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What is the Impact of TDM (Targeted Direct Mails that are Tailored Based on Past Purchases) on Purchase Behavior of Customers?

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Abstract

This research explores the influence of Targeted Direct Mail (TDM) on consumer purchase behavior, along with how this influence is moderated by the history of direct mail communications and customer characteristics. The analysis utilizes empirical panel data of 7.839 customers, collected on a quarterly basis, resulting in a total of 179.110 observations. The data is collected by 12 optical retailers in the Netherlands, measured from the fourth quarter of 2011 to the fourth quarter of 2018.

Empirical findings demonstrate that TDM positively affects purchase behavior. Additionally, the study reveals that TDM's effectiveness cannot be assessed in isolation. The impact of TDM on purchasing behavior significantly varies based on prior communications and customer characteristics. Specifically, engaging with customers who have a longer relationship with the company, frequently receive TDMs, or have not received a non-personalized mass mail of the company for an extended period, significantly increases the probability of purchase and spending when receiving TDM. Retailers could enhance the effectiveness of TDM communications by considering these factors in their marketing strategies.

Overall, the findings of this study highlight the necessity of monitoring customers beyond basic demographic details (age and gender) during a TDM campaign, with a particular emphasis on communication and relationship history. This approach allows retailers to efficiently manage their TDM strategies and underscores the importance of tracking metrics and key performance indicators, thereby improving purchase probability and revenue.

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1. Introduction

Between 2018 and 2021, numerous articles emerged stating that the old-fashioned direct mail had found new relevance, since businesses currently have more tools than ever to reach consumers and build relationships with target audiences in the digital marketing landscape (Forbes, 2023). As a result, direct mailing is becoming more and more targeted, with marketeers reallocating more of their digital marketing budget towards direct mail strategies, and ad spending in the direct mail advertising market worldwide being forecasted to reach $58.21 billion and experiencing an annual growth rate of 1.14% (Forbes, 2023; Statista, 2024).

When sending out direct mails, customers can be selected based on their demographic variables like age and gender (Rust and Verhoef, 2005). As a result, according to Jonker et al. (2006), direct mail permits companies to address customers in a more personalized way. However, with the emerge of marketing analytics, retailers try to leverage further amounts of data to make direct mails even more targeted and increase its efficiency.
At present, retailers can customize their direct marketing communications by considering differences in customer relationship history, like the recency, frequency, and monetary value of previous purchases (Neslin et al., 2012; Rust and Verhoef, 2005). In the context of this paper, a targeted direct mail (TDM) is defined as a physical direct mail where the message in the mail in tailored to the purchase recency of this customer.

While many previous studies explored the performance of non-personalized, mass direct mails, there is no excessive research on the impact of TDM. Nevertheless, there are several indicators that TDM could have either a weaker or stronger effect on purchase behavior compared to mass direct mails. For example, an article by Gould (2018) included a study which found that 84% of customers reported to be more likely to open a direct mail because of the personalized aspect. On the other hand, in the context of ads, which highly differs from the direct mail context, research conducted by Lambrecht and Tucker (2013) finds that targeted ads are on average less effective than generic ads.

Even so, with the use of empirical rich data there is no conclusive research written on the effectiveness of TDM on purchase behavior. Purchase behavior in this study is defined as the combination of purchase incidence (whether the customer makes a purchase) and purchase spending (the amount spent per quarter). Hence, the following main research question is proposed:

What Is the Impact of TDM (Targeted Direct Mails that are Tailored Based on Past Purchases) on Purchase Behavior of Customers?

Moreover, this research will investigate for several moderating effects when looking at the effect of TDM on purchase behavior. Prior research investigating the effect of other targeted communication has concluded that the effect of targeted communication compared to generalized communication is largely dependent on different moderators (Bleier & Eisenbeiss, 2015; Van Doorn & Hoekstra, 2013).

Regarding direct mails specifically, other previous studies have explained that customer response to direct marketing is heterogonous and have called for further research on the moderating effects of relationship and direct mail characteristics (Gázquez-Abad et al., 2011; Rust and Verhoef, 2005). For instance, the previously mentioned study by Rust and Verhoef (2005) indicate that loyal, compared to less loyal customers, are less responsive to direct mailings. This is explained by the finding that loyal customers value relational marketing activities more, whilst less loyal customers prefer short-term rewards. Therefore, this research will investigate for a potential moderating effect of customer loyalty, which is expressed by the characteristics purchase recency, purchase frequency, and relationship duration.

Furthermore, regarding direct mail history, Gázquez-Abad et al. (2011) finds that customer response to direct mail is influenced by the recency and frequency of such mailings. Additionally, in the context of ads the impact of targeted ads is also moderated by the frequency and timing of these ads (Sahni et al., 2019). As a result, this paper will also accommodate for a possible moderating effect of direct mail recency and frequency.

Overall, it can be expected that customers respond differently to TDM based on their loyalty and timing of direct mails. However, it remains unclear how response on TDM differs based on these characteristics. Due to the main difference between mass direct mails and TDM being that the latter is more personalized, and research regarding the moderating effect of customer characteristics on TDM not being extensive, research on eventual moderation is needed to study the proper effect of TDM on purchase behavior.

Ultimately, this study builds on previous findings that have been primarily centered around mass direct mail or other forms of communication and make them applicable to the context of TDM as well. From existing literature, it is evident that TDM cannot be analyzed in isolation. Thus, this research emphasizes the importance of examining how the effects of TDM are moderated by the recency and frequency of direct mail interactions, and how these moderators specifically influence purchasing behavior (Neslin et al., 2012).

Additionally, this study explores the role of various customer loyalty characteristics in moderating this effect, thereby responding to calls for incorporating these moderating factors into the analytical framework (Rust & Verhoef, 2005; Gázquez-Abad et al., 2011). Consequently, this research provides valuable insights into the impact of TDM on purchase behavior and explains how this effect is moderated by several factors.

With the use of empirical purchase and consumer behavior data, the findings presented in this study provide valuable insights for retailers and marketers aiming to optimize their direct marketing strategy to sustain customer engagement and encourage consumer responses. Consequently, it offers a framework for the efficient allocation of marketing budgets by serving as an initial guide for identifying the optimal targets and timing to increase purchase probabilities and ultimately maximize revenue.

2. Literature Review

In this chapter, relevant studies concerning the impact of TDM on purchase behavior will be investigated, whilst also considering the potential moderating effects of direct mail history and customer loyalty. After considering the conclusions of previous literature, hypotheses will be formulated according to these findings.

2.1.1 Impact of Direct Mail on Purchase Behavior

Various empirical case studies have highlighted the impact of direct mailing campaigns. For instance, a study by the United States Postal Service (USPS) reveals that direct mail creates more attention and evokes stronger emotional responses (USPS Delivers, 2019). Likewise, Naik and Piersma (2002) illustrate that direct mail campaigns positively affect consumer behavior by enhancing favorable attitudes towards the sender, which subsequently improves the likelihood of purchase.

Furthermore, according to the formal theory of reciprocity, Godfrey et al. (2011) conclude that direct mailing has a positive impact on customer purchase behavior. Reciprocity implies that individuals tend to reward kind actions and penalize unkind ones (Falk & Fischbacher, 2000). The theory of reciprocal actions describes that individuals assess the kindness of an action based not solely on its outcomes but also on the intentions behind it (Falk & Fischbacher, 2000). Applied to the realm of direct mail, this theory suggests that investments in customer relationships foster a psychological connection with the company, as customers recognize the resource commitment by the firm. As a result, customers are inclined to reciprocate by making a purchase.

However, due to direct mails generally being dispatched to customers without the explicit interest of the receiver, there is a risk of the message being perceived as manipulative (Chang & Marimoto, 2003; Godfrey et al., 2011). In addition, it can provoke feelings of annoyance or anger (Ekhlassi et al., 2012).

Moreover, prior research has revealed that there is significant diversity in how customers react to direct mailing efforts, which initiates the need for further research how factors such as customer characteristics and relationship dynamics may further influence these diverse consumer responses (Gázquez-Abad et al., 2011; Rust and Verhoef, 2005). Additionally, Palmatier et al. (2006) elaborate on how marketing initiatives providing diverse benefits, such as financial or social benefits, can result in various types of customer connections.

2.1.2 Impact of TDM on Purchase Behavior

As explained by prior studies, customer reactions to specific types of direct mail vary depending on both individual characteristics and the nature of the direct mail itself. This brings up the question of whether this is also true for TDMs. TDM differentiates itself from traditional mass mailing due to its capacity for flexible and personalized messaging (Kotler, 2009). To achieve success in a personalized direct mailing campaign, the message must address a specific desire or need of the customer (Gould, 1987).

Most importantly, there is no empirical research written yet on this subject with the use of rich customer-level data. However, to provide an overview of the current state of literature which could offer an indication of the estimated effect of TDM on purchase behavior, Table 1 is presented. Generally, the studies in Table 1 indicate that although not always directly, TDM positively influences purchase probability and amount spent.

The findings of these studies will be further conducted and reviewed in this chapter to provide hypotheses about the relevant main effect of TDM on purchase behavior and moderating effects of communication history and customer loyalty characteristics.

Table 1. Comparison Table of Relevant Literature on Estimated Effect of TDM on Purchase Behavior.

Paper	Context	Focal Construct/ Objective	Outcome Measure	Endogeneity Correction	Moderators		
					Incentive Type	Customer Loyalty	Direct Mail History
Vafainia et al. (2019)	Retailing	Impact of Call-to-action Direct Mail	Purchase Incidence	Yes	Yes	Yes	Yes
Neslin et al. (2012)	Meal Preperation Service	Purchase recency, Direct Mail targeting	Profit	Yes	Yes	Yes[a]	No
Gázquez-Abad et al. (2011)	Retailing	Impact of Call-to-action compared to relational Direct Mail	Purchase Incidence, visit/ purchase frequency	No	No	Yes[a]	Yes[a]
Van Diepen et al. (2009)	Non-Profit	Impact of personal vs. competitive Direct Mail	Donation Incidence	Yes	No	Yes[a]	No
Drèze and Bonfer (2008)	Entertainment Industry	Impact of communication frequency	Customer Equity	Yes	No	No	Yes[a]
Rust and Verhoef (2005)	Financial Service	Optimization of marketing efforts (Including Direct Mail)	Profit	No	No	Yes	No
Gönül and Shi (1998)	Cataloger of household products	Direct Mail optimization	Profit	Yes	Yes	Yes	No

a: This characteristic was included as a main effect in the paper, instead of a moderator.

As previously mentioned, TDM has been empirically observed to generate positive responses. One theory that potentially explains the improved effectiveness of TDM, is the "Mere Exposure Effect", as described by Zajonc (1968) and further discussed by Fishman (2020). This theory suggests that repeated exposure to a stimulus, such as a product or brand, increases a person's positive attitude toward it. In the context of TDMs, consumers repeatedly encounter products and brands they have previously expressed interest in via mail, which reinforces familiarity and subsequently leads to positive purchase behavior.
Additionally, an empirical investigation by Ansari and Mela (2003) finds that personalized emails significantly boost click-through rates. This is corroborated by findings from De Wulf et al. (2001), who demonstrated through empirical research on direct mailing campaigns that customer perceptions of their relationship with a firm are positively influenced when the direct mail content is tailored to their needs, or in other words, when it is personalized. Furthermore, Sahni et al. (2019) in their study on the impact of targeted advertisements in an online setting, concluded that sending targeted advertisements enhances the probability of website returns and improved engagement.

Despite multiple empirical studies indicating positive effects of TDM, this effect probably depends similarly to the traditional direct mail on other moderating factors as well, which is ultimately why the impact of these moderators will be considered in this paper. For instance, Lambrecht and Tucker (2013) found that online targeted advertising surpasses mass advertising efficacy once consumers are participating in the information search or alternatives evaluation phase of the consumer decision-making process. Conversely, in a more general context where consumers are merely browsing, mass advertising has been demonstrated to be more effective (Lambrecht & Tucker, 2013).

Moreover, consumer intentions and responses to personalized content are influenced by their willingness to share personal information (such as cookies) to receive specifically targeted and relevant advertisements (White et al., 2007). Privacy concerns are a significant factor in this regard, as many consumers provide false addresses or other personal details when signing up for permission lists that include personalized emails (Tezinde et al., 2002). Even when consumers voluntarily provide accurate information, the transaction costs and extensive questionnaires may deter them from completing or updating their information (Tezinde et al., 2002). These privacy concerns may contribute to another negative factor that could diminish the effectiveness of TDM, which is also a factor observed in the regular direct mail: the perception of being closely monitored and manipulated (Tucker, 2012; White et al., 2007). This perception is consistent with the moderating role of customer trust towards the company, as highlighted by Bleier and Eisenbeiss (2015) in their empirical research on the impact of online targeted banner advertisements on click-through rates. They found that high levels of trust result in a positive effect of direct advertising on click-through rates, while low levels of trust lead to a negative effect (Bleier & Eisenbeiss, 2015).

While multiple empirical studies indicate that TDM may have a positive impact on purchase behavior, there is no academic research that measures this effect with consumer rich data. This study intends to fill this gap in the literature. Although TDM may carry potential negative repercussions, like the increased privacy concerns for example, it is assumed that the positive effects will outweigh the negative ones. Consequently, the first hypothesis is stated as follows:

H1: TDM has a positive effect on customer purchase behavior.

2.2 Moderating Effect of Targeted Direct Mail Communication History

There is evidence that heterogeneous response to TDM efforts is possibly caused by a moderating effect of communication history. For instance, Gázquez-Abad et al. (2011) concludes that customer response to direct mail is influenced by the recency and frequency of direct mailings. Furthermore, the influence of targeted ads is also moderated by the frequency and recency (Sahni et al., 2019). Therefore, to investigate for a potential moderating effect of communication history on the impact of TDM on purchase behavior, a moderating role will be given to direct mail recency and frequency in the framework.

2.2.1 Moderating Effect of Direct Mail Recency

Numerous predictive models indicate that sending TDMs influences the purchase behavior of a customer, with the recency of previous communication serving as a crucial moderating factor. Drèze and Bonfrer (2008) affirm that the recency of email solicitations impacts both customer retention and their engagement with messages, a notion supported by Neslin et al. (2012), who suggest that this phenomenon may be attributed to carryover and saturation effects. Carryover denotes the positive influence of marketing activities in one period on purchase behavior in the subsequent period, with direct mail exhibiting a notably strong carryover effect, especially when interacting with recency (Neslin et al., 2012). The positive sign of this interaction indicates that as customers transition to higher recency states, they become even more responsive to direct mail. Regarding TDM, this indicates that the impact of receiving a TDM not only influences present purchase decisions but also decisions made in following periods. However, saturation, where marketing activities in one period diminish the impact of those in the next, is also observed, albeit marginally significant for direct mail (Neslin et al., 2012).

Consequently, Neslin et al. (2012) advocate for patience before sending an additional direct mail. When following up with additional direct mails and keeping the recency state low, these additional mails will be ignored due to the saturation effect. Van Diepen et al. (2009) corroborate this, advising against sending direct mails in short intervals to prevent customer disregard. It is therefore recommended to wait for an extended period and mail the customer again when he is more receptive to it.

Moreover, Drèze and Bonfer (2008) found that increased time since the last mail reduces the likelihood of customers unsubscribing, while also revealing an inverted U-shaped relationship between mail recency and retention likelihood. This aligns with the findings of Van Diepen et al. (2009), who state that the effect of a direct mail is almost completely forgotten after a year, but as previously mentioned, messaging in short time intervals is also not optimal.

Returning to the saturation effect, a counter argument for this effect is the “foot in the door” effect introduced by Freedman and Fraser (1966). In communication terms, this effect suggests that initial compliance with a message increases the likelihood of compliance with subsequent messages, potentially advocating for more frequent and recent messaging. Likewise, Sheth and Parvatlyar (1995) and Strong (1977) state that receiving messages within shorter intervals may improve the impact of the message on the memory. Additionally, it can lead to familiarity and a positive attitude toward the company (Naik & Piersma, 2002).

This would result in an increased effect of a TDM for customers who have received direct mails on a more recent basis. Indeed, research conducted on a similar topic as this paper resulted in the finding that customers who received a TDM with lower recency have a higher probability to make a purchase when targeted with a new TDM, although this moderating effect size was minimal (Vafainia et al., 2019). This is supported by an empirical study conducted by Sahni et al. (2019) on targeted advertisements, which concludes that the positive effect of targeted advertisements significantly decreases when the time since the first website visit increases.

In another context, several election campaign studies have also found evidence that the recency of messages has a significant effect. Findings in the context of election campaigns could potentially enrich the insights of the expected effect of direct mail recency on TDM campaigns, given that both campaigns have an advertising dimension. For instance, Kreiss et al. (2017) underscored the importance of timing in campaign strategies through extensive interviews with campaign professionals during United States elections. Moreover, a study by Nickerson (2007) revealed that messages communicated closer to the Election Day exhibit higher effectiveness compared to earlier communications, which often fail to effect voter behavior. Additionally, Zaller (1992) developed a compelling theoretical framework emphasizing the importance of timing in political messaging. Zaller (1992) suggests that recently encountered ideas or concepts are more readily available for mental retrieval, due to their recent activation in short-term memory, thus resulting in "recency effects" (Crowder, 1976).

Conversely, a "primacy effect" also appears to influence memory retention, implying that items encountered early in a sequence enjoy a memory advantage (Crowder, 1976). Pragmatically, early campaign messages may sensitize voters to an upcoming election, by establishing awareness in a voter's mind when they are still invested in the political contest, while late messages are likely to reach majority of the voters after decisions have already been made (Panagopoulos, 2010).

Lastly, to underscore the varying conclusions regarding the impact of timing in election campaign studies, a more recent publication by Murray and Matland (2013) states that the effect of timing does not matter.

To conclude, the contradicting results of prior research indicates that the expected moderating effect of mail recency on TDM is difficult to predict. While numerous studies forecast a positive moderating effect, others, conversely, predict a negative effect. Moreover, there are several studies that predict an inverted U-shaped effect. Therefore, as there is no clear direction to expect based on previous studies, opposing hypotheses will be stated as follows:

H2a: The impact of a TDM on purchase behavior is higher for customers with a longer time since they last received a direct mail.
H2b: The impact of a TDM on purchase behavior is lower for customers with a longer time since they last received a direct mail.

2.2.2 Moderating Effect of Direct Mail Frequency

The frequency of communication significantly influences how customers respond to future contacts (Drèze & Bonfrer, 2008; Neslin et al., 2012). Research suggests that optimizing the frequency of direct mailings over a specific period impacts overall retention success (Elsner et al., 2004; Piersma & Jonker, 2004). Moreover, maintaining frequent communication can strengthen the bond between a company and its customers (Schumann et al., 1990), aligning with the findings proposed by Vafainia et al. (2019) that higher-frequency TDM recipients are more likely to make purchases when targeted again.

Furthermore, frequent advertising communication has been noted to keep the company in a customer's mind and decrease the likelihood of the customer forgetting the company over time (Naik & Piersma, 2002; Sheth & Parvatlyar, 1995). Additionally, in the context of targeted advertisements, advertising frequency did not negatively moderate the positive influence of targeted advertisements on website return visits (Sahni et al., 2019).

On the other hand, there is also evidence that communicating frequently with customers has a negative effect. Several studies have established that sending many direct mails in a short period of time may have a negative long-term effect on the perception of the company, potentially due to irritation (Diamond & Noble, 2001; Elliot & Speck, 1998). This notion is further supported by Van Diepen et al. (2009), who found that beyond a certain threshold of frequent mailings, each additional mail diminishes the likelihood of future responses due to heightened irritation. Moreover, beyond this threshold, each extra mailing not only irritates the customer but also diminishes the revenue potential of subsequent mailings (Van Diepen et al., 2009). This suggests that a frequent amount of TDMs negatively impact the effect of TDM on purchase behavior.

Given these points, it seems that there is an optimal mailing frequency, and once a company crosses this frequency, the effect of each extra TDM diminishes. This idea is further emphasized by Naik and Piersma (2002), that indicate communication frequency does build goodwill and positively impacts response probability, however, cumulative exposure significantly reduces this goodwill. Venkatesan and Kumar (2004) have a similar conclusion, in the sense that there is an optimal level of communication frequency and communication past this threshold may result in diminishing returns of purchase frequency. As a result, the expected moderating effect of TDM frequency on customer purchase behavior is stated as follows:

H3: The impact of TDM on customer purchase behavior is higher for customers with a higher TDM frequency.

For this hypothesis, given that multiple studies indicate a possible inverted U-shaped relationship, it will also be shortly investigated whether this positive relationship is valid until an optimal threshold, where further communication past this threshold results in diminishing returns. This outcome will be discussed briefly in Chapter 4.2.2.

2.3 Moderating Effect of Customer Loyalty

Variations in purchase behavior occur as a consequence of individual differences among consumers (Bolton, 1998; Verhoef et al., 2001; Weiss & Kurland, 1997). Many of these personal characteristics can be proposed to measure customer loyalty. To measure the loyalty of customers, this study will follow the definition of loyalty proposed by Rust and Verhoef (2005), where behavioral loyalty is expressed as a larger cumulative number of purchases and a longer relationship duration.

When researching the moderating effect of purchase frequency, relevant literature about the moderating effect of purchase recency is also included, as these two characteristics share many similarities. This allows a more precise hypothesis to be outlined about the moderating effect of purchase frequency.

2.3.1 Moderating Effect of Purchase Frequency

In the realm of consumer behavior and marketing strategy, there exists a phenomenon known as the "recency trap," formulated by Neslin et al. (2012), wherein the likelihood of a consumer making a purchase diminishes as the time since their last purchase lengthens. This trap poses a challenge for businesses, as customers who abstain from purchasing within a certain timeframe become less inclined to buy in subsequent periods, potentially leading to the permanent loss of this customer. Faced with this dilemma, firms using TDMs must decide whether to intensify marketing efforts targeted at customers with less recent purchases or relinquish their focus on these individuals and target customers with a lower purchase recency. The study by Neslin et al. (2012) concludes that recency is negatively related to purchase probability, thus setting up the recency trap. According to this study, the probability of purchase in the current period for a customer who last purchased 5 months ago is approximately 5 times less compared to a customer who bought in the last period (Neslin et al., 2012).

Likewise, a study by Vafainia et al. (2019) found that when targeting customers with a low purchase recency instead of high purchase recency, purchase probability increases by 57%. In addition, this paper concludes that TDMs have a higher impact on purchase incidence for customers with lower purchase recency (Vafainia et al., 2019). Furthermore, several other studies find similar evidence, including a paper by Van Diepen et al. (2009) that concludes when researching the effect of donation recency, that increased recency of the last donation has a negative effect on response likelihood. Moreover, a common finding in multiple studies is that higher recency is associated with lower purchase likelihood or spending (Bitran & Mondschein, 1996; Bult et al., 1997; Fader et al., 2005; Rhee & McIntyre, 2008). As a result of several papers drawing the same conclusion, many direct marketeers believe that this negative relationship is a fundamental principle (Blattberg et al., 2008).

However, there is also evidence of a positive relationship, meaning that higher recency results in more positive purchase behavior. For instance, Gönül and Shi (1998) state that it is not optimal to mail individuals at low recency levels, as they are predicted to make a purchase regardless. Instead, they advocate for allocating directing marketing resources toward customers with high recency levels (Gönül & Shi, 1998). Evidence of this suggestion is also given with a specific finding, as the purchase probability for a certain product, that is on average replaced in two years, declined until up to two years of recency and started increasing afterwards. This suggestion is supported by empirical evidence demonstrating a positive interaction between purchase recency and direct mail responsiveness (Neslin et al., 2012). Although Neslin et al. (2012) identify a negative correlation between purchase recency and purchase probability, this paper advocates for intensified marketing efforts to transform customers with higher recency values from being negligible and unprofitable to becoming valuable customers in the long run.

Thus, both Gönül and Shi (1998) and Neslin et al. (2012) advocate for a strategic reallocation of resources towards retaining customers with high purchase recency, recognizing them as valuable assets whose move to competitors can be diminished through targeted retention initiatives.

Regarding purchase frequency, it is observed that customers tend to decrease their purchase frequency before completely ending their association with a company (Dwyer et al., 1987; Jap, 2001). On the other hand, customers who make frequent purchases, known as heavy users, accumulate more experiences with the company, enhancing their ability to make informed decisions in future interactions (Vafainia et al., 2019). This heightened familiarity allows heavy users to increasingly engage with the firm's communication efforts (Vafainia et al., 2019). As a result, Vafainia et al. (2019) concludes that TDM campaigns have a larger impact on purchase incidence among customers with a history of frequent purchases.

Similarly, studies in the context of blood donation frequency suggest that individuals who donate more frequently are more likely to become loyal donors, continuing to donate regularly in the future (Callero & Piliavin, 1983; Kasraian & Tavassoli, 2012; Schreiber et al., 2005).

Conversely, there is also the possibility of a U-shaped effect of purchase frequency on future purchase behavior (Gönül & Shi, 1998). This study suggests that it is optimal to mail customers who are at low to medium ranges of purchase frequency because they are still in trial mode. This suggestion is supported by Gázquez-Abad et al. (2011), which concludes customers who buy once or twice at the retailer are key candidates for receiving promotional mailings, instead of customers who buy on a more frequent basis. Infrequent buyers present both a relatively high chance of additional purchases and a notable risk of shifting to competitors (Gönül & Shi, 1998). In contrast, frequent buyers are already loyal and likely to respond regardless of additional promotional efforts, making further mailing campaigns unnecessary (Gönül & Shi, 1998).

To conclude, given that lower recency largely corresponds to higher frequency and vice versa, the moderating effect of these two characteristics will be merged into one hypothesis. Therefore, it is decided to research the effect of purchase frequency in this study to measure the potential moderating effect of both purchase frequency and recency.

Despite several studies indicating that less recent and frequent buyers provide a larger moderating effect on the impact of TDM on purchase behavior, due to majority of studies suggesting a stronger effect of more recent and frequent buyers, the hypothesis is written as follows:

H4: The impact TDM on purchase behavior is higher for customers with higher purchase frequency.

2.3.2 Moderating Effect of Relationship Strength

In numerous prior investigations, the duration of the relationship between customers and companies has served as a variable for examining the impact of relationship strength (Grégoire et al., 2009; Rust & Zahorik, 1993; Storbacka et al., 1994). This study follows suit, presuming that a lengthier relationship duration correlates with a stronger relationship. Older relationships are expected to possess clearer and more effective communication, increased trust, and heightened commitment (Weiss & Kurland, 1997). Supporting this, Jones et al. (2000) provides further evidence emphasizing the pivotal role of relationship strength in fostering customer loyalty.

Moreover, various studies suggest that relationship duration moderates the primary effect of TDM on purchase behavior. Notably, research in relationship marketing, such as that by Bult et al. (1997), concludes that relationship duration significantly influences future consumer behavior. Similarly, Verhoef et al. (2001) estimate that majority of attitudinal aspects of purchase behavior improve with relationship duration, largely due to the learning process.

Additionally, prior marketing literature suggests that longer relationships bring higher levels of intimacy, more positive attitudes, and satisfactory interactions with the company, consequently increasing customer engagement with the firm (Swann & Gill, 1997; Verhoef et al., 2002). According to Oskamp and Schultz (2005) and a likelihood model proposed by Petty (1986), these engaged customers are more likely to respond to promotional activities and advertising media.

Conversely, it could be argued that loyal customers may have reached their peak value in terms of the number of purchases (Dwyer et al., 1987; Grant & Schlesinger, 1995). Consequently, they may be less inclined to purchase additional products despite receiving direct mail. This aligns with several previous studies suggesting that promotions are less effective among brand loyalists (Bawa & Shoemaker, 1987; Kahn & Louie, 1990). As customers become more experienced with a company over time, the impact of promotions may diminish (Bolton et al., 2004). This could be attributed to the theory proposed by Heilman et al. (2000), suggesting that consumers who are more brand-aware are likely to be more influenced by non-price factors, primarily basing their purchasing behavior on previous experiences with the brand rather than promotions (Verhoef et al., 2002).

Furthermore, there are also studies which indicate that relationship duration has no significant moderating effect. For instance, Verhoef (2002) finds that affective commitment does not enhance the positive effect of direct mailings on changes in customer share. Similarly, Palmatier et al. (2006) concluded, in a Business-to-Business context, that relationship duration did not influence the effect of relationship marketing investments. Rust and Verhoef (2005) further support this, stating that the effect of relationship duration on the response to direct mails is essentially negligible.

Above all, an empirical study examining the moderating effect of relationship strength on customer response to direct mailings indicates that relational strength does indeed influence the impact of direct mailings on consumers' purchase behavior (Gázqued-Abad et al., 2011). Similarly, Vafainia et al. (2019) established that the effect of direct mail on purchase incidence increases with the duration of the relationship. However, this impact appears to be dependent on the type of direct mail (Gázqued-Abad et al., 2011).

Overall, based on the above literature, it is difficult to predict the moderating effect of relationship duration when researching TDM impact on purchase behavior. Nevertheless, given that majority of literature predicts a positive moderating effect, including the two last mentioned empirical papers which studied a similar topic, the expectation is that the effect of TDM increases with longer relationship duration. Hence, the hypothesis is stated as follows:

H5: The impact of TDM on purchase behavior is higher for customers with a longer relationship duration.

2.4 Conceptual Framework

When considering a metric to assess the moderating effect of customer loyalty (customer purchase frequency and relationship strength) and TDM communication history (communication recency and frequency) on the impact of TDM on purchase behavior, the conceptual framework developed by Vafainia et al. (2019) was considered. In this framework, the effect of Call-to-action (CTA) direct mail on customer purchase incidence was measured. Similarly, the moderating effects of direct mail history and customer loyalty were measured. In like manner, this framework will follow a similar approach to the framework of Vafainia et al. (2019).

To further illustrate the stated hypotheses and their relations, a conceptual research model is illustrated below in Figure 1.

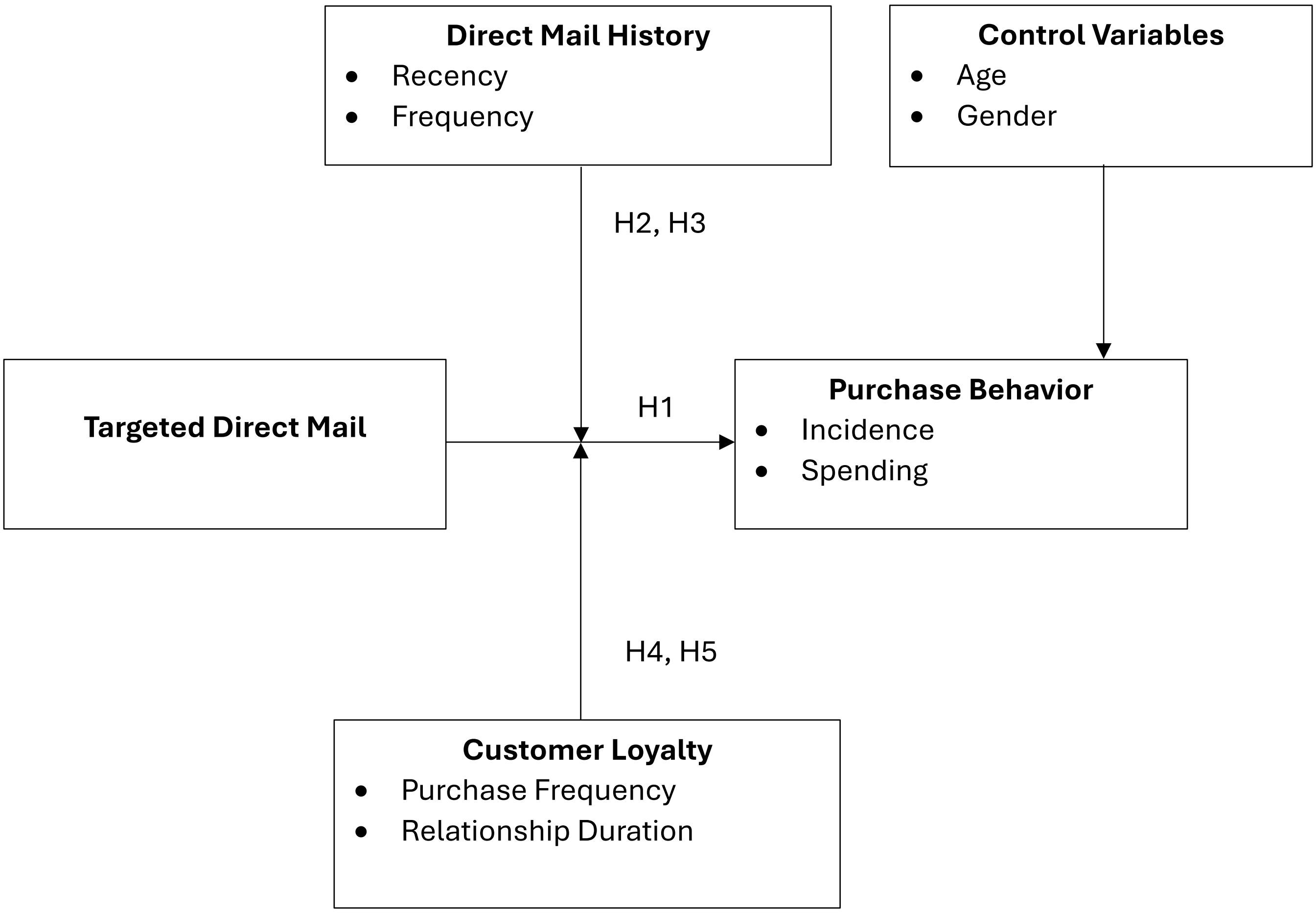

Figure 1. Conceptual research model for the hypotheses, visualizing their main concepts and relationships.

3. Methodology

3.1 Data Description

To test the hypotheses, we examine customer purchase behavior of 12 optical retailers in the Netherlands. These retailers are not affiliated with large chains and several retailers have incorporated TDM campaigns into their marketing strategies. Other similar characteristics of these retailers is that they are homogeneous in terms of size, customer demographics, and location.

The dataset contains information on customer characteristics, purchase behavior, and TDM communication history of 7.839 different customers on a quarterly basis, with a total of 179.110 observations. The analyzed observation period starts in the fourth quarter of 2011 and ends in the fourth quarter of 2018. Each observation corresponds to a specific customer denoted as *i* in quarter *t*. Customers in this dataset are specifically associated with a single retailer, ensuring that all purchases and communications relate to the same retailer.

Furthermore, to rule out "trial" customers who have made just one purchase, customers included in the dataset have made at least two purchases from the respective retailer. This could either be before the observation period or during the observed phase. Therefore, given that the initial purchase period varies per customer, it is noteworthy to emphasize that the number of observations per customer differ, ranging from 1 to 29 instances per customer. Moreover, these customers have received at least one direct mail in the observation period.

Lastly, it is important to state that interpurchase frequency in the optical sector are not as frequent as in the fast-moving consumer goods sector, due to consumers needing more time to solve the purchase process (Grewal et al., 2004). Products that are commonly sold by optical retailers include glasses and lenses, which are not replaced or repurchased often. This is substantiated by our data, which reveals a median interval between purchases of 7 quarters. Moreover, in the context of our dataset, it is standard practice for retailers to distribute direct mail on a quarterly schedule.

3.2 Variables

3.2.1 Dependent Variable

The focus of this study is customer purchase incidence (*purchase_incidence*) and spending (*spending_q*) in each quarter. Specifically, we define the outcome variable *purchase_incidence* as a binary indicator, which takes the value of 1 if customer *i* makes a purchase in quarter *t* and 0 otherwise. *Spending_q* is a scale variable, which measures the amount spent (in €) by customer *i* in quarter *t*.

For each customer, the estimation period begins in the fourth quarter of 2011 if they were a client before 2010. For those who became customers during the study period, the estimation begins one year after their initial registration or purchase. The initial year is established as a baseline for the independent variables. Someone's consumer behavior is measured from the point of their initial purchase because it is at this point that retailers start including them in their direct mail campaigns. The estimation period concludes in the final quarter of our observation period.

3.2.2 Independent Variables

The primary variable of interest in this study is the TDM variable (*clc_fill*). Optical retailers start the distribution of TDM once a customer is entered into their database, which occurs following their initial purchase. Subsequently, TDMs are sent to customers based on their recent purchase activity, with the criterion being a maximum recency span of four years. The objective is to (re)engage existing customers and affect their purchasing behavior, either by prompting a purchase decision or encouraging a higher expenditure on subsequent purchases.

The dummy variable *clc_fill* indicates whether a customer received a TDM in a specific quarter, taking the value of 1 if a TDM was received and 0 otherwise. Therefore, *clc_fill* = 1 denotes that a customer *i* received a TDM in quarter *t*. It is important to note that each customer can receive a maximum of one TDM per quarter.

To study the moderating effect of TDM frequency, the variable *DM_Frequency* will be created in the dataset. *DM_Frequency* is derived from the sum of the TDMs received in the last four quarters. Therefore, for each customer *i* in quarter *t*, the TDMs in quarter t-4, t-3, t-2, and t-1 will be summed up. Additionally, for each quarter a decay factor of 0.75 will be applied. This means that more recent TDMs are given stronger weight compared to older TDMs. This method is similar to the one used by Van Diepen et al. (2009).

Furthermore, the effect of direct mail recency will be measured by using the variable *N_recency*, which indicates how many quarters ago customer *i* last received a direct mail.

Lastly, to study the moderating effect of customer loyalty, the variables *frq_purchase* and *customerduration* will be conducted. *frq_purchase* measures the number of purchases by customer *i* in the observation window, while *customerduration* considers how many quarters in total customer *i* has joined the retailer.

3.3 Transition from Raw Dataset to Final Dataset

As previously mentioned, the raw dataset contains empirical data on 7.839 different customers. These customers provided a total of 179.110 observations, measured on a quarterly basis from 2011 to 2018.

Firstly, the variable *age* was investigated. All cases where a customer was aged below 18 years old in the observation window were omitted, to exclude children from the dataset. Furthermore, there were multiple cases where the age was estimated to be too high to be investigated, with the highest age being 121 years old. Therefore, all cases with ages over 90 years old were removed. It is presumed that majority of these cases are from inactive customers who incorrectly remain in the mailing list or family members who have continued to utilize the account of a relative.

Furthermore, the variable *gender* was analyzed. Customers with the gender code "O", were also omitted from the database due to missing information. To test the effect of this control variable, it is important to have values that can be interpreted and are informative.

Additionally, to transit to the final dataset, potential outliers were investigated. With the aim of detecting outliers, boxplots were created (presented in Figure 2-4 below) and z-scores were calculated for the following variables: *frq_purchase* (purchase frequency for customer *i*), *customerduration* (the number of quarters since customer *i* has joined the retailer), and spending_q (the total amount spent per quarter for customer *i*). For the boxplots, only the large outliers were excluded, whilst for the z-scores a cut-off threshold of 4 was selected. It is chosen to not be too selective when deleting the outliers, as otherwise many observations may be deleted, and outliers still potentially contain important information.

As a result of the previously stated implementations, 13.650 observations were omitted from the dataset.

Purchase Frequency

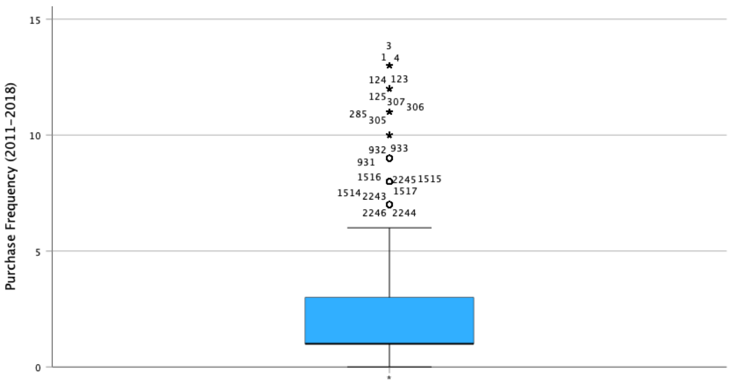

Figure 2: Boxplot frq_purchase

Purchase Spending

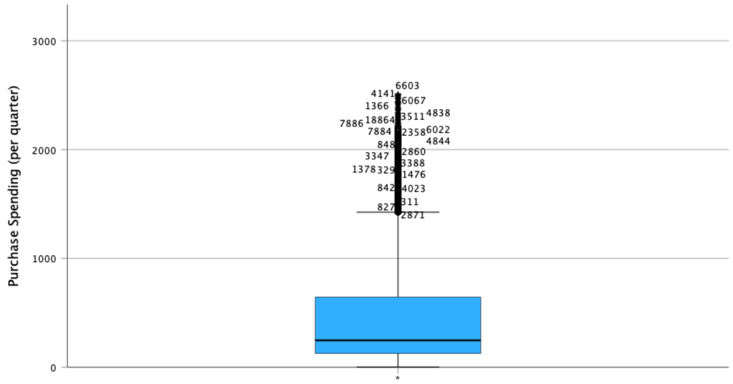

Figure 3: Boxplot spening_q

Relationship Duration

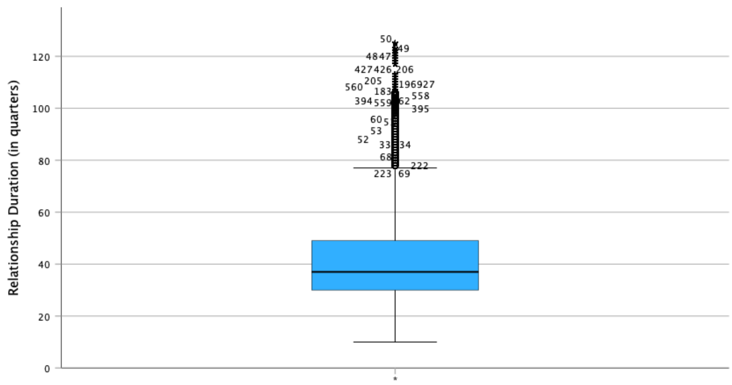

Figure 4: Boxplot customerduration

3.4 Descriptive Statistics

Using the final dataset with a total of 165.460 observations, descriptive statistics with explanatory graphs will be presented to provide a brief introduction to the data. Firstly, when observing the dependent variables *purchase_incidence* and *q_spending* for all customers, a growing trend can be seen within the observation window for both variables (see Figure 5 and 7).

Furthermore, when analyzing the trend for the dependent variables but only for customers that are enrolled for targeted TDMs (subscribed customers), a similar trend is visualized for both variables (see Figure 6 and 8). Regarding H1, according to this initial observation, it is estimated that targeted TDMs do have a positive effect on spending and purchases, however there is no stronger impact compared to all customers in the data.

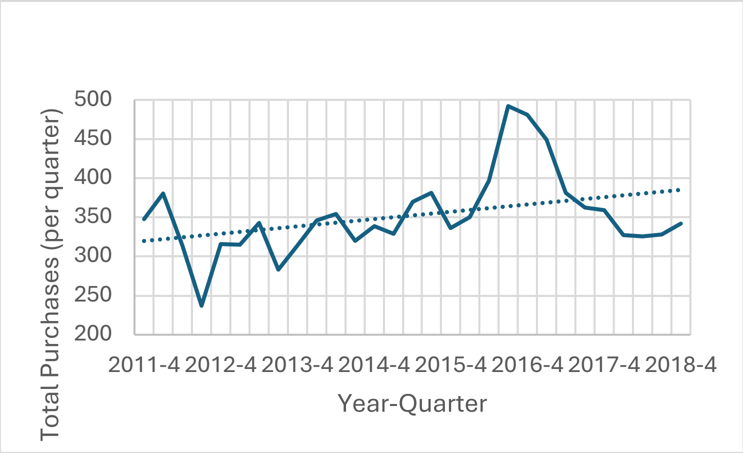

Figure 5: Total Purchases over time (all customers)

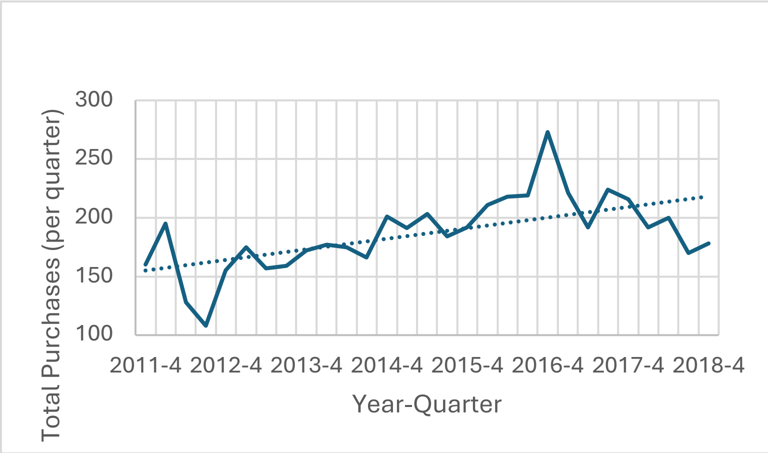

Figure 6: Total Purchases over time (subscribed customers)

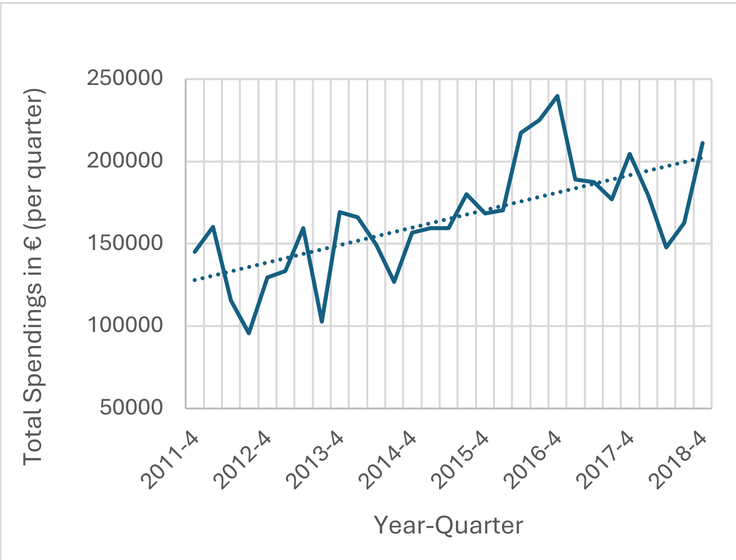

Figure 7: Total Spendings over time (all customers)

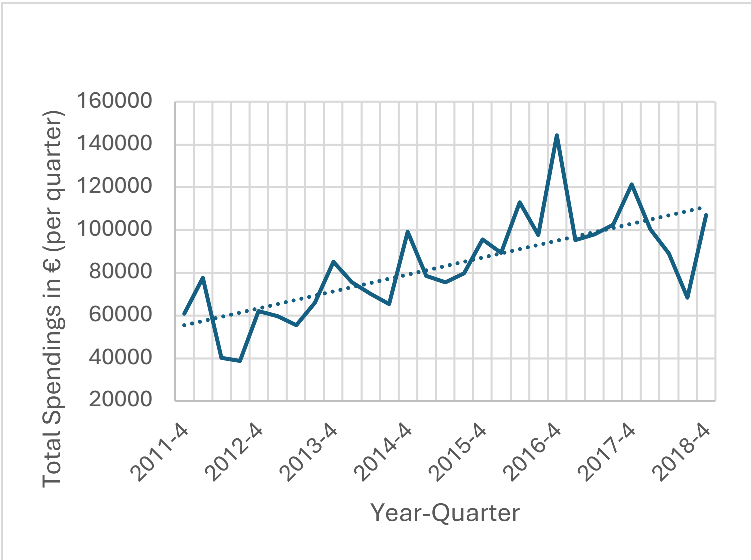

Figure 8: Total Spendings over time (subscribed customers)

Additionally, regarding the dependent variable *purchase_incidence*, the average number of purchases made by a customer in the observation window is 1.57. The maximum number of purchases made by a customer is 10, whilst the minimum amount is 0.

With respect to the other dependent variable *q_spending*, the average amount spent in the observation window by a customer equals €744.10. The maximum amount spent by a single customer is €8383.00 and the minimum amount spent is €0.

Secondly, several independent variables and the number of customers were investigated. The number of customers were 3.737 in the first quarter of the observation window (fourth quarter of 2011), which nearly doubled to 7.263 in the last quarter of the observation window (fourth quarter of 2018). This growth in customers could also partially explain the previously mentioned growing trend of purchases and spendings over time. The increase in the number of customers per quarter is presented in Figure 9 below.

Moreover, looking into the average purchase recency, there is an almost linear increase in recency over time (see Figure 10). Regarding, the sum of TDMs sent per quarter, there is a clear growth that can be seen over time (see Figure 11). This could partially be explained by the increasing number of customers, but also potentially by the increase in purchase recency over time. Measured over the entire observation window, the maximum amount of TDMs received by a customer is 13, while the minimum is 0. On average, a customer receives 1.62 TDMs in the observation window.

Considering the recency of direct mails, a growing line can be seen which diminishes around the beginning of 2016 (see Figure 12). The initial course of this line indicates that customers on average do not suffer from constant reception of direct mails by the retailers. On the other hand, the decreasing course from 2016 onward could indicate that customers receive slightly more direct mails than before.

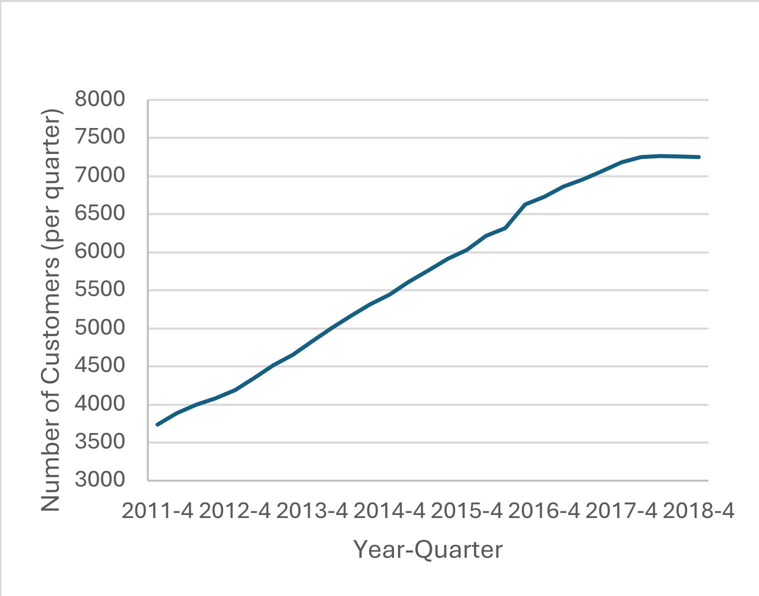

Figure 9: Number of Customers over time

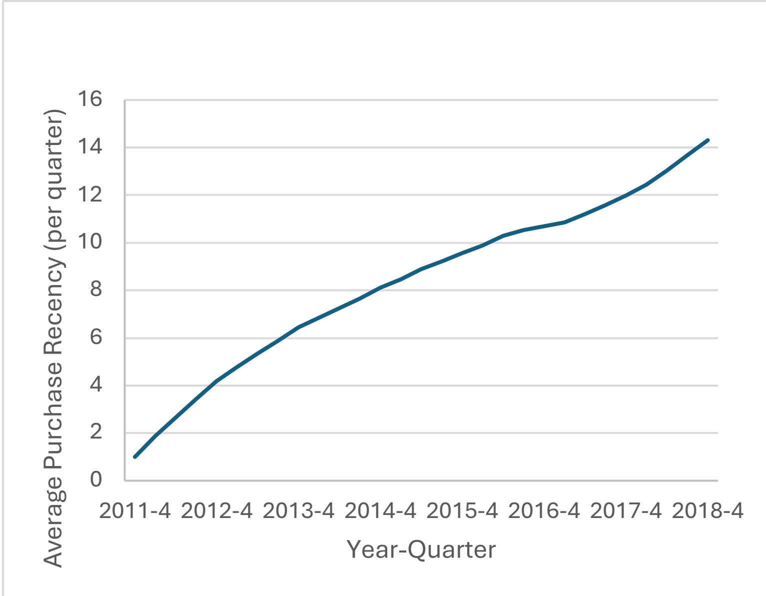

Figure 10: Average Purchase Recency over time

Figure 11: Number of TDMs sent over time

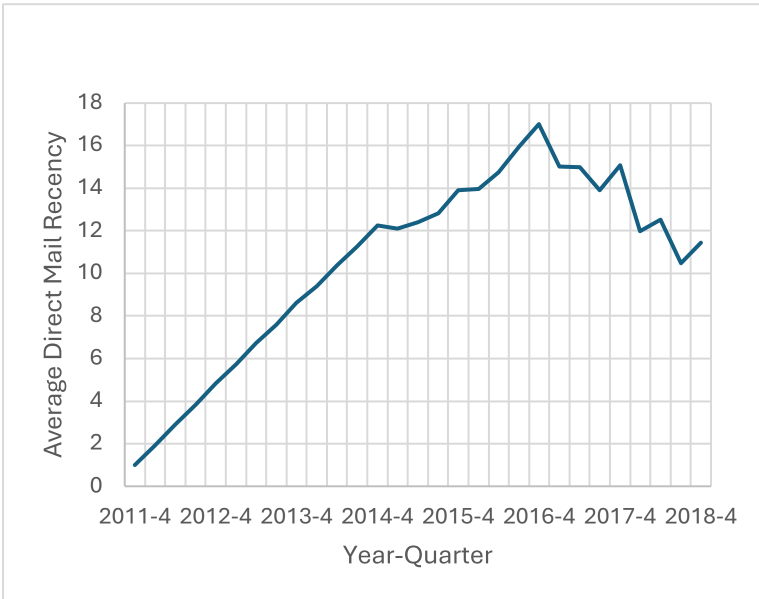

Figure 12: Average Direct Mail Recency over time

Lastly, Table 2 below presents a brief description and descriptive statistics of all relevant variables used to answer the hypotheses. The mean, standard deviation (SD), minimum (Min.), and maximum (Max.) of all variables are described.

Table 2. Descriptive Statistics of all Conducted Variables

	Variable	Description	Mean	SD	Min.	Max.
Dependent Variables	purchase_incidence	Dummy expressing whether customer *i* makes a purchase in a quarter or not	0.060	0.241	0	1
	spending_q	Spending of customer *i* in each quarter	28.95	160.460	0	2250
Independent Variables	clc_fill	Dummy variable indicating whether customer *i* receives a TDM	0.070	0.253	0	1
	customerduration	How many quarters customer *i* has joined the retailer	41.840	18.885	10	110
	frq_purchase	How many purchases customer *i* has made in observation window	1.870	1.828	0	10
	DM_Frequency	Frequency of TDMs received for customer *i*, measured in the previous four quarters	0.141	0.314	0	2.05
	recency_N	Time since the last time customer *i* received a non-personalized Direct Mail	11.290	8.273	1	29
Control Variables	age	Age of customer *i*	57.640	17.887	18	90
	gender	Gender of customer *i* (1= male, 0= female)	0.470	0.499	0	1

3.5 Data Analysis Techniques

Given that the conducted dataset contains panel data, the hypotheses will be analyzed using a panel regression. The use of panel data allows us to test more complicated behavioral models and presents a more accurate outcome compared to cross-section or time-series data (Baltagi, 2005). Furthermore, regression analysis in general provides an estimation of the relationships among dependent and independent variables and its significance (Schneider et al., 2010). This is useful in this study as it is investigated in what way TDM relates to purchase behavior, in a model considering potential moderating effects from multiple independent variables.

To test for the effect of TDMs on purchase incidence, a binary logistic regression will be used. A logistic regression can be used when the dependent variable is binary and to model the probability of obtaining a specific outcome (whether a customer makes a purchase in this case) (Wilson & Lorenz, 2015). Another benefit of the binary logistic regression is that no normal distribution is required (Wilson & Lorenz, 2015).

To test for the effect on purchase spending, a linear regression model will be constructed. In this regression model with the logarithm of purchase spending as dependent variable, it will be analyzed how the independent and control variables mentioned previously influence the estimated spendings per customer on a quarterly basis. Given that the dependent is the logarithm of purchase spending, which contains values of 0, a constant of 0.1 will be added to all values to ensure all values are positive.

Lastly, to draw significant conclusions, a significance level of $p = 0.05$ is used.

3.6 Model Assumptions

As previously mentioned, regressions will be used to test the hypotheses. When performing these regressions, there are multiple assumptions that must be met to draw valid and representative conclusions. Below, the assumptions are investigated.

3.6.1 Heteroscedasticity

An essential assumption in linear regression analysis is homoscedasticity, which indicates that the variance of the error terms remains constant across all levels of the explanatory variables. In other words, the spread of residuals cannot change depending on the values of the predictors. If this assumption is violated it results in heteroscedasticity, which can cause the estimated standard errors to be unreliable and, consequently, lead to biased regression coefficients and misleading inferences (Breusch & Pagan, 1979).

To test for the presence of heteroscedasticity, all models were subjected to the Breusch-Pagan test (Breusch & Pagan, 1979). To address this issue and lessen the impact of heteroscedasticity, robust standard errors were calculated for all models. The results consistently indicated significance at the 1% level, suggesting that heteroscedasticity was present in each model.

3.6.2 Multicollinearity

Multicollinearity arises when two or more independent variables in a regression analysis are significantly correlated with each other (Daoud, 2017). This high correlation impairs the ability of the model to accurately identify the distinct influence of each explanatory variable, which complicates the interpretation of the regression coefficients. Even if these variables would theoretically demonstrate significance, their individual coefficients might appear insignificant due to increased standard errors (Daoud, 2017).

To detect potential issues with multicollinearity, a correlation matrix of all explanatory variables is conducted. According to Shrestha (2020), a threshold with an absolute value of |0.8| should be maintained for identifying problematic multicollinearity, where correlations exceeding this absolute value indicate a significant multicollinearity concern. When using this threshold, no instance of multicollinearity could be identified for any of the explanatory variables.

3.6.3 Nonnormality

The assumption of normality states that the observations are normally distributed (Box, 1953). When the conducted data has no normal distribution, the conclusions drawn from this data can be practically unrepresentative. For linear regressions, this assumption is important.

To investigate for nonnormality, the Kolmogorov Smirnov (K-S) test will be utilized. Even after investigating for outliers (as described in Chapter 3.3), all resulting p-values were significant, which indicates that nonnormality is present in this data for all conducted variables. To minimize the impact of this nonnormal distribution of data, robust standard errors will be used.

4. Results

To test all hypotheses, 15 binary logistic regressions (models a) and 15 linear regressions (models b) are constructed. All models control for the effect of gender and age. R^2 is added at the bottom of each model, to present the explanatory power.

As mentioned previously, the binary logistic regression applies to the dependent variable *purchase_incidence*, whilst the linear regressions apply to dependent variable *spending_q*. The number of the first five models correspond to the number of the hypothesis tested (both model a and b). In these isolated models, the appropriate variable and its interaction with *clc_fill* (in the case of a moderating variable) is added to the regression, with the addition of the TDM variable (*clc_fill*), and the control variables *age* and *gender*. For example, model 1 investigates the effect of TDM on purchase incidence for model 1a and the effect on purchase spending in model 1b. Therefore, this model will be partly considered to answer H1.

Furthermore, for model 6, the previous models are combined and all independent variables are added in. This model will mainly be looked upon to answer the hypotheses, as it provides insights how all variables relate to each other by testing them in one complete model. The formula of the complete models 6a and 6b is presented below. The formula of all other regression models is described in Part 1 of the Appendix.

$$P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}} \text{, where } X = \beta_0 + \beta_1{*}clc\_fill + \beta_2{*}recency\_N + \beta_3{*}(recency\_N{*}clc\_fill) + \beta_4{*}DM\_Frequency + \beta_5{*}(DM\_Frequency{*}clc\_fill) + \beta_6{*}frq\_purchase + \beta_7{*}(frq\_purchase{*}clc\_fill) + \beta_8{*}customerduration + \beta_9{*}(customerduration{*}clc\_fill) + \beta_{10}{*}age + \beta_{11}{*}gender \tag{6a}$$

$$log(spending) = \beta_0 + \beta_1{*}clc\_fill + \beta_2{*}recency\_N + \beta_3{*}(recency\_N{*}clc\_fill) + \beta_4{*}DM\_Frequency + \beta_5{*}(DM\_Frequency{*}clc\_fill) + \beta_6{*}frq\_purchase + \beta_7{*}(frq\_purchase{*}clc\_fill) + \beta_8{*}customerduration + \beta_9{*}(customerduration{*}clc\_fill) + \beta_{10}{*}age + \beta_{11}{*}gender + \epsilon \tag{6b}$$

Moreover, to further interpret the moderating effects, eight additional logistic regressions and eight linear regressions are constructed. These regressions are all similar to model 6 in the sense that it contains all variables, but in each model solely the low- or high-level outcomes of one of the moderating variables is considered. For instance, models 7 and 8 account for the moderating variable *recency_N*, where model 7 considers approximately the top 50% of values, whilst model 8 considers approximately the bottom 50% of values. For the other three moderating variables this is also the case. Details about the results of these regressions can be found in Table 10 - 17 in Part 2 of the Appendix.

Lastly, to test for an inverted U-shaped moderating effect or diminishing returns after a certain threshold of TDM frequency on the impact of TDM on purchase behavior, one more logistic and linear regression is designed. This model is similar to model 3, however, only the higher values are considered in this regression, to control for diminishing returns after a certain value. Similarly to the above models, the outcome of this regression is presented in Part 2 of the Appendix, in Table 18.

4.1 Regression Results

4.1.1 Logistic Regression Results

Table 3 and 4 provide an overview of the logistic regression results for model 1a-5a. All coefficients in the models are significant, except for the variable *customerduration* in model 6a. Regarding the R^2 of the models, purchase frequency offers the clearest interpretation of the variance of purchase incidence. However, all models have little explanatory power.

Table 3. Logistic Regression Results (Part 1) – Dependent Variable: purchase_incidence

Variables	Model 1a			Model 2a			Model 3a		
	Coefficient	SE	Odds Ratio	Coefficient	SE	Odds Ratio	Coefficient	SE	Odds Ratio
Intercept	-2.014***	0.033	0.133	-1.914***	0.039	0.148	-2.154***	0.034	0.116
clc_fill	0.613***	0.033	1.845	0.451***	0.052	1.570	1.027***	0.053	2.794
recency_N				-0.007***	0.001	0.993			
clc_fill * recency_N				0.015***	0.004	1.015			
DM_Frequency							2.193***	0.107	1.706
clc_fill * DM_Frequency							-4.839***	0.244	0.008
DM_Frequency^2							-1.654***	0.107	0.191
clc_fill * DM_Frequency^2							4.257***	0.222	70.601
age	-0.012***	0.001	0.988	-0.013***	0.001	0.987	-0.012***	0.001	0.988
gender (1 = male)	-0.142***	0.021	0.868	-0.141***	0.021	0.869	-0.136***	0.021	0.871
R^2	0.014			0.015			0.026		

*Note. *** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.10*

Table 4. Logistic Regression Results (Part 2) – Dependent Variable: purchase_incidence

Variables	Model 4a			Model 5a		
	Coefficient	SE	Odds Ratio	Coefficient	SE	Odds Ratio
Intercept	-3.997***	0.045	0.018	-1.985***	0.039	0.137
clc_fill	0.678***	0.057	1.970	0.338***	0.068	1.402
frq_purchase	0.425***	0.005	1.529			
clc_fill * frq_purchase	-0.041***	0.014	0.960			
customerduration				-0.001	0.001	0.999
clc_fill * customerduration				0.007***	0.001	1.007
age	0.002***	0.001	1.002	-0.013***	0.001	0.988
gender (1 = male)	-0.035	0.022	0.965	-0.141***	0.021	0.868
R^2	0.158			0.014		

*Note. *** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.10*

4.1.2 Linear Regression Results

Table 5 and 6 present the results of the first five linear regressions, where the quarterly spendings of a customer is the dependent variable. Again, almost all variables are significant. Furthermore, the R^2 of the models are valued at a low level. Based on this R^2, the models presented in the two tables below explain minority of the results of quarterly spending by a customer. Again, purchase frequency offers the clearest interpretation of the dependent variable.

Table 5. Linear Regression Results (Part 1) – Dependent Variable: spending_q

Variables	Model 1b		Model 2b		Model 3b	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Intercept	-1.604***	0.016	-1.555***	0.019	-1.663***	0.016
clc_fill	0.360***	0.018	0.275***	0.028	0.691***	0.034
recency_N			-0.003***	0.001		
clc_fill * recency_N			0.008	0.002		
DM_Frequency					1.080***	0.053
clc_fill * DM_Frequency					-3.367***	0.149
DM_Frequency^2					-0.808***	0.050
clc_fill * DM_Frequency^2					3.111***	0.139
age	-0.004***	0.000	-0.004***	0.000	-0.004***	0.000
gender (1 = male)	-0.058***	0.009	-0.057***	0.009	-0.055***	0.009
R^2	0.004		0.004		0.009	

*Note. *** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.10*

Table 6. Linear Regression Results (Part 2) – Dependent Variable: spending_q

Variables	Model 4b		Model 5b	
	Coefficient	SE	Coefficient	SE
Intercept	-2.389***	0.017	-1.615***	0.019
clc_fill	0.021	0.028	0.175***	0.038
frq_purchase	0.263***	0.003		
clc_fill * frq_purchase	0.109***	0.010		
customerduration			0.000	0.000
clc_fill * customerduration			0.005***	0.001
age	0.001***	0.000	-0.004***	0.000
gender (1 = male)	-0.007	0.009	-0.057***	0.009
R^2	0.070		0.004	

*Note. *** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.10*

4.1.3 Complete Model Results

In addition, two regressions were performed with all independent variables and control variables included. Model 6a is a logistic regression with *purchase_incidence* as dependent variable. Firstly, the R^2 of this model is larger than all other logistic models, being slightly larger than model 4a. Moreover, the signs and values are in general similar to the previous logistic models. The only variables that are not significant in this model is the interaction between *clc_fill* and *DM_Frequency* and *gender*.

Model 6b presents the linear regression which includes all independent and control variables. In this case, *spending_q* is the dependent variable. This model has a negative value for the TDM variable, whilst in model 1b this value was large and positive. This can potentially be explained by the moderating effects of the independent variables and the interactions, which are in general significant. Furthermore, the signs and values of the other independent variables are generally similar to the previous linear models.

Lastly, given that the interaction between *clc_fill* and *DM_Frequency* is insignificant in both models, other models that are specifically designed to measure this moderation effect (model 3, 9, 10, and 15) will be considered stronger.

Table 7. Logistic/ Linear Regression Results using all Independent and Control Variables

Variables	Model 6a			Model 6b	
	Coefficient	SE	Odds Ratio	Coefficient	SE
Intercept	-3.779***	0.057	0.023	-2.352***	0.023
clc_fill	0.237**	0.110	1.268	-0.119**	0.056
recency_N	-0.008***	0.001	0.992	-0.004***	0.001
clc_fill * recency_N	0.014***	0.004	1.014	0.006***	0.002
DM_Frequency	0.285***	0.033	1.330	0.095***	0.016
clc_fill * DM_Frequency	-0.131	0.097	0.877	-0.043	0.052
frq_purchase	0.423***	0.005	1.527	0.261***	0.003
clc_fill * frq_purchase	-0.043***	0.014	0.958	0.107***	0.010
customerduration	-0.004***	0.001	0.996	0.000	0.000
clc_fill * customerduration	0.006***	0.002	1.006	0.002**	0.001
age	0.002***	0.001	1.002	0.001**	0.000
gender (1 = male)	-0.034	0.022	0.967	-0.006	0.009
R^2	0.160			0.070	

*Note. *** significant at $p < 0.01$, ** significant at $p < 0.05$, * significant at $p < 0.10$*

4.2 Hypotheses Tests

4.2.1 Impact of Targeted Direct Mail

The first hypothesis states that TDM has a positive effect on purchase behavior. Looking at the values in model 1a and 1b, it can be stated that H1 is supported, as the values in the models are both significantly positive and relatively sizeable.

4.2.2 Moderating Effect of Targeted Direct Mail Communication History

To test for the moderating effect of direct mail history, H2 and H3 were stated. H2 is an ambiguous hypothesis as it consists of a hypothesis that expects a positive moderating effect of direct mail recency (H2a) and a hypothesis that expects a negative moderating effect of direct mail recency (H2b). To answer H2, model 6,7, and 8 will be conducted and model 2 will only be looked upon.

Firstly, model 2 indicates that there is a negative moderation between direct mail recency and the impact of TDM on purchase behavior. On the other hand, according to model 6a, the interaction term between direct mail recency and TDM is significantly positive. This means that the probability of purchase increases when the time since the last direct mail received is longer. This positive interaction between direct mail recency and TDM can also be found in model 6b. This indicates likewise that the spendings increase when the time since the last direct mail is larger.

Furthermore, when investigating model 7 and 8, a relatively large negative and significant interaction term can be found in model 8b. This could perhaps indicate that in the first few quarters since the last direct mail (first 10 quarters in this case), customers are less willing to spend money when targeted with a TDM.

As both model 6a and 6b provide evidence that higher direct mail recency values result in an increased positive effect of TDM on purchase behavior and model 8b advocates for more patience as well, H2a is supported H2b is rejected.

H3 states that the effect of TDM on purchase behavior is larger for customers that receive TDMs on a more frequent basis. Model 3 provides an estimation that this is not the case, as both model 3a and 3b present a large and significant negative value.

Moreover, as mentioned earlier, model 6 does not provide a significant value for the moderating effect. Therefore, the models 9 and 10 will be analyzed to construct an answer to H3. The negative and significant interaction effect between TDM and TDM frequency in model 10a and 10b indicates that receiving TDMs on a repeating basis decreases the effect of a TDM on purchase probability and spending for customers who do not receive TDMs on a frequent basis. However, when analyzing model 9a and 9b a large and significant positive value is found. This means that customers who frequently receive TDMs increase their purchases and amount spent when targeted with a new TDM.

Given that both models promote for targeting frequent TDM receivers, and the effect size is relatively large and significant in both instances, H3 is supported.

Additionally, it is investigated whether there may be evidence of an inverted U-shaped relationship between the moderating effect of TDM frequency on the impact of TDM on purchase behavior. Therefore, the interaction term between TDM and the squared variable of *DM_Frequency* is presented in model 3a and 3b, and the models 15a and 15b are created (presented in Table 18 in the Appendix). The models 15a and 15b are similar to models 3a and 3b, however, the values of all *DM_Frequency* related variables in models 15a and 15b correspond to only the observations where a frequent number of TDMs were received. In these models, 6,9% of all observations and 52,24% of all instances where a customer received a TDM in the last year are used. As a result, due to the values of the independent variables in the models 15a and 15b being insignificant, no estimation can be drawn on a potential inverted U-shaped relationship based on these models.

However, the findings in model 9 and 10 mentioned above potentially reveal there is an U-shaped relationship, as the moderating effect of TDM frequency in these models is negative for infrequent receivers and positive for frequent receivers.

4.2.3 Moderating Effect of Customer Loyalty

To analyze the moderating effect of customer loyalty, which purchase frequency and relationship duration, H4 and H5 were constructed. To test these hypotheses, model 6, 11, 12, 13, and 14 will be investigated.

H4 suggests that customers who buy on a more frequent basis are more likely to express positive purchase behavior in the future as well when receiving a TDM. To answer this hypothesis the models 4a and 4b will also be observed.

Model 4 indicates that purchase probability decreases but purchase spending increases when a frequent buyer receives a TDM. Furthermore, in model 6a a significant and negative interaction effect can be found between purchase frequency and TDM. This indicates that customers that buy more frequently are less likely to make a purchase when targeted with a TDM. Regarding model 6b there is an adversative result, as the interaction between purchase frequency and TDM seem to have a significantly positive effect on the spending amount. Overall, the two models in model 6 contradict each other and models 11 and 12 do not provide any additional relevant findings.

Given that the positive value of the interaction term on purchase spending in model 6b outweighs the negative value of the interaction term on purchase probability in model 6a, H4 is supported. However, the conclusion will be drawn that targeting customers who frequently make a purchase with a TDM decreases the purchase probability but increases the amount spent.

Lastly, H5 illustrates that the effect of TDM on purchase behavior is larger for customers who have a longer relationship history with the company. Model 5 suggests that this is the case for both purchase probability and purchase spending.

To precisely answer this hypothesis, model 6a and 6b will firstly be considered. When investigating model 6a, a significant and positive interaction effect between relationship duration and TDM is presented. This is also evident in model 6b where another positive interaction effect is found. Similarly, models 13 and 14 provide evidence for targeting customers who have made a purchase at the firm more time ago with TDM. In model 13, where only customers are considered who have bought from the company nine years ago or less, the interaction effect is negative in both model 13a and 13b. On the other hand, in models 14a and 14b where only customers are considered that have made their initial purchase more than nine years ago, a positive interaction term is found. This further demonstrates that customers who have been with the company for longer time, improve their purchase incidences and spending when receiving a TDM.

Despite the relatively little values of the interaction effects, due to all three models suggesting a positive moderating effect of relationship duration on the impact of TDM on purchase behavior, H5 is supported.

4.3 Effect of Control Variables

The control variable *age* is statistically significant in all the first six logistic and linear models. However, the sign differs per model, so an effect of age on purchase behavior is evident, but the sign of the effect cannot be determined. On the other hand, gender is statistically insignificant in several models, including the complete model 6. Therefore, no conclusion is drawn on the effect of gender.

5. Conclusion

5.1 Discussion

As noted in the introduction, companies are increasingly favoring TDM over mass direct mail campaigns, yet research on TDM is limited. This paper is among the first to empirically explore the effects of TDM with the use of rich consumer-level data, particularly in a physical context rather than an online one. Furthermore, this study lays the groundwork to support previous findings which were based on mass direct mail or other communication methods. In this chapter, it is demonstrated how past findings are applicable to the newly developed TDM approach.

What can be derived from prior research and this study is that TDM cannot be examined in isolation. Consumers' responses vary based on the recency and frequency of TDM interactions. Thus, this study highlights the need to investigate how the impact of TDM is influenced by the recency and frequency of direct mail, and specifically how this impacts the outcome of purchasing behavior (Neslin et al., 2012).

Additionally, customer characteristics also play a significant role in moderating the effect of TDM on purchasing behavior. Therefore, this research has examined how various customer traits affect this impact and has responded to the call to incorporate these moderating factors into the model (Rust & Verhoef, 2005; Gázquez-Abad et al., 2011). As a result, this study provides key insights into how TDM affects purchase behavior and how this effect is moderated by multiple factors.

Moreover, by utilizing empirical panel data from customers, another academic gap is addressed, which calls for data on customers who began their relationship with the company at different time points and how this influences the effect of direct marketing communication on purchase behavior over time (Kim & Kumar, 2018).

The relevant findings from this paper will be discussed below. Firstly, a summary of the hypotheses and the outcomes is presented in Table 8 below.

Table 8. Hypotheses and Corresponding Results

Variable	Hypothesis	Estimated Effect	Result
clc_fill	H1	Positive	Supported
recency_N	H2a	Positive	Supported
recency_N	H2b	Negative	Rejected
DM_Frequency	H3	Positive	Supported
frq_purchase	H4	Positive	Supported
customerduration	H5	Positive	Supported

Regarding H1, previous research has indicated that TDM exerts a positive influence on purchasing behavior. For instance, Naik and Piersma (2002) revealed that direct mail campaigns can enhance consumer behavior by fostering favorable attitudes towards the sender, thereby elevating the probability of a purchase. Furthermore, Sahni et al. (2019), in their investigation of the impact of targeted advertisements in an online context, concluded that sending targeted advertisements boosts the likelihood of improved engagement. These indications are corroborated by the empirical findings of this study, which provide support for the positive effect of TDM on purchase behavior.

Secondly, empirical evidence from this study confidently asserts that higher values of direct mail recency increase the effect of TDM on both the incidence and the spending of purchases. This aligns with the findings of Neslin et al. (2012), who recommend a patient approach before dispatching additional direct mails. Thus, this research supports the saturation effect, indicating that when subsequent direct mails are sent and recency is maintained low, these additional mails are likely to be disregarded. This study also substantiates the conclusions of Van Diepen et al. (2009), which advises against dispatching direct mails in short intervals to avoid customer indifference. It is, therefore, more prudent to wait for an extended period before re-engaging the customer when they are more receptive.

Thirdly, this study suggests that frequent TDM dispatches increase the chances of purchases and the amount spent by customers. Schumann et al. (1990) support this idea, indicating that frequent communication can strengthen the relationship between a company and its customers. This aligns with Vafainia et al. (2019), who found that customers receiving frequent TDMs are more likely to make purchases when targeted again. Moreover, this conclusion draws evidence for the finding that regular advertising communication keeps the company in the customer's mind and reduces the chances of the customer forgetting about the company over time (Naik & Piersma, 2002; Sheth & Parvatlyar, 1995).

Furthermore, this study empirically demonstrates that frequent buyers are less likely to make a purchase but more likely to spend additional money when targeted with TDM. This aligns with the conclusion of Gázquez-Abad et al. (2011), who note that the frequency of past purchases affects the effectiveness of direct mailings on consumer purchasing behavior. The decreasing likelihood of making a purchase for a customer when receiving a TDM corresponds to the finding of Gönül and Shi (1998), who states it is optimal to send mails to customers with low to medium purchase frequency because they are still in the trial phase. Infrequent buyers have a relatively high chance of making additional purchases (Gönül and Shi, 1998). On the other hand, frequent buyers are already loyal and likely to continue buying without extra promotional efforts, making additional mailing campaigns unnecessary (Gönül and Shi, 1998). This idea is supported by Gázquez-Abad et al. (2011), who conclude that customers who have made one or two purchases at a retailer are prime candidates for promotional mailings, rather than those who buy more frequently.

Lastly, various studies suggest that the duration of the relationship moderates the effect of TDM on purchase behavior, such as the study by Bult et al. (1997), which concludes that the duration of the relationship significantly influences future consumer behavior. Similarly, Verhoef et al. (2001) estimate that many aspects of purchase behavior improve with relationship duration. According to Oskamp and Schultz (2005) and a likelihood model proposed by Petty (1986), engaged customers are more likely to respond to promotional activities and advertising media. Above all, a study examining the moderating effect of relationship strength on customer response to direct mailings indicates that relational strength indeed influences the impact of direct mailings on consumers' purchase behavior (Gázquez-Abad et al., 2011). Similarly, Vafainia et al. (2019) established that the effect of direct mail on purchase incidence increases with the duration of the relationship. This research provides further evidence for the above findings, as the regression models suggest that customers targeted with TDM are more likely to purchase and spend more when they have a longer relationship with the company. However, it can be concluded that this effect is minimal. Rust and Verhoef (2005) further support this, asserting that the effect of relationship duration on the response to direct mails is essentially negligible.

5.2 Managerial Implications

This research provides empirical evidence that is beneficial for retailers. Ultimately, it demonstrates that targeting customers through TDM especially increases the likelihood of purchase and the spending amount. The findings indicate that TDM is more effective than mass direct mail campaigns, suggesting that retailers monitor previous customer interactions and behaviors to optimize their TDM efforts effectively.

Additionally, there is evidence of variability in customer responses to TDM, further emphasizing the importance of tracking customer behavior and interactions. The impact of TDM on purchasing behavior varies significantly based on previous communications and customer characteristics. To maximize the effectiveness of TDM communications, retailers could consider these factors when crafting marketing strategies.

Firstly, regarding direct mail communication history, this study suggests that targeting customers who have not received a non-personalized direct mail or customers who have frequently received TDMs in the past year significantly increases both purchase likelihood and spending.

Secondly, customer loyalty characteristics also have a moderating effect on the impact of TDM on purchase behavior. For instance, frequent buyers are less likely to make a purchase when receiving a TDM. On the other hand, when they are targeted with a TDM and they do make a purchase, the amount spent increases compared to when they do not receive a TDM. This finding poses a challenge for firms and their managers, as there is a consideration whether to prioritize sales or profit when targeting consumers based on their purchase frequency. Furthermore, this paper concludes that consumers who have experienced a longer history with the company increase their purchases and amount spent when targeted with a TDM.

Overall, the results underscore the importance of tracking customers beyond basic demographic information (age and gender), focusing particularly on communication and relationship history. This enables retailers to effectively manage their TDM strategies, ultimately enhancing purchase probability and revenue. This approach underscores the importance of tracking metrics and key performance indicators in a well-designed robust Customer Relationship Management system.

5.3 Limitations and Future Research

Given that this study is analyzed using data from a large cohort of optical retailers based in the Netherlands, it is plausible that the findings may lack applicability to other sectors or regions. As indicated by Gönül and Shi (1998), variations in outcomes could emerge when considering durables with high purchase frequencies or low consumer involvement. Consequently, replicating this study in diverse contexts, whether across different consumer durable industries or in other geographical areas, would be informative.

Future research could also benefit from examining additional characteristics of TDM, such as the impact of varying content decisions. For example, how consumer response differs when the content of the TDM is differentiated and monetary incentives or discount coupons are included, for example.

Another constraint is that the consumer response to TDM is measured solely in terms of purchase incidence and expenditure, thus neglecting a comprehensive behavioral response. Exploring other behavioral variables, or perhaps attitudinal variables like feelings towards the company, may enrich literature regarding TDM.

A further limitation pertains to the temporal dimension of consumer response. It is conceivable that there is a delay between the receipt of TDM and the resultant consumer action, implying that purchases could occur not just immediately but also in subsequent periods following the receipt of TDM. Future researchers might consider carrying out simulations to assess potential saturation or carryover effects.

An imbalance in the dataset represents another limitation. The final sample includes only 7% of observations where *purchase_incidence* = 1, leading to a significant imbalance and potential bias favoring the overrepresented class. This imbalance aligns with the finding in Chapter 3.6.3, where a nonnormal distribution was detected. To mitigate this issue, future studies could consider employing alternative distributions of dependent variables when modeling. This problem stems from the nature of the data, which was not collected with the intent of theoretical testing. Consequently, all observations, including consumer responses and the retailers' decisions to participate in the TDM program and the timing of TDM dispatch, reflect natural variation. More valid results could be achieved through randomized field experiments, which would allow for the testing of specific TDM-related interventions and the disentanglement of causal effects.

Lastly, variables like *customerduration* and *frq_purchase* were constant throughout the panel dataset for all customers. Perhaps having a more dynamic dataset where the number representing these variables increase during the observation window could result in more precise and representative results.

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Appendix

1. **Model Formulas**

Table 9. Reminding Other Model Equations

Model	Formulas
1a	$P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}}$, where $X = \beta_0 + \beta_1 * clc\_fill + \beta_2 * age + \beta_3 * gender$
1b	$log(spending) = \beta_0 + \beta_1 * clc\_fill + \beta_2 * age + \beta_3 * gender + \epsilon$
2a	$P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}}$, where $X = \beta_0 + \beta_1 * clc\_fill + \beta_2 * recency\_N + \beta_3 * (recency\_N * clc\_fill) + \beta_4 * age + \beta_5 * gender$
2b	$log(spending) = \beta_0 + \beta_1 * clc\_fill + \beta_2 * recency\_N + \beta_3 * (recency\_N * clc\_fill) + \beta_4 * age + \beta_5 * gender + \epsilon$
3a	$P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}}$, where $X = \beta_0 + \beta_1 * clc\_fill + \beta_2 * DM\_Frequency + \beta_3 * (DM\_Frequency * clc\_fill) + \beta_4 * age + \beta_5 * gender$
3b	$log(spending) = \beta_0 + \beta_1 * clc\_fill + \beta_2 * DM\_Frequency + \beta_3 * (DM\_Frequency * clc\_fill) + \beta_4 * age + \beta_5 * gender + \epsilon$
4a	$P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}}$, where $X = \beta_0 + \beta_1 * clc\_fill + \beta_2 * frq\_purchase + \beta_3 * (frq\_purchase * clc\_fill) + \beta_4 * age + \beta_5 * gender$
4b	$log(spending) = \beta_0 + \beta_1 * clc\_fill) + \beta_2 * frq\_purchase + \beta_3 * (frq\_purchase * clc\_fill) + \beta_4 * age + \beta_5 * gender + \epsilon$
5a	$P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}}$, where $X = \beta_0 + \beta_1 * clc\_fill + \beta_2 * customerduration + \beta_3 * (customerduration * clc\_fill) + \beta_4 * age + \beta_5 * gender$
5b	$log(spending) = \beta_0 + \beta_1 * clc\_fill + \beta_2 * customerduration + \beta_3 * (customerduration * clc\_fill) + \beta_4 * age + \beta_5 * gender + \epsilon$

7a $P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}}$, where $X = \beta_0 + \beta_1$*clc_fill + β_2*recency_N + β_3*(recency_N*clc_fill) + β_4*DM_Frequency + β_5*(DM_Frequency*clc_fill) + β_6*frq_purchase + β_7* (frq_purchase*clc_fill) + β_8*customerduration + β_9* (customerduration*clc_fill) + β_{10}*age + β_{11}*gender & recency_N ≥ 10

7b log(spending) = $\beta_0 + \beta_1$*clc_fill + β_2*recency_N + β_3* (recency_N*clc_fill) + β_4*DM_Frequency + β_5* (DM_Frequency*clc_fill) + β_6*frq_purchase + β_7*(frq_purchase*clc_fill) + β_8*customerduration + β_9*(customerduration*clc_fill) + β_{10}*age + β_{11}*gender + ϵ & recency_N ≥10

8a $P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}}$, where $X = \beta_0 + \beta_1$*clc_fill + β_2*recency_N + β_3*(recency_N*clc_fill) + β_4*DM_Frequency + β_5*(DM_Frequency*clc_fill) + β_6*frq_purchase + β_7* (frq_purchase*clc_fill) + β_8*customerduration + β_9* (customerduration*clc_fill) + β_{10}*age + β_{11}*gender & recency_N < 9

8b log(spending) = $\beta_0 + \beta_1$*clc_fill + β_2*recency_N + β_3* (recency_N*clc_fill) + β_4*DM_Frequency + β_5* (DM_Frequency*clc_fill) + β_6*frq_purchase + β_7*(frq_purchase*clc_fill) + β_8*customerduration + β_9*(customerduration*clc_fill) + β_{10}*age + β_{11}*gender + ϵ & recency_N < 9

9a $P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}}$, where $X = \beta_0 + \beta_1$*clc_fill + β_2*recency_N + β_3*(recency_N*clc_fill) + β_4*DM_Frequency + β_5*(DM_Frequency*clc_fill) + β_6*frq_purchase + β_7* (frq_purchase*clc_fill) + β_8*customerduration + β_9* (customerduration*clc_fill) + β_{10}*age + β_{11}*gender & DM_Frequency ≥ 0.75

9b log(spending) = $\beta_0 + \beta_1$*clc_fill + β_2*recency_N + β_3* (recency_N*clc_fill) + β_4*DM_Frequency + β_5* (DM_Frequency*clc_fill) + β_6*frq_purchase + β_7*(frq_purchase*clc_fill) + β_8*customerduration + β_9*(customerduration*clc_fill) + β_{10}*age + β_{11}*gender + ϵ & DM_Frequency≥ 0.75

10a $P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}}$, where $X = \beta_0 + \beta_1 * clc\_fill + \beta_2 * recency\_N + \beta_3 * (recency\_N * clc\_fill) + \beta_4 * DM\_Frequency + \beta_5 * (DM\_Frequency * clc\_fill) + \beta_6 * frq\_purchase + \beta_7 * (frq\_purchase * clc\_fill) + \beta_8 * customerduration + \beta_9 * (customerduration * clc\_fill) + \beta_{10} * age + \beta_{11} * gender$ & $DM\_Frequency < 0.75$

10b $log(spending) = \beta_0 + \beta_1 * clc\_fill + \beta_2 * recency\_N + \beta_3 * (recency\_N * clc\_fill) + \beta_4 * DM\_Frequency + \beta_5 * (DM\_Frequency * clc\_fill) + \beta_6 * frq\_purchase + \beta_7 * (frq\_purchase * clc\_fill) + \beta_8 * customerduration + \beta_9 * (customerduration * clc\_fill) + \beta_{10} * age + \beta_{11} * gender + \epsilon$ & $DM\_Frequency < 0.75$

11a $P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}}$, where $X = \beta_0 + \beta_1 * clc\_fill + \beta_2 * recency\_N + \beta_3 * (recency\_N * clc\_fill) + \beta_4 * DM\_Frequency + \beta_5 * (DM\_Frequency * clc\_fill) + \beta_6 * frq\_purchase + \beta_7 * (frq\_purchase * clc\_fill) + \beta_8 * customerduration + \beta_9 * (customerduration * clc\_fill) + \beta_{10} * age + \beta_{11} * gender$ & $frq\_purchase \geq 2$

11b $log(spending) = \beta_0 + \beta_1 * clc\_fill + \beta_2 * recency\_N + \beta_3 * (recency\_N * clc\_fill) + \beta_4 * DM\_Frequency + \beta_5 * (DM\_Frequency * clc\_fill) + \beta_6 * frq\_purchase + \beta_7 * (frq\_purchase * clc\_fill) + \beta_8 * customerduration + \beta_9 * (customerduration * clc\_fill) + \beta_{10} * age + \beta_{11} * gender + \epsilon$
& $frq\_purchase \geq 2$

12a $P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}}$, where $X = \beta_0 + \beta_1 * clc\_fill + \beta_2 * recency\_N + \beta_3 * (recency\_N * clc\_fill) + \beta_4 * DM\_Frequency + \beta_5 * (DM\_Frequency * clc\_fill) + \beta_6 * frq\_purchase + \beta_7 * (frq\_purchase * clc\_fill) + \beta_8 * customerduration + \beta_9 * (customerduration * clc\_fill) + \beta_{10} * age + \beta_{11} * gender$ & $frq\_purchase < 2$

12b $log(spending) = \beta_0 + \beta_1 * clc\_fill + \beta_2 * recency\_N + \beta_3 * (recency\_N * clc\_fill) + \beta_4 * DM\_Frequency + \beta_5 * (DM\_Frequency * clc\_fill) + \beta_6 * frq\_purchase + \beta_7 * (frq\_purchase * clc\_fill) + \beta_8 * customerduration + \beta_9 * (customerduration * clc\_fill) + \beta_{10} * age + \beta_{11} * gender + \epsilon$
& $frq\_purchase < 2$

13a $P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}}$, *where* $X = \beta_0 + \beta_1 * clc\_fill + \beta_2 * recency\_N + \beta_3 * (recency\_N * clc\_fill) + \beta_4 * DM\_Frequency + \beta_5 * (DM\_Frequency * clc\_fill) + \beta_6 * frq\_purchase + \beta_7 * (frq\_purchase * clc\_fill) + \beta_8 * customerduration + \beta_9 * (customerduration * clc\_fill) + \beta_{10} * age + \beta_{11} * gender$ & $customerduratation \geq 37$

13b $log(spending) = \beta_0 + \beta_1 * clc\_fill + \beta_2 * recency\_N + \beta_3 * (recency\_N * clc\_fill) + \beta_4 * DM\_Frequency + \beta_5 * (DM\_Frequency * clc\_fill) + \beta_6 * frq\_purchase + \beta_7 * (frq\_purchase * clc\_fill) + \beta_8 * customerduration + \beta_9 * (customerduration * clc\_fill) + \beta_{10} * age + \beta_{11} * gender + \epsilon$ & $customerduratation \geq 37$

14a $P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}}$, *where* $X = \beta_0 + \beta_1 * clc\_fill + \beta_2 * recency\_N + \beta_3 * (recency\_N * clc\_fill) + \beta_4 * DM\_Frequency + \beta_5 * (DM\_Frequency * clc\_fill) + \beta_6 * frq\_purchase + \beta_7 * (frq\_purchase * clc\_fill) + \beta_8 * customerduration + \beta_9 * (customerduration * clc\_fill) + \beta_{10} * age + \beta_{11} * gender$ & $customerduration < 37$

14b $log(spending) = \beta_0 + \beta_1 * clc\_fill + \beta_2 * recency\_N + \beta_3 * (recency\_N * clc\_fill) + \beta_4 * DM\_Frequency + \beta_5 * (DM\_Frequency * clc\_fill) + \beta_6 * frq\_purchase + \beta_7 * (frq\_purchase * clc\_fill) + \beta_8 * customerduration + \beta_9 * (customerduration * clc\_fill) + \beta_{10} * age + \beta_{11} * gender + \epsilon$ & $customerduration < 37$

15a $P(purchase\_incidence = 1 \mid X) = \frac{1}{1+e^{-X}}$, *where* $X = \beta_0 + \beta_1 * clc\_fill + \beta_2 * DM\_Frequency + \beta_3 * (DM\_Frequency * clc\_fill) + \beta_4 * DM\_Frequency^2 + \beta_5 * (DM\_Frequency^2 * clc\_fill) + \beta_6 * age + \beta_7 * gender$ & $DM\_Frequency \geq 0.75$

15b $log(spending) = \beta_0 + \beta_1 * clc\_fill + \beta_2 * DM\_Frequency + \beta_3 * (DM\_Frequency * clc\_fill) + \beta_4 * DM\_Frequency^2 + \beta_5 * (DM\_Frequency^2 * clc\_fill) + \beta_6 * age + \beta_7 * gender + \epsilon$ & $DM\_Frequency \geq 0.75$

2. Additional Regression Results

Table 10. Logistic/ Linear Regression Results using all Independent and Control Variables

Variables	Model 7a			Model 7b	
	Coefficient	SE	Odds Ratio	Coefficient	SE
Intercept	-3.228***	0.096	0.036	-2.240***	0.038
clc_fill	0.379*	0.225	1.461	0.032	0.125
recency_N	-0.024***	0.003	0.976	-0.008***	0.001
clc_fill * recency_N	0.002	0.009	1.002	-0.003	0.005
DM_Frequency	0.382***	0.048	1.465	0.151***	0.024
clc_fill * DM_Frequency	0.180	0.138	1.197	0.173**	0.079
frq_purchase	0.423***	0.006	1.526	0.254***	0.004
clc_fill * frq_purchase	-0.073***	0.020	0.930	0.091***	0.014
customerduration	-0.009***	0.001	0.991	-0.001*	0.000
clc_fill * customerduration	0.008***	0.002	1.009	0.001	0.001
age	0.003***	0.001	1.003	0.001***	0.006
gender (1 = male)	-0.049	0.030	0.952	-0.009	0.012
R^2	0.166			0.070	

*Note. *** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.10*
Note. Only observations where recency_N is valued 10 or higher are used

Table 11. Logistic/ Linear Regression Results using all Independent and Control Variables

Variables	Model 8a			Model 8b	
	Coefficient	SE	Odds Ratio	Coefficient	SE
Intercept	-3.936***	0.083	0.020	-2.372***	0.033
clc_fill	0.421***	0.155	1.523	-0.001	0.076
recency_N	-0.002	0.006	0.998	-0.001	0.003
clc_fill * recency_N	-0.034*	0.020	0.966	-0.034***	0.010
DM_Frequency	0.217***	0.047	1.242	0.058***	0.021
clc_fill * DM_Frequency	-0.453***	0.137	0.636	-0.210***	0.069
frq_purchase	0.425***	0.007	1.529	0.268***	0.004
clc_fill * frq_purchase	0.003	0.022	1.003	0.130***	0.015
customerduration	0.000	0.001	1.000	0.001**	0.000
clc_fill * customerduration	0.006***	0.002	1.006	0.002**	0.001
age	0.001	0.001	1.001	0.000	0.000
gender (1 = male)	-0.012	0.031	0.988	-0.002	0.013
R^2	0.158			0.071	

*Note. *** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.10*
Note. Only observations where recency_N is less than 10 are used

Table 12. Logistic/ Linear Regression Results using all Independent and Control Variables

Variables	Model 9a			Model 9b	
	Coefficient	SE	Odds Ratio	Coefficient	SE
Intercept	-3.221***	0.221	0.040	-2.147***	0.117
clc_fill	-2.667***	0.424	0.069	-2.645**	0.291
recency_N	-0.002	0.004	0.998	-0.003	0.002
clc_fill * recency_N	0.041***	0.008	1.042	0.026***	0.005
DM_Frequency	-0.458***	0.162	0.632	-0.255***	0.086
clc_fill * DM_Frequency	3.107***	0.386	22.353	2.720***	0.297
frq_purchase	0.415***	0.014	1.515	0.340***	0.010
clc_fill * frq_purchase	-0.018	0.014	0.982	0.089***	0.025
customerduration	0.004***	0.002	1.004	0.002**	0.001
clc_fill * customerduration	0.000	0.003	1.000	0.002	0.002
age	-0.003	0.002	0.997	-0.002*	0.001
gender (1 = male)	-0.106*	0.063	0.899	-0.047	0.034
R^2	0.199			0.108	

*Note. *** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.10*
Note. Only observations where DM_Frequency is valued 0.75 or higher are used

Table 13. Logistic/ Linear Regression Results using all Independent and Control Variables

Variables	Model 10a			Model 10b	
	Coefficient	SE	Odds Ratio	Coefficient	SE
Intercept	-3.773***	0.057	0.023	-2.354***	0.023
clc_fill	0.502**	0.101	1.652	0.054	0.051
recency_N	-0.008***	0.001	0.992	-0.004***	0.001
clc_fill * recency_N	0.016***	0.004	1.016	0.008***	0.002
DM_Frequency	0.919***	0.072	2.508	0.436***	0.037
clc_fill * DM_Frequency	-2.116***	0.161	0.120	-1.205***	0.081
frq_purchase	0.422***	0.005	1.525	0.260***	0.003
clc_fill * frq_purchase	-0.044***	0.015	0.957	0.106***	0.010
customerduration	-0.004***	0.001	0.996	0.000	0.000
clc_fill * customerduration	0.007***	0.002	1.007	0.002**	0.001
age	0.002***	0.001	1.002	0.001**	0.000
gender (1 = male)	-0.034	0.022	0.966	-0.006	0.009
R^2	0.162			0.071	

*Note. *** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.10*
Note. Only observations where DM_Frequency is less than 0.75 are used

Table 14. Logistic/ Linear Regression Results using all Independent and Control Variables

Variables	Model 11a			Model 11b	
	Coefficient	SE	Odds Ratio	Coefficient	SE
Intercept	-2.655***	0.057	0.023	-2.144***	0.049
clc_fill	0.123	0.125	1.131	-0.053	0.107
recency_N	-0.009***	0.002	0.991	-0.007***	0.001
clc_fill * recency_N	0.008*	0.005	1.008	0.001	0.004
DM_Frequency	0.246***	0.035	1.279	0.198***	0.028
clc_fill * DM_Frequency	-0.012	0.103	0.988	-0.044	0.091
frq_purchase	0.286***	0.006	1.331	0.258***	0.005
clc_fill * frq_purchase	-0.011	0.017	0.989	0.084***	0.018
customerduration	-0.006***	0.001	0.994	-0.003***	0.001
clc_fill * customerduration	0.005***	0.002	1.005	0.003**	0.001
age	-0.002***	0.001	0.998	0.000	0.001
gender (1 = male)	-0.023	0.023	0.977	-0.005	0.018
R^2	0.082			0.039	

*Note. *** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.10*
Note. Only observations where frq_purchase is valued 2 or higher are used

Table 15. Logistic/ Linear Regression Results using all Independent and Control Variables

Variables	Model 12a			Model 12b	
	Coefficient	SE	Odds Ratio	Coefficient	SE
Intercept	-22.014	226.660	0.023	-2.352***	0.017
clc_fill	-0.094	1945.993	0.910	-0.114*	0.063
recency_N	-0.011***	0.004	0.989	-0.001**	0.000
clc_fill * recency_N	0.055***	0.010	1.057	0.013***	0.002
DM_Frequency	0.009	0.097	1.009	0.004	0.013
clc_fill * DM_Frequency	-0.374	0.279	0.688	-0.071	0.044
frq_purchase	17.503	226.660	39935055.5	0.205***	0.008
clc_fill * frq_purchase	0.1371	1945.993	1.147	0.045	0.053
customerduration	0.016***	0.001	1.016	0.003***	0.000
clc_fill * customerduration	-0.002	0.003	0.998	0.002**	0.001
age	0.003	0.002	1.003	0.001***	0.000
gender (1 = male)	-0.053	0.058	0.948	-0.007	0.007
R^2	0.109			0.012	

*Note. *** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.10*
Note. Only observations where frq_purchase is less than 2 are used

Table 16. Logistic/ Linear Regression Results using all Independent and Control Variables

Variables	Model 13a			Model 13b	
	Coefficient	SE	Odds Ratio	Coefficient	SE
Intercept	-4.028***	0.089	0.018	-2.269***	0.034
clc_fill	0.435**	0.190	1.546	-0.172*	0.099
recency_N	-0.014***	0.002	0.986	-0.004***	0.001
clc_fill * recency_N	0.011*	0.006	1.011	-0.001	0.004
DM_Frequency	0.687***	0.046	1.988	0.356***	0.025
clc_fill * DM_Frequency	-0.537***	0.139	0.585	-0.254***	0.081
frq_purchase	0.400***	0.006	1.493	0.232***	0.003
clc_fill * frq_purchase	-0.061***	0.021	0.940	0.091***	0.014
customerduration	0.000	0.001	1.000	-0.001**	0.000
clc_fill * customerduration	0.005**	0.002	1.005	0.005***	0.001
age	0.004***	0.001	1.004	0.001**	0.000
gender (1 = male)	-0.057*	0.031	0.945	-0.003	0.013
R^2	0.169			0.071	

*Note. *** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.10*
Note. Only observations where customerduration is valued 37 or higher are used

Table 17. Logistic/ Linear Regression Results using all Independent and Control Variables

Variables	Model 14a			Model 14b	
	Coefficient	SE	Odds Ratio	Coefficient	SE
Intercept	-2.892***	0.103	0.055	-2.129***	0.043
clc_fill	0.586**	0.268	1.797	0.368***	0.135
recency_N	-0.016***	0.002	0.984	-0.006***	0.001
clc_fill * recency_N	0.013**	0.006	1.013	0.002	0.003
DM_Frequency	-0.239***	0.052	0.787	-0.111***	0.021
clc_fill * DM_Frequency	0.414***	0.139	1.513	0.134*	0.069
frq_purchase	0.464***	0.007	1.590	0.302***	0.004
clc_fill * frq_purchase	0.034	0.023	1.035	0.149***	0.015
customerduration	-0.031***	0.003	0.969	-0.008***	0.001
clc_fill * customerduration	-0.022**	0.009	0.978	-0.021***	0.004
age	0.001	0.001	1.001	0.000	0.000
gender (1 = male)	0.020	0.031	1.020	-0.001	0.013
R^2	0.165			0.075	

*Note. *** significant at $p < 0.01$, ** significant at $p < 0.05$, * significant at $p < 0.10$*
Note. Only observations where customerduration is less than 37 are used

Table 18. Logistic/ Linear Regression Results) – Investigation of Inverted U-Shaped moderating effect of direct mail frequency

	Model 15a			Model 15b	
	Coefficient	SE	Odds Ratio	Coefficient	SE
Intercept	-4.605***	1.562	0.010	-1.383***	0.342
clc_fill	2.388	1.687	10.892	1.206	1.297
DM_Frequency	1.529	1.267	4.616	0.654	0.651
clc_fill * DM_Frequency	2.286	3.124	9.837	-4.553*	2.455
DM_Frequency^2	-0.919	0.610	0.399	-0.414	0.305
clc_fill * DM_Frequency^2	0.749	1.402	2.116	3.807***	1.130
age	-0.018***	0.002	0.982	-0.009***	0.001
gender (1 = male)	0.239***	0.059	1.270	-0.147***	0.035
R^2	0.042			0.019	

*Note. *** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.10*
Note. Only observations where DM_Frequency is valued 0.75 or higher are used