  13   0.0016 0.013  0.55
D3      0.93      0.93    0.94      0.57  13   0.0016 0.013  0.55
D4      0.92      0.93    0.94      0.56  13   0.0016 0.013  0.53
BE      0.93      0.93    0.94      0.57  14   0.0015 0.014  0.55

 Item statistics
      n raw.r std.r r.cor r.drop mean  sd
P1 4799  0.80  0.80  0.78   0.75  8.6 1.7
P2 4799  0.80  0.80  0.78   0.75  8.8 1.7
P3 4799  0.80  0.80  0.79   0.75  8.4 1.9
P4 4799  0.75  0.75  0.71   0.69  8.7 1.8
P5 4799  0.80  0.80  0.78   0.75  8.7 1.7
P6 4799  0.83  0.83  0.82   0.79  8.7 1.8
D1 4799  0.72  0.72  0.69   0.66  8.8 1.7
D2 4799  0.79  0.79  0.78   0.74  8.7 2.0
D3 4799  0.73  0.74  0.72   0.68  9.3 1.5
D4 4799  0.80  0.80  0.79   0.75  9.0 1.8
BE 4799  0.71  0.70  0.65   0.63  8.8 2.1
```

Stage 3. Hypothesis Testing: Impact of service Failure and Moderating role of Recovery of Speed

Severity of Failure:

```
> #h1a-c: sEVERITY OF FAILURE impact on Product experince/dELAER eXPERINCE/Brand Experince
> #product experience
> model_1a <- lm(PE ~ CX_data$Severity_Failure_weighted, data = CX_data)
> model_1a.1 <- lm(PE ~ Severity_Failure_weighted*Recovery_Speed_weighted, data = CX_data)
>
> #Dealer Experience
> model_1b <- lm(DE ~ Severity_Failure_weighted, data = CX_data)
> model_1b.1 <- lm(DE ~ Severity_Failure_weighted*Recovery_Speed_weighted, data = CX_data)
>
> #Brand Experince
> model_1c <- lm(BR ~ Severity_Failure_weighted, data = CX_data)
> model_1c.1 <- lm(BR ~ Severity_Failure_weighted*Recovery_Speed_weighted, data = CX_data)
```

Repeated Failure:

```
> #h2a-c: Repeated failure(Claims) impact on Product experince/dELAER eXPERINCE/Brand Experince
>
> #product experience
> Unresolved_failure <- CX_data[complete.cases(CX_data$Unresolved_Failure.y), ]
> View(Unresolved_failure)
>
> model_2a <- lm(PE ~ CX_data$Claims, data = CX_data)
> model_2a.1 <- lm(PE ~ Claims*Recovery_Speed_weighted, data = CX_data)
>
> #Dealer Experience
> model_2b <- lm(DE ~ Claims, data = CX_data)
> model_2b.1 <- lm(DE ~ Claims*Recovery_Speed_weighted, data = CX_data)
>
> #Brand Experince
> model_2c <- lm(BR ~ Claims, data = CX_data)
> model_2c.1 <- lm(BR ~ Claims*Recovery_Speed_weighted, data = CX_data)
```

Unresolved Failure:

```
> #h3a-c: Unresolved filure impact on Product experince/dELAER eXPERINCE/Brand Experince
> #product experience
> Unresolved_failure <- CX_data[complete.cases(CX_data$Unresolved_Failure.y), ]
> View(Unresolved_failure)
> model_3a <- lm(PE ~ Unresolved_Failure.y, data = Unresolved_failure)
> model_3a.1 <- lm(PE ~ Unresolved_Failure.y*Recovery_Speed_weighted, data = Unresolved_failure)
> #Dealer Experience
> model_3b <- lm(DE ~ Unresolved_Failure.y, data = Unresolved_failure)
> model_3b.1 <- lm(DE ~ Unresolved_Failure.y*Recovery_Speed_weighted, data = Unresolved_failure)
>
> #Brand Experince
> model_3c <- lm(BR ~ Unresolved_Failure.y, data = Unresolved_failure)
> model_3c.1 <- lm(BR ~ Unresolved_Failure.y*Recovery_Speed_weighted, data = Unresolved_failure)
> # Display the summary of the regression model
> summary_model_3a <- summary(model_3a)
> summary_model_3a.1 <- summary(model_3a.1)
> summary_model_3b <- summary(model_3b)
> summary_model_3b.1 <- summary(model_3b.1)
> summary_model_3c <- summary(model_3c)
> summary_model_3c.1 <- summary(model_3c.1)
> library(ggplot2)
>
> # Scatterplot with regression lines for PE
> ggplot(Unresolved_failure, aes(x = Unresolved_Failure.y, y = PE)) +
+   geom_point() +
+   geom_smooth(method = "lm", se = FALSE) +
+   labs(title = "Linear Regression: PE vs. Unresolved_Failure.y", x = "Unresolved_Failure.y", y = "PE")
`geom_smooth()` using formula = 'y ~ x'
```

Severity of failure plot with customer satisfaction:

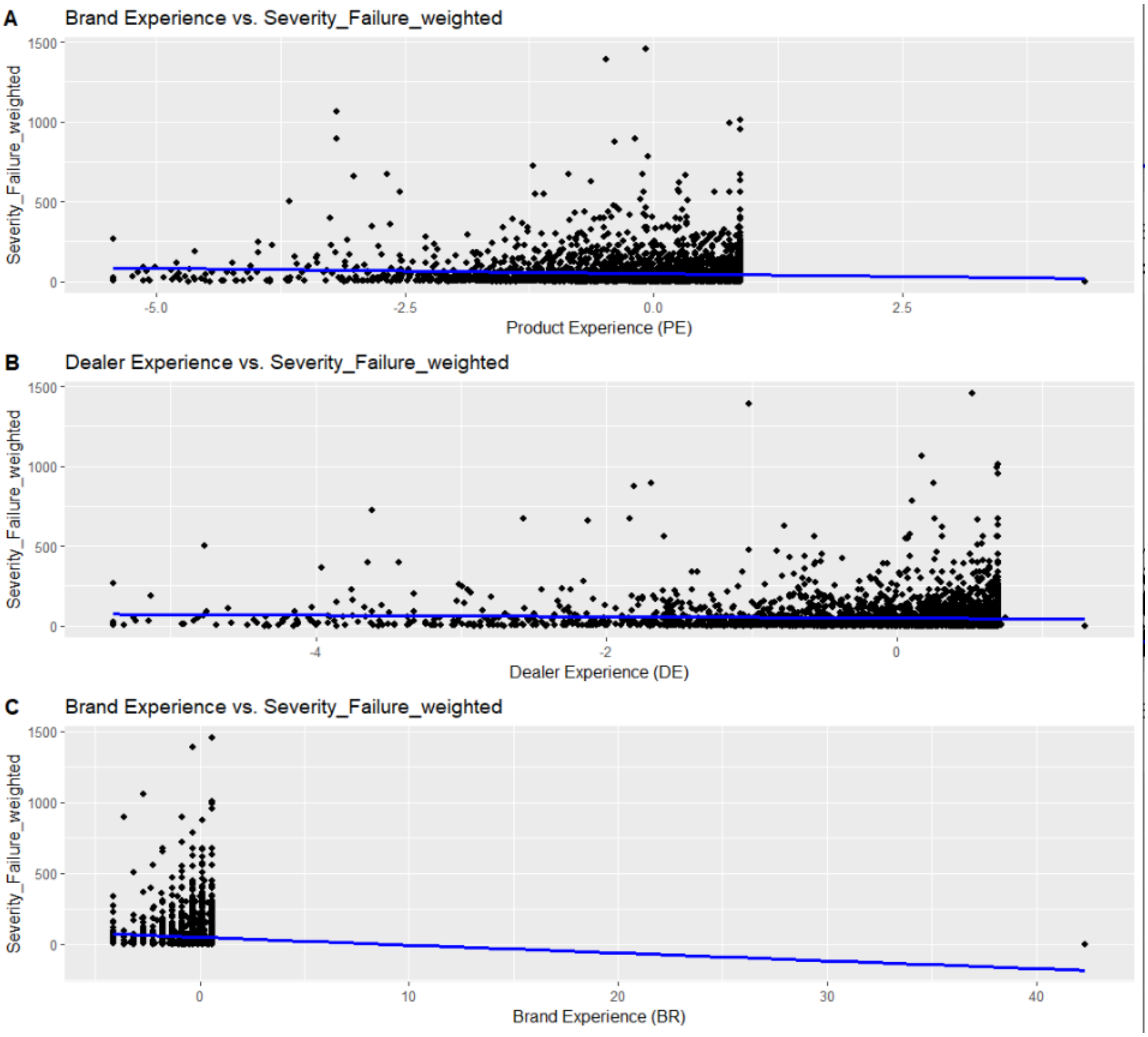

Figure 1. Customer satisfaction vs Severity Failure

Repeated failure Vs. Customer Satisfaction

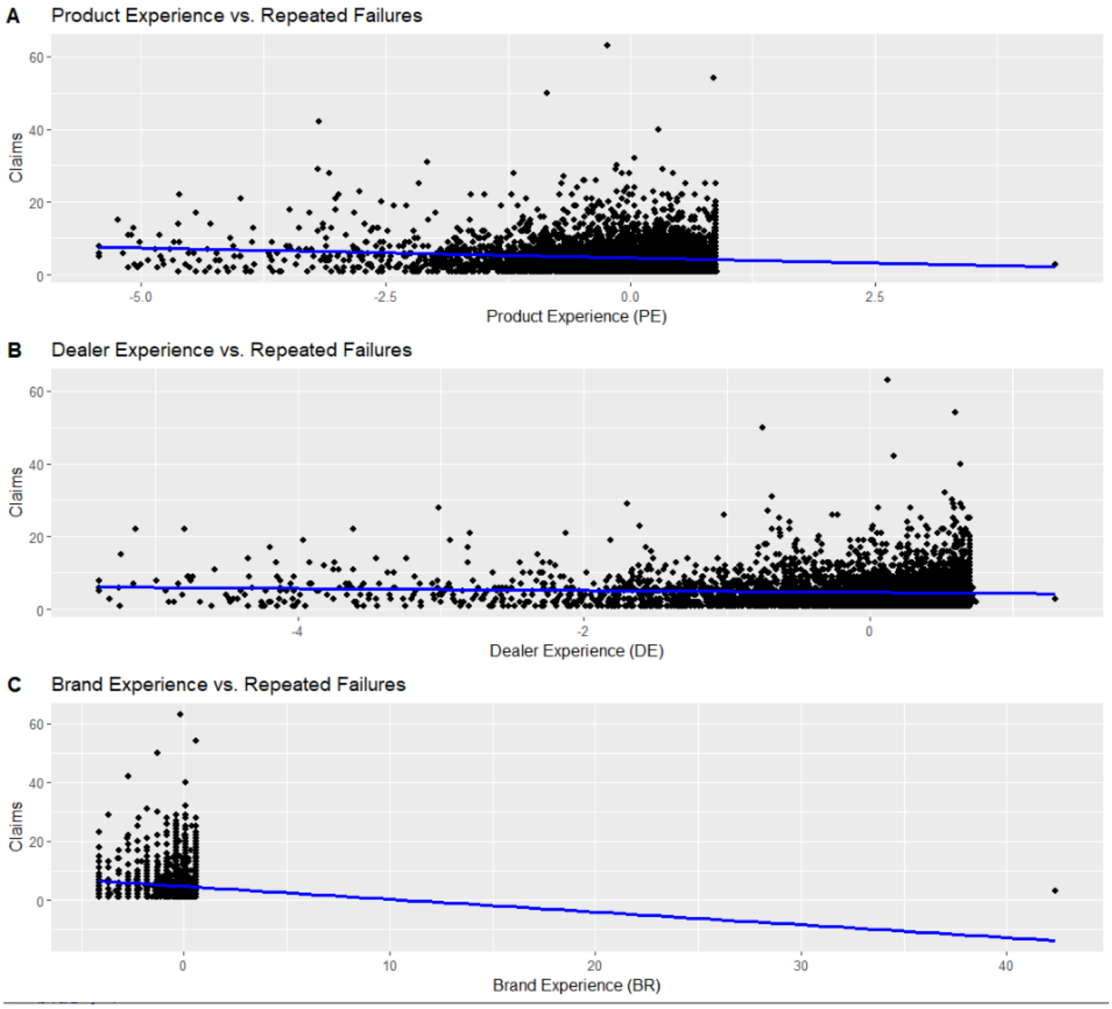

Figure 2. Customer satisfaction vs Severity Failure

Unresolved Failure vs Customer Satisfaction

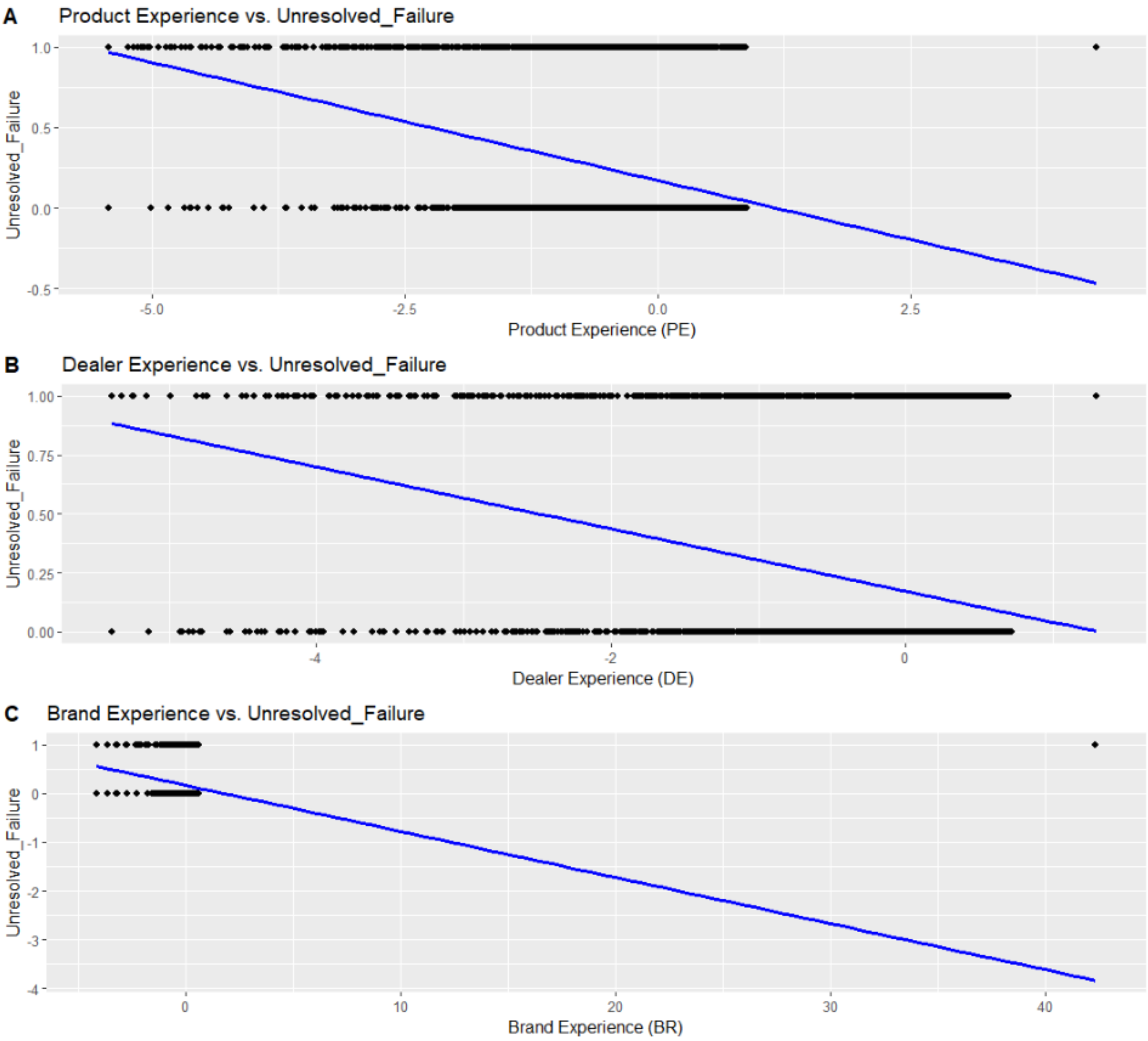

Figure 3. Customer satisfaction vs Severity Failure

Interaction effect of Recovery Speed with Severity of failure:

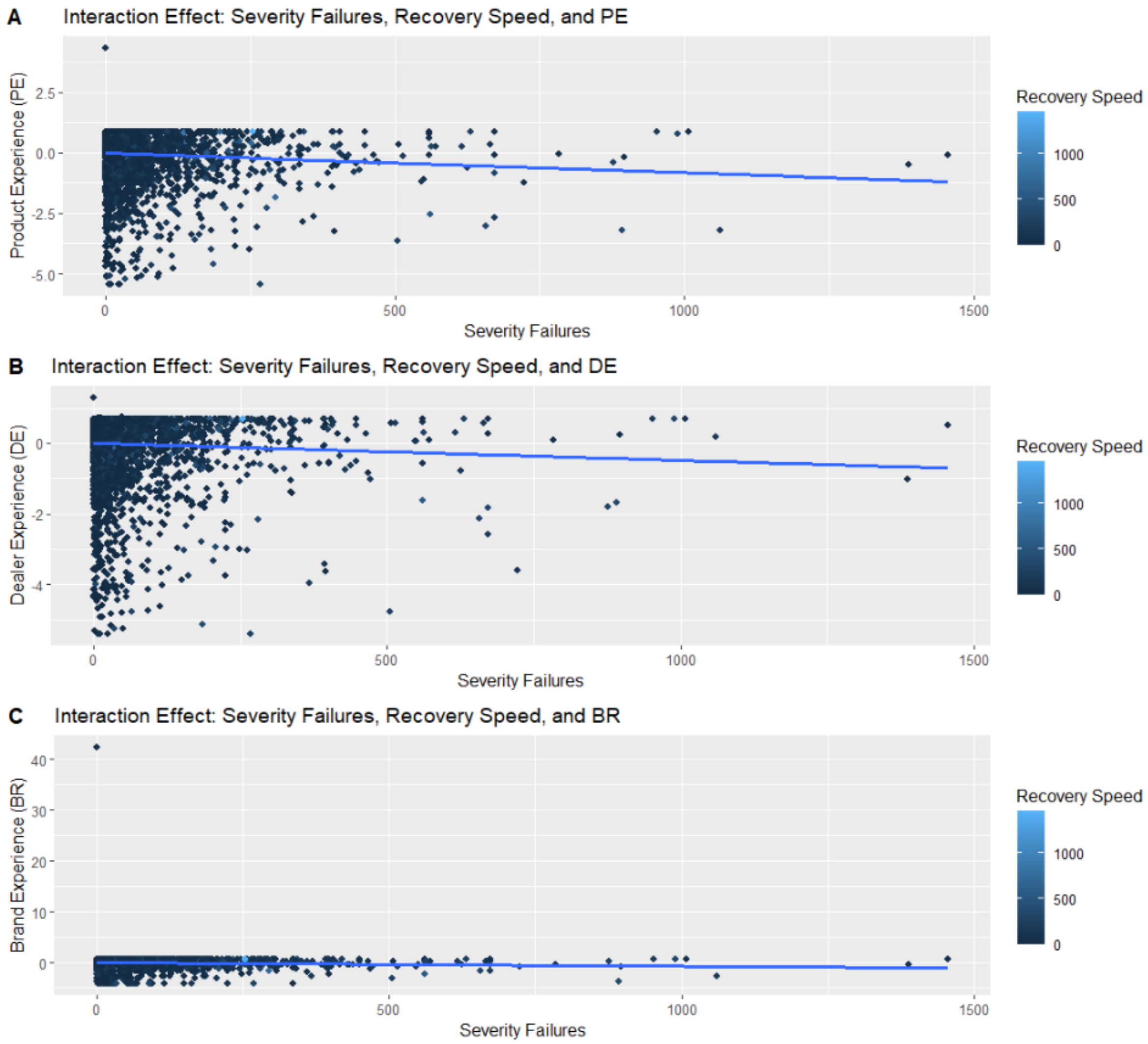

Figure 4. Interaction effect: Severity Failure, Recovery Speed

Interaction effect of Recovery Speed with Repeated failure:

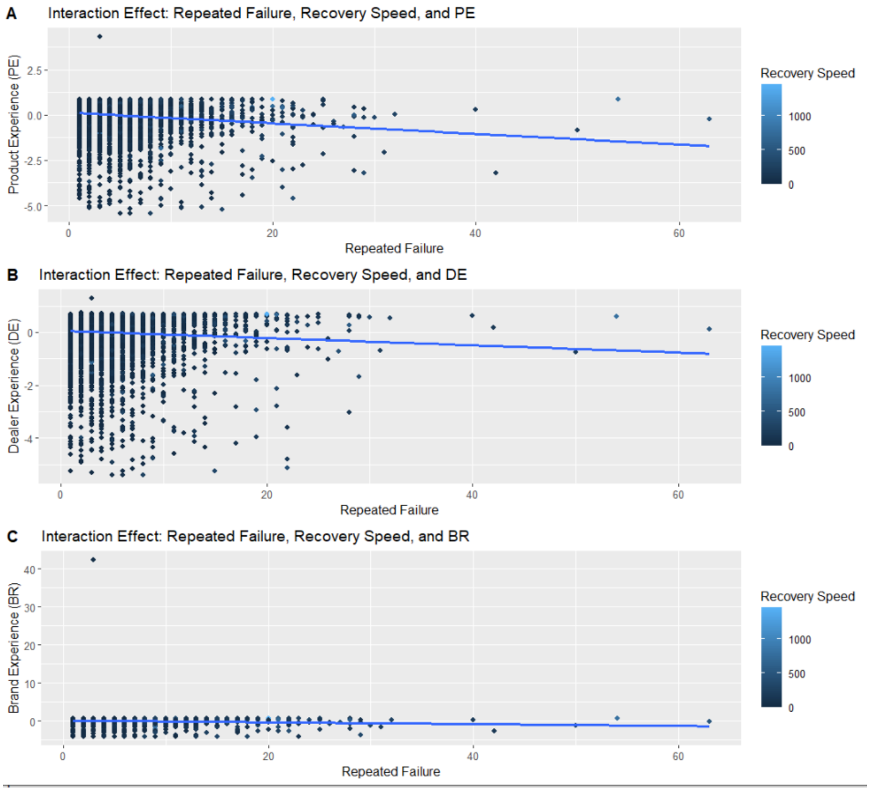

Figure 5. Interaction effect: Repeated Failure, Recovery Speed

Interaction effect of Recovery Speed with Unresolved failure:

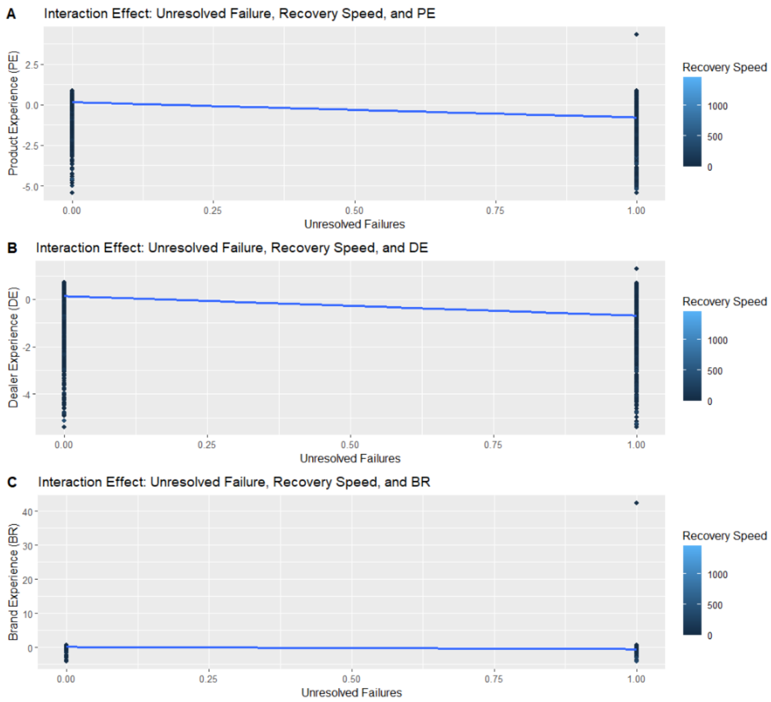

Figure 6. Interaction effect: Unresolved Failure, Recovery Speed

Stage 4: Repurchase Intention:

4.1 Logistic Regression

Step 1: First calculate the direct corelation between variables:

```
> correlation_matrix <- cor(na.omit(CX_data[, c("PE", "DE", "BR")]))
> cor_PE_DE <- cor(CX_data$PE, CX_data$DE)
> cor_PE_BR <- cor(CX_data$PE, CX_data$BR)
> cor_DE_BR <- cor(CX_data$DE, CX_data$BR)
> correlation_matrix
          PE        DE        BR
PE 1.0000000 0.7559499 0.7310020
DE 0.7559499 1.0000000 0.5430057
BR 0.7310020 0.5430057 1.0000000
```

Step 2: analyse the hypothesis where direct significant impact on repurchase intention with each variable:

Product Experience

```
> #  dependent variable :convert in factor
> CX_data$RI <- as.factor(CX_data$RI)
> #creat Repurchase table
> Repurchase_Data <- CX_data[, c("SURVEY_ID", 'PE', 'DE', 'BR', 'RI', "Severity_Failure_weighted", "Recovery_Speed_weighte
d", "Extended_Warranty", "Unresolved_Failure.y", "Claims")]
> #drop row with missing value in RI
> Repurchase_Data <- na.omit(Repurchase_Data, cols = "RI")
> #perform logistc regression with RI(Repurchase Intention)
>
> library(caret)
> library(glm2)
> library(pROC)
> library(ROSE)
> set.seed(123)  # for reproducibility
> # 'Repurchase_data' is the name of  dataset
> trainIndex <- createDataPartition(Repurchase_Data$RI, p = 0.7, list = FALSE)
> train_data <- Repurchase_Data[trainIndex, ]
> test_data <- Repurchase_Data[-trainIndex, ]
> #Oversample the minority class
> #'RI' is the name of  dependent variable in train_data
> test_data <- as.factor(test_data$RI)
> oversampled_data <- upSample(x = train_data[, -which(colnames(train_data) == "RI")],
+                              y = train_data$RI)
> #perform logistic model, where class is RI(Repurchase Intetion), and PE is product experience
> model_ov_pe <- glm(Class ~ PE, data = oversampled_data, family = "binomial")
> summary(model_ov_pe)

Call:
glm(formula = Class ~ PE, family = "binomial", data = oversampled_data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9297  -0.8160   0.0076   0.8079   3.5607

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.41703    0.03815   10.93   <2e-16 ***
PE           1.46375    0.05099   28.71   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 5797.5  on 4181  degrees of freedom
Residual deviance: 4257.1  on 4180  degrees of freedom
AIC: 4261.1

Number of Fisher Scoring iterations: 5
```

Dealer Experience:

```
> model_ov_de <- glm(Class ~ DE, data = oversampled_data, family = "binomial")
> summary(model_ov_de)

Call:
glm(formula = Class ~ DE, family = "binomial", data = oversampled_data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5918  -1.0422   0.2620   0.9167   3.0377

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.20492    0.03460   5.922 3.17e-09 ***
DE           1.04928    0.04409  23.801  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 5797.5  on 4181  degrees of freedom
Residual deviance: 4853.8  on 4180  degrees of freedom
AIC: 4857.8

Number of Fisher Scoring iterations: 5
```

Brand Experience:

```
> model_ov_br <- glm(Class ~ BR, data = oversampled_data, family = "binomial")
Warning message:
glm.fit: Angepasste Wahrscheinlichkeiten mit numerischem Wert 0 oder 1 aufgetreten
> summary(model_ov_br)

Call:
glm(formula = Class ~ BR, family = "binomial", data = oversampled_data)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.76183  -0.79982  -0.03001   0.95416   3.12128

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.37087    0.03708   10.00   <2e-16 ***
BR           1.62639    0.05928   27.43   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 5797.5  on 4181  degrees of freedom
Residual deviance: 4421.1  on 4180  degrees of freedom
AIC: 4425.1

Number of Fisher Scoring iterations: 6
```

Step 3:Make the prediction model:

```
> set.seed(123)  # for reproducibility
>
> # Split data into train and test
>
> trainIndex <- createDataPartition(Repurchase_Data$RI, p = 0.7, list = FALSE)
> train_data <- Repurchase_Data[trainIndex, ]
> test_data <- Repurchase_Data[-trainIndex, ]
> oversampled_data <- upSample(x = train_data[, -which(colnames(train_data) == "RI")],
+                              y = train_data$RI)
> # Fit the logistic regression model
> model <- glm(Class ~ PE + DE + BR, data =  oversampled_data, family = "binomial")
Warning message:
glm.fit: Angepasste Wahrscheinlichkeiten mit numerischem Wert 0 oder 1 aufgetreten
>
> # Summary of the model
> summary(model)

Call:
glm(formula = Class ~ PE + DE + BR, family = "binomial", data = oversampled_data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9357  -0.8191  -0.0124   0.7871   3.5643

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.42967    0.03856  11.142  < 2e-16 ***
PE           0.82552    0.08378   9.853  < 2e-16 ***
DE           0.19709    0.05129   3.843 0.000122 ***
BR           0.72434    0.09034   8.018 1.08e-15 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 5797.5  on 4181  degrees of freedom
Residual deviance: 4174.7  on 4178  degrees of freedom
AIC: 4182.7

Number of Fisher Scoring iterations: 5
```

Step 4: Model Evaluation

Check confusion matrix

```
> predictions <- predict(model, newdata = test_data, type = "response")
>
> # 5. Convert probabilities to class labels (e.g., 0 or 1)
> predicted_classes <- ifelse(predictions > 0.5, 1, 0)
> conf_matrix <- confusionMatrix(data = factor(predicted_classes), reference = factor(test_data$RI))
>
> # 7. Print the confusion matrix and accuracy
> print(conf_matrix)
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 118 199
         1  48 697

               Accuracy : 0.7674
                 95% CI : (0.7408, 0.7925)
    No Information Rate : 0.8437
    P-Value [Acc > NIR] : 1

                  Kappa : 0.3566

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.7108
            Specificity : 0.7779
         Pos Pred Value : 0.3722
         Neg Pred Value : 0.9356
             Prevalence : 0.1563
         Detection Rate : 0.1111
   Detection Prevalence : 0.2985
      Balanced Accuracy : 0.7444

       'Positive' Class : 0

> cat("Accuracy: ", conf_matrix$overall["Accuracy"], "\n")
Accuracy:  0.76742
```

Develop a table showcasing customers' repurchase intentions against their actual buying behavior to elucidate disparities in decision-making.

```
> # Set a threshold (e.g., 0.5)
> threshold <- 0.5
>
> # Categorize customers for each independent variable
> repurchase_predictions_product <- ifelse(predictions_pe >= threshold, "Repurchase", "Not Repurchase")


> repurchase_predictions_dealer <- ifelse(predictions_de >= threshold, "Repurchase", "Not Repurchase")
> repurchase_predictions_brand <- ifelse(predictions_br >= threshold, "Repurchase", "Not Repurchase")
> # Combine customer IDs and predictions for each independent variable into a data frame
> Repurchase_Intention <- data.frame(
+   SURVEY_ID = test_data$SURVEY_ID,  # Adjust based on your actual column names
+   Repurchase_Prediction_Product = repurchase_predictions_product,
+   Repurchase_Prediction_Dealer = repurchase_predictions_dealer,
+   Repurchase_Prediction_Brand = repurchase_predictions_brand,
+   Probability_Product = predictions_pe,
+   Probability_Dealer = predictions_de,
+   Probability_Brand = predictions_br,
+   Repurchase_INTENTION = test_data$RI,
+   Machine_Downtime = test_data$Severity_Failure_weighted,
+   RecoverySpeed =test_data$Recovery_Speed_weighted,
+   Extended_Warranty = test_data$Extended_Warranty,
+   Unresolved_Failures = test_data$Unresolved_Failure.y,
+   Repeated_Failures = test_data$Claims
+
+ )
```

ROC Curve:

```
> library(ggplot2)
> #Get ROC CURVE data
> # Convert repurchase_intention to a factor with specific levels
> test_data$RI <- factor(test_data$RI, levels = c(0, 1))
> # Get ROC curve data
> roc_curve <- roc(test_data$RI, predicted_probs)
Setting levels: control = 0, case = 1
Setting direction: controls < cases
> # Plot ROC curve
> plot(roc_curve, main = "ROC Curve", col = "blue", lwd = 2)
> abline(a = 0, b = 1, lty = 2, col = "red")  # Add diagonal reference line
>
```

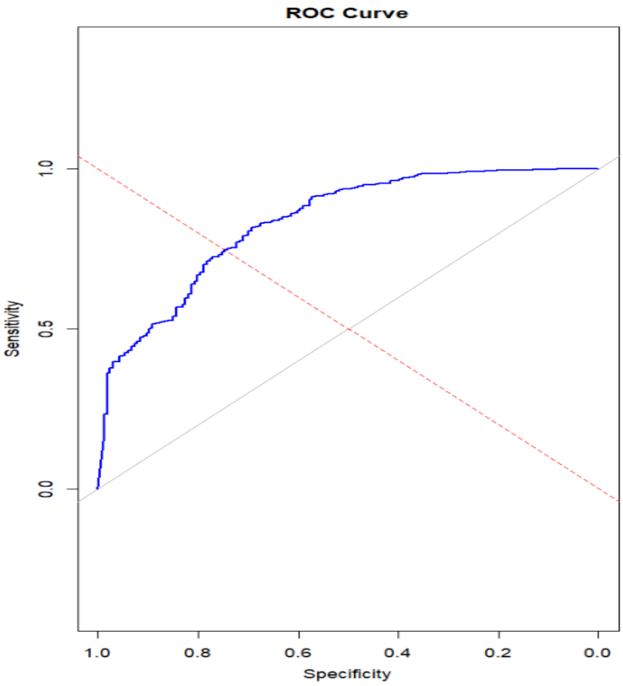

Figure 7. ROC Curve: Repurchase Intention

Stage 5. Decision Tree Model Analysis

Step 5.1 Training & test

```
> #performing analysis only on one customer reponse that is overall experience on product(P6) , dealer(D4) and brand(BE)
> library(rpart)
> library(rpart.plot)
> library(ROSE)
> library(caret)
> set.seed(123)  # Set seed for reproducibility
> split <- createDataPartition(CX_data$RI, p = 0.7, list = FALSE)
>
> # Subset the dataset into training and testing sets
> training_set <- CX_data[split, ]
> testing_set <- CX_data[-split, ]
> #Model fitting
> # Create a decision tree model on the training set
> tree_model <- rpart(RI ~ P6 + D4 + BE, data = train_data, method = "class")
> rpart.plot(tree_model)
> # Get a summary of the decision tree
> tree_summary <- summary(tree_model)
```

Step 5.2 Model Evaluation

```
> #Model Evaluation
>
> # Make predictions on the test set
> predictions <- predict(tree_model, newdata = test_data, type = "class")
>
> # Evaluate performance
> confusion_matrix <- confusionMatrix(predictions, test_data$RI)
> print(confusion_matrix)
```


```
> #Model Evaluation
>
> # Make predictions on the test set
> predictions <- predict(tree_model, newdata = test_data, type = "class")
>
> # Evaluate performance
> confusion_matrix <- confusionMatrix(predictions, test_data$RI)
> print(confusion_matrix)
```


```
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0   80   11
         1  145 1253

               Accuracy : 0.8952
                 95% CI : (0.8786, 0.9103)
    No Information Rate : 0.8489
    P-Value [Acc > NIR] : 1.061e-07

                  Kappa : 0.4593

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.35556
            Specificity : 0.99130
         Pos Pred Value : 0.87912
         Neg Pred Value : 0.89628
             Prevalence : 0.15111
         Detection Rate : 0.05373
   Detection Prevalence : 0.06111
      Balanced Accuracy : 0.67343

       'Positive' Class : 0
```

Step 5.3 Pruned Visualization

```
> #Prunning Visualization
> # Load the rpart.plot package
> library(rpart.plot)
> # Visualize the pruned decision tree model
> prp(pruned_tree_model, extra = 1, type = 4, nn = TRUE, fallen.leaves = TRUE, branch = 1)
> # Convert the confusion matrix to a matrix
> conf_matrix <- as.matrix(confusion_matrix)
>
> # Calculate accuracy and error rate
> accuracy <- sum(diag(conf_matrix)) / sum(conf_matrix)
> error_rate <- 1 - accuracy
> # View the accuracy and error rate
> accuracy
[1] 0.8952317
> error_rate
[1] 0.1047683
> # Precision, Recall, and F1-Score
> precision <- conf_matrix[2, 2] / sum(conf_matrix[, 2])
> recall <- conf_matrix[2, 2] / sum(conf_matrix[2, ])
> f1_score <- 2 * (precision * recall) / (precision + recall)
> cat("Accuracy:", accuracy, "\n")
Accuracy: 0.8952317
> cat("Error Rate:", error_rate, "\n")
Error Rate: 0.1047683
> cat("Precision:", precision, "\n")
Precision: 0.9912975
> cat("Recall:", recall, "\n")
Recall: 0.8962804
> cat("F1-Score:", f1_score, "\n")
F1-Score: 0.9413974
```

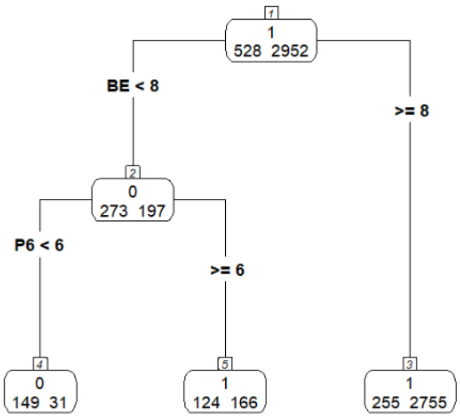

Figure 8. Pruned Model

Step 5.4 ROC Curve

```
> # Plot the ROC curve
> plot(roc_obj, col = "blue")
> # Calculate AUC-ROC
> auc_value <- auc(roc_obj)
> cat("AUC-ROC:", auc_value, "\n")
AUC-ROC: 0.6734265
```

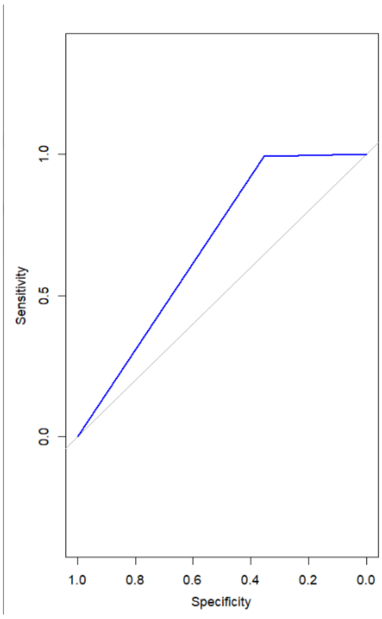

Figure 9. ROC Curve: Repurchase Intention, Decision tree model

Step 5.5 Considering Product experience and Dealer experience survey questions' response and overall brand experience score

```
> library(rpart)
> library(rpart.plot)
> library(ROSE)
> library(caret)
> # Create a stratified training and testing split
> set.seed(123)  # Set seed for reproducibility
> split <- createDataPartition(CX_data$RI, p = 0.7, list = FALSE)
>
> # Subset the dataset into training and testing sets
> training_set <- CX_data[split, ]
> testing_set <- CX_data[-split, ]
> #Model fitting
> # Create a decision tree model on the training set
> tree_model <- rpart(RI ~ P1+P2+P3+P4+P5+P6+D1+D2+D3+D4+BE, data = train_data, method = "class")
> # Get a summary of the decision tree
> tree_summary <- summary(tree_model)
```

```
> rpart.plot(tree_model)
> # Make predictions on the test set
> predictions <- predict(tree_model, newdata = test_data, type = "class")
> # Evaluate performance
> confusion_matrix <- confusionMatrix(predictions, test_data$RI)
> print(confusion_matrix)
>
> # Calculate accuracy and error rate
> accuracy <- sum(diag(conf_matrix)) / sum(conf_matrix)
> error_rate <- 1 - accuracy
>
> # View the accuracy and error rate
> accuracy
[1] 0.8938885
> error_rate
[1] 0.1061115
> # Precision, Recall, and F1-Score
> precision <- conf_matrix[2, 2] / sum(conf_matrix[, 2])
> recall <- conf_matrix[2, 2] / sum(conf_matrix[2, ])
> f1_score <- 2 * (precision * recall) / (precision + recall)
> cat("Accuracy:", accuracy, "\n")
Accuracy: 0.8938885
> cat("Error Rate:", error_rate, "\n")
Error Rate: 0.1061115
> cat("Precision:", precision, "\n")
Precision: 0.9897152
> cat("Recall:", recall, "\n")
Recall: 0.8961318
> cat("F1-Score:", f1_score, "\n")
F1-Score: 0.9406015
> ### ROC Curve and AUC-ROC

Setting direction: controls < cases
> # Plot ROC Curve
> plot(roc_obj, main = "ROC Curve", col = "blue", lwd = 2)
> # Calculate AUC-ROC
> auc_value <- auc(roc_obj)
> cat("AUC-ROC:", auc_value, "\n")
AUC-ROC: 0.6726354
```

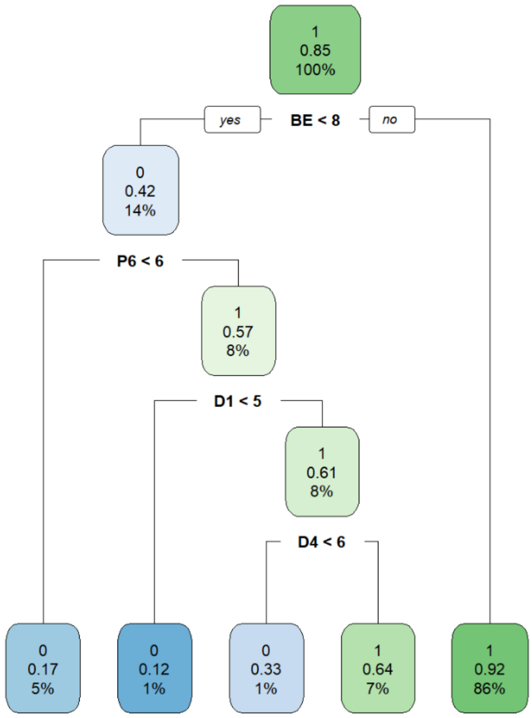

Figure 10. Decision tree model, predicting repurchase intention

Step 5.6 Considering only Product experience and Dealer experience survey questions' response

```
> library(rpart)
> library(rpart.plot)
> library(ROSE)
> library(caret)
> # Create a stratified training and testing split
> set.seed(123)  # Set seed for reproducibility
> split <- createDataPartition(CX_data$RI, p = 0.7, list = FALSE)
>
> # Subset the dataset into training and testing sets
> training_set <- CX_data[split, ]
> testing_set <- CX_data[-split, ]
> #Model fitting
> # Create a decision tree model on the training set
> tree_model <- rpart(RI ~ P1+P2+P3+P4+P5+D1+D2+D3, data = train_data, method = "class")
> # Get a summary of the decision tree
> tree_summary <- summary(tree_model)
```

```
> # Plot the decision tree
> rpart.plot(tree_model)
> #Model Evaluation
>
> # Make predictions on the test set
> predictions <- predict(tree_model, newdata = test_data, type = "class")
>
> # Evaluate performance
> confusion_matrix <- confusionMatrix(predictions, test_data$RI)
> print(confusion_matrix)
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0   55   20
         1  170 1244

               Accuracy : 0.8724
                 95% CI : (0.8544, 0.8889)
    No Information Rate : 0.8489
    P-Value [Acc > NIR] : 0.00548

                  Kappa : 0.3149

 Mcnemar's Test P-Value : < 2e-16

            Sensitivity : 0.24444
            Specificity : 0.98418
         Pos Pred Value : 0.73333
         Neg Pred Value : 0.87977
             Prevalence : 0.15111
         Detection Rate : 0.03694
   Detection Prevalence : 0.05037
      Balanced Accuracy : 0.61431

       'Positive' Class : 0
```

```
> # Convert the confusion matrix to a matrix
> conf_matrix <- as.matrix(confusion_matrix)
>
> # Calculate accuracy and error rate
> accuracy <- sum(diag(conf_matrix)) / sum(conf_matrix)
> error_rate <- 1 - accuracy
>
> # View the accuracy and error rate
> accuracy
[1] 0.8723976
> error_rate
[1] 0.1276024
> # Precision, Recall, and F1-Score
> precision <- conf_matrix[2, 2] / sum(conf_matrix[, 2])
> recall <- conf_matrix[2, 2] / sum(conf_matrix[2, ])
> f1_score <- 2 * (precision * recall) / (precision + recall)
> cat("Accuracy:", accuracy, "\n")
Accuracy: 0.8723976
> cat("Error Rate:", error_rate, "\n")
Error Rate: 0.1276024
> cat("Precision:", precision, "\n")
Precision: 0.9841772
> cat("Recall:", recall, "\n")
Recall: 0.8797737
> cat("F1-Score:", f1_score, "\n")
F1-Score: 0.9290515
> ### ROC Curve and AUC-ROC
>
> # ROC Curve
> roc_obj <- roc(testing_set$RI, predictions)
Setting levels: control = 0, case = 1
Error in roc.default(testing_set$RI, predictions) :
  Predictor must be numeric or ordered.
> # Convert the predictions to numeric probabilities
> numeric_predictions <- as.numeric(predictions)
> # Create the ROC curve
> roc_obj <- roc(testing_set$RI, numeric_predictions)
Setting levels: control = 0, case = 1
Setting direction: controls < cases
> # Plot the ROC curve
> plot(roc_obj, col = "blue")
> # Plot ROC Curve
> plot(roc_obj, main = "ROC Curve", col = "blue", lwd = 2)
> # Calculate AUC-ROC
> auc_value <- auc(roc_obj)
> cat("AUC-ROC:", auc_value, "\n")
AUC-ROC: 0.6143108
```

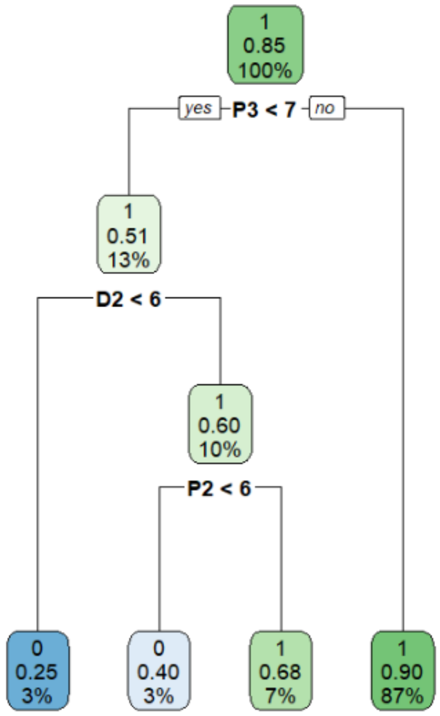

Figure 10. Decision tree model, predicting repurchase intention with Product and Dealer experience factors