How does Retargeted Direct Mailing influences customer churn among independent opticians in the Netherlands, considering the moderating effects of customer characteristics?

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Abstract (English)

Title: How does Retargeted Direct Mailing influence customer churn among independent opticians in the Netherlands, considering the moderating effects of customer characteristics?

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Reducing customer churn is crucial for business profitability, with personalized marketing strategies playing a key role. Despite the rise of digital marketing, traditional methods like Direct Mailing (DM) remain effective due to their tangible presence and high response rates. Retargeted Direct Mailing (RDM) leverages customer data to create personalized and well-timed mailings, re-engaging lost or at-risk customers. Understanding different customer types and their responses to various incentives within RDMs significantly influences campaigns effectiveness. Tailoring RDM strategies to individual preferences and characteristics optimizes customer retention.

This thesis investigates the impact of RDM on customer churn among independent opticians in the Netherlands, considering customer characteristics. Panel data from 7,839 customers across 13 optical retailers over 8 years were analyzed using panel and logistic regression models.

RDM effectively reduces customer churn by shortening purchase intervals, increasing purchase likelihood, and boosting spending. Responses to incentivized RDMs vary by customer characteristics, significantly improving purchase intervals and spending. Additionally, lower churn rates are observed across different customer segments, with older customers, female customers, and frequent buyers exhibiting the lowest churn rates.

Limitations of the study include data sparsity, potential biases due to zero entries, and limited generalizability beyond the Dutch optical retail market.

This research offers insights for retail marketing, particularly for the optician industry, in designing effective RDM (with and without incentives) campaigns tailored to customer characteristics to improve retention and increase spending.

Keywords: Customer Churn, Customer Relationship Management, Customer Retention, Direct Mailing, Incentives, Optician, Retargeted Direct Mailing, Retail

Abstract (French)

Titre: Influence du Retargeted Direct Mailing sur la fidélisation des clients des opticiens indépendants aux Pays-Bas, en fonction des caractéristiques des clients?

Auteur: Marie Johanna Westermann

Réduire le taux de désabonnement est crucial pour la rentabilité. Malgré le marketing digital, le Direct Mailing (DM) reste efficace grâce à sa présence tangible et ses taux de réponse élevés. Le Retargeted Direct Mailing (RDM) utilise les données clients pour créer des courriers personnalisés, réengageant les clients perdus ou à risque. Comprendre les types de clients et leurs réactions aux incitatifs dans les RDM est essentiel pour optimiser la fidélisation.

Cette thèse analyse l'impact du RDM sur le taux de désabonnement des clients des opticiens indépendants aux Pays-Bas, en tenant compte des caractéristiques des clients. Des données de 7 839 clients sur 13 détaillants optiques sur 8 ans ont été analysées.

Le RDM réduit efficacement le désabonnement en raccourcissant les intervalles d'achat, augmentant la probabilité d'achat et les dépenses. Les réactions aux RDM incitatifs varient selon les caractéristiques des clients. Les clients plus âgés, les femmes et les acheteurs fréquents présentent les taux de désabonnement les plus bas.

Les limitations de l'étude incluent la rareté des données, les biais potentiels dus aux entrées nulles et la généralisation limitée au-delà du marché de détail optique néerlandais.

Cette recherche offre des perspectives pour le marketing de détail, en particulier pour l'industrie des opticiens, dans la conception de campagnes RDM efficaces (avec et sans incitatifs) adaptées aux caractéristiques des clients pour améliorer la fidélisation et augmenter les dépenses.

Mots-clés: Désabonnement des clients, Gestion de la relation client, Fidélisation, Mailing direct, Incitations, Opticien, Retargeted Direct Mailing, Vente au détail

Abstract (Portuguese)

Título: Influência do Retargeted Direct Mailing na fidelização de clientes entre óticas independentes na Holanda, considerando as características dos clients?

Autor: Marie Johanna Westermann

Reduzir a rotatividade de clientes é crucial para a rentabilidade. Apesar do marketing digital, o Direct Mailing (DM) continua eficaz devido à sua presença tangível e altas taxas de resposta. O Retargeted Direct Mailing (RDM) usa dados dos clientes para criar correspondências personalizadas, reengajando clientes perdidos ou em risco. Compreender os tipos de clientes e suas respostas aos incentivos nos RDMs é essencial para otimizar a fidelização.

Esta tese analisa o impacto do RDM na rotatividade de clientes entre óticas independentes na Holanda, considerando as características dos clientes. Dados de 7.839 clientes em 13 varejistas ópticos ao longo de 8 anos foram analisados.

O RDM reduz efetivamente a rotatividade ao encurtar os intervalos de compra, aumentar a probabilidade de compra e estimular os gastos. As respostas aos RDMs incentivados variam de acordo com as características dos clientes. Clientes mais velhos, mulheres e compradores frequentes apresentam as menores taxas de rotatividade.

As limitações do estudo incluem a escassez de dados, potenciais vieses devido a entradas nulas e generalização limitada além do mercado de varejo óptico holandês.

Esta pesquisa oferece insights para o marketing de varejo, particularmente para a indústria de óticas, na criação de campanhas RDM eficazes (com e sem incentivos) adaptadas às características dos clientes para melhorar a retenção e aumentar os gastos.

Palavras-chave: Rotatividade de clientes, Gestão de Relacionamento com o Cliente, Retenção de clientes, Mala direta, Incentivos, Ótica, Retargeted Direct Mailing, Varejo

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List of Abbreviations

CLC	Customer Life Cycle
CLV	Customer Lifetime Value
CRM	Customer Relationship Management
DM	Direct Mail
DMA	Data & Marketing Association
ELM	Elaboration Likelihood Model
H	Hypothesis
IBLP	Item-Based Loyalty Programs
RDM	Retargeted Direct Mail
RFM	Recency, Frequency, Monetary
ROI	Return on Investment
TPB	Theory of Planned Behavior

1. Introduction

In today's competitive business environment, in which reducing customer churn is critical to profitability, leading consulting firms such as McKinsey & Company emphasize the critical role of personalized marketing strategies in reducing churn rates (José Carluccio et al., 2021). Research indicates that even slight improvements in customer churn rates can substantially increase a company's profits (Harvard Business Review, 2021). Advancements in technology enable the implementation of CRM systems that tailor marketing campaigns to individual customer needs, fostering greater engagement and loyalty (Charles Lange, 2023).

Customer churn is defined as the rate at which customers discontinue their relationship with a business. Research consistently highlights the economic advantages of customer retention over acquisition, with studies indicating that retaining an existing customer can be significantly less costly than acquiring a new one (Pfeifer, 2005; Kotler & Keller, 2009). Moreover, a 5% increase in customer retention rates can boost profits by 25% to 95% (Reichheld & Sasser, 1990; Tatikonda, 2013). These figures underscore the urgent need for effective strategies to retain customers and ensure sustainable business growth.

Despite technological advancements, the significance of traditional marketing strategies is still recognized. Reports indicate that traditional marketing methods, due to their tangible presence and extensive reach, continue to be indispensable, particularly in local markets where they help build trust and have a significant impact (The Media Ant, 2024). Furthermore, discussions in journals like the Harvard Business Review reveal a resurgence in the application of traditional marketing techniques, valued particularly for their distinctiveness in a digital-heavy landscape. These methods, such as Direct Mailing (DM), are noted for their efficacy in targeting specific demographics or local audiences (Christine Moorman et al., 2022).

Direct Mailing (DM) is still a powerful marketing tool for enhancing customer retention. Despite the rise of digital marketing, DM's tangible and personalized nature continues to effectively capture consumer attention and reduce churn. According to the Data & Marketing Association (DMA, 2018), DM boasts higher response rates compared to many digital channels, with a notable 5.1% response rate for DM versus 0.6% for email marketing. Integrating DM into multi-channel marketing strategies can create a seamless customer experience that fosters engagement and loyalty (Steffes, 2018).

Building on the traditional DM approach, Retargeted Direct Mailing (RDM) has emerged as an advanced strategy to tackle customer churn. RDM combines customer data from previous interactions to craft highly personalized and timely mailings aimed at re-engaging lost or at-risk customers (USPS Delivers, n.d.; Gibson, 2021; Bobnak, 2021). This targeted approach focuses on individuals with an existing brand relationship, delivering relevant messages and offers that increase the likelihood of customer retention. By proactively addressing potential disengagement, RDM is particularly effective in reducing churn (Malthouse & Blattberg, 2005).

To proactively address potential disengagement, understanding customer types and segmentation is crucial for the personalization and thus the effectiveness of RDMs. Customers can be segmented based on demographic factors like age, gender, and income, as well as behavioural patterns such as purchase frequency and loyalty (Bucklin & Gupta, 1992; Jiang & Tuzhilin, 2006). Psychographic factors, including lifestyle and values, further refine targeting (Mor, 2014). Geographic segmentation helps in addressing regional preferences (Moscardo, Pearce, & Morrison, 2001). By combining these segmentation criteria, businesses can tailor their marketing efforts to meet the unique needs of different customer groups, enhancing campaign effectiveness (Weinstein, 2004).

Equally important is the strategic use of incentives in marketing campaigns. Incentives can be monetary, such as discounts and vouchers, or non-monetary, like exclusive offers and premium services (Simon et al., 2010; Vafainia et al., 2019). The choice of incentive can significantly impact customer response and engagement. Personalized incentives that align with customer preferences and behaviours can drive higher engagement and loyalty, thereby reducing churn (Jahromi et al., 2014). Leveraging data analytics to understand customer behaviour allows businesses to craft incentives that resonate more deeply with targeted segments, optimizing the impact of RDM campaigns (Shirazi & Mohammadi, 2019).

However, there remains a notable gap in the literature regarding RDM's specific impact on customer churn. Most existing research on RDM centers on short-term engagement metrics or immediate sales uplift rather than long-term retention. For instance, studies by Lambrecht and Tucker (2013) focus on the effectiveness of online retargeting advertisements in driving immediate sales without exploring long-term retention outcomes. Similarly, Malthouse and Elsner (2006) investigate the personalization of marketing communications but do not delve into its impact on customer churn over extended periods. Additionally, the role of customer segmentation and the effectiveness of different incentives in RDM campaigns are underexplored. Research by Li and Kannan (2014) and De Haan et al. (2016) also highlights short-term effectiveness without addressing sustained customer relationships and the specific influences of various customer types and incentives. Therefore, this thesis seeks to bridge this gap by exploring the following Research Question:

How does RDM influence customer churn among independent opticians in the Netherlands, considering the moderating effects of customer characteristics?

To answer this, the study focuses on three detailed sub-questions:

What role do customer-specific characteristics (age, gender, relationship duration, and purchase frequency) play in moderating the impact of RDM on churn? Understanding how different demographics and purchasing behaviours affect responses to RDM can help businesses better segment their customer base and tailor campaigns to specific needs (Ansari & Mela, 2003). Furthermore, analyzing these characteristics provides insights into the effectiveness of RDM across different stages of the Customer Lifecycle (CLC), enabling more targeted retention strategies (Verhoef, 2003).

What types of incentives in RDM campaigns (discounts and premium offers) are effective in reducing customer churn? Identifying effective incentives helps businesses tailor RDM campaigns to maximize retention, enhancing campaign efficiency and return on investment (ROI) (Blattberg & Deighton, 1996).

How do RDMs influence the spending behaviour of the customer? Insights into spending responses to RDM campaigns allow businesses to craft targeted strategies that significantly improve ROI and strengthen customer retention in competitive markets (Kumar & Reinartz, 2016; Lemon & Verhoef, 2016).

By addressing these questions, this study aims to provide valuable insights for both academic understanding and practical application in the marketing landscape and further in the retail industry. The findings will help opticians and other retailers design more effective RDM campaigns, ultimately improving customer satisfaction and retention (Venkatesan & Kumar, 2004). Further, this research underscores the strategic importance of RDM in contemporary marketing, highlighting its potential to significantly reduce customer churn and foster long-term business success.

1.1. Structure of the Study

This study is structured as follows. First, underlying concepts are introduced to provide context and understanding of the topic. This includes an overview of the existing literature on customer churn, Direct Mailing (DM), Retargeted Direct Mailing (RDM), Customer Relationship Management (CRM), Customer Lifecycle (CLC), Customer Lifetime Value (CLV), customer types, and incentives. This overview forms the basis for developing the hypotheses to answer the proposed research questions. Second, the research design is then presented in detail, followed by the presentation and discussion of the empirical results. Third, the study concludes with scientific and business management implications. Finally, the limitations of the study are discussed and suggestions for future research are made.

2. Literature Review

2.1. Customer Churn

Customer churn, also known as customer attrition, refers to the state in which one or more customers end their business relationship(s) with a company, resulting in a significant impact on CLV and profitability (Sundararajan & Gursoy, 2020; Aeri et al., 2023). In retail, churn is primarily driven by the lack of repeat purchases, affecting CLV more than in sectors like telecommunications, where churn is often due to high transfer rates between providers (Huang, Zeng, & Chen, 2012; Castéran, Meyer-Waarden, & Benavent, 2022).

Reducing churn is economically advantageous, as acquiring new customers is costlier than retaining existing ones (Gupta & Lehmann, 2005). A 5% reduction in churn can enhance profits by 25% to 95% (Reichheld, 1996). Studies confirm that the costs of preventing churn are generally 5 to 25 % lower than those associated with acquiring new customers (Farris, Bendle, Pfeifer, & Reibstein, 2010; Blattberg & Deighton, 1996). Therefore, investing in effective customer retention strategies is crucial for businesses to maximize profitability.

In retail, where interactions are often more personal and less frequent compared to transaction-heavy industries, distinct challenges and strategies for reducing churn emerge. Customer experience and satisfaction are central to customer retention in retail, with personal interactions playing a crucial role (Jones et al., 2010). Enhanced customer care and targeted post-purchase communication significantly mitigate churn rates, emphasizing the importance of personalized customer engagement (King, 2018). Research by Ayuningtias and Saraswati (2019) and Biscaia et al. (2017) highlights that retail service quality directly influences customer loyalty. Additionally, Powers, Choi, and Jack (2017) found that both store and service satisfaction are critical for maintaining customer retention in retail settings. Vesel and Žabkar (2009) further underscore the role of satisfaction in managing retention and loyalty, particularly within loyalty programs. This comprehensive approach to customer care aligns with the principles of maintaining trust and quality in customer interactions, ultimately reducing churn and enhancing customer retention.

Churn management can be divided into *proactive* and *reactive* strategies. Proactive churn management uses predictive analytics to identify and engage at-risk customers before they decide to leave, tailoring communications and offers to individual preferences to reduce churn rates. Ansari and Mela (2003) demonstrate that personalized emails enhance customer satisfaction and reduce churn. Renjith (2015) shows that integrated models using data analysis to predict churn and personalize retention strategies effectively engage customers. Proactive targeting can significantly increase revenue and reduce churn, as evidenced by a German grocery retailer's field experiment (Ringbeck et al., 2019).

Reactive churn management addresses churn after it occurs by analyzing post-churn behaviour to identify triggers and deploying corrective measures. Venkatesan and Kumar (2004) highlight that targeted communications based on precise customer segmentation can improve retention and reduce churn. Combining proactive and reactive strategies, supported by robust data analytics, can optimize customer retention rates and profitability in the retail sector (Sweidan et al., 2022).

Several theoretical models offer in-depth insights into the dynamics of customer churn, specifically in the retail sector. The *psychological contract model*, introduced by Rousseau (1989), suggests that churn often results from a perceived breach of the implicit agreement between the customer and the company. This breach typically occurs when customer expectations about product quality and service standards are not met. Failing to meet these expectations significantly impacts customer retention, as supported by Payne and Holt (2001), who demonstrate that fulfilling psychological contracts enhances customer satisfaction and loyalty, thereby reducing churn rates.

In addition to psychological contracts, the *theory of perceived switching costs* is crucial for understanding customer retention. Burnham, Frels, and Mahajan (2003) argue that the financial, psychological, and time-related costs associated with switching providers can deter customers from changing, even when dissatisfied. Customers must consider the time and effort required for new examinations and the risk of adapting to a new provider. Empirical research by Jones, Mothersbaugh, and Beatty (2002) highlights that high perceived switching costs act as a barrier to churn, suggesting that businesses can retain more customers by increasing the perceived difficulty of switching.

Heide and Wathne (2006) integrate these theories, suggesting that companies can manage customer relationships more effectively by understanding the dual impact of psychological contracts and switching costs. They propose that it is crucial to meet and exceed customer expectations to avoid breaches of psychological contracts while also managing perceived switching costs to retain customers who might otherwise feel compelled to churn.

Empirical studies further underline the importance of customer satisfaction in influencing churn. Satisfaction, often determined through surveys and feedback mechanisms, is directly correlated with churn rates. Anderson and Sullivan (1993) confirmed that higher customer satisfaction significantly reduces churn. Technological advances and data analytics enhance the ability to predict and mitigate churn by identifying at-risk (focusing on *proactive churn management*) customers through their behavioural patterns and promoting targeted marketing efforts to increase satisfaction and strengthen loyalty (Burez & Van den Poel, 2009).

2.2. Direct Marketing

2.2.1. Direct Mailing

Digitalization and advancements in technology have provided endless tools and methods to communicate and interact with consumers. Surprisingly for some, despite the surge in digital marketing, traditional Direct Mailing (DM) remains a widely used tool in the world of direct marketing due to its tangible and personalized nature. The ability of DM to effectively capture consumer attention and reduce customer churn underscores its enduring relevance (Smith & Taylor, 2004; Peppers & Rogers, 2017; Eckersley & Hodge, 2020).

DM is a strategic component of direct marketing that aims to build one-to-one relationships with consumers through private, personalized messages (Kotler et al., 2009). This form of marketing is characterized by targeting individuals flexibly, often without prior request from the consumer, to drive product or service purchases (Chang & Morimoto, 2003). DM campaigns typically involve sending materials that “call to action,” such as special offers or relevant information at critical moments, effectively stimulating purchase decisions and reducing customer churn through interactive communication (Ekhlassi et al., 2012; Rust & Verhoef, 2005).

From its initial primitive methods to the modern era marked by advanced data analytics and digital technologies, DM has transformed from a broad-reaching form of mass communication into a highly personalized marketing strategy (Smith & Fletcher, 2004; Peppers & Rogers, 2017). This transformation is largely due to its enhanced capacity for customization. Tailoring DM campaigns to meet the specific needs of individual consumers significantly reduces customer churn, making DM an effective component in customer relationship management (CRM) (Chang & Morimoto, 2003; Ekhlassi et al., 2012). Studies confirm that personalizing these campaigns increases their effectiveness, leading to heightened customer engagement and loyalty, which are critical in minimizing customer churn (Gould, 1987; Risselada et al., 2014).

Additionally, integrating digital technologies with traditional DM has further amplified its impact. The combination of data analytics and machine learning enables more precise targeting and personalization, fostering a sense of appreciation among customers and enhancing their customer lifetime value (CLV) (Peppers & Rogers, 2017). Research also suggests that blending digital and physical marketing strategies can create more comprehensive and effective customer engagement (Blattberg, Kim, & Neslin, 2008). This strategic focus on personalization and integration continues to be a cornerstone in building and maintaining customer relationships in a competitive marketplace.

In addition to academic research, several case studies from the field demonstrate the impact and efficiency of DM campaigns. Several prominent companies have successfully integrated DM into their marketing strategies.

Sephora, a leading cosmetics chain, leverages DM within its acclaimed "Beauty Insider" loyalty program to deliver highly customized offers. This program taps into detailed data analytics to craft personalized invitations and offers that are often enhanced with incentives such as coupons or product samples. Such targeted communication not only encourages purchases but also significantly boosts customer retention by making customers feel valued and understood. This strategy has been instrumental in reducing customer churn, thereby strengthening Sephora's market position (TheBigMarketing, 2024).

Similarly, Vodafone, a global telecommunications giant, has adeptly harnessed targeted DM campaigns to engage customers just before their contract renewals. These personalized campaigns are strategically designed to offer tailored incentives that not only encourage contract renewals but also significantly enhance customer loyalty. By delivering customized offers that resonate with individual customer needs, Vodafone successfully proactively mitigates churn and strengthens its customer relationships (Matt Watson, 2020). These examples underscore how meticulously executed, customer-centric DM strategies can markedly boost customer loyalty and minimize churn, showcasing its widespread adoption among major corporations.

Despite its benefits, DM is often perceived as intrusive, especially when sent unsolicited, as above mentioned. Managing the frequency and content of communication is crucial to avoid irritation and not undermine the positive effects of DM campaigns. Brehm's (1966) *Reactance Theory* explains how unsolicited DM can be perceived as a threat to autonomy and thus lead to negative reactions or even outright rejection (Fitzsimons & Lehmann, 2004; Miron & Brehm, 2006). To effectively reduce customer churn, DM strategies must be carefully calibrated to meet consumer preferences as well as data privacy concerns.

2.2.2. Retarget Direct Mailing

Retargeted Direct Mailing (RDM) represents a significant advancement in direct marketing by combining the precision of digital retargeting with the tangible impact of traditional DM. The concept of retargeting, as explained by Sahni et al. (2019), specifically targets individuals who are familiar with a product or brand, typically through online engagement, but have not completed a purchase. This approach leverages advanced online tracking technologies to identify users who previously visited a website and analyze their search and navigation behaviour. With this detailed behavioural data, marketers can create highly personalized communications that address the needs or interests of consumers through both online advertisements and DM (Kutty & Prabhakaran, 2006; Sahni, Wheeler, & Chintagunta, 2019).

Unlike traditional DM, which generally relies on broad demographic and geographic data for targeting, RDM leverages specific insights from a customer's digital activities to send personalized physical mail (Bose, 2009). This targeted approach not only heightens the relevance of the communication but also enhances the likelihood of re-engaging the customer (*pro- and reactive churn management*) (Coussement, Harrigan, & Benoit, 2015). By linking a customer's recent online behaviour with physical mail, RDM effectively bridges the gap between digital engagement and tangible marketing efforts, creating a seamless experience that merges online and offline channels (Guido et al., 2011).

The effectiveness of RDM lies in its capacity to tailor communications based on real-time data, positioning it as an indispensable tool in contemporary marketing strategies aimed at reducing customer churn and boosting engagement (Zaiyong, 2011). This methodology reflects the broader marketing trend of combining digital precision with the inherent advantages of physical mail, such as increased engagement rates and the tactile quality that often leads to enhanced recall and response rates (Muñoz-Leiva, Liébana-Cabanillas, & Hernández-Méndez, 2018). Studies confirm that personalizing these (retargeted) DM campaigns increases their effectiveness, leading to heightened customer engagement and loyalty, critical factors in minimizing customer churn (Gould, 1987; Risselada et al., 2014).

Building on the fundamental principles of RDM, the integration of the *Elaboration Likelihood Model* (ELM) and the *Theory of Planned Behavior* (TPB) provides a nuanced understanding of how personalized marketing strategies can significantly impact customer behaviour and reduce churn. The ELM, proposed by Petty and Cacioppo (1986), posits that there are two routes to persuasion: the central route and the peripheral route. The central route involves deep, thoughtful processing of the information presented, while the peripheral route involves more superficial processing based on cues outside the message content, such as the attractiveness of the source or the quality of the presentation. According to Cacioppo et al. (1981), DM can effectively leverage both routes by providing substantive, personalized content that engages customers on a deeper level, while also utilizing the tangible, high-quality nature of DM to attract attention through peripheral cues. This dual approach can enhance the overall impact of RDM, making it a powerful tool for reducing customer churn (Petty, Cacioppo, & Schumann, 1983).

The TPB, developed by Ajzen (1991), explains how attitudes, subjective norms, and perceived behavioural control influence an individual’s intentions and behaviours. In the context of RDM, personalized communications can positively influence customer attitudes by addressing their specific needs and preferences, enhance subjective norms through perceived social endorsements, and increase perceived behavioural control by simplifying the decision-making process with clear, targeted “calls to action”. This comprehensive approach ensures that RDM strategies are not only persuasive but also align with the psychological factors that drive customer behaviour (Ajzen, 1991; Gardner et al., 2012).

While retargeting is a widely used marketing method (Helft & Vega, 2010; Peterson, 2013; Sengupta, 2013), the specific application of RDM in direct marketing is less well studied, particularly in terms of its impact on customer churn. Sahni et al. (2019) highlight that online retargeting significantly increases user engagement and finds a significant increase in website revisits when retargeting is used within two weeks of the initial visit. This suggests that the precise timing of retargeting plays a critical role in maintaining consumer interest and can encourage customers to make a new purchase and not churn. However, this is not specifically researched further. Li et al. (2021) found that retargeting too quickly can sometimes backfire and reduce the effectiveness of such campaigns. These findings underscore the importance of optimizing the timing of RDM efforts to enhance their effectiveness.

Research on retargeting strategies also examines the moderating effects of demographic characteristics and previous consumer behaviour. Yeo et al. (2017) examined online purchase conversions and highlighted how customer and product-level characteristics can alter the impact of retargeting campaigns. Their findings suggest that factors such as previous interactions with the brand and the type of products viewed play crucial roles. Zarouali et al. (2017) explored how young adults' privacy concerns and their awareness of being targeted affect their perceptions of online retargeting ads, indicating that subjective norms and perceived behavioural control - core components of Ajzen's TPB - moderate the impacts of retargeting strategies.

Extending these insights to RDM, where physical mailings play a crucial role, remains underexplored. Jiang et al. (2017) investigated the effectiveness of search-based retargeting and how consumers' search behaviours affect retargeting outcomes. Applying these findings to RDM strategies suggests that personalized physical mail, informed by digital behaviour, can significantly influence customer retention. However, the direct application of these insights to physical mail campaigns needs further research.

To effectively use RDM within a broader marketing strategy, it is essential to understand its role in Customer Relationship Management (CRM).

2.3. Customer Relationship Management

CRM is an indispensable part of strategic planning, particularly within the retail sector, where establishing and nurturing long-term customer relationships is crucial. CRM integrates strategic, procedural, technological, and philosophical elements to manage and understand customer interactions comprehensively. The diversity of definitions and conceptualizations of CRM in academic literature reflects its complexity and multidimensionality (Boulding et al., 2005; Payne & Frow, 2005). CRM is not merely seen as a data collection tool but as a holistic strategy that places the customer at the center (Boulding et al., 2005). This customer-centric orientation enables companies to create personalized experiences that strengthen customer engagement and ultimately help reduce customer churn (Verhoef, 2003).

The technological component of CRM, including the integration of CRM systems into a retailer’s business strategy, provides crucial insights into the customer, essential for developing targeted marketing strategies (Verhoef et al., 2002). By leveraging these technologies, retailers can gather and analyze data on customer behaviours, preferences, and purchasing patterns, which can then be used to tailor marketing efforts and improve overall customer satisfaction.

Reinartz et al. (2004) articulate CRM as a systematic process that manages the customer lifecycle (CLC) of customer relationships across all touchpoints, aiming to maximize the relationship portfolio's value by tailoring interactions based on collected insights into customer behaviour and needs. This approach not only helps in accurately targeting customers but also in nurturing each relationship according to its specific value and maturity, thereby enhancing customer retention and satisfaction (Reinartz et al., 2004). Swift (2001) emphasizes that CRM strategies are not only about understanding customer behaviours but also about effectively influencing these behaviours through meaningful communications, fostering a deeper connection with the customer.

Kotler et al. (2009) expand on this by incorporating the customer’s perspective into CRM, defining it as the creation of customer satisfaction through superior value, which underscores the reciprocal nature of customer-firm interactions aimed at building mutual loyalty. This perspective highlights the importance of delivering consistent value to customers to maintain and strengthen relationships.

The challenge for retailers lies in integrating the various perspectives within CRM to develop strategies that are both technologically advanced and deeply rooted in an understanding of customer needs throughout their whole CLC (Lemon & Verhoef, 2016).

2.3.1. Customer Lifecycle

The relationships between customers and firms evolve through distinct phases known as the Customer Lifecycle (CLC), encompassing consideration, purchase, and product or service usage. However, academia lacks consensus regarding the CLC's division, including the number of phases and their concrete labels.

Reinartz et al. (2004) delineate the CLC into three phases: relationship initiation, maintenance, and termination. In contrast, Rousseau et al. (1998) advocate for three phases: building, stability, and dissolution. Dwyer et al. (1987) extend this further to five stages: awareness, exploration, expansion, commitment, and dissolution. Alternatively, Kotler (1997) defines CLC stages based on customer roles, including suspect, prospect, first-time customer, repeat customer, client, advocate, member, and partner.

The fundamental concept underlying these approaches is the dynamic nature of customer-firm relationships, with attributes like strength and trust evolving across CLC stages. Consequently, consumer needs and communication objectives are intrinsically linked to these stages. Aligning CRM processes and marketing methods with CLC stages is essential for effectively addressing consumer needs and achieving communication goals. Neslin & Shankar (2009) emphasize the necessity of matching communication channels to CLC stages, recognizing that different channels yield varying outcomes based on the individual's CLC stage. Additionally, the content conveyed through these channels resonates differently with consumers at different CLC stages.

Like new customer acquisition, customer churn also has its phase in each self-defined cycle. Although there is additional evidence that customer retention is often more profitable for companies, marketing research and practice prioritizes the acquisition of new customers. This imbalance has drawn criticism from various authors, including Kotler et al. (2009) and Ahmad & Buttle (2001). However, studies have shown that a 1% increase in customer retention rates can lead to a significant 5% increase in company value, emphasizing the critical importance of focusing on customer retention for long-term business success (Gupta et al., 2004). This strategic shift towards customer retention not only drives immediate revenue but also secures long-term financial health.

2.3.2. Customer Lifetime Value

Customer Lifetime Value (CLV) is a crucial metric in assessing the value each customer brings to a company over the entirety of their relationship. It is defined as the net present value of the future cash flows attributed to the customer during their entire relationship with a company, representing the total worth of a customer to a business over time. This includes not only the total revenue a customer generates but also the costs associated with serving them, both factors adjusted to present value using a discount rate to account for the time value of money (Lemon & Lemon, 2010). According to Kotler et al. (2009), CLV can be simplified as the total revenue a customer generates throughout their relationship with a company, encapsulating the entire duration of their engagement. This simplification highlights the importance of long-term customer relationships in sustaining and enhancing company profitability by focusing primarily on revenue.

In practice, CLV is calculated by summing the net profits (revenue minus costs) from a customer for each period of their relationship, discounted back to the present value. The formula used is:

$$\mathrm{CLV} = \sum_{t=1}^{n} \frac{Rt - Ct}{(1+d)^t}$$

Equation 1: Customer Lifetime Value Formula

where:

- Rt = Revenue from the customer in period tt
- Ct = Cost to serve the customer in period tt
- d = Discount rate
- T = Total number of periods

This formula, reflecting the discussions in literature such as Andon, Baxter, & Bradley (2003) and Groeger & Buttle (2015), provides a more nuanced understanding of CLV by incorporating both revenue (R) and costs (C) into the estimation of a customer's value to the firm, thus ensuring a comprehensive assessment of profitability over the customer lifecycle (Andon, Baxter, & Bradley, 2003; Groeger & Buttle, 2015).

Enhancing customer retention is paramount for increasing CLV. Chang and Zhang (2016) elaborate on how various channel experiences and direct marketing tactics can influence customer retention positively, thus stabilizing and potentially increasing CLV over time. Their research underscores the importance of multi-channel engagement strategies in maintaining active customer relationships, which are essential for sustained profitability (Chang & Zhang, 2016).

In the context of RDM, strategic enhancements can significantly elevate CLV by influencing key variables such as *purchase frequency* and *transaction value.* Research by Blattberg, Malthouse, and Neslin (2009) illustrates that targeted marketing efforts through RDM can effectively increase purchase frequency, reinforcing customer engagement, which is a critical driver of CLV (Blattberg, Malthouse, & Neslin, 2009). These interactions cultivate a sustained revenue stream by maintaining a high level of customer activity over time.

Moreover, Dawes (2009) discusses that careful management of price increases, particularly with loyal customers who are less price sensitive, can increase CLV through higher spending per act of purchase (Dawes, 2009). Additionally, the strategic retargeting of high-value customers via RDM can maximize CLV by focusing on those who exhibit higher purchase frequencies and greater transaction values. By tailoring communications and offers to fit the specific needs and past behaviours of these customers, firms can significantly enhance their profitability. Fader, Hardie, and Lee (2005) highlight how segmenting customers based on detailed behavioural data can lead to more personalized marketing efforts that effectively increase CLV (Fader, Hardie, & Lee, 2005).

2.4. Customer Types

Following the comprehensive understanding of CLV and its critical role in enhancing marketing strategies and customer retention, it is essential to delve into the categorization of customer types. Understanding the diverse customer types is crucial for developing effective marketing strategies that maximize business success.

Yao Zuo-wei (2002) significantly expands the traditional view by identifying a broad array of customers beyond direct buyers, including internal customers, supplier customers, financiers, intermediaries, competitors, end customers, the public, and the government. This classification underscores that customers are any individual or group that can directly or indirectly influence a business, thus offering a profound understanding of the complexities of market relationships (Yao Zuo-wei, 2002). In this thesis, the focus lies on end customers, who are categorized differently in various studies.

Swan and Pruden (1977) classify end customers in service industries as Instrumental Service Customers and Expressive Service Customers. The former view the service as an end, prioritizing efficiency, cost, and convenience, while the latter regard the service as an end in itself, focusing on quality and experience (Swan & Pruden, 1977). Thomas and Preethi (2022) define additional customer types based on shopping motives and behaviours: Loyal customers, discount customers, impulse customers, and need-based customers. Loyal customers have a long-term commitment to a brand or company, often less sensitive to price and more focused on value and quality. Discount customers are attracted to promotions and discounts and are primarily motivated by getting the best deal. Impulse customers make spontaneous purchases without prior planning, often influenced by effective in-store promotions or appealing product displays. Need-based customers make purchases based on specific, immediate needs, focusing on fulfilling a particular requirement rather than brand loyalty or price considerations (Thomas & Preethi, 2022).

Market Segmentation

To effectively categorize a company's diverse end customers, market segmentation is crucial. Market segmentation is defined as the process of dividing a heterogeneous customer base into homogeneous groups based on shared characteristics. This strategic approach enhances the alignment of marketing efforts with the specific needs and preferences of each customer segment, thereby optimizing resource efficiency and customer satisfaction (Smith, 1956).

There are five segmentation criteria often mentioned: behavioural, demographic, psychographic, geographic, and purchase-based segmentation. Behavioural segmentation focuses on customers' behaviour patterns, such as purchasing frequency and loyalty. Demographic segmentation involves characteristics such as age, gender, income, and education level. Psychographic segmentation delves into lifestyle, values, and personality traits.

Geographic segmentation considers location and regional preferences. Purchase-based segmentation looks at past purchasing behaviours and patterns. Each of these segmentation criteria plays a pivotal role in enhancing marketing strategies by aligning them more closely with the diverse needs and behaviours of end customers (Art Weinstein, 2004).

Utilizing transaction-based data, Jiang and Tuzhilin (2006) demonstrated that behavioural segmentation facilitates a nuanced understanding of customer habits and preferences. This approach has been shown to improve engagement and conversion rates significantly, making marketing campaigns more relevant and effective. Their findings suggest increases in campaign effectiveness by as much as 30%, highlighting the critical role of precise behavioural targeting (Jiang & Tuzhilin, 2006).

Bucklin and Gupta (1992) revealed that demographic factors such as age, gender, and income strongly influence purchasing decisions and brand loyalty. Integrating these insights with other segmentation data allows for a more refined targeting strategy, enhancing the effectiveness of marketing efforts by up to 24%, and ensuring that the right demographic receives the right message (Bucklin & Gupta, 1992).

Psychographic segmentation, which involves understanding the psychological and lifestyle characteristics of consumers, has been shown by Mor (2014) to significantly match marketing strategies with consumer motivations and preferences, potentially increasing marketing effectiveness by 15-20%. This method emphasizes the importance of aligning marketing messages with the deeper psychological drivers of consumer behaviour (Mor, 2014).

Geographic segmentation has been shown by Moscardo, Pearce, and Morrison (2001) to enhance the relevance of marketing campaigns by addressing regional consumer behaviour and preferences, improving campaign effectiveness by ~ 25%. This strategy is crucial for adapting marketing efforts to fit local consumer characteristics and cultural nuances (Moscardo, Pearce, & Morrison, 2001).

Focusing on purchasing behaviours such as frequency and volume, Fader, Hardie, and Lee (2005) have illustrated how this segmentation leads to better prediction of future buying behaviours and tailoring marketing efforts, which is particularly beneficial for enhancing CLV. Their study highlights that understanding these patterns can lead to a 30-35% improvement in marketing ROI, crucial for optimizing marketing resource allocation and maximizing customer lifetime value (Fader, Hardie, & Lee, 2005).

A widely adopted analytical framework in market segmentation is the *Recency, Frequency, and Monetary* (RFM) model. This model classifies customers based on their purchasing behaviour, which is critical for developing personalized marketing strategies that resonate with different customer segments. By segmenting customers according to how recently they have purchased (Recency), how often they purchase (Frequency), and how much they spend (Monetary), businesses can gain invaluable insights into customer loyalty and their potential future behaviour (Fader, Hardie, & Lee, 2005; Hughes, 1996; Stone & Jacobs, 2008; Kumar & Reinartz, 2018).

The strategic application of the RFM model has proven effective in enhancing customer engagement and retention. Roshan & Afsharinezhad (2017) integrated the RFM model with the Firefly Algorithm, optimizing customer segmentation by profitability. Tavakoli et al. (2018) extended the model to R+FM with K-Means clustering, significantly improving marketing effectiveness in a Middle Eastern e-commerce company through increased purchase frequency and spending. Ernawati et al. (2021) further advanced this by combining the RFM model with various data mining methods within Geographic Information Systems, enhancing targeting precision and marketing effectiveness.

For segmentation to be truly effective, it must adhere to certain criteria: substantiality, measurability, accessibility, responsiveness, and consistency. Each segment must be large enough to justify targeted marketing efforts, identifiable through measurable characteristics, reachable via marketing communications, responsive to tailored strategies, and aligned with the organization's objectives and capabilities. These criteria ensure that the segmented marketing approach is not only strategic but also practical and aligned with the broader goals of the organization (Andaleeb, 2016).

2.5. Incentives

The use of incentives in marketing is a common practice aimed at influencing consumer behaviour (Peattie & Charter, 1994; Kotler, 2009; Verhoef, 2003; Rust & Verhoef, 2005). These incentives, often incorporated into call-to-action (CTA) DM strategies, play a crucial role in encouraging consumers to take specific actions, such as making a purchase.

Incentives in DM campaigns can be broadly categorized into two types: monetary and non-monetary incentives. Monetary incentives, such as price discounts, appeal directly to consumers' rational propensity for financial savings, effectively lowering perceived financial barriers to purchase (Simon et al., 2010). Research by Toker-Yildiz et al. (2017) highlights the influence of online social interactions combined with monetary incentives on consumers' repeat behaviour, indicating the importance of integrating social dynamics into incentive strategies to enhance consumer engagement further.

Non-monetary incentives, such as free products or unique experiences, appeal to different consumer motivations by providing value beyond financial savings (Vafainia et al., 2019). These incentives can be categorized into hedonic and utilitarian rewards, adding strategic complexity to DM efforts. Vafainia et al. (2019) emphasize the efficacy of non-monetary, especially utilitarian, incentives in driving consumer purchase behaviour DM.

Understanding the effectiveness of monetary versus non-monetary incentives is crucial for optimizing consumer response rates in direct marketing. Personalization also plays a significant role in enhancing the impact of incentives, as evidenced by research on personalized incentives' effect on customer retention campaign profitability (Tamaddoni Jahromi et al., 2014). Similarly, predictive churn models leveraging big data offer insights into tailoring marketing strategies to individual consumer behaviour thereby enhancing engagement and loyalty (Shirazi & Mohammadi, 2019).

Consumer behaviour and churn represent critical areas of study within incentive-driven marketing strategies. Research by Sun (2021) suggests that consumer resistance to innovation can impact churn rates, with tailored incentive schemes potentially mitigating such resistance and enhancing retention. Understanding behavioural patterns preceding customer churn informs effective incentive strategies aimed at reducing churn (Erdem Kaya et al., 2018). Competing risk methodologies enable marketers to design incentive programs addressing various factors contributing to churn (Routh et al., 2021). Furthermore, personalized pricing emerges as a novel incentive mechanism with the potential to bolster customer retention through tailored pricing plans (Capponi et al., 2021).

Strategically incorporating incentives into CTA DMs presents a significant opportunity for direct marketers. The research underscores the importance of aligning incentives with consumer characteristics to maximize response rates in DM campaigns (Vafainia et al., 2019). These findings highlight the dynamic nature of direct marketing and emphasize the need for well-designed incentives based on an understanding of consumer motivation and behaviour to maintain effectiveness and increase engagement in evolving marketing landscapes.

Discounts

In the complex ecosystem of direct marketing, discounts act as important financial incentives to motivate customers to engage with products or services at more attractive prices. These incentives, which manifest themselves in the form of discounts, special offers or complementary value-added services, have proven to be effective in increasing customer response rates and attracting their attention, thereby increasing the likelihood of purchase intent. Their strategic use can significantly increase customer response rates, emphasizing how effective they are in attracting attention and encouraging purchase intent (Arora, N. & Stoner, C., 1992; Vafainia et al., 2019). This effect is not only immediate but can also have an impact on strengthening customer relationships, as regular discount offers are perceived positively, increasing brand loyalty and perceived value (Lal, R. & Bell, D., 2003; Villanueva et al., 2008).

Discounts serve a dual purpose in mitigating customer churn: incentivizing repeat purchases and maintaining competitive advantage. Customers enticed by regular discounts exhibit a higher propensity for loyalty, deterred from switching to competitors potentially due to the anticipation of future benefits (Dekimpe, M. G. et al., 1997; Rust et al., 2006). This highlights the strategic value of discounts not just in immediate sales uplift but in cultivating long-term customer retention.

Explorations into the "loyalty-discount cycle" reveal that while discounts can deepen loyalty, they also pose challenges in maintaining price strategies, suggesting a delicate balance between offering value and safeguarding profitability (Wieseke et al., 2014). Furthermore, the advent of item-based loyalty programs (IBLPs) replacing direct discounts with reward point promotions opens new avenues for enhancing consumer response, underscoring the evolving nature of incentive strategies in direct marketing (Zhang & Breugelmans, 2012).

Several studies have brought to light additional dimensions of discounts in direct marketing, including their effects on customer churn and the dynamics of loyalty programs. Research by (Tamaddoni Jahromi et al., 2014) emphasizes the necessity of predictive models for identifying potential churners, thereby enabling targeted (incentive) discount strategies. Additionally, the study by German, Retana and Fernández (2015) warns of the long-term risks associated with discount-driven churn prevention strategies in contractual services, indicating the complexity of discount effectiveness over time.

Premium

Premiums, as non-monetary incentives, significantly captivate consumer attention and incentivize engagement, thereby amplifying direct marketing campaign outcomes. Studies have shown that the inclusion of premiums in marketing materials can capture recipients' attention and increase response rates (d'Astous & Jacob, 2002). Premiums provide added value to the offer, making it more attractive and compelling for customers to respond to (Palazon & Delgado-Ballester, 2013). Additionally, the perceived value and uniqueness of premiums can differentiate a company's DM campaign from competitors, further enhancing its impact (Diamond & Sanyal, 1990).

The use of premiums in DM can also contribute to building stronger customer relationships. Offering valuable premiums can create a sense of reciprocity and goodwill among customers, leading to increased loyalty and positive brand perceptions (Nunes & Park, 2003). Customers may feel appreciated and valued by the company, fostering long-term relationships and repeat purchases (Villanueva et al., 2008). Premiums can serve as tangible tokens of appreciation, strengthening the emotional connection between customers and the brand (d'Astous & Jacob, 2002).

Offering a premium can help mitigate customer churn by incentivizing repeat purchases and fostering brand loyalty. Customers who receive premiums as part of their purchase may feel compelled to continue buying from the company to maintain access to these benefits (Foubert et al., 2018). Premiums can serve as a barrier to switching to competitors, as customers may be reluctant to forgo the benefits and advantages associated with their current provider (Richard Thaler, 1985). By offering attractive premiums, companies can increase customer retention rates and reduce churn, ultimately contributing to long-term business success (Rust et al., 2006).

2.6. Hypothesis

To comprehensively examine the effects of RDM on customer churn among independent opticians in the Netherlands and consider the moderating effects of customer characteristics, several hypotheses have been formulated based on a detailed literature review and identified research gaps.

Hypothesis 1 (H1): It is hypothesized that RDM significantly influences customer churn and therefore its likelihood.

To scrutinize this hypothesis, the isolated effects of various RDM strategies will be assessed through the below named ‘base model’ incorporating RDM, age, and gender code. This model serves as a baseline to device the primary influence of RDM on customer churn before introducing more nuanced interactions.

Hypothesis 2 (H2): Customer-specific characteristics are expected to moderate the impact of RDM on churn. This hypothesis is subdivided into specific assertions:

> *H2a:* The age of the customer is presumed to moderate the impact of RDM, with older customers potentially exhibiting different responsiveness to retargeting initiatives.
>
> *H2b:* Gender differences are anticipated to influence the efficacy of RDM, reflecting variances in how male and female customers respond to marketing communications.
>
> *H2c:* The frequency of purchases by a customer is predicted to intensify the effect of RDM, with frequent purchasers more likely to react positively to DM campaigns.
>
> *H2d:* The duration of the customer relationship with the retailer is posited to moderate the RDM effect, where long-standing customers may show distinct behaviours compared to newer customers in response to RDM.

Hypothesis 3 (H3): The efficacy of RDM is depending on the type of incentive offered:

> *H3a:* RDM campaigns with premium incentives are hypothesized to be more effective at reducing churn compared to campaigns without such incentives.
>
> *H3b:* RDM strategies involving discount incentives are expected to significantly mitigate churn rates, highlighting the potent influence of financial incentives on customer retention strategies.

Hypothesis 4 (H4): RDM significantly increases customer spending, with the effectiveness further enhanced by the type of incentive offered (premium or discount).

H4a: RDM campaigns with premium incentives are expected to significantly increase customer spending compared to campaigns without such incentives.

H4b: RDM strategies with discount incentives are also predicted to enhance customer spending significantly, illustrating the impact of financial incentives on increasing consumer expenditures.

2.7. Conceptual Framework

The subsequent diagram provides a visual representation of the relationships among the concepts from the literature review and aligns them with the hypotheses formulated for this study. Furthermore, variables in the dataset were included already for a clear and complete presentation. These variables mentioned will be further elaborated upon in the next chapter. This framework is a roadmap to navigate the research methodology employed in this thesis.

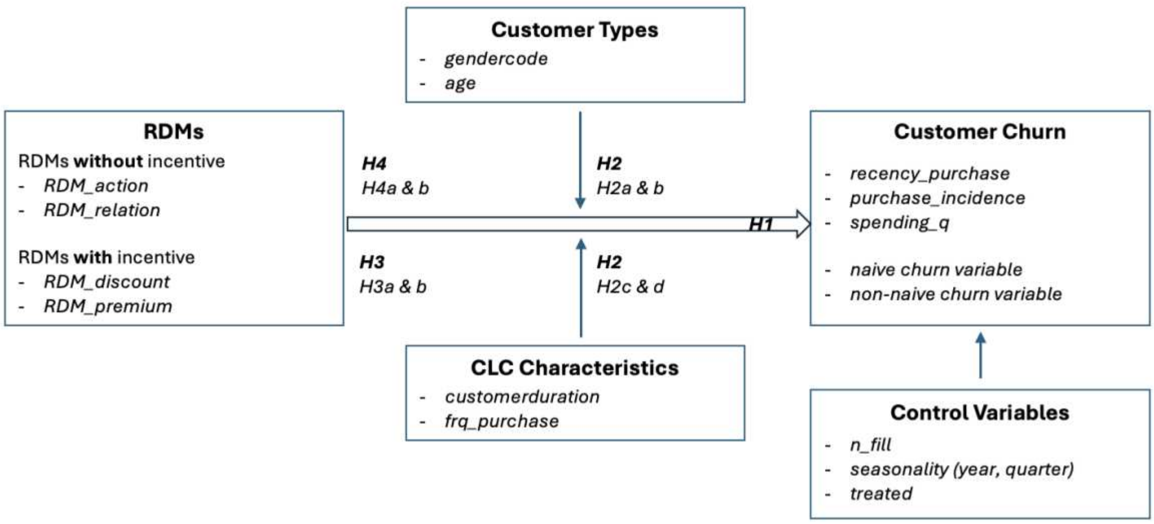

Figure 1: Theoretical framework including variables from the dataset

3. Research Design

3.1. Data Description

The analysis is based on a customer-level dataset spanning eight years, from 2011 to 2018, and includes data from 13 opticians serving a total of 7,839 customers. These retailers are independent and not affiliated with other companies. During the observation period, some of these retailers implemented (up to four) different RDM programs as part of their marketing strategies. Both participating and non-participating retailers are comparable in terms of size, customer types, and location. The coordination of customer databases was managed by a marketing consulting firm.

The dataset contains detailed information on customer characteristics, purchasing behaviour, customer expenditures and the history of RDM communications. It comprises records of customers every quarter, with each observation representing a customer in a specific quarter, uniquely linked to one of the retailers. In the optician industry, customers do not purchase as frequently as in the fast-moving consumer goods sector (Dibie, 2019; Kumari et al., 2023), and they are highly involved in their purchasing decisions. Consequently, the studied retailers send their RDMs every quarter.

The observation period starts in the first quarter (q1) of 2011 and ends in the fourth quarter (q4) of 2018, covering a total of 29 quarters. The dataset includes actual customers, i.e., individuals who were already customers before 2011 or who made their first purchase within the specified period.

3.1.1. Dependent Variables

The study aims to determine the influence of RDM on customer churn, regarding the moderating effects of customer characteristics. In the literature, customer churn is defined as a lack of repeat purchases (Castéran et al., 2022). However, in response to detailed theoretical frameworks as well as provided variables in the data set, a more comprehensive approach will be adopted to explore the effect of RDM on churn by using four different dependent variables related to customer churn, purchasing patterns, and customer expenditures.

Recency_purchase measures the duration since a customer's last purchase in quarters, providing insights into how long it has been since the last transaction, with values ranging from 0 to 29 quarters.

Purchase_incidence is a binary variable indicating whether a customer made a purchase (1) or not (0) within a specific quarter, highlighting patterns in customer activity and retention.

Spending_q captures the amount spent per quarter by each customer, offering insights into purchasing habits and identifying high-value customers.

Additionally, two different *churn* variables were created. Both variables were created based on the variable *recency_purchase*. The first churn (binary) variable indicates customer attrition, with a value of 1 if no purchase was made within 12 consecutive quarters and 0 if there was any purchase activity within that timeframe. The second churn variable considers potential purchases beyond the twelve quarters and revises the churn classification if a customer becomes active again later, aggregating data to minimize autocorrelations and provide a clearer depiction of customer churn dynamics over time.

By incorporating these variables, the analysis evaluates hypotheses related to customer churn, providing a comprehensive understanding of retention dynamics in the independent optician industry. Each hypothesis will be tested using regression models, allowing for detailed insights and comparisons across different models.

3.1.2. Independent Variables

The focus is on understanding the influence of RDM on customer churn, specifically differentiating between RDMs with incentives and those without, as the primary explanatory variable. Each RDM sent is classified to determine whether it contained an incentive and, if so, what type.

RDMs with incentive

The binary variable *RDM_incentive* indicates whether an RDM contained an incentive (1) or not (0).

In addition, the type of incentive is characterised by the binary variables *RDM_discount* and *RDM_premium* as a discount or premium. A value of 1 for *RDM_discount* means that a monetary incentive, such as a discount, was offered with the RDM. Conversely, a value of 1 for *RDM_premium* means that the RDM contained a non-financial bonus, e.g. an exclusive item or service. If both variables are set to 0, but still an RDM has been sent out, it can either be a *RDM_relation* or *RDM_action* or both.

RDMs without incentive

The binary variables *RDM_relation* and *RDM_action* are examined as important variables to create a relationship with the customer without an incentive. *RDM_relation* assesses the influence of DM campaigns designed to enhance customer relationships without offering direct incentives, whereas *RDM_action* measures the impact of direct mail campaigns aimed at prompting immediate customer actions such as store visits or purchases. For both variables, a value of 1 indicates that the respective type of RDM has been sent to the specific customer in the quarter.

Customer Characteristics

The variables of *gendercode* and *age* were recognized as demographic variables that could significantly influence the effectiveness of RDM campaigns.

Gendercode is a categorical variable representing the gender of the customer. It serves as an essential control variable due to its potential impact on how individuals of different genders respond to various types of direct mail. By incorporating *gendercode*, the study can account for differences in preferences and behaviors between male and female customers, ensuring that the analysis accurately reflects the influence of gender on RDM effectiveness.

Age is a continuous variable representing the customer's age in years. Distinct age groups may exhibit different responses to RDM campaigns. These differences reflect diverse preferences and behaviours across generational cohorts. By including age in the analysis, the study can account for the varying impacts of direct mail campaigns on different age groups, allowing for a more nuanced understanding of customer responses.

Customer Lifecycle (CLC) Characteristics

The variables *frq_purchase* and *customerduration* are identified as crucial numeric variables, essential for minimizing potential biases and enhancing the precision of the results.

Frq_purchase is a numeric variable representing the frequency of a customer's purchases. By considering purchase frequency, the study can differentiate between customers who shop regularly and those who do so less frequently.

Customerduration is a numeric variable representing the length of time a customer has been with the retailer. The inclusion of this variable provides valuable insights into customer loyalty and relationship stability. Customers with longer tenures may respond differently to RDM campaigns compared to new customers.

The inclusion of these variables is crucial for several reasons. By accounting for *frq_purchase* and *customerduration*, the study can mitigate potential confounding factors and ensure that the observed differences in response to DM campaigns are not solely due to variations in purchase frequency or customer affiliation. This detailed approach provides a deeper understanding of how these factors influence customer responses to RDM efforts and facilitates the refinement and optimization of RDM strategies tailored to specific customer segments.

3.1.3. Control Variables

Treated

The variable *treated* was identified as another crucial control variable that could significantly influence the effectiveness of RDMs. *Treated* is a binary variable indicating whether a customer has received any RDMs (1) or not (0). By including *treated* as a control variable, the study can account for potential differences in response between customers who have received RDMs and those who have not. This inclusion allows for a more accurate assessment of the true impact of RDMs while controlling for other factors that may influence customer behaviour. This ensures that any observed effects are attributable to the RDMs themselves rather than other external influences.

Mass Direct Mails

n_fill represents a variable indicating that mass direct mail communications were sent to all customers with the same content (not personalized), either with a value of 1 n_fill was sent out or 0 n_fill was not sent out.

3.2. Data Cleaning and Preparation

To enhance the accuracy and relevance of the data, three specific filters were applied, as well as three different variables were created.

Customers under the age of 18 during any observation period were excluded to omit children from the sample. Similarly, observations of customers over the age of 90 were also removed, as these entries are likely due to outdated IT systems or instances where a family continues to use the client status of a deceased relative - originally, the dataset included ages up to 119 years.

Additionally, customers identified with the gender code “0” were excluded because one can assume this category represents missing data or individuals who opted not to disclose their gender. These steps were taken to ensure that the dataset contains valid and interpretable information, facilitating the operationalization of the independent variables.

Furthermore, outliers, as well as negative spending, were removed to enhance data quality and ensure more accurate statistical results. Z-scores were calculated for specific numerical variables that are relevant to the investigations: *spending_q, recency_purchase,* and *frq_purchase*. These variables were chosen because outliers were detected in them. Values with an absolute Z-score greater than 4 were considered extreme outliers and removed. This method helps ensure that the analysis results are not skewed by extremely deviating values, thereby increasing the reliability of the statistical evaluations (detailed figures of the before and after cleaning process of the variables are provided in the appendix).

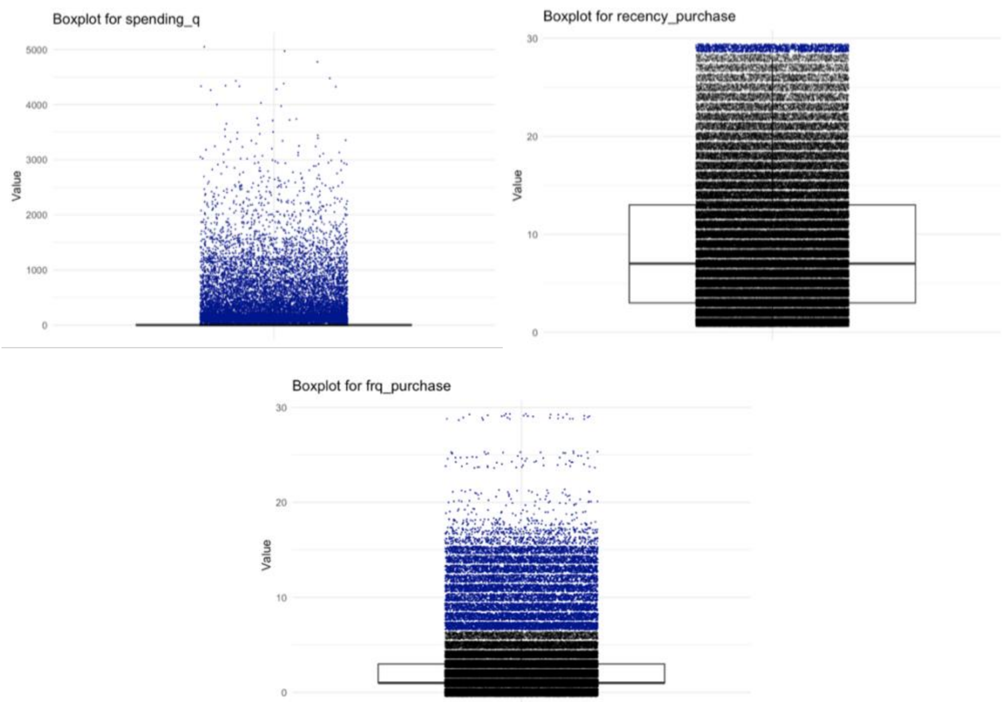

Figure 2: Boxplots of numeric variables with outliers (in blue)

Following, another critical step involved creating two different dummy variables named *churn* based on the available variable *recency_purchase* as well as a dummy variable *treated* (detailed explanation in chapter 3.1.1. Dependent variables and 3.1.3. Control variables).

3.3. Descriptive Statistics

The subsequent section provides a comprehensive overview of the descriptive statistics within the dataset, emphasizing the demographic distribution of customers, the evolution of the numeric dependent variables over time, and their RDM interactions. Additionally, it includes a visual comparison of churn behaviours between the treated and control groups.

Succeeding the data cleaning process, the dataset includes 174,007 observations representing 7,563 unique customers, split between 3,492 males and 4,071 females, who shop across 13 different retailers over a period spanning 29 quarters. Age distribution within the dataset is detailed as follows: 926 customers are aged between 18-30, 589 between 31-40, 836 between 41-50, 1,727 between 51-60, and 3,485 are aged 61 and above (Figure 11, see Appendix).

A closer look at the aggregated time series data from 2011 to 2018 for customer purchasing and spending trends shows significant increases that illustrate the dynamics of the market and consumer behaviour (Figures 3 and 4). The rise in the time series of both the total number of purchases and total spending is characterized by considerable fluctuations, peaking in the first quarter of 2017. This remarkable trend can be partially attributed to increases in the number of shop IDs, which uniquely identify retailers within the dataset. Specifically, the number of documented retailers expanded from 10 to 11 between the second and third quarters of 2016, correlating with increased consumer spending and purchase activities.

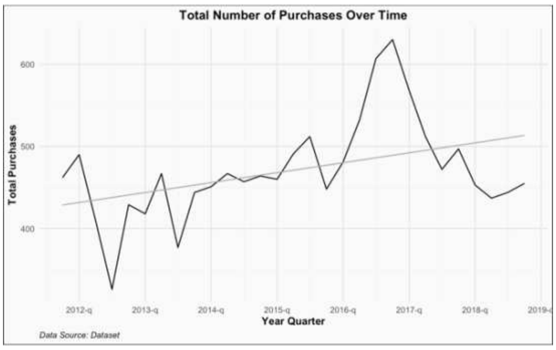

Figure 3: Total number of purchases over time

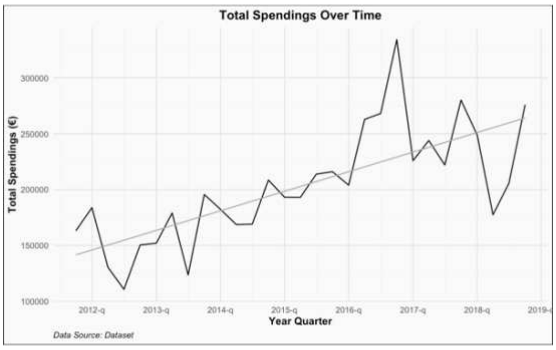

Figure 4: Total spending over time

Concurrently, the trajectory of the total number of DMs sent shows a continuous upward trend, suggesting intensified marketing activity that may influence purchasing and spending trends (Figures 5 and 6). Incentive mails such as discount mails and premium mails are particularly notable for their strategic use in driving specific consumer behaviours. Discount mails, marked by significant peaks and troughs. It can be interpreted as a correlation between the peaks of discount mail and subsequent increases in purchasing activities could underscore their effectiveness in catalyzing immediate buying responses. Premium mails, while used more sporadically, aligns still with rises in spending. This could suggest that premium incentives can be seen as powerful motivators that drive considerable revenue, particularly from higher-spending market segments. In contrast, action mails and relationship mails contribute to a continuous marketing foundation aimed at maintaining and deepening customer relationships. Action mail's steady presence throughout the period supports regular customer engagement, keeping the retailer prominently in consumers' minds. Meanwhile, relationship mails focus on long-term loyalty, maintaining a consistent presence that, while not directly correlated with immediate spikes in spending, can play a crucial role in sustaining brand engagement over time.

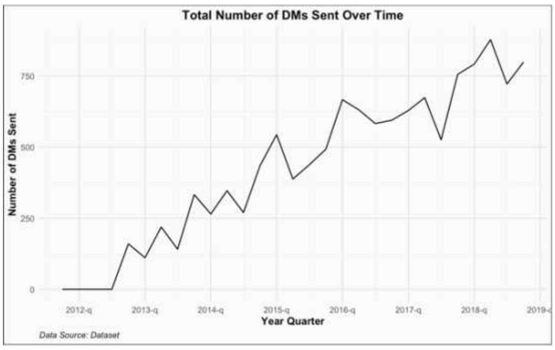

Figure 5: Total number of DMs over time

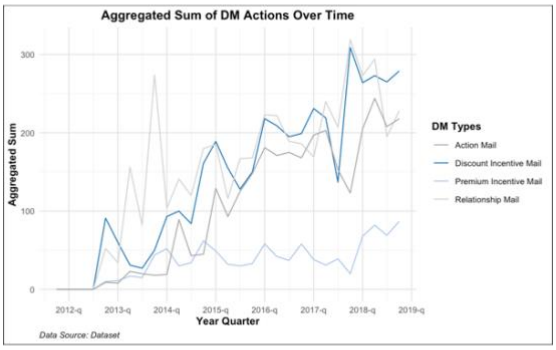

Figure 6: Total number of DMs (differentiated) over time

Furthermore, the dataset reveals a distinct difference in churning behaviour and spending between the control and treated groups, particularly influenced by their exposure to RDM campaigns (Figure 7). The control group, which did not receive any RDMs, showed a consistently higher churn rate throughout the observation period from early 2014 to late 2018. In contrast, the treated group, recipients of the RDMs as previously illustrated in Figure 6, exhibits a lower churn rate, indicating the effectiveness of the RDM campaigns in enhancing customer retention. It's important to note that since churn is considered over this fixed period of three years, data post-2017 may be less reliable for immediate analysis, as customers who churned at the beginning of the period are still included in the later data without being filtered out. Despite these considerations, the aggregated data provides valuable insights into the churn behaviours of the two differently treated groups. This approach allows for a clear comparative analysis, highlighting the impact of RDMs on customer retention.

Alongside the observed variances in churning behaviour, the spending patterns per quarter also reveal significant differences between the groups (Figure 8). The treated group (Group 1, dark blue), which received the RDMs, shows markedly higher expenditure levels in several quarters compared to the control group, which received no RDMs. The total expenditure per quarter of the treated group, reported significantly higher spending amounts, amounting to €3,397,775 over the entire observation period. In contrast, the control group, which did not receive any direct marketing, accumulated a total of €2,485,831 in expenditures. This stark difference in spending between the two groups highlights the impact of targeted direct marketing efforts on consumer spending behaviour.

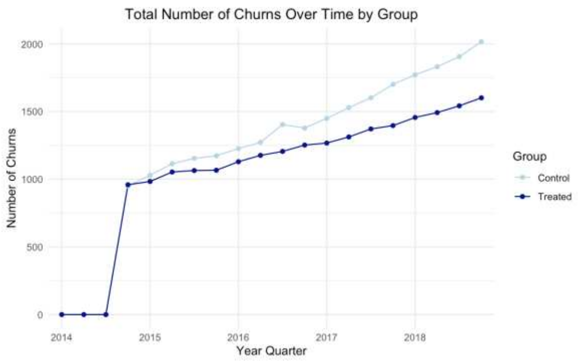

Figure 7: Total number of churns over time by group

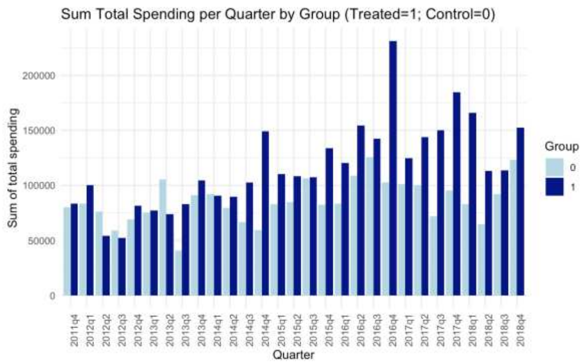

Figure 8: Total spending by group (treated vs. control)

3.4. Model Design

Exploring the effect of RDM on customer churn, this thesis considered moderating factors such as customer characteristics. Given the longitudinal nature of the dataset, which recorded individual customer interactions across multiple periods, it was imperative to adopt an analytical framework that captured complexities and individual-specific variations within the data. To address these complexities, a panel data approach was adopted, allowing for the observation of changes in customer behaviour over time while accounting for individual-level characteristics.

The analysis incorporated three distinct dependent variables to capture various dimensions of customer churn dynamics: recency of purchase (*recency_purchase*), purchase incidence (*purchase_incidence*), and spending per quarter (*spending_q*). For each dependent variable, three types of models were built: a ‘base model’, an ‘interaction model 1’, and an ‘interaction model 2’.

Base model: This model evaluated the direct effect of RDM on the dependent variable while including age and gender as moderating (control) variables. These demographic factors are critical in understanding the impact of RDM without additional complexities.

Interaction model 1: This model incorporated all previously explained control variables. Additionally, it includes all customer characteristic variables explaining age (*age*), gender (*gendercode*), the frequency of purchases (*frq_purchase),* customer duration (*customerduration*). Further the four different types of RDMs are separately included. By including all variables, this model accounts for potential confounding factors, offering a more detailed analysis of the RDM effects on customer behaviour. In addition, this model includes multiple interaction terms that are deemed significant.

Interaction model 2: This model includes every variable and interaction term as the described models before, while factor variables for year and quarters were added as well.

In addition to these panel regression models a logistic regression model was incorporated to address the binary nature of the churn variable. In this model the dataset was divided into 80% train data and 20% test data, to train the model and then evaluate its performance on new, unknown data, thereby avoiding overfitting and evaluating the generalization capability. The thesis develops two operationalizations of the dependent variable churn to capture different aspects of customer churn behaviour:

Naive Model: Assumed that a customer who has not purchased in twelve quarters is considered to have churned. This model reflects the continuous observation of customers over multiple time points.

Non-Naive Model: Considered potential purchases beyond the twelve quarters and revises the churn classification if a customer becomes active again later. For instance, a customer initially classified as churned (churn = 1) after not purchasing for 12 quarters can be reclassified as non-churned (churn = 0) if they purchase in the 16th quarter. In this model, time points are consolidated into a single aggregated data point per variable. This approach minimizes the risk of autocorrelations, which occur when consecutive observations are not independent and thus can distort statistical analysis. By aggregating the data, this model enabled analysis of temporal patterns in purchasing behaviour without biases, providing a clearer and more accurate depiction of customer churn dynamics over time. This adjustment was crucial to account for the long-term nature of customer relationships and avoid misleading results that could arise from unaddressed autocorrelations.

By incorporating these variables and models, the study systematically evaluated hypotheses related to customer churn, providing a comprehensive understanding of retention dynamics within the independent optician industry. The use of a panel data approach, along with detailed control variables and interaction terms, ensured that the models were robust and accurately captured the dynamics at play.

Furthermore, sensitivity analyses were conducted, scrutinizing various assumptions underlying the regression framework and refining the approach accordingly. This methodology ensured the validity and reliability of the findings, laying the foundation for meaningful insights into the effectiveness of RDM in mitigating customer churn. It also sought to guide the development of targeted marketing strategies that enhance customer retention.

3.5. Model Assumption

Before proceeding to the detailed regression analysis, the following assumptions were made and tested to ensure the robustness and reliability of the models. The table below summarizes each assumption, the methodology used for testing, the outcomes of these tests, and the implications for the regression analysis. A detailed description and testing of the individual assumptions can be found in the appendix.

Assumption	Methodology/Test	Result/Observation
Linearity	Scatterplots with trendlines for continuous variables (see Appendix)	Linear relationships confirmed for frq_purchase, customerduration, and age. Binary variables inherently meet linearity.

Multicollinearity	Correlation matrix analysis (see Appendix)	No correlation between variables is equal or higher than |0.8|. No perfect multicollinearity is expected in the models.
Heteroskedasticity	Breusch-Pagan test	Significant heteroskedasticity was detected in all models, indicating non-constant variance of residuals. Robust standard errors were adopted to correct for heteroskedasticity.
Independence of Observation and Autocorrelation	Breusch-Godfrey/Wooldridge tests, residual plots (see Appendix)	Significant autocorrelation was detected, with a consistent spread of residuals over time. Robust standard errors were used to mitigate the effects of autocorrelation.
Endogeneity	Hausman test	Endogeneity is indicated by the Hausman test, suggesting a correlation between RDM and the error term.
Godness-of-Fit	R-squared, Adjusted R-squared, F-statistics (see Models)	Enhancing fit, especially for the first two panel regression models with higher R-squared values in the interaction models. Model 6 (DV *spending_q*) showed lower R-squared values, indicating a potential need for additional predictors.
Normality	Q-Q plots (see Appendix)	Significant deviations from normality were observed, with heavier tails and skewness in the residuals, particularly in models 5 and 6. Despite deviations, no further modifications due to comprehensive prior data cleaning.

Table 1: Assumption Overview

4. Results

To understand the regression results (Models 2, 3, 4 and 5 below), one examines the coefficients that indicate the influence of the individual independent variables X (listed on the right-hand side of each table) on the dependent variable Y (at the bottom of each table). A positive coefficient indicates a positive influence, a negative coefficient a negative influence. It is interpreted as follows: If the independent variable increases by 1 unit, the dependent variable increases/decreases by the specified number of units. The numbers in brackets are standard errors that indicate the precision of the coefficients. Asterisks (*) indicate significance: *** ($p < 0.01$), ** ($p < 0.05$), * ($p < 0.1$).

The study employed a series of panel regression models to determine the effect of RDM on customer churn metrics across three critical dimensions: recency of purchase (*recency_purchase*), purchase incidence (*purchase_incidence*), and spending per quarter (*spending_q*). Each model was developed to assess the influence of RDM under various conditions, including customer-specific moderating variables (*age, gendercode, frq_purchase, customerduration*), RDMs which included incentives (*RDM_incentive, RDM_premium, RDM_discount*), RDMs which did not include incentives (*RDM_action and RDM_relation*) and control variables (*treated, n_fill* and time variables). Further, a logistic regression model (*Model 5*) was created to examine the likelihood of customer churn.

The results from Model 2 (see Table 2 below), which examined the recency of purchase, indicated that RDM significantly reduced the time between customer purchases, highlighting its effectiveness in increasing purchase frequency. The base model showed that RDM reduced the time between purchases by ~1.38 quarters (~4 months), ceteris paribus. Interaction models further revealed that RDMs with incentives, such as premium and discount offers, had a substantial impact on shortening the time between purchases, with premium incentives reducing recency by ~2.55 quarters (~8 months) and discount incentives by ~2.74 quarters (~8 months), ceteris paribus. Relationship-building RDMs showed the most significant impact, reducing recency by ~4.90 quarters (~15 months), ceteris paribus, emphasizing the importance of maintaining customer relationships. Additionally, action-oriented RDMs increased recency by ~1.79 quarters (~5 months), ceteris paribus, suggesting they may disrupt regular purchasing patterns. Age interacted positively with RDM, suggesting that older customers responded slightly better to targeted RDM efforts. Male customers showed a lower response compared to female customers. RDM campaigns are particularly effective for customers who make frequent purchases, as they further shorten purchase intervals. Conversely, the longer a customer has been with the company, the less effective RDM measures seem to be, suggesting that long-term customers respond less to such marketing efforts.

The results from Model 3 (see Table 3 below), which examined purchase incidence, indicated that RDM significantly increased the likelihood of a new purchase, confirming its role in enhancing customer engagement. The base model showed that RDM increased purchase incidence by ~0.05 percentage points, ceteris paribus. The interaction models revealed that incentive-based RDMs negatively impacted purchase incidence, with premium incentives decreasing it by ~0.04 percentage points and discount incentives by ~0.04 percentage points, ceteris paribus. Conversely, relationship-focused RDMs positively influenced purchase incidence, increasing it by ~0.03 percentage points, ceteris paribus. Moreover, action-oriented RDMs decreased purchase incidence by ~0.03 percentage points, ceteris paribus. The results also highlighted that older customers were less likely to make frequent purchases, whereas frequent purchasers were more responsive to RDM. Gender did not show a significant effect, while customers with higher spending per quarter positively influenced purchase incidence. Longer customer relationships had a minimal negative impact on purchase incidence, ceteris paribus.

Regression Results Recency Purchase

	Dependent variable:		
		recency_purchase	
	Base Model	Interaction Model 1	Interaction Model 2
	(1)	(2)	(3)
RDM	-1.375*** (0.073)	0.590 (0.492)	1.324*** (0.418)
RDM_premium		-2.545*** (0.460)	-2.667*** (0.391)
RDM_discount		-2.742*** (0.429)	-3.295*** (0.365)
RDM_action		1.790*** (0.434)	0.772** (0.369)
RDM_relation		-4.895*** (0.407)	-4.979*** (0.345)
age	0.028*** (0.001)	-0.017*** (0.001)	-0.010*** (0.001)
gendercode	-0.546*** (0.038)	-0.161*** (0.035)	-0.173*** (0.030)
n_fill		3.777*** (0.062)	1.323*** (0.056)
spending_q		0.001*** (0.0001)	0.002*** (0.0001)
frq_purchase		-1.034*** (0.006)	-1.017*** (0.005)
customerduration		0.032*** (0.001)	0.070*** (0.001)
factor(year)2012			2.867*** (0.108)
factor(year)2013			5.623*** (0.107)
factor(year)2014			7.565*** (0.106)
factor(year)2015			9.164*** (0.106)
factor(year)2016			10.645*** (0.105)
factor(year)2017			11.659*** (0.105)
factor(year)2018			13.515*** (0.105)
factor(quarter)04			0.478*** (0.041)
factor(quarter)07			1.050*** (0.041)
factor(quarter)10			1.271*** (0.042)
treated		-0.441*** (0.036)	-0.300*** (0.031)
RDM:age		0.009** (0.004)	-0.005 (0.003)
RDM:gendercode		0.052 (0.132)	-0.018 (0.112)
RDM:n_fill		-1.488*** (0.178)	0.767*** (0.151)
RDM:spending_q		0.004*** (0.0003)	0.003*** (0.0002)
RDM:frq_purchase		0.376*** (0.023)	0.297*** (0.020)
RDM:customerduration		-0.019*** (0.003)	-0.043*** (0.002)
Constant	7.579*** (0.066)	10.758*** (0.073)	-0.918*** (0.123)
Observations	139,206	139,206	139,206
R^2	0.009	0.210	0.430
Adjusted R^2	0.009	0.210	0.430
F Statistic	441.947*** (df = 3; 139202)	2,058.145*** (df = 18; 139187)	3,756.534*** (df = 28; 139177)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2: Model 2 estimation results – Dependent variable: recency_purchase

Regression Results Purchase Incidence

	Dependent variable:		
		purchase_incidence	
	Base Model	Interaction Model 1	Interaction Model 2
	(1)	(2)	(3)
RDM	0.050*** (0.003)	0.024 (0.015)	0.021 (0.015)
RDM_premium		-0.035** (0.014)	-0.034** (0.014)
RDM_discount		-0.039*** (0.013)	-0.037*** (0.013)
RDM_action		-0.035*** (0.013)	-0.032** (0.013)
RDM_relation		0.025** (0.012)	0.026** (0.012)
age	-0.001*** (0.00004)	-0.001*** (0.00003)	-0.001*** (0.00003)
gendercode	0.016*** (0.001)	-0.001 (0.001)	-0.001 (0.001)
spending_q		0.001*** (0.00000)	0.001*** (0.00000)
frq_purchase		0.029*** (0.0002)	0.029*** (0.0002)
treated		-0.005*** (0.001)	-0.006*** (0.001)
n_fill		-0.015*** (0.002)	-0.006*** (0.002)
customerduration		0.00002 (0.00003)	-0.0001*** (0.00003)
factor(year)2012			-0.017*** (0.004)
factor(year)2013			-0.028*** (0.004)
factor(year)2014			-0.033*** (0.004)
factor(year)2015			-0.036*** (0.004)
factor(year)2016			-0.036*** (0.004)
factor(year)2017			-0.043*** (0.004)
factor(year)2018			-0.050*** (0.004)
factor(quarter)04			-0.0003 (0.001)
factor(quarter)07			-0.004*** (0.001)
factor(quarter)10			-0.006*** (0.001)
RDM:age		-0.00002 (0.0001)	0.00002 (0.0001)
RDM:gendercode		0.001 (0.004)	0.001 (0.004)
RDM:n_fill		0.015*** (0.005)	0.008 (0.005)
RDM:spending_q		-0.0001*** (0.00001)	-0.0001*** (0.00001)
RDM:frq_purchase		0.004*** (0.001)	0.004*** (0.001)
RDM:customerduration		-0.0001 (0.0001)	-0.00004 (0.0001)
Constant	0.145*** (0.003)	0.014*** (0.002)	0.058*** (0.004)
Observations	139,206	139,206	139,206
R^2	0.012	0.501	0.503
Adjusted R^2	0.012	0.501	0.503
F Statistic	551.040*** (df = 3; 139202)	7,768.001*** (df = 18; 139187)	5,023.289*** (df = 28; 139177)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3: Model 3 estimation results – Dependent variable: purchase_incidence

Model 4 (see Table 4 below) examined spending. The results demonstrated that RDM significantly boosted customer spending per quarter, underscoring its role in enhancing customer expenditure. The base model indicated that RDM increased spending by ~€33 per quarter, ceteris paribus. Further analysis through interaction models showed that incentivized RDMs, such as those offering premium and discount incentives, had a marked positive effect, raising spending by around ~€71 and ~€79 per quarter, respectively, ceteris paribus. Relationship-building RDMs exhibited the highest impact, increasing spending by ~€217 per quarter, ceteris paribus. Moreover, action-oriented RDMs did not significantly affect spending.

The interaction with age was positive, suggesting older customers tended to spend more in response to RDMs. Higher purchase frequency and recent purchases also positively influenced RDM effectiveness, with frequent and recent buyers showing increased spending. Gender did not significantly interact with RDM, while longer customer relationships had a slight negative impact on spending, ceteris paribus.

The logistic regression model (Model 5, see Table 5 below) provided insights into factors influencing the likelihood of customer churn. The results indicated that RDMs with a call to action significantly increased the likelihood of churn, with a positive coefficient for *RDM_action_sum* (~0.61). In terms of customer characteristics, gender and age reacted differently. The coefficient for *gendercode1* (female) was ~-0.21, indicating that female customers were less likely to experience churn compared to male customers. Age also played a significant role, with a negative coefficient of ~-0.01, indicating that older customers were less likely to churn. Customer duration, reflecting the length of time a customer has been with the company, had a negative effect on churn with a coefficient of ~-0.02. This demonstrated that customers with longer relationships were less likely to churn, highlighting the importance of long-term customer engagement in reducing churn rates. Additionally, relationship-building RDMs (*RDM_relation_sum*) had a negative but not statistically significant effect on churn. Conversely, *RDM_premium_sum* and *RDM_discount_sum* did not show significant effects on churn.

This research demonstrates that RDM effectively mitigates customer churn by reducing the time between purchases, increasing the likelihood of new purchases, and boosting spending per quarter. Additionally, the logistic regression model highlights the importance of customer characteristics and showed that *RDM_action*s increase churn while older customers, female customers, and those with longer relationships are less likely to churn. These insights underscore the need for targeted RDM strategies that consider customer demographics and relationship duration to enhance customer retention.

Regression Results Spending

	Dependent variable:		
	spending_q		
	Base Model (1)	Interaction Model 1 (2)	Interaction Model 2 (3)
RDM	33.480*** (1.933)	-274.129*** (14.594)	-272.331*** (14.585)
RDM_premium		71.430*** (13.361)	73.586*** (13.355)
RDM_discount		78.759*** (12.457)	81.600*** (12.453)
RDM_action		-2.529 (12.850)	0.711 (12.844)
RDM_relation		216.496*** (11.726)	218.980*** (11.723)
age	0.306*** (0.028)	0.559*** (0.029)	0.555*** (0.029)
gendercode	4.565*** (0.996)	1.483 (1.018)	1.629 (1.018)
recency_purchase		1.069*** (0.079)	1.699*** (0.093)
frq_purchase		8.810*** (0.200)	9.413*** (0.205)
treated		1.830* (1.049)	1.881* (1.049)
n_fill		7.356*** (1.815)	9.081*** (1.905)
customerduration		-0.076*** (0.026)	-0.176*** (0.027)
factor(year)2012			-8.099** (3.708)
factor(year)2013			-16.526*** (3.701)
factor(year)2014			-18.809*** (3.699)
factor(year)2015			-21.096*** (3.715)
factor(year)2016			-19.999*** (3.731)
factor(year)2017			-26.650*** (3.759)
factor(year)2018			-33.984*** (3.814)
factor(quarter)04			-2.720* (1.411)
factor(quarter)07			-4.427*** (1.412)
factor(quarter)10			-0.051 (1.424)
RDM:age		0.603*** (0.115)	0.624*** (0.115)
RDM:gendercode		-1.716 (3.838)	-1.659 (3.835)
RDM:n_fill		-26.376*** (5.283)	-28.686*** (5.290)
RDM:recency_purchase		17.875*** (0.468)	17.429*** (0.469)
RDM:frq_purchase		11.992*** (0.734)	11.644*** (0.734)
RDM:customerduration		0.008 (0.075)	0.068 (0.075)
Constant	11.713*** (1.750)	-29.175*** (2.269)	-8.772** (4.196)
Observations	139,206	139,206	139,206
R^2	0.003	0.038	0.039
Adjusted R^2	0.003	0.038	0.039
F Statistic	146.407*** (df = 3; 139202)	304.267*** (df = 18; 139187)	203.232*** (df = 28; 139177)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4: Model 4 estimation results – Dependent variable: spending_q

```
Call:
glm(formula = y_trainvec ~ RDM_sum + RDM_premium_sum + RDM_action_sum +
    RDM_relation_sum + RDM_discount_sum + gendercode + age +
    customerduration, family = binomial(link = "logit"), data = X_train)

Coefficients:
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)       1.534909   0.142746  10.753  < 2e-16 ***
RDM_sum          -0.131831   0.182933  -0.721  0.47113
RDM_premium_sum   0.125176   0.208390   0.601  0.54805
RDM_action_sum    0.608132   0.193278   3.146  0.00165 **
RDM_relation_sum -0.155857   0.171642  -0.908  0.36386
RDM_discount_sum -0.061805   0.203856  -0.303  0.76175
gendercode1      -0.209705   0.077827  -2.694  0.00705 **
gendercode2       1.202293   0.785375   1.531  0.12581
age              -0.012677   0.002131  -5.948 2.71e-09 ***
customerduration -0.015230   0.001965  -7.750 9.18e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 4048.0  on 2919  degrees of freedom
Residual deviance: 3799.9  on 2910  degrees of freedom
AIC: 3819.9

Number of Fisher Scoring iterations: 4
```

Table 5: Non-naive Model 5 estimation results – Dependent variable: churn

4.1. Significance and Performance of the Regression Results

At the bottom of the tables are the model statistics such as R^2 and Adjusted R^2, which indicate the quality of the model - higher values mean a better model. The F-statistic checks the overall significance of the model; higher values mean that the model is significant overall. The table helps to evaluate and interpret the influence of various factors on the dependent variable.

Table 2 presents a detailed analysis of the effects of various predictors on *recency_purchase*. Except for the interaction effects of *RDM:gendercode* and the *RDM* variable in the interaction model 1 and the interactions of *RDM:age* and *RDM: gendercode* in the interaction model 2, all explanatory variables showed significant impacts on the outcome, highlighting the comprehensive influence of RDM on the timing of customer purchases.

Table 3 shifts focus to *purchase_incidence* as the outcome variable. The base model in this table demonstrated robust significance across all variables included. The interaction model 1 showed only significant variables despite *RDM*. The interaction model 2 introduces additional complexity, revealing some variables - such as *RDM, gendercode, RDM:age*, *RDM:gendercode* and *RDM:n_fill* - that did not have statistical significance, suggesting potential areas for further investigation or model refinement.

Table 4 explored the determinants of *spending_q*. In the base model, all variables are significant. The interaction model 1 nearly all variables demonstrated significant effects, except for the variables *RDM_action, gendercode*, and *RDM:customerduration*. The interaction model 2 showed two non-significant variables - *RDM_action* and *gendercode.*

Table 5 identified several significant factors influencing the likelihood that a customer will churn. RDM_action showed the only significant positive RDM type coefficient. No other RDM variable was significant in this model. Further *Gendercode1* (female), *age*, *customerduration* and the intercept were significant variables. Thus, all other variables were not significant in this model.

For completeness, additional panel regression models were estimated to predict *recency_purchase, purchase_incidence* and *spending_q* with the help of the explanatory variables. All interaction terms were tested to achieve the best-performing model. The results accorded with and confirmed the model's separate results.

Looking at the performance metrics for the *recency_purchase* models, despite a modest R^2 of 0.009 to 0.430 across the models, the F statistics (ranging from 441.947 to 3,756.534, and significant at the 1% level) indicated that the variables jointly had explanatory power. This confirmed the model's utility for capturing factors influencing the timing of purchases. In the *purchase_incidence* models, the explanatory power significantly increased, with the adjusted R^2 reaching up to 0.503 in the most complex model. This suggested a stronger relationship between the model variables and purchase behaviour, supported by a high F statistic of 5,023.289, confirming the robustness of the model. The *spending_q* models demonstrated the lowest (adjusted) R^2 of up to 0.039. Although the low proportion of variance was explained, due to the complexity of spending behaviours, the joint significance of the variables was still confirmed by a robust F statistic of 203.232. Overall, complex outcome variables, such as purchase decisions and spending, are dependent on a variety of internal and external factors and cannot be predicted by a limited number of explanatory variables.

Additional models were also estimated to predict the likelihood of churn comparing several naive and non-naive logistic models. The accuracy check of various naive logistic models and non-naive logistic models demonstrated that the non-naive approach consistently yielded more precise results than naive models, with the most accurate model shown in Figure 7, which had an accuracy of 59.73%. This underscores the importance of careful modelling of the dependent variable and avoiding time series issues in the analysis of customer churn data.

4.2. Hypotheses Tests

4.2.1. H1: RDM significantly influences customer churn

Analyzing the impact of RDM on customer churn yielded insightful conclusions, particularly when observing the behaviour of the *recency_purchase* variable across the models. This directly addresses H1 which proposed that RDM significantly influences customer churn. In Model 2's base model, RDM demonstrated a significant negative coefficient of -1.375 ($p < 0.01$), suggesting that the introduction of RDM significantly decreases the time between purchases. Concretely, this implied that each unit of RDM reduces the quarters between purchases by ~1.4 quarters, on average, assuming all other factors remain constant. This allows to assume an effective reduction in churn, as customers are returning to make purchases sooner than they would without the influence of RDM. As model complexity increased with additional variables in the interaction model 1 and 2, the direction and significance of *RDM*'s coefficient changed. In interaction model 1, the coefficient turned positive (*0.590*) but was not statistically significant, indicating that when other variables are considered, the clear-cut influence of RDM observed in the base model becomes obscured. However, in interaction model 2, the coefficient again became significant (*1.324,* $p < 0.01$), revealing a complex interaction between RDM and other variables. This positive coefficient in the context of recency suggested that certain interactions might lead to increased time between purchases under specific conditions, which could imply a nuanced or conditional effectiveness of RDM strategies. The interaction terms, such as *RDM:n_fill*, *RDM:spending_q*, *RDM:frq_purchase*, and *RDM:customerduration* yielded insights (insights follow in chapter 4.2.2., 4.2.4. and 4.3.).

Model 3 followed a similar structure but focused on the *purchase_incidence* variable. The base model showed a small but significant positive impact of RDM (*0.050,* $p < 0.01$), indicating an increase in the likelihood of a customer purchasing within a given quarter due to RDM. This aligned with the hypothesis by showing that RDM might effectively decrease churn by making purchases more frequent.

4.2.2. H2: Customer-specific characteristics moderate the impact of RDM on churn

To assess H2 regarding the moderation of RDM's impact on churn by customer-specific characteristics, the regression results across Models 2, 3 and 5 are relevant.

Age

In Model 2, *age* moderated the impact of RDM on recency purchase. In the base model, older customers initially showed a longer time between purchases (0.028, $p < 0.01$). However, this effect became less pronounced or even reversed when interactions were considered, with *age* showing a negative coefficient in interaction model 1 (-0.017, $p < 0.01$) and interaction model 2 (-0.010, $p < 0.01$). The interaction term *RDM:age* was significant in interaction model 1 (0.009, $p < 0.05$), indicating that the effect of RDM was less effective for older customers, but it was not significant in interaction model 2 (-0.005).

In Model 3, *age* consistently showed a negative effect on purchase incidence (-0.001, $p < 0.01$), meaning older customers purchased less frequently. The interaction terms *RDM:age* was not significant in both interaction models 1 and 2.

Gender

The variable *gendercode* moderated the impact of RDM on recency purchase. In the base model, being female (gendercode = 1) was associated with a shorter time between purchases (-0.546, $p < 0.01$). This effect remained negative but less pronounced in interaction model 1 (-0.161, $p < 0.01$) and interaction model 2 (~-0.173, $p < 0.01$).

Model 3 revealed too that being female was associated with a higher purchase incidence (~0.016, $p < 0.01$) in the base model. This effect remained positive but was not significant in interaction model 1 (~0.001) and interaction model 2 (~0.001).

The logistic regression model (Model 5) indicates that females (gendercode1 = ~0.21, $p < 0.01$) are less likely to churn compared to males.

Frequency of Purchase

The variable *frq_purchase*, representing the frequency of customer purchases, shows statistically significant positive coefficients. Considering both interaction models, the term was the coefficients of 0.376 and 0.297 ($p<0.01$), suggesting that the positive impact of RDM on reducing churn was more pronounced among frequent purchasers. This means that when RDM strategies are employed, frequent purchasers tend to make their subsequent purchases sooner than they might have otherwise, compared to less frequent purchasers.

In Model 3, the interaction term *RDM:frq_purchase* continued to be significant, though the effect size was smaller, with a coefficient of 0.004 ($p<0.01$). While this effect was less pronounced, it still confirmed the trend observed in Model 2.

Customer Duration

The variable *customerduration*, which measured the length of the customer relationship with the retailer in quarters, exhibited a complex influence on customer purchase and therefore churn behaviour in the context of RDM strategies. In Model 2's interaction model 1, the coefficient for the *customerduration* was positive (*0.032*) and significant ($p<0.01$), suggesting that customers with longer relationships with the retailer generally had longer intervals between purchases. However, the interaction term *RDM:customerduration* introduced a nuanced dynamic into this observation. This interaction term was significantly negative (*-0.043*, $p<0.01$) in the interaction model 2, revealing that the impact of RDM strategies tended to diminish as the duration of the customer-retailer relationship increased. Specifically, while RDM efforts are generally aimed at reducing the time between purchases by reinforcing customer engagement and encouraging repeat purchases, their effectiveness appears to diminish for customers who have been with the retailer for a longer period.

4.2.3. H3: The effectiveness of RDM depends on the type of incentives

The third hypothesis of the study focused on differentiation in the efficacy of RDM campaigns based on the type of incentive offered - specifically, premium versus discount incentives.

Premium

In Model 2, premium incentives significantly shorten purchase intervals, with *RDM_premium* coefficients being -2.545 and -2.667 in interaction models 1 and 2. This supports hypothesis H3a, indicating that premium incentives encourage quicker repeat purchases.

In Model 3, the likelihood of a purchase is negatively influenced by *RDM_premium*, with significant coefficients of -0.035 and -0.034 in both interaction models. This means premium incentives slightly reduce the overall purchase incidence despite encouraging quicker purchases.

Model 4 showed that *RDM_premium* is non-significant in influencing churn rates, indicating premium incentives do not significantly impact customer retention in preventing churn.

Discounts

Similarly, *RDM_discount*, which represented RDM strategies involving discount incentives, also showed a significant negative effect on the intervals between purchases. With *RDM_discount* coefficients of -2.742 and -3.295 in interaction models 1 and 2. This demonstrates that discounts are effective in prompting quicker repeat purchases, supporting hypothesis H3a.

In Model 3, discount incentives have a small but significant negative impact on the likelihood of a purchase, with coefficients of -0.039 and -0.037 in both interaction models. This suggests that while discounts accelerate purchases, they slightly decrease the overall purchase incidence during the campaign period.

The logistic regression revealed that *RDM_discount* is non-significant in affecting churn rates.

4.2.4. H4: RDM significantly increases customer spending, with the effectiveness further enhanced by the type of incentive offered

Analyzing the effects of RDM on spending within the context of Model 4, it is evident that RDM significantly impacts customer spending behaviour. The base model indicated a notable coefficient for RDM at 33.480 ($p<0.01$), suggesting that when RDM campaigns are executed, spending among customers tends to increase by approximately €33 on average, holding all other factors constant.

As the model progressed to include additional variables and interaction terms, the direct effect of RDM exhibited a dramatic shift, with the extended model displaying a coefficient of -

274.129 ($p<0.01$) and the interaction model showing -272.331 ($p<0.01$). This substantial negative coefficient in the more complex model could be influenced by the interactions between RDM and other variables such as age, purchase frequency, and the type of incentive involved.

For instance, the interaction between RDM and age (*RDM:age*) was significant with a positive coefficient of 0.624 ($p<0.01$) in the interaction model, indicating that the influence of RDM on spending increased slightly with the age of the customer. The RDM interaction with non-personalized (mass) DM campaigns (*RDM:n_fill*) also showed a significant negative effect on spending, with a coefficient of -28.686 ($p<0.01$). This suggests that the simultaneous execution of personalized RDM and mass non-personalized campaigns may dilute the effectiveness of personalized communications or perhaps overload customers, leading to reduced spending.

Interestingly, RDM's interaction with the recency of purchase (*RDM:recency_purchase*) had a large positive coefficient of 17.429 ($p<0.01$), implying that the effectiveness of RDM increases as the time since the last purchase extends. This indicates that RDM campaigns are particularly effective in re-engaging customers who have not made recent purchases.

When examining the specific effects of premium and discount incentives on spending, the results are noteworthy. Premium incentives (*RDM_premium*) showed significant positive coefficients of 71.430 and 73.586 in interaction models 1 and 2, respectively. This indicates that campaigns featuring premium incentives lead to an average increase in customer spending by about €71 to €73. Premium incentives, often comprising higher-value items or exclusive offers, seem to strongly motivate customers to spend more.

Similarly, discount incentives (*RDM_discount*) also demonstrated a significant positive impact on spending, with coefficients of 78.759 and 81.600 in interaction models 1 and 2, respectively. These findings suggest that discounts are even more effective in boosting customer expenditure, increasing spending by approximately €79 to €82. Discounts provide immediate financial benefits to customers, making them a powerful tool for driving higher spending in RDM campaigns.

4.3. Effect of additional control variable

Mass Direct Mailing

Controlling for the impact of *n_fill* (Mass Direct Mailing) both models revealed their significant influence on reducing the time intervals between customer purchases. Specifically, *n_fill* had a coefficient of 3.777 in Model 2, -0.015 in Model 3, and 9.081 in Model 4, all statistically significant at the $p<0.01$ level. This suggested that mass direct mail communications, which are not personalized to individual customer preferences, still played a role in maintaining customer engagement.

Treated

The variable *treated*, distinguishing customers participating in the RDM initiative, consistently showed significant impacts on purchase behaviour across all models. In Model 2, the treated variable was associated with shorter intervals between purchases, with a coefficient of -0.441 ($p<0.01$), indicating that RDM efforts led to more frequent purchases. In Model 3, however, the treated variable decreased the likelihood of a new purchase incidence, with a coefficient of -0.005 ($p<0.01$), suggesting that while RDM boosted purchase frequency among existing customers, it might not effectively drive immediate new purchases. In Model 4, the treated variable positively affected spending per quarter, with a coefficient of 1.881 ($p<0.01$), highlighting that RDM initiatives can increase customer expenditure. These findings underscored the effectiveness of targeted RDM strategies in enhancing customer engagement, retention, and spending.

Time Variables

The analysis of year and quarter dummies revealed significant seasonal and annual trends that affect purchasing behaviour. The year dummies from 2012 onward exhibited an increasing trend of negative coefficients in Model 3, suggesting that as time progresses, customers may take longer to repeat purchases, potentially due to market saturation or evolving consumer preferences. Nevertheless, year and quarter dummies were not consistently significant throughout all models. However, as most of the year and quarter dummies were significant and the models all increased by its (adjusted) R^2, one could conclude that it was important to control for time effects to prevent potential omitted variable bias.

4.4. Theoretical Discussion

Customer churn remains a significant challenge for businesses, as acquiring new customers is often more costly than retaining existing ones (Pfeifer, 2005; Kotler & Keller, 2009). This study explored the effectiveness of RDM in mitigating customer churn among independent opticians in the Netherlands, with a focus on the moderating effects of customer characteristics. The following discussion is structured around the key research questions, integrating outcomes from the regression models with insights from the literature review.

To address the research question, *how does RDM influence customer churn among independent opticians in the Netherlands, considering the moderating effects of customer characteristics?,* the focus is on the impact of RDM on reducing customer churn within the optician landscape.

In retail opticians, personalized customer interactions and satisfaction are key to retention (Jones et al., 2010; King, 2018). Enhanced customer care and targeted post-purchase communication significantly reduce churn rates (Vesel and Žabkar, 2009). The regression analyses in the study showed that RDM has a significant impact on customer behaviour. Model 2 indicated that RDM reduces the time between customer purchases, thus increasing purchase frequency. This supports the idea that personalized marketing efforts can enhance retention by maintaining engagement (Malthouse and Blattberg, 2005; Reichheld and Sasser, 1990). Further, a small but significant positive impact can be seen of RDM on purchase incidence, suggesting that RDM increases the likelihood of customers purchasing within a given quarter, thereby decreasing churn. This supports the broader literature that suggests targeted direct mail can effectively drive immediate sales (Lambrecht & Tucker, 2013).

Additionally, both results can be explained by theoretical perspectives. Opticians have higher perceived switching costs compared to other retailers, leading to better retention (Heide and Wathne, 2006). Customers expect high-quality service and personalized care (Jones et al., 2010). RDM helps manage these expectations and switching costs, reducing churn by fostering frequent and personalized interactions. Moreover, the TPB suggests that conduct is driven by behavioural intentions influenced by attitudes, subjective norms, and perceived behavioural control (Ajzen, 1991). The positive effects of RDM on reducing churn and increasing engagement align with TPB, indicating that these forms of communication can positively influence customer attitudes and perceived control, thereby enhancing retention (Gardner et al., 2012; Rhodes & Courneya, 2003).

The effects of RDM became insignificant in the interaction models, highlighting the importance of context-specific factors and more targeted approaches, such as customer characteristics, lifecycle stages or seasonal influences, in determining its efficacy.

Addressing the first sub-question, *what role do customer-specific characteristics play in moderating the impact of RDM on churn?,* the analysis revealed significant insights into how age, gender, purchase frequency, and customer duration influence RDM's effectiveness.

The analysis revealed that age significantly moderates the impact of RDM. Older customers showed a tendency to have longer intervals between purchases when exposed to RDM (Model 2). Additionally, they were less likely to purchase within a given quarter (Model 3), suggesting that while RDM increases purchase frequency overall, its effectiveness diminishes with older customers. This aligns with psychological contract theory, which posits that older customers have higher expectations for personalized communication (Rousseau, 1989). Furthermore, older customers are less likely to churn (Model 5), which supports the theory of perceived switching costs, indicating that older customers face higher switching costs and are more inclined to remain loyal (Burnham et al., 2003). These findings highlight the importance of investing in long-term customer relationships to enhance loyalty (Reinartz et al., 2004) and suggest that demographic factors, such as age, significantly influence purchasing decisions and customer retention (Bucklin & Gupta, 1992).

Gender differences in response to RDM were less pronounced than age. However, female customers were found to be less likely to churn compared to male customers (Model 5). This finding aligns with research indicating that demographic factors like gender influence purchasing decisions and brand loyalty (Bucklin & Gupta, 1992). Furthermore, the analysis showed that women tend to purchase more frequently and have higher spending than males (Model 2, 3 and 4), suggesting different purchase behaviours influenced by marketing campaigns. These insights underscore the necessity of considering gender-specific strategies in RDM to maximize its effectiveness. Effective market segmentation, which includes demographic segmentation (Smith, 1956), can help tailor marketing efforts to these gender-specific behaviours, enhancing customer satisfaction and retention (Weinstein, 2004).

Frequent purchasers were notably more responsive to RDM. The analysis showed a strong negative coefficient for *recency_purchase*, indicating that frequent purchasers have shorter intervals between purchases, thus reducing churn. This supports the hypothesis that targeting active customers with tailored messaging can enforce and reinforce their purchasing behaviours (Verhoef, 2003). By increasing purchase frequency through targeted RDM, opticians can enhance customer retention and reduce churn rates. This aligns with research on CLV which highlights the importance of frequent engagement to sustain high levels of customer activity and profitability (Blattberg, Malthouse, & Neslin, 2009). Strategic re-targeting of high-value customers can further maximize CLV by focusing on those with higher purchase frequencies (Fader, Hardie, & Lee, 2005).

Customer duration also played a crucial role in moderating the impact of RDM. Long-term customers demonstrated increased loyalty in the literature, although the impact seen in the different models on RDM tended to diminish with customers who had been with the retailer for a longer period. This suggests the need for refreshing RDM strategies over time to maintain their effectiveness (Reinartz et al., 2004). The TPB supports this approach, indicating that effective communication can positively influence customer attitudes and perceived control, thereby enhancing retention (Ajzen, 1991; Gardner et al., 2012). Managing customer relationships through lifecycle stages and aligning CRM processes with these stages can optimize communication objectives and address evolving customer needs (Neslin & Shankar, 2009).

Exploring the second sub-question, w*hat types of incentives in RDM campaigns are most effective in reducing customer churn?*, the analysis provided valuable insights into the roles of monetary (discounts) and non-monetary (premium offers) incentives.

RDM campaigns offering premium incentives significantly reduce the time between purchases, indicating that premium incentives encourage quicker repeat purchases. These findings align with studies by Vafainia et al. (2019), who highlighted the effectiveness of non-monetary incentives in driving consumer purchase behaviour. The perceived value and uniqueness of premiums can capture recipients' attention and increase response rates (d'Astous & Jacob, 2002), making the offers more attractive and compelling (Palazon & Delgado-Ballester, 2013). However, premium incentives slightly reduce the overall purchase incidence during the campaign period, suggesting that premiums might prompt customers to consolidate their purchases into fewer, more substantial transactions.

While premium incentives do not significantly impact churn rates, offering them can create a sense of reciprocity and goodwill among customers, fostering long-term relationships and repeat purchases (Nunes & Park, 2003; Villanueva et al., 2008). Premiums also act as tangible tokens of appreciation, strengthening the emotional connection between customers and the brand (d'Astous & Jacob, 2002). These findings underscore the importance of incorporating premium incentives into RDM strategies to enhance customer engagement and retention, aligning with the TPB (Ajzen, 1991) and increasing CLV by reinforcing customer engagement (Blattberg, Malthouse, & Neslin, 2009).

RDM strategies involving discount incentives effectively prompt quicker repeat purchases, demonstrating that discounts are effective in reducing the time between purchases. Discounts lower perceived financial barriers to purchase (Peattie & Charter, 1994; Kotler, 2009), enhancing customer engagement and purchase behaviour. However, discount incentives slightly decrease the overall purchase incidence during the campaign period. This finding corroborates the work of Simon et al. (2010), who emphasized that monetary incentives appeal directly to consumers' rational propensity for financial savings.

Although discount incentives do not significantly impact churn rates, they serve a dual purpose in mitigating customer churn: incentivizing repeat purchases and maintaining competitive advantage. Regular discount offers are perceived positively, increasing brand loyalty and perceived value (Lal & Bell, 2003; Villanueva et al., 2008). Additionally, the strategic use of discounts can cultivate long-term customer retention by deterring customers from switching to competitors due to the anticipation of future benefits (Dekimpe et al., 1997; Rust et al., 2006).

Addressing the third sub-question - *How do RDMs influence the spending behaviour of customers?* - the outcomes related to customer spending behaviour were particularly revealing.

The results demonstrated that RDM campaigns led to a significant overall increase in customer consumption. Especially, *RDM_relation* campaigns, aimed at strengthening customer relationships, significantly boosted customer spending per quarter. This aligns with the research by Gardner et al. (2012), which demonstrated that personalized communication strategies significantly improve customer engagement and satisfaction. Personalized messages based on accurate customer history can make customers feel valued and understood, thus increasing their spending. Blattberg and Deighton (1996) also showed that well-designed incentives can positively influence purchasing behaviour, further corroborating these findings.

Interestingly, the effect of RDM turned negative within the interaction model, suggesting that interactions with other variables might reduce the effectiveness of RDM in certain contexts. This negative effect could also be explained by the theory of psychological reactance (Brehm, 1966), where customers react negatively to frequent non-specific RDM campaigns, feeling overwhelmed or manipulated, which leads to reduced spending.

RDM campaigns offering premium incentives significantly boost customer spending. These incentives, often including higher-value items or exclusive offers, effectively motivate customers to spend more. This aligns with Vafainia et al. (2019) and Palazon & Delgado-Ballester (2013), who highlight the efficacy of non-monetary incentives in driving consumer behaviour. Premiums capture customer attention by providing added value beyond financial savings, making offers more attractive and compelling (d'Astous & Jacob, 2002). They foster long-term relationships and repeat purchases by creating a sense of reciprocity and goodwill (Nunes & Park, 2003). The sense of exclusivity and enhanced perceived value associated with premium offers encourages increased spending, supporting the TPB (Ajzen, 1991) by positively influencing customer attitudes and intentions.

Discount incentives also positively impact customer spending, effectively encouraging higher expenditure. Discounts lower perceived financial barriers, appealing to customers' desire for savings (Peattie & Charter, 1994; Kotler, 2009). This immediate financial benefit drives quick purchasing decisions, aligning with findings by Simon et al. (2010) that monetary incentives enhance spending behaviour. Regular discount offers increase brand loyalty and perceived value (Lal & Bell, 2003; Villanueva et al., 2008), and help maintain a competitive advantage by deterring customers from switching to competitors (Dekimpe et al., 1997; Rust et al., 2006). Thus, strategically using discounts in RDM campaigns significantly boosts customer spending and engagement.

Additional findings on churn behaviour were found within the models. The positive and significant coefficient for *RDM_action_sum* can be interpreted through the lens of the ELM proposed by Petty and Cacioppo (1986). According to ELM, messages requiring active cognitive involvement lead to deeper processing and more enduring attitude changes. In the context of RDM campaigns, this means that actions designed to engage customers in a more thoughtful and involved manner are likely to result in more substantial and lasting behavioural changes.

Further, some findings challenged existing literature. The negative impact of incentive-based RDMs on purchase incidence contrasted with the generally positive impacts noted in the literature (Blattberg & Deighton, 1996). This discrepancy might be due to the potential oversaturation of incentives or customers perceiving frequent incentives as indicative of lower product value, highlighting the complexity of customer responses to different types of incentives.

5. Conclusion

With 2,293 opticians in the Netherlands as of 2022 and a steady upward trend, the optical retail environment is highly competitive (Statista, 2022). This competitive landscape reflects broader retail industries and regions, emphasizing the need for companies to attract new customers while maintaining existing ones and maximizing CLV (Kotler et al., 2009; Ahmad & Buttle, 2001). In an era where consumers are overwhelmed with messages through various channels, making a memorable, actionable impact is increasingly challenging.

To continue to stand out amidst this overwhelming number of influences, DMs remain a popular marketing strategy despite innovative technologies. RDM, specifically, is employed to nurture or re-activate existing customer relationships through personalized information (Bleier & Eisenbeiss, 2015). Consequently, it is crucial for companies aiming to reduce customer churn by effectively understanding how RDM campaigns can provoke purchases and increase spending by delivering the right message at the right time to the right customer.

5.1. Academic Implications

This work extends the scope of existing research on direct marketing (e.g., De Wulf & Odekerken-Schröder, 2003; Verhoef, 2003; Naik & Piersma, 2002) and focused on a less researched area of (physical) RDM, distinct from its digital counterparts (e.g., Sahni et al., 2019; Bleier & Eisenbeiss, 2015; Lambrecht & Tucker, 2013).

Drawing on seminal works that explore the psychological impacts of marketing (Rousseau, 1989; Burnham et al., 2003), the thesis identified key consumer segments differentiated by age, gender, purchase frequency, and customer duration, which exhibit varying responses to RDM. This variability underscored the need for precision in marketing strategies as advocated by Kotler et al. (2009) and Ahmad & Buttle (2001) and highlighted the importance of incorporating CLC characteristics as a moderating influence in understanding marketing effectiveness, a call supported by Rust & Verhoef (2005) and Gázquez-Abad et al. (2011).

Empirical findings concerning spending behaviours and churn rates among groups who are treated differently showed that personalized and optimally timed (re)targeted DM campaigns significantly bolster both customer retention and expenditure. These thesis findings support Jonker et al. (2006), Venkatesan & Kumar (2004), and Feld et al. (2013), and fill a gap in the existing literature. This thesis examines how different RDM incentive types and customer relationship durations, such as the length of the customer-firm relationship and purchase frequency, impact RDM's effectiveness on customer churn.

The partially significant positive effects of different incentives in RDM campaigns prompt a reassessment of the established literature and highlight the need for a more in-depth investigation. Several psychological models suggest additional variables that could be included in future models to better predict churn and the effects of RDM. Based on TPB by Ajzen (1991), we can identify key variables such as attitudes towards the behaviour, subjective norms, and perceived behavioural control. For instance, the perceived value of incentives (e.g., discounts, and personalized offers) can shape positive customer attitudes towards RDM. Additionally, social influence and cultural factors can serve as subjective norms. Moreover, ease of redemption and access to resources can enhance perceived behavioural control, encouraging customer engagement with RDM efforts.

The concept of the psychological contract (Rousseau, 1989) also provides insights into customer expectations and responses to RDM campaigns. Incorporating variables like customer satisfaction and expectation management could help understand how meeting or exceeding customer expectations through personalized DM can enhance loyalty and reduce churn. The theory of perceived switching costs (Burnham, Frels, & Mahajan, 2003) highlights factors such as monetary costs (financial implications of switching brands), time and effort (required to switch brands), and emotional costs (attachment to the current brand). These can act as significant deterrents to switching and could be integrated into the model to understand how RDM influences customer retention by increasing perceived switching costs.

In sum, this thesis not only advances the academic understanding of (physical) RDM strategies within a retail context, but also establishes a groundwork for future studies concerning the dynamics of direct marketing, customer behaviour, and CRM.

5.2. Managerial Implication

This thesis provides insights for managers in the optical retail market in the Netherlands and beyond, offering guidance on how strategic use of RDM can enhance customer retention and profitability.

Tailor RDM strategies to specific demographics for maximum effectiveness. Older customers respond best to personalized messages that emphasize trust, superior service, and product quality, aligning with psychological contract theory and the Theory of Perceived Switching Costs (Ahmad & Buttle, 2001; Burnham et al., 2003; Rousseau, 1989).

Focus on frequent purchasers and long-term customers to boost retention and spending. Personalized offers and incentives for these segments enhance their shopping experience and satisfaction, driving repeat purchases and deeper engagement (Verhoef, 2003; Reinartz et al., 2004).

Incorporate well-designed monetary (discounts) and non-monetary (premium offers) incentives to drive engagement and expenditure. Data analytics can help design targeted incentives that resonate with different customer segments, improving RDM campaign effectiveness (Palazon & Delgado-Ballester, 2013; Vafainia et al., 2019).

RDM campaigns can significantly increase customer spending by tailoring messages and incentives to specific demographics. Premium offers and exclusive discounts attract initial purchases and encourage subsequent spending, creating a cycle of increased engagement and expenditure (Bleier & Eisenbeiss, 2015; Vafainia et al., 2019).
Effective RDM strategies reduce customer churn by strengthening relationships and loyalty through personalized communication and relevant incentives. Regular and timely engagement

helps maintain a connection with customers, making them less likely to switch to competitors (Kotler et al., 2009; Gardner et al., 2012).

By implementing these strategic actions, managers can enhance customer retention, increase spending, and sustain growth in a competitive market. Integrating data-driven RDM strategies is essential for navigating market complexities and achieving long-term business success.

5.3. Limitations and Future Research

Despite the robust dataset underpinning this thesis, several limitations must be acknowledged. The dataset's sparsity, with numerous entries marked by zeros, posed challenges in accurately modelling customer churn. These zeros may not genuinely indicate non-engagement but rather the absence of recorded interactions, potentially leading to biased estimates. Additionally, the dataset where most observations represented non-engagement, exacerbated this issue. Future research should explore advanced statistical techniques like multiple imputation and oversampling to address data sparsity and imbalances.

The temporal scope of this study may not fully capture the long-term effects of RDM campaigns, particularly in the optician industry where purchase cycles can extend over several years. Extending the analysis timeframe could provide a more comprehensive understanding of RDM's effectiveness.

This study focuses exclusively on the optical retail market in the Netherlands, limiting the generalizability of the findings. Replicating the study in different industries or regions can enhance the scope of the findings.

The construction of the churn variable was a critical limitation. Different operationalizations of churn can yield varying insights. Future research should explore alternative definitions and their impact on predictive accuracy.

While this study primarily relied on purchasing frequency and spending amounts, these variables may not capture other critical dimensions of customer behaviour. Future research should incorporate additional variables such as purchase quantity, product preferences, and brand loyalty. Psychological models like the *Theory of Planned Behavior* (TPB) and the

Psychological Contract Theory can provide deeper insights into customer attitudes and perceived behavioural control.

The lack of experimental design in data collection limited the ability to establish causal relationships between RDM campaigns and customer retention. Conducting randomized field experiments can provide stronger evidence of causality by manipulating RDM variables and observing their effects on customer behaviour.

Future research should focus on refining segmentation criteria to identify more granular customer segments and their specific responses to RDM. Additionally, exploring the long-term effects of RDM on customer loyalty and lifetime value, as well as the integration of RDM with digital marketing channels, would be valuable. By continuing to explore these avenues, researchers and practitioners can enhance their understanding of the dynamic interactions between direct marketing strategies and customer behaviour.

6. References

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Appendix

Appendix A

Further details on data preparation and cleaning

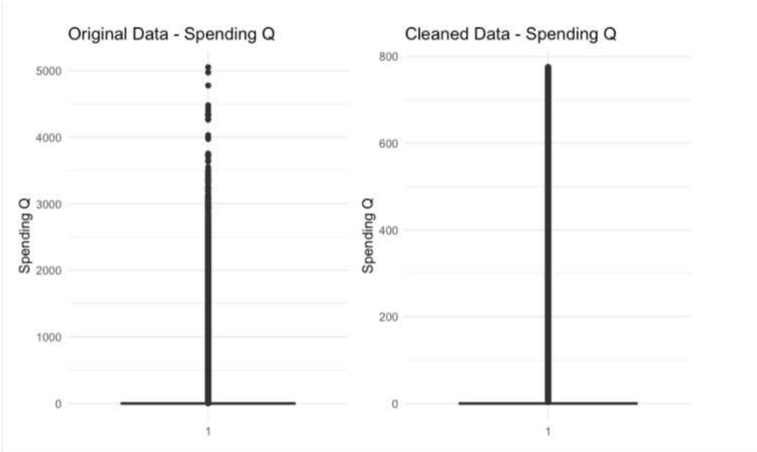

Figure 9: Before vs after data cleaning of the variable spending_q

Figure 9 illustrates the impact of data preparation and cleaning on the variable *spending_q* before and after the cleaning process. The plot on the left shows the distribution of spending values in the uncleaned dataset. The original data contains numerous high-value outliers, with spending amounts reaching up to 5000 units. This indicates a significant skew in the data, where a small number of transactions exhibit exceptionally high spending, potentially distorting the overall analysis. In contrast, the plot on the right demonstrates the dataset after data cleaning. The spending values have been capped at 800 units, effectively removing extreme outliers and normalizing the distribution. This process results in a more uniform and manageable range of spending values, reducing the skewness and making the data more suitable for analysis.

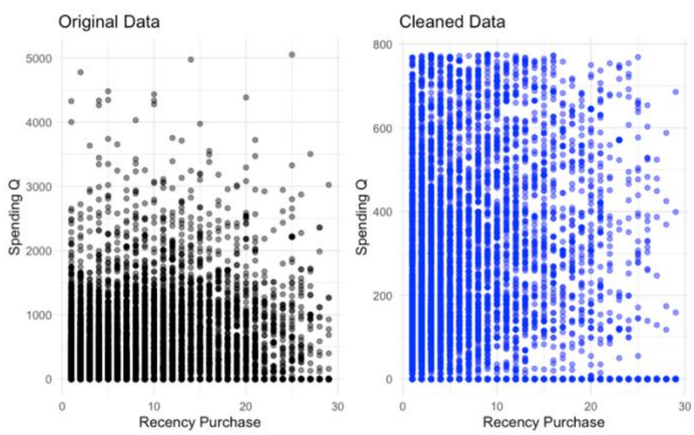

Figure 10: Before vs after data cleaning of the variable recency purchase

Figure 10 illustrates the state of the data for the variable *recency_purchase* before and after data preparation and cleaning. The scatter plot on the left, labelled *Original Data*, shows the raw data with a significant spread in spending values (spening_q) across different recency purchase intervals. Notably, the original data contains numerous high-spending outliers, reaching up to 5000 units, with a dense clustering of points towards lower recency purchase values, indicating higher spending concentrated among more recent purchasers. In contrast, the scatter plot on the right, labelled *Cleaned Data*, demonstrates the effects of data cleaning and preparation. The cleaned data shows a more uniform distribution with spending values capped at 800 units, which suggests the removal or adjustment of extreme outliers. Additionally, the points are more evenly spread across the recency purchase intervals, indicating a more consistent relationship between recency purchase and spending.

Appendix B

Further details descriptive statistic

Gender and age distribution

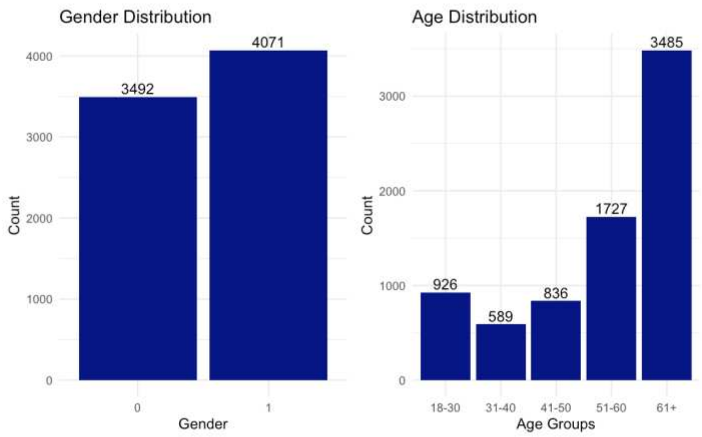

Figure 11: Gender and Age distribution after data preparation and cleaning

Figure 11 illustrates the distribution of gender and age groups after data preparation and cleaning. The gender distribution, depicted in the left bar chart, shows 3,492 records for gender male (0) and 4,071 records for gender female (1) indicating a nearly balanced sample with a slight predominance of females. The age distribution, presented in the right bar chart, categorizes the data into five age groups. The counts for each group are as follows: 926 records for the 18-30 age group, 589 for the 31-40 group, 836 for the 41-50 group, 1,727 for the 51-60 group, and 3,485 for the 61+ group. This distribution reveals that the majority of the records fall within the 61+ age group, followed by the 51-60 age group. In contrast, younger age groups are significantly less represented, which may reflect the demographic characteristics of the customer base in the optical retail market being studied.

Appendix C

Further details to model assumptions

Linearity

Spending_q, as one of the three dependent variables this study focuses on, is modelled using a linear regression model. One of the main assumptions of multiple linear regression analysis is a linear relationship between the dependent variable and every independent variable (Woolridge, 2015). In the case of binary independent variables (*RDM, RDM_incentive, RDM_discount, RDM_premium, RDM_relation, RDM_action, n_fill, treated, gender,* and all *year* and *quarter* variables) this condition is always met. The two other dependent variables recency_purchase and purchase incidence are binary variables as well and therefore by the nature of binary variables linearity is inherently met as they represent shifts rather than trends. It is therefore relevant to assess the relationship between spending_q and the three continuous independent variables frq_purchase, customerduration and age, respectively. For this purpose, scatterplots that include a trendline are generated. As the underlying dataset is quite imbalanced, i.e., 93% of observations report a spending_q of 0, the data is being stratified by spending_q > 0 to be able to reveal any patterns and identify the nature of the relationship between the predictors and the outcome variable. Looking at figures 12 to 14 it can be confirmed that there are linear relationships in all cases and that the assumption of linearity is thereby fulfilled.

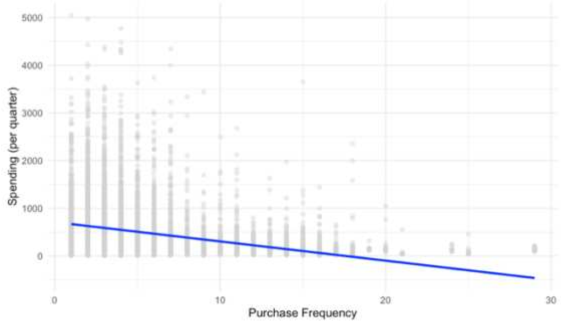

Figure 12: Scatter Plot - frq_purchase vs. spending_q

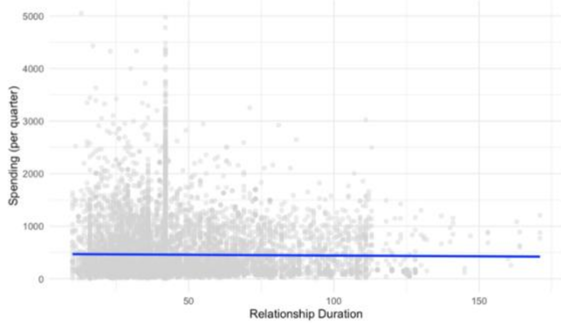

Figure 13: Scatter Plot customerduration vs. spending_q

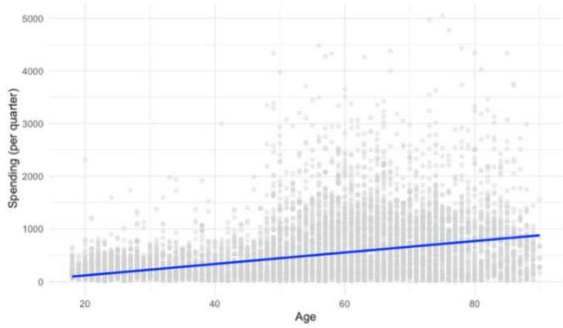

Figure 14: Scatter Plot age vs. spending_q

Multicollinearity

Multicollinearity represents a pivotal statistical consideration that pertains to the correlation between independent variables within a regression model. Multicollinearity complicates the attribution of effects to individual predictors, as they no longer offer distinct information due to their intercorrelation (Daoud, 2017). When variables are highly correlated, the model confronts difficulty in isolating the impact of each variable, leading to potentially inflated standard errors and erroneous insignificance of coefficients (Siegel, 2016).

To proactively detect and mitigate multicollinearity, a preliminary correlation analysis among the independent variables was imperative. In this, one, adhered to Shrestha's (2020) guideline, which designates |0.8| as the benchmark for concerning levels of correlation.

Table 6: Correlation matrix – explanatory variables (excluding year and quarter)

Correlation matrix of the explanatory variables

	RDM	RDM_discount	RDM_premium	RDM_relation	RDM_action	spending_q	frq_purchase	customerduration	age	gendercode	zipcode	treated
RDM	1	0.562	0.281	0.564	0.479	0.046	0.049	0.013	-0.013	0.008	-0.063	0.276
RDM_discount	0.562	1	-0.012	-0.016	-0.020	-0.006	0.028	0.003	-0.008	0.005	-0.036	0.155
RDM_premium	0.281	-0.012	1	0.005	-0.010	-0.002	0.018	-0.006	-0.001	0.002	-0.017	0.078
RDM_relation	0.564	-0.016	0.005	1	-0.009	0.091	0.039	0.003	-0.002	0.007	-0.046	0.163
RDM_action	0.479	-0.020	-0.010	-0.009	1	0.002	0.009	0.025	-0.011	0.002	-0.021	0.132
spending_q	0.046	-0.006	-0.002	0.091	0.002	1	0.111	0.014	0.028	0.013	-0.020	0.028
frq_purchase	0.049	0.028	0.018	0.039	0.009	0.111	1	0.061	-0.230	0.077	-0.090	0.119
customerduration	0.013	0.003	-0.006	0.003	0.025	0.014	0.061	1	0.133	0.007	-0.053	0.191
age	-0.013	-0.008	-0.001	-0.002	-0.011	0.028	-0.230	0.133	1	-0.025	0.027	-0.025
gendercode	0.008	0.005	0.002	0.007	0.002	0.013	0.077	0.007	-0.025	1	-0.074	0.005
zipcode	-0.063	-0.036	-0.017	-0.046	-0.021	-0.020	-0.090	-0.053	0.027	-0.074	1	-0.121
treated	0.276	0.155	0.078	0.163	0.132	0.028	0.119	0.191	-0.025	0.005	-0.121	1

As seen in the correlation matrix there is no correlation between two variables equal or higher than |0.8|, therefore no perfect multicollinearity is expected in the models. Furthermore, VIF was calculated for all three models, nevertheless, VIF is not the best measurement for these types of data and won't be considered.

Heteroskedasticity

Homoskedasticity is a critical assumption in multiple linear regression, implying that the error terms exhibit constant variance across the explanatory variables' values. Heteroskedasticity, which occurs when this assumption is violated, can lead to biased standard errors and, consequently, misleading coefficient estimates and statistical inferences. To address this, each model in this study was subjected to a Breusch-Pagan test to detect heteroskedasticity (Breusch & Pagan, 1979). The Breusch-Pagan tests for Models 2, 3, and 4 reveal significant heteroskedasticity, indicating that the variance of residuals is not constant across the explanatory variables. Given the substantial test statistics and p-values of zero in all models, standard error estimates may be biased. To ensure valid inference, it is advisable to adopt robust standard errors in subsequent analyses, which correct for heteroskedasticity and provide more reliable estimates of coefficients and standard errors.

Independence of Observations

The independence of error terms is crucial for ensuring the reliability of regression models. In the context of panel data, where the same subjects are observed over multiple time points, autocorrelation - also known as serial correlation - poses a significant challenge. This phenomenon occurs when errors are not independent but influenced by previous errors, potentially leading to non-random sampling effects and biased inferences (Durbin & Watson, 1992). To investigate this, the Breusch-Godfrey/Wooldridge tests for serial correlation were applied to all three models. The results, which showed notably large test statistics and a p-value of 0, decisively rejected the null hypothesis of no serial correlation. The accompanying plot of residuals over time further confirms the presence of autocorrelation, as evidenced by the consistent spread of residuals across years. To mitigate this issue and enhance the reliability of the model estimates, robust standard errors were implemented, ensuring more accurate and reliable statistical inferences.

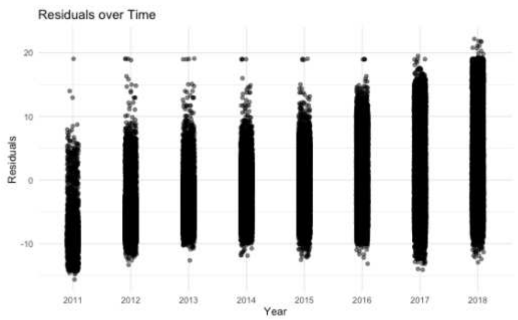

Figure 15: Residuals over time to elaborate the independence of observation

Endogeneity

In this thesis on the impact of RDM on customer churn, addressing the exogeneity of RDM is crucial due to potential endogeneity issues. RDM's decision process might be influenced by several unobserved factors like past purchasing behaviours and omitted variables, which also affect churn, leading to biased estimates. Although a Hausman test indicated endogeneity, implementing Instrumental Variables (IV) was not feasible due to challenges in identifying suitable instruments. Instead, the analysis incorporated control variables to mitigate endogeneity, ensuring the robustness of the findings and adhering to rigorous econometric standards. Nevertheless, future research may explore advanced techniques like IV for a more refined analysis.

Goodness-of-Fit

In evaluating the goodness-of-fit for the models used in this thesis on RDM's impact on churn, the R-squared and Adjusted R-squared values along with the F-statistics were primarily considered. The first two models show a great fit with high R-squared values and significant F-statistics (in the following section “Results” further elaborated), suggesting these models explain a substantial amount of variance in their respective dependent variables. However, model 6, concerning spending, displayed a relatively low R-squared value, indicating it might require additional predictors to adequately model spending behaviours.

Normality of Residuals

Normality means that the residuals are normally (identically) distributed. Conversely, "Violation of the normality assumption may lead to the use of suboptimal estimators, invalid inferential statements and inaccurate conclusions" (Jarque & Bera, 1987). To detect nonnormality quantile-quantile plots (QQ plots) were used to provide a graphical analysis for all three models (see Table 3). The QQ plots for the three models in this thesis indicate significant deviations from the expected normal distribution, particularly visible in the form of heavier tails and skewness. This deviation suggests the presence of outliers or extreme values, raising concerns about the normality of residuals, an essential assumption in regression analyses for reliable hypothesis testing and confidence intervals. Despite these concerns, no further modifications to the models will be undertaken at this stage. This decision is based on comprehensive data preparation and cleaning processes that were previously implemented. During the initial stages, outliers were rigorously identified and filtered out using z-score analysis among other techniques, which should have mitigated their impact. Furthermore, attempts were made to transform some variables using logarithmic and square root transformations to stabilize variance and normalize distributions. However, these transformations were ultimately abandoned due to the complications they introduced in interpreting the results and their minimal impact on improving model fit. Therefore, it is assumed that the data are sufficiently cleaned, and the current models are robust enough for further analysis. This approach allows the study to proceed with the existing model specifications, focusing on extracting meaningful insights from the cleaned dataset without further complicating the analysis framework.

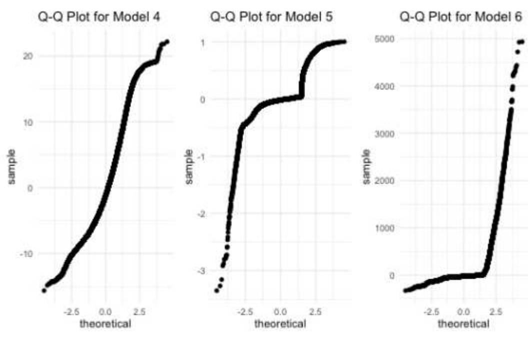

Figure 16: QQ plot of models 4, 5 and 6

Model 2 (recency_purchase): The Q-Q plot displays a pronounced deviation from the line at both tails, indicating that the residuals have heavier tails than expected under normality.

Model 3 (purchase_incidence): The residuals in this model also show a strong deviation from the line, particularly in the lower tail, where data points drastically veer away from the theoretical line. This indicates skewness towards negative values and possible under-dispersion relative to the normal distribution.

Model 4 (spending_q): The most extreme departure is seen here, where residuals do not follow the normal line at all, particularly at higher quantiles. This pattern is indicative of severe positive skewness and potential issues with large outliers.