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Factors influencing coupon redemption in direct marketing campaigns in the South African retail market

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DECLARATION

I, Reagan Wonder Dlamini, declare that this research article is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration in the Graduate School of Business Administration, University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Reagan Wonder Dlamini

Signed at Helderwyk Estate, Brakpan

On the 14 day of February 2023.

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ABSTRACT

Coupons are discounts offered by businesses to drive consumers to buy specific products or services. Companies continue to invest in coupons as a marketing tool however, the redemption of these coupons remain extremely low at around 2% mainly due to little being known about the factors that influence coupon redemption. This study focuses on identifying factors influencing coupon redemption within the South African retail industry. Secondary data was collected from one of the South African retail companies. The data consisted of consumers that the retailer had targeted with a coupon campaign during the period June 2020 to June 2021. A Quantitative method was used where a set of independent variables from demographics, consumer behaviour and coupon design were identified and analysed to understand their influence on coupon redemption. The study finds that factors such as offering coupons that are redeemable in a wider range of products, targeting consumers that have shown previous redemption behaviour and offering a deeper discount increases coupon redemption. While, offering coupons on a product where a consumer has never spent or has low spending behaviour, framing coupons in percentages as well as sending more coupons to a consumer at the same time decreases coupon redemption.

Keywords: Coupons, redemption, consumers, retail

1. INTRODUCTION

1.1 Background

Marketing is a key strategic function in business which plays the role of letting customers know about products and services offered by a company (Moorman & Rust,1999). It helps grow company sales as customers get to be informed of the company's product offering through the marketing efforts (Nayal & Panday, 2020). Over many decades now companies have used and continues to use Coupons as one of their key marketing promotion tools (Reibstein & Traver, 1982; Clark et al., 2013; Nayal & Panday, 2020; Li et al., 2020).

Coupons are defined differently in differing context. In the marketing context, coupons are defined as a form of discount that retailers offer customers in certain products and services (Borrego-Jaraba et al.,2013). Retailers issue coupons to consumers to offer them a reduced price on certain products and services from the retailer (Išoraitė, 2015) and the customer must present the coupon together with payment to redeem the coupon. In a similar vein, vouchers are like coupons in that they also offer customers access to products and services at a reduced price (Kamdar,2019). However, vouchers differ in that they can also be exchanged for products and services without customer paying anything (van Zyl, 2013). Coupons are purely for discounting while vouchers can be used for discounting and for free exchange of products and services. The focus of this study will be on coupons, to understand the factors influencing customers' redemption of coupon discounts.

Businesses are continuously putting investments of their marketing budget into couponing with the aim to help increase the buying power of consumers and in turn helps drive sales, product adoption and repeat buying behaviour, however the redemption of these coupons remain low (Clark et al., 2013). With the proven effectiveness of coupons in increasing sales, marketers are therefore continuously looking for ways to address the never-ending challenge of lower coupon redemptions to help improve return on investment (Lalwani & Wang, 2018). Studies show redemption rates to generally range around 2 to 3% (Wang

& Lalwani, 2018; Nayal & Panday, 2020). This is mainly due to customer behaviour and the limited understanding of the factors influencing higher redemptions to inform the correct positioning of coupon campaigns.

Companies use coupons as a key strategic driver for sales, though with limited understanding of the key factors to consider when formulating coupon marketing campaigns(Li et al., 2020) .Thus warranting the need to investigate the factors influencing coupon redemption to help businesses understand how to better position their coupon campaigns and successfully drive the business objective of increasing sales while exposing consumers to the savings opportunity lost from none redemption (Clark et al., 2013). **Coupon redemption** happens when a consumer buys a product that is shown on a coupon and present the coupon together with payment at point of sale or check out, where the discount shown in the coupon is then applied in the transaction so that the consumer pays a reduced price for the goods or service (CCBA, n.d.)**.**

It is worthy to note that, over the past decades there has been several studies conducted into understanding the factors influencing coupon redemption. Nearly two decades ago, Yin and Dubinsky (2004) previously found that the framing and face value of the coupon influence redemption. This is further collaborated in recent findings where Montazeri et al. (2021) found that framing do have an impact on redemption , while Pandey and Nayal (2020) found that if face value is high, coupon redemption will also be high. Li et al. (2020) agrees and state that the face value of a coupon has a positive influence in the likelihood of future coupon redemption. Furthermore, Clark et al. (2013) found that ethnicity together with other demographic variables such as age and income are key contributors for coupon redemption. Wang and Lalwani (2018) agree and emphasise that cultural backgrounds are key in determining the likelihood of coupon redemption.

The understanding of the factors will help with allocation of marketing budgets and the positioning of coupon campaigns through tailoring them in line with the factors that are likely to influence redemptions to get return on investment (Reibstein & Traver, 1982; Wang & Lalwani, 2018). Over 40 decades ago, Ward and Davis (1978) previously drew a conclusion that, understanding the factors influencing coupon redemption is key to informing businesses on how they set up

their coupon campaigns for success. This remains true for businesses even in current times.

In South Africa, the use of coupons as a promotional tool has been present for over a decade and is mainly popular within the retail industry, consisting of retailers such as Shoprite Checkers, Pick n' Pay, Woolworths and Spar, who are thriving to compete for market share (Morgan, 2006). Groceries and clothing mainly dominate the Retail industry (StatsSA,2018). The industry plays an important part in the livelihoods of South Africans through providing basic human needs for daily survival such as food (Ngouapegne, 2019) and clothing. In addition, "Retail is an important sector that contributes to the growth of the economy in many ways, such as the reduction in unemployment and an increase in the gross domestic product (GDP) (Nalla & Varalaxmi, 2014)" as cited in (Udekwe & de la Harpe, 2017). This is achieved from the sales the industry generates which amounted to R1 trillion in 2017 and continues to grow (StatsSA,2018)

1.2 Problem statement

In the US coupons to the value of $321 billion were issued by consumer-packaged goods in 2015 (Wang & Lalwani, 2018). This continued to grow with 2018 showing coupons to the value of $497 billion being distributed (Zhang et al., 2019). This indicates the popularity of coupon usage however, the redemption of these coupons has been and continues to remain low (Statista, 2015; Wang & Lalwani, 2018; Nayal & Panday, 2020). In South Africa however, due to the limited research in the space, little can be found on coupon redemption which mainly indicated that the redemption of coupons is mainly in the retail space with Pick Pay showing about 1.8 million in 2017 and Shoprite following at 800 thousand (CCBA, 2018). Spar grew from about 500 thousand to about 1 million in 2018, an indication that the retailers are accelerating their usage of coupons (CCBA,2018).

With companies such as retailers continuing to invest in coupons as a promotional tool while having to deal with budget constraints (Huchzermeier &

Von Matius, 2021), and the redemption of these coupons being as low as around 2% (Pandey & Nayal, 2020), there is a need to study and understand what factors are driving coupon redemption. This will help retailers make informed decisions on how to better target and position their coupon campaigns and optimize their budget spending to get return on their marketing investments.

However, several studies that has been done to identify factors influencing coupon redemption has been mainly conducted in the United States of America and other first world countries (Ward & Davis,1978; Reibstein & Traver, 1982; Green, 1995; Colombo et al., 2003; Montazeri et al., 2021). With some of the factors that were reported to influence redemption being the attributes of the coupon such as face value and framing (Ward & Davis 1978; Li et al.,2020; Montazeri et al., 2021), the demographics such as age, income, and cultural background (Reibstein & Traver, 1982; Green, 1995; Wang & Lalwani, 2018) and the consumer's behaviour (Colombo et al., 2003). These studies have limited focus on the African continent, and particularly South Africa (Pandey & Nayal, 2020).

Though the studies conducted in the western countries have reported some factors influencing coupon redemption, these factors will vary with changing cultures, geopolitical environments, income, interests, and habits (Pandey & Nayal, 2020). Furthermore, with multi-national companies continuing to use couponing as a promotional tool (Reibstein & Traver, 1982; Clark et al., 2013; Nayal & Panday, 2020; Li et al., 2020), and South Africa being one of the developing countries where these multi-nationals are dominant (Nayal & Panday, 2020), there is a need to conduct more studies on factors affecting coupon redemption within the South Africa context, to help inform better campaign positioning.

Retailers need to constantly find ways to entice consumers to purchase their products. Coupons is one of the means that retailers use to drive purchasing behaviour by increasing the consumers buying power through discounts. However, coupon redemption remains low with little being known about the factors influencing consumers' coupon redemption within the South African retail industry. As a result, the aim of this paper is to conduct a study to identify factors

influencing coupon redemption within the South African retail industry. To help South African retailers to better position their coupon campaigns.

1.3 Research questions

1. What factors encourages coupon redemption in the South African retail industry?
2. What factors discourages coupon redemption in the South African retail industry?
3. How can South African retail companies increase coupon redemptions?

1.4 Objectives

1. To identify whether factors such as demographics, coupon design and consumer behaviour do influence coupon redemption in South African retail industry
2. To identify interventions that South African retailers can use to improve coupon redemption
3. To inform how to better position coupon campaigns within the South African retail industry context

1.5 Assumptions

The assumptions made in this study are.

1. Coupon redemption is influenced by demographic variables, coupon design variables and consumer behaviour variables
2. Coupons are commonly used in the retail industry as a marketing tool to drive consumer purchasing behaviour
3. Retail consumers turn to buy across retailers, thus using one retail company for the population sample will give a fair representation of the South African population from which inferences can be drawn about coupon redemption

4. The use of logistic regression model will provide reliable results on the relationship between the independent variables and the dependant variable coupon redemption. This will be ensured by performing cross validation of the output model.

2. Literature Review

2.1 Introduction

Billions of coupons are distributed each year while only a small fraction of that get redeemed (Clark et al. ,2013). Generally, “coupons are an effective way to attract new, existing, loyal, and competitors' customers, as well as to build a brand by delivering messages that increase consumer awareness of the brand (Santella and Associates, 2000)” as cited in (Yin & Dubinsky 2004). Companies normally use coupons to entice consumers to engage in price discounts while not changing the consumers’ perception of the price of an item (Ward & Davis, 1978). With coupons playing the role of driving purchasing behaviour from customers and companies continuing to invest in coupons as a marketing tool, the study of the factors influencing coupon redemption remains important. Furthermore, such factors can be used to development models that can forecast redemption rates and the impact that each of the factors have on coupon redemption (Reibstein & Traver, 1982). A literature review on coupon redemption will be explored to help identify some of the factors that have been broadly reported to be influencing coupon redemption in various contexts and geographies. The findings will subsequently be used to draw a conclusion on the factors that can be investigated further, to understand their role on coupon redemption in the context of South Africa’s retail industry.

The Theory of Planned Behaviour will be used and is found to be more appropriate for this study since it predicts human social behaviour (Ajzen, 2011). The redemption of coupons is related to how consumers behave and how they make decisions to use or not use coupons, as well as what drives that decision-making process. Thus, the study will explore how factors such as consumer behaviour and coupon design help influence the decision for a consumer to use or not use a coupon. The Consumer behaviour refers to the decision-making process of how consumers buy and dispose goods and services (Finney,2014). This construct will be explained using the basis of segmentation in the

subsequent sections while coupon design will be explained based on the features that are included in a coupon.

2.2 Segmentation

Segmentation is defined as the process of grouping consumers into different groups such that consumers in one group have similar needs and disires (Palmatier & Sridhar, 2017, p. 44). Segmenting consumers into the similar groups help business to better target their consumers to help increase sales and profits (Palmatier & Sridhar, 2017, p. 43). Similarly with the coupon campaigns, business need to understand the segments that are likely to respond to coupon camapigns in order to get return on invetment.

Ren et al. (2021) found that customers are heterogenous and that retailers should consider that customers behave differently, and then use this to inform how they structure their coupon campaigns to be more targeted to specific groups based on similar behviours. Colombo et al. (2003) agreed that customers differ , and they respond differently to different coupon types. Thus, when companies design coupon campaigns they must consider different customer segments and approach them differently as this will help achieve good engagement and positively influenece the redemption of coupons (Ren et al., 2021).

Furthemore, customers should not be treated as a homogeneous group as this will negatively impact how they respond to the coupon campaigns(Ren et al., 2021). Montazeri et al. (2021) agrees and add that the heterogenity of customers will play a role in the coupon usage and as such customers must be grouped into segments and targeted per segment since their reaction to coupon campaigns will vary. Consumers can be segmented by considering their demographics, geographic , psychographic or behavioural factors. The below subsection mainly focuses on exploring the literature on the role that demographic and behavioural factors have in influencing coupon redemption.

2.2.1. Demographic Factors

Gender

Danaher et al. (2015) found that there was no major difference between redeemers and non-redeemers in terms of gender, however men were found to have a slightly higher redemption rate when compared to female. Indicating that though there are slight differences, gender does have some influence on redemption. Wang and Lalwani (2018) agree in their findings and state that gender came up as a significant variable in their logit model and further adds that men showed to be more likely to redeem than females. However, Li et al. (2020) differs in their finding and state that there is no major impact of gender in purchasing decision using coupons.

H1: Gender has an influence on coupon redemption such that males are more likely to redeem their coupons than females.

Age

Clark et al. (2013) found that age do play a part in influencing coupon redemption. Danaher et al. (2015) agrees in their findings which shows that the highest redemption rates are seen in those consumers who are in their teen ages as well as in the age range 30 to 40 years old. Though, Clark et al. (2013) agrees that age plays a role in coupon redemption, they do differ slightly in their findings which showed that younger consumers do not seem to be attracted to coupon marketing campaigns. Thus, implying that older consumers are those more likely to redeem coupons.

H2: Age has a positive influence on coupon redemption such that older customers are more likely to redeem their coupons.

Race

Over two decades ago, Green (1995) previously found that ethnicity have an impact on consumers redemption of coupons and emphasised that African American redeemed at a lower rate than Anglo-American. In a similar vein, Clark et al. (2013) later argues that ethnic group, do play a part in coupon redemption and adds that 75% of coupon users in the United States of America are Caucasian. This suggests that being Caucasian will result in higher redemption. Wang and Lalwani (2018) agree that ethnicity is a significant variable in predicting

coupon redemption, however, differs in their findings and states that Asians are more likely to redeem than Caucasians.

H3: Africans are more likely to redeem coupons than other races

Income

Green (1995) previously found that that income does not seem to be a key influencer of coupon redemption since even the African American that have the same income as the Anglo American still redeemed less. Chiou-Wei and Inman (2008) later argues that income does have a positive effect on consumer's redeeming coupons. This is because higher income level speaks to affordability and higher spending capacity. In a similar vein, Clark et al. (2013) argues that household income does play a part in influencing coupon redemption and that the higher income consumers are those more likely to redeem. However, in recent years, Wang and Lalwani (2018) differs in their findings where they found income as a nonsignificant factor for coupon redemption. This contradicts most of previous studies that showed income as a factor that influence coupon redemption which could be because of changes in consumer behaviour overtime.

H4: Income has a positive influence on coupon redemption, higher income results in higher coupon redemption

Education

Morgan (2006) states that consumer knowledge about how coupons work in the South African context has an impact in increasing the redemption of coupons and hence the more retailers use these coupons as a measure of driving customer engagement, the more consumers will learn how they work and subsequently increase the redemption rate. Chiou-Wei and Inman (2008) later argues that education does have a positive effect on coupon redemption. This is mainly because education makes it easier for consumers to understand the coupon redemption process. In a similar vein, Clark et al. (2013) emphasised that demographic factors such as education do play a part in influencing coupon redemption. This is collaborated by Wang and Lalwani (2018) who found

education to be a significant predictor of coupon redemptions though its impact was marginal when compared to other variables.

2.2.2 Psychographic Factors

Culture

Culture can be defined “as a set of taken-for-granted beliefs and values that are shared within a particular group” (Whittington, Regnér, Angwin, Johnson, & Scholes, 2020). Hofstede’s cultural theory states that people behave differently based on different geographies, nations, and religions (Whittington et al.,2020). Wang and Lalwani (2018) found that cultural backgrounds have an influence on consumer’s coupon usage, and states that consumers that comes from independent cultural backgrounds such as North America and some Western societies turn to have a lower coupon redemption than those from the South and East Asia due to their interdependence. This agrees with Hofstede’s theory which states that individualistic cultures such as the United States do not value team approaches while collective cultures such as South Americans and Asians do value team approaches (Whittington et al.,2020). Wang and Lalwani (2018) further emphasize that the interdependence culture amongst the South and East Asia is what motivates these consumers to engage in self-regulation and as such engaging in all the steps needed to locate and redeem coupons, as they are more prone to engage in activities that will have short term pain for long term gains such as the savings from the discounts. Thus, agreeing with Hofstede’s cultural theory that, Asian cultures are mainly long term oriented while North American and African cultures turn to be short term-oriented (Whittington et al.,2020). Yi (2016) agrees that cultural differences have a role to play in influencing coupon redemptions.

However, Yi (2016) argues that those with an individualistic culture are found to have a higher likelihood to redeem coupons when compared to those with a collective culture. This is because individualists see the usage of coupons as something that makes them seem sophisticated and smart consumers while collectivists cultures are found to be less likely to redeem because they see

coupon usage as a sign to be seen as cheap (Yi, 2016). With these differing views the question remains as to what role does cultural difference play in coupon redemption, and whether those with an individualist culture are more likely to redeem than collective cultures, or vice versa?

H5: Consumers with a collectivist cultural orientation are more likely to redeem than those with individualistic cultural orientation.

2.2.3 Behavioural Factors

2.2.3.1 Previous Purchasing Behaviour

Taylor (2001) found that the existing consumer purchasing behaviour before a coupon is received does have an impact in predicting the likelihood of coupon redemption. Consumers that have repeat purchase behaviour in the past were found to be more likely to redeem a coupon (Taylor, 2001). Furthermore, if a consumer is given a coupon for a product that falls into the brand that they are loyal to, they will most likely redeem the coupon as it is something already in line with what they would normally buy (Mills & Zamudio, 2018). Osuna et al. (2016) agrees and states that the objective that a business aims to drive will impact coupon redemption. If a business aims to drive loyalty and prevent lossing sales on customers that are already buying specific categories they will issue coupon campaigns on those specific categories, and these campaigns will have higher redemption rates since consumers are already purchasing the categories. Furthermore , if the objective is to drive consumers to shop into a new category that they do not buy into, the redemption rate will likely be lower for those kinds of coupon campaigns though there will be higher incremental sales (Osuna et al., 2016)

According to the above views , retailers will have to understand which brands and categories customers buy and do not buy then use this to inform the positioning of their coupon campaigns. This will help achieve the inteded business objective whether it is higher redemption or higher incremental sales. Furthermore, if retailers better understand the purchasing behaviour from consumers, they will

be able to predict the propensity of redeeming a coupon and then send targeted coupon campaigns to customers who have a high likelihood to redeem (Li et al., 2020).

H6: Offering coupons in a product that a consumer purchases frequently will increase coupon redemption

2.2.3.2 Decision-making and previous redemption behaviour

Pandey and Nayal (2020) found that coupon proneness has a high influence on coupon redemption. “Coupon proneness is defined as the propensity for responding promptly to coupon campaigns (Swaminathan & Bawa, 2005)” (as cited in Pandey & Nayal, 2020). Colombo et al. (2003) found that coupon proness will vary based on the type of coupon due to the fact that customers differ , and that if a customer has generic coupon proness it doesn’t necessary mean that they will respond to all coupon types. Furthermore, Some customers can respond consistently to coupons of a specific type since it resonates with their already existing behavior , but this should not be confused with coupon proness in general since when exposed to different coupon types the same customer may not have coupon proness to those specific types (Colombo et al., 2003).

According to Wang and Lalwani (2018), consumers who have a tendency not to discount the future very much (i.e., have patience) will likely engage with coupons since they are the kind of consumers that are more likely to save. The use of coupons will help consumers save but it requires that the consumer engage in the necessary steps to complete the redemption and reap the benefits of saving on their purchases (Wang & Lalwani, 2018). Mills and Zamudio (2018) examined the redemption of more than one coupon campaigns and found that factors such as coupon value, reference price, brand loyalty and the number of coupons have an impact on coupon redemption. The pair further emphasize in their findings that giving more than one coupon can result in lower redemption as consumers turn to avoid making choice when presented with many choices (Mills & Zamudio, 2018). This is due to the costs associated with the choice and the fact that consumers generally do not like to engage in too much thought when deciding,

hence resulting in decision or choice avoidance (Mills & Zamudio, 2018). In a similar vein Li et al. (2020) agrees and add that the number of coupons received in the past has a negative correlation with the coupon usage, meaning that the more coupons' customers get the less likely they redeem. Marketers must better manage the frequency and volume in which coupons are sent to customers to reduce the chances of these campaigns becoming spam and as such customers start disengaging thus reducing coupon redemption.

H7: Offering more coupons to consumers overtime will decrease the chances of coupon redemption

H8: Consumers who have shown a previous behaviour of coupon redemption will have a higher chance of redeeming coupons in future

2.3 Coupon Design Factors

Coupon design speaks to the information provided in the coupon such as the value of the coupon, expiry date, the products with which the coupon can be redeemed, or the way in which information is presented in the coupon such as percentage-off, cents-off or price reduction. The below subsections explore previous literature on the features of the coupon and the influence they have on coupon redemption.

2.3.1 Face Value

Face value is the discount that a consumer gets when redeeming a coupon and is seen as a key determiner of whether a consumer will redeem a coupon or not (Zhang et al., 2019). In past research, Ward and Davis (1978) previously found that the coupon face value influences coupon redemption as consumers are more likely to redeem coupons with high discounts. This was later collaborated by Reibstein and Traver (1982) who agreed that the value of the coupon do have a positive relationship with coupon redemption. Chiou-Wei and Inman (2008) emphasize this and state that, a high coupon face value adds a positive effect in coupon redemption as it is one of the key attributes that attracts consumers to use a coupon.

Similary, Morgan (2006) agrees and states that, a higher discount offered in a coupon will have an impact on the copupon redemption and that consumers will most likely redeem coupons that have a higher discount . Similary, more recent studies continue to emphasise this, where they find that face value have a positive influence on coupon reemption(Li et al., 2020; Pandey & Nayal, 2020). Mills and Zamudio (2018) found that consumers turn to judge the attractiveness of a coupon value based on prices that they may have been exposed to, for the type of product on offer from the past or in other places. Hence, giving a higher discount will result on higher redemptions.

H9: Offering coupons with higher face value will increase coupon redemption

2.3.2 Framing

Framing is the way in which information is presented in a coupon (Yin & Dubinsky, 2004). Yin and Dubinsky (2004) previously found that the framing of the face value of a coupon does impact coupon redemption. The coupon face value can be framed mainly in three ways, such as, using percentage off, cents off, or a reduced price (Yin & Dubinsky, 2004). Montazeri et al. (2021) agrees that the framing of coupons have an impact on how consumers redeem and use those coupons, and finds that even though both dollar-off discount coupons and percentage off coupons have a positive impact on consumer buying behaviour, the percentage-off is however more effective. In addition, it drives customers to spend much higher as they optimise the discount since buying more means more discount as there is no dollar limit to the amount of discount a customer can get (Montazeri et al.,2021).

However, in past research, Yin and Dubinsky (2004) argued that the level of the item price will have an impact in determining which framing option to choose since each option will have different effects for low prices than it will for higher prices. If the item price is higher, the cents-off will be more effective than the percentage-off while for lower prices the percentage-off is more effective (Yin & Dubinsky, 2004).

H10: Framing coupons in percentage-off will increase coupon redemption, as there is no limit to the amount a customer can spend

2.3.3 Coupon duration

Coupon duration is the length of time allocated for the coupon to be redeemed before it expires and is found to have an influence in coupon redemption (Zhang et al., 2019). Previous research found that the length of time in which the coupon is valid for has a direct correlation with the coupon redemption rate and the longer the time in which the coupon is valid for the higher is the redemption (Ward & Davis,1978). Montazeri et al. (2021) agrees and emphasize with their findings that if coupons are so generic that they do not even have an expiry date, it turns to delay a consumer's purchase as they don't get the pressure of going to redeem since they can do this any time they want.

However , Chiou-Wei and Inman (2008) argues that the coupon expiration date does not seem to have any effect on the redemption of coupons , and that whether there is a validity duration on the coupon or not , consumers will still redeem at the same rate. With these differing views the question that remains whether the duration of the coupon have an impact on coupon redemption.

H11: A longer coupon duration will result in higher coupon redemption as consumers get more time to redeem

2.3.4 Category where coupon can be redeemed

Categories generally refers to the different products that a retailer offers such as "Alcohol, Bakery, Beverages, Dairy, Fruits and Vegetables, Food, Meat" (Montazeri et al., 2021). Huchzermeier and Von Matius (2021) states that due to budgetary contraints retailers will either use coupon marketing strategies that are single category or multi-category. It was found that the single catergory coupons will result in less redemption rates than multi-category coupons and as such, retailers may want to consider using coupons that are open to a wide range of categories as this will stimulate the redemption (Huchzermeier & Von Matius, 2021).

If a coupn is multi-category, customers will have more choice, while when it is single category the chances are that the specific category in the voucher may appeal to fewer customers thus resulting in lower redemptions. Furthermore , Montazeri et al. (2021) agrees that having coupons that are across any category in the store will have a positive impact on the redemption of coupons as customers turn to have more choice. Though in the contrary, this could delay the purchase as there really is no pressure of possible stock outs since the coupon can be redeemed with anything (Montazeri et al., 2021).

H12: Offering coupons that are open in a wider product range will increase coupon redemption due to customers having more choice

2.4 Conclusion

Studies show that factors such as demographics, coupon design and consumer behaviour have an impact in influencing coupon redemption. The demographics such as income, age, ethnicity, and education have been identified as some of the factors. Furthermore, the consumers' previous purchasing behaviour, previous coupon usage and the volumes of coupons sent to a consumer do influence a consumer's future purchasing decisions with coupons. Finally, the coupon design such as face value, framing, duration, and the categories where a coupon can be redeemed are the key influencers for coupon redemption.

However, most of the previous research has studied the factors influencing coupon redemption in isolation, however every coupon will generally have all the variables (Zhang et al, 2019), thus an integrated approach of looking at these factors in conjunction will bring new insights in their impact on coupon redemption when considered together with all the other relevant variables.

3. Research Methodology

3.1 Introduction

A methodology is a set of procedures outlining how a particular task was accomplished (Creswell & Creswell, 2018). It helps give a clear structure of how work was done and in the context of research it helps the researcher clearly structure the actions taken for their enquiry. This section outlines the research approach that was used in the study. The section covers how data was collected and analysed for the study.

3.2 Delimitations

This study focuses specifically on consumers coupon redemption in the retail industry of South Africa. The delimitation to the retail industry is because it is where coupons are widely used. Secondary data was collected from one retailer due to the ease of access of their data which ensured the study was manageable. The study specifically examines only numerical variables from demographics, coupon design and consumer behaviour. Categorical variables were converted to dummy variables to ensure all data is quantitative in nature. Relationships between the dependent numerical variable and a set of independent numerical variables was assessed using statistical analysis to prove or disprove a set of hypotheses on the factors affecting coupon redemption. This study does not involve any qualitative data which is why the qualitative method was not chosen. Instead, the quantitative method was selected due to the data being numerical in nature and requiring statistical analysis to derive inferences.

3.3 Paradigms or research approaches

There are generally three widely known research approaches, namely Quantitative, Qualitative and Mixed Methods (Creswell & Creswell, 2018, p.41). The Quantitative approach refers to an approach used for testing relationships amongst variables that contain numerical data and is deductive in nature (Creswell & Creswell, 2018). Qualitative approach involves “exploring and

understanding the meaning individuals or groups ascribe to a social or human problem" and is inductive in nature (Creswell & Creswell, 2018, p.41). Mixed methods involve both Quantitative and Qualitative data. According to Creswell and Creswell (2018) a choice of research approach is generally informed by the nature of the research problem. The purpose of this research is to study the factors that influence coupon redemption either positively or negatively. This involved performing analysis that examines whether there exist relationships between a set of numerical variables within the demographics, coupon design and consumer behaviour constructs, with coupon redemption, as a result the Quantitative approach was used as the research approach in this study.

3.4 Target population

The target population for the study was the South African retail consumers between the ages 22 to 60 years old. These consumers were targeted or sent a coupon campaign by one of the largest retail companies in South Africa during the period June 2021 to June 2022. The reason for the choice of this period was to ensure the study covers various times within a year to cater for seasonality. The consumers had received at least one coupon campaign asking them to redeem a specific coupon. The population consists of both consumers who have either redeemed or did not redeem a coupon received from the retailer during the period. At least 1 million unique consumers that were targeted by these coupon campaign over the period were considered as part of this study.

3.5 Sampling

Since the study used secondary data, the characteristics of the population were known before sampling. Thus, a random stratified sampling method was used to ensure the sample is a true representation of the population. Stratification "means that specific characteristics of individuals (e.g., females and males) are represented in the sample and the sample reflects the true proportion in the population of individuals with certain characteristics." (Creswell & Creswell, 2018, p.212).

The sample consisted of 292,302 coupons sent to consumers split into 50% responders and 50% non-responders. To be able to draw inferences from a sample about a population, the sample size needs to be adequate (Taherdoost, 2017). To ensure the size was adequate the below formula for finite population correction was used (Naing et al., 2006).

$$Sample\ size = \frac{NZ^2\ P(1-P)}{d^2\ (N-1) + (1-P)PZ^2}$$

Were.

N = Population size

P = expected responses (the percentage of the redemptions in the population)

D = the margin of error

Z= 2.57 (the statistical value of 99% confidence interval)

Which resulted on a sample of 292,302.

3.6 Collecting the data

3.6.1. Data Collection

The study used secondary data that was collected from one of the South African retailers. This was historical campaigns data which gave details of consumers that were targeted for coupon campaigns as well as the associated details of the coupons that were offered to the consumers. The data collected was over the period June 2021 to June 2022. Data was extracted from the retailer's database using a query language called Structure Query Language (SQL) and imported into Python programming language for the analysis. The data comprised of independent variables from the three constructs and a dependant variable called coupon redemption. "A variable refers to a characteristic or attribute of an individual or organisation that can be measured or observed and that varies among the people or organisation being studied" (Creswell & Creswell, 2018,

p.93). Independent variables are variables that can influence a study and they can be manipulated to get an outcome, while dependent variables are those that are the outcome and cannot be manipulated (Creswell & Creswell, 2018, p.93).

To derive the dependent variable (coupon redemption) the performance period January 2022 to June 2022 was used, where those consumers who have used the discount offered in the coupons during this period were flagged as redemptions (i.e., redemption variable was allocated a value of 1) and those who did not use the coupon were flagged as non-redemptions (i.e., redemption variable was allocated the value of 0). All coupons in the dataset had already expired meaning their redemption period was over.

The independent variables were derived by considering different observation periods due to the difference in the variables per construct. The demographics variables such as age, race, gender, and household income were selected by observing the customer record one month before the campaign. For example, if a campaign was sent in January 2022, the age, income, gender, and race of the consumer that was used is what reflected on the customer record as of December 2021 similarly for campaigns sent in February 2022 these demographic variables were selected as of January 2022.

The behavioural variables such as previous purchasing behaviour on the offered product and previous redemption behaviour from past coupon campaigns were derived by observing the behaviour over a rolling 6-month period before a coupon campaign was sent to a consumer. For example, for a campaign sent in January 2022 the purchasing and/or previous redemption behaviour for a consumer was observed over the July 2021 to December 2022, similarly for a campaign sent in February 2022 these behaviours were observed over the period August 2021 to January 2022. The approach of using the rolling periods was to ensure that independent variables are fairly observed with a constant number of periods for each coupon campaign.

Other variables such as the coupon design variables (i.e., discount, threshold, face value, framing, etc) were derive from the campaign period since they are only available after a coupon is sent to consumers. To create the full dataset, 6

separate monthly datasets for each month's campaign sent to consumers over the period January 2022 to June 2022 were created, each capturing the details relevant to the specific months campaign with its associated observation periods to ensure all are observed over the same periods. Finally, these datasets were appended to each other to create one big dataset containing the information for campaigns that had coupons redeemable in the period January 2022 to June 2022. The table below gives detailed descriptions of the variables in the dataset in line with the above explanation of the data collection process.

Table 1: List of variables contained in the dataset with their descriptions

Construct	Variable Name	Definition	Data type	Example(s)
Coupon Design Factors	Threshold	Amount to be spent to redeem coupon	Continous	R350
	Campaign_Name	The name of the campaign where coupon was offered, mainly describe the lowest level product categories for the campaign	String	Biltong or VegCombo
	Business unit name	Business unit where coupon campaign is applicable ,normally consist of 2 values which are inline with the 2 major business units for the organisation	String	Foods or FBH (meaning Fashion , Beuty, Home)
	Campaign Type	Product group where redemption is allowed	String	Foods, Fashion , Beauty , Home
	Offer	Coupon value represented as the combination of the discount and threshold	String	R150 off R750 or 15% off R100
	Discount	the amount discounted when redeeming	Continous	R150
	Face value as percentage	The discount amount divided by the threshold amount and multiplied by 100	Continous	15
	Duration	The number of days redemption is allowed for a coupon . Calculated by taking the difference between expiry date and start date	Continous	14
	Framing is percentage	An indicator of whether offer is presented in percentage or in rands off, derived from variable Offer . Where a value 1 is allocated if presented in percentage and 0 otherwise	Binary	1 or 0
Demographics Factors	Gender	Targeted consumer's gender	Categorical	Male, Female
	Race	Targeted consumer's race	Categorical	White , African
	Province	Targeted consumer's geographical location	Categorical	Gauteng
	Household income band	Income band in which the consumer's household fell into (one month before campaign)	Categorical	R20,000 - R49,999
	Age	Age of consumer one month before campaign	Continous	41
Behavioural Factors	Coupons_per_campaign	Number of coupons offered to a consumer in one campaign . Derived by counting the number of coupons sent to a consumer in one campaign	Continous	2
	Coupons_per_month	Number of coupons offered to a consumer within a month. Derived by counting coupons sent to a consumer in one month	Continous	4
	Coupons_received_past_6months	Number of coupons sent to a consumer over the 6 months period leading to the campaign month	Continous	16
	Coupon_redemptions_past_6months	Number of coupons redeemed in the 6 months before current campaign excecution	Continous	
	Macrosegment	Segments that drive shopping decisions . Defined as per the retailer (see Macrosegment table below for detail)	Categorical	Savvy
	Prior_spending_on_targeted_product	Spending level in the products coupon is offered. Derived by getting average spend on the targeted product over 6 months (see table below explaining this variable in more detail	Categorical	High, Medium, Low
	Redemption	the dependent variable (1=redeemed , 0= not redeemed)	Binary	1,0

Further explanation of the Macrosegment variable

Macrosegment	Described as per retailer's explanation
Trendspotters	These consumers are driven by trends, newness, and difference. They are fashion forward and prefer to look different from others. They like focusing more on self, and values quality more than price.
Savvys	These consumers do not like to spend too much time in a store, they prefer easy shopping for the whole family. They value quality over price and thus they are willing to pay more for good quality products.
Shopaholics	These consumers get happiness from shopping. They get any excuse to go shopping. Their shopping is driven more by quality, trends, and style and will value these over prices.
Habituals	These consumers buy only what they need. They are family focused and quality is important to them. However, price matters more to them. They prefer quality products that are affordable to them.
Dealhunters	These consumers are driven by bargains. They shop where they get the best deals. They are family oriented, and price is very important to them. They prefer quality at low prices.
Aspirers	These consumers are future focused. They are more focused on investing on self. Price is always a concern to them, but they will invest in things that will help them achieve their goals.
None	Customer is not segmented

Further description of the values in variable "Prior spending on target product", as explained by retailer.

Product	None	Low	Medium	High
Fashion	R0	R1-R1854	R1855 - R3229	>R3229
Foods	R0	R1-R923	R924 - R1903	>R1903
Beauty	R0	R1 - R610	R611 - R1209	>R1209
Home	R0	R1 - R430	R431 - R820	>R820

3.6.2. Data Transformation

To get the data ready for the analysis a few transformations were done. Those included treating for missing values, outliers, and creating other variables from existing variables in the dataset, including generating dummy variables for the categorical or string variables since the model that was used is best suited to interpret numerical values. Below subsections briefly describe the

transformations and any new variables that were created because of the transformation.

3.6.2.1 Treating for missing values

There are several ways of treating missing values in data such as deleting of the rows that have missing information or imputing the missing values (Kumar, 2020). For this study, the imputing method was used since it prevents the loss of data while the other methods may result on data loss. Most of the numerical variables had data fully populated except for age, coupon_received_past_6months and coupon_redemption_past_6months. To treat for missing values in the age variable the mode of age was used to replace the missing values. To treat the missing values in the other two variables the missing values were replaced with the value 0 since if a value was missing in these variables, it implied there was either no coupons offered in the past to the consumer or there were no previous redemptions for the record.

For the categorical variables, there were 5 variables that had missing values and those were gender, race, province, macrosegment, prior_spending_on_targeted_product. To treat for the missing value all nulls were replaced with a string value of the format “no_variablename”. For example, missing gender will be replaced by “no_gender”, missing race will be replaced by “no_race”, etc.

3.6.2.2 Treating for outliers

A distribution analysis of all the numerical/continuous variables was done to detect outliers. Where outliers were detected, the method of capping mainly at the 95th percentile was used where values exceeding the value in the 95th percentile were replaced by the value in the 95th percentile. Below table shows the variables that were treated for outliers and the new variable names that were generated as a result.

Table 2: Table showing new variable names after treating for outliers

Variable name from original dataset	Variable name after transformation
Threshold	threshold_capped
face_value_as_percentage	face_value_as_percentage_capped
Duration	duration_capped
Age	Age_capped
Coupons_per_campaign	Coupons_per_campaign _capped
Coupons_per_month	Coupons_per_month_capped
Coupons_received_past 6 months	Coupons_received_past 6 months_capped
Coupon_redemptions_past_6months	Coupon_redemptions_past_6months_Capped

3.6.2.3 Creating new variables from other variables

A new variable called multi_category_coupon which is seen later in the analysis was derived from the campaign_name variable and it indicates whether a coupon is redeemable in one product category or in multiple categories of products. For example, when campaign_name was 'biltong' the variable multi_category_coupon was allocated a value 0 indicating that it is a single category coupon while if campaign_name was foods, then the variable was allocated 1 indicating that it can be redeemed in more than one category within the foods department.

Furthermore, since logistic regression works best with numerical data, all categorical and string variables were converted to dummy variables. A dummy variable "is an artificial variable created to present an attribute with two or more distinct categories/levels" (Skrivanek, 2009). This transformation resulted in several more variables being derived from other variables. Below table shows a detailed view of the categorical variables that were converted to dummy variables and the associated values / new variables that were created from the categories / levels of the original variable.

Table 3: List of dummy variables created from categorical variables

Original variable	Dummy variables created after transformation
gender	gender_F
	gender_M
	gender_No_Gender
race	race_African
	race_No_race
	race_Other
	race_White
household_income_band	household_income_band_None
	household_income_band_Less than R10,000
	household_income_band_R10,000-R19,999
	household_income_band_R20,000-R49,999
	household_income_band_R50,000-R99,999
	household_income_band_R100,000 or more
prior_spending_on_targeted_product	prior_spending_on_targeted_product_High
	prior_spending_on_targeted_product_Medium
	prior_spending_on_targeted_product_Low
	prior_spending_on_targeted_product_No_Prior_spend
macrosegment	macrosegment_Aspirers
	macrosegment_Dealhunters
	macrosegment_Habituals
	macrosegment_No_segment
	macrosegment_Savvys
	macrosegment_Shopaholics
	macrosegment_Trendspotters
business_unit_name	business_unit_name_Beauty
	business_unit_name_Fashion
	business_unit_name_FBH
	business_unit_name_Foods
	business_unit_name_Home
channel	channel_EMAIL
	channel_SMS
province	province_Eastern Cape
	province_Free State
	province_Gauteng
	province_KwaZulu-Natal
	province_Limpopo
	province_Mpumalanga
	province_Mpumalanga
	province_North West
	province_North West
	province_Western Cape

3.7 Analysing the data

After the data was collected and imported to Python, three stages/processes of analysis were conducted to empirically assess how the variables from the three constructs impact coupon redemption. Those stages of analysis were.

1. Descriptive Analysis
2. Correlational Analysis
3. Inferential Analysis

3.7.1 Descriptive Analysis

The Descriptive analysis mainly involved measuring statistics such as central tendency (the mean), the distribution of the data and variations to help understand the general statistics of the data (Creswell & Creswell, 2018). This analysis helped with the understanding of the data and if it is usability for a regression model. Understanding the descriptive statistics of the data helped with the interpretation of the results of the inferential analysis later in the process.

3.7.2 Correlational analysis

The correlation analysis was used to measure if there was a relationship between the independent variables (demographics, coupon design and consumer behaviour) and the dependent variable (coupon redemption) (Creswell & Creswell, 2018, p.49). Assessing the correlation between the dependent and independent variables helped inform which independent variables correlate with coupon redemption. Those variables that showed a strong correlation with coupon redemption were then taken into the model building stage.

3.7.3 Inferential analysis

The study was causal in nature. Causation implies that a variable X causes another variable Y (Creswell & Creswell, 2018, p.92). In the context of this study, this means variables from demographics, coupon design and consumer behaviour constructs were assessed to understand if they cause coupon redemption. There are several techniques that can be used to assess which variables cause or not cause another variable. However, for the purposes of this study the **Logistic Regression** modelling was used. This is because logistic regression is considered an efficient way to analyse data that consists of multiple independent variables and one dependent variable that has a binary outcome (Stoltzfus,2011).

The logistic regression model is represented by the equation**.**

Logit(p) = $a_0 + a_1x_1 + a_2x_2 + \ldots + a_nx_n$, where a_i for i in $(1\ldots, n)$ are the coefficients and $x_i \ldots x_n$ are the independent variables (Kisselev,2021). Logit(p) is the log-odds ratio that indicates the impact of any one of the independent variables on the dependent variable (coupon redemption) when holding the other variables constant.

The logistic regression model iteratively found the strongest linear combination of the independent variables in demographics, coupon design and consumer behaviour that correctly predicts whether a coupon will be redeemed or not redeemed.

3.8 Validity

There are threats that arise for the validity of a study, and those threats can be either internally or externally (Creswell & Creswell, 2018). In the context of this study, internal validity refers to ensuring that the inferences or causal relationships drawn from the data are correct about the population, while external validity refers to how generalisable the results of a study can be, that is, can the outcome of the study be inferred to context outside the study (Creswell & Creswell, 2018).

3.8.1 Internal validity

To ensure internal validity, the sample of the population was selected such that it represents the population (Creswell & Creswell, 2018) of consumers targeted for coupon campaigns by using stratified random sampling. Furthermore, a data cleaning exercise was conducted before any analysis was done to ensure that values that were seen as outliers or missing values were treated to ensure that the results were not influenced by variable values that were outside the expected ranges of the data. In addition, the model fit statistics such as Accuracy, Precision, Recall and F1-Score were used to assess the internal validity of the model results (Stoltzfus, 2011). This involved looking at where the model predicted a consumer as a redeemer and comparing that to what was in the actual data. If the predicted coupon redemption value was the same as the actual coupon redemption flag in the original data, then this was flagged as an accurate prediction otherwise not an accurate prediction.

Furthermore, only variables with a significant correlation with coupon redemption were included in the model building, this was ensured by only considering variables that had a p-value < 0.05 (Hair et al., 2015). A multicollinearity check was also done by using the Variance Inflation Factor (VIF) method. This was to ensure that strong relationships that exists between independent variables were removed to prevent any model instabilities that can be introduced by such relationships.

3.8.2 External validity

To ensure external validity of the study, the method of cross-validation approach was used (Huberty & Olejnik, 2006). This specifically involved the hold out method, where the sample used for the model building was split into two groups, the training set, and the test set (Huberty & Olejnik, 2006). The training set was used to train the model using the Logistic regression technique and the test set was then used to validate the results of the Logistic regression model. The split between the training and test set was done randomly to ensure the test set was a fair representation of the training set. The results found when applying the

trained model into the test set showed that the model can be used in unseen data implying that model results can be generalised to other similar datasets and hence ensuring external validity of the model.

Furthermore, since the population was across South Africa because generally retail consumers turn to buy across all retailers the model results are therefore inferred to the population of consumers within the retail industry.

3.9 Limitations

The main limitation of this study was that the data was collected from a single South African retailer which may introduce some biases and possibly affect the generalisability of the results. This is because other retailers' data may introduce slight variations due to slight changes in their customer profile. However, since retail consumers turn to buy across retailers, the assumption was that a single retailer's data will have enough representation of the South African population from which inferences were drawn. Furthermore, the data collected did not have information on the level of education and the cultural orientation of the consumers, as a result these were not explored in the study.

Another limitation for the analysis was that seasonality may influence the results however, the analysis was done using data that covers a much longer period, from June 2021 to June 2022 which helped ensure seasonality is catered for in the analysis.

The random selection of samples may result on samples that are not an accurate representation of the population, however, to cater for this the stratified random sampling approach was used to ensure sample used in the model building was like the entire population that was targeted with coupon campaigns from the retailer.

3.10 Ethical issues

To ensure ethical issues were adhered to there was not any mentioning of a specific retail organisation in the dataset, the analysis, or the final report on findings, though the data used was sourced from one specific retailer. Furthermore, all data was anonymised to ensure that personal identifiable information was not included. All variables did not have any information that could lead to data being traced back to the retailer where the sample population was selected or the actual customer details for this matter. All this was ensured by including only the variables that were necessary for the analysis of this study.

4. Data Analysis and Results

4.1 Introduction

A series of data analysis processes have been conducted to get an understanding of how the variables from demographics, coupon design and consumer behaviour influence coupon redemption. This section outlines the results of the data analysis. It covers the descriptive analysis to give an understanding of the statistics and distribution of the data, the correlational analysis to see what relationships exist amongst all the variables and the inferential analysis which shows the variables that influence coupon redemptions. Finally, a conclusion of the variables that have a positive or negative impact on redemption is drawn. The full analysis was done using an open-source tool called python. This is a programming language that has a wide range of uses and widely used for data analysis and reporting, and is accessible for free (Hillier, 2023).

4.2 Descriptive Analysis

Table 4: Descriptive statistics for the numerical variables

Variable name	Sample of coupons sent	Mean	std	min	25th percentile	50th percentile	75th percentile	max
Discount	292,302	55	64	4	10	10	100	500
framing_is_percentage	292,302	0	0	0	0	0	1	1
redemption	292,302	0	1	0	0	0	1	1
threshold_capped	292,302	272	256	40	100	125	500	1000
face_value_as_percentage_capped	292,302	15	8	5	10	10	20	40
duration_capped	292,302	19	11	3	14	14	16	38
Age_capped	292,302	44	11	22	35	43	54	60
Coupons_per_campaign_capped	292,302	3	2	1	1	3	6	6
Coupons_per_month_capped	292,302	4	2	1	2	5	7	8
Coupons_received_past_6months_capped	292,302	16	9	0	8	16	23	33
Coupon_redemptions_past_6months_Capped	292,302	1	1	0	0	0	1	4
Multi_Category_coupon	292,302	0	0	0	0	0	1	1

Table4 shows the distribution of the numerical variables in the dataset. The **Mean** shows the average value for the variable, the **std** is the standard deviation which shows how far apart are the values in the variable from its **Mean**, the **min** shows the smallest value in the variable. The 25th to 75th percentiles show values of the variable in that position when the data is sorted in an increasing order. For

example, in the variable discount the 25th percentile is 10 which means 25% of the discounts in the dataset are below the value 10. **Max** – shows the highest value in the variable.

Table 5: Averages of independent variables split by redemption vs non-redemption

Variable name	Did not Redeem	Redeemed
Discount	R30	R80
framing_is_percentage	0.44	0.31
threshold_capped	R175	R370
face_value_as_percentage_capped	13%	18%
duration_capped	16 days	21 days
Age_capped	44 years	44 years
Coupons_per_campaign_capped	4.09	2.19
Coupons_per_month_capped	5.09	3.89
Coupons_received_past_6months_capped	15.20	16.21
Coupon_redemptions_past_6months_Capped	0.13	1.39
Multi_Category_coupon	0.2	0.6
Sample of coupons	146,151	146,151

Table5 shows the average (mean) values for the numerical variables grouped by redeemed vs not redeemed coupons. It aims to compare a variable for redeemers to non-redeemers. For example, the variable discount has R30 under the column **did not redeem** and R80 under the column **redeemed** this means that the non-redeemers' discount on average is R30 while the redeemers discount is R80.

4.2.1 Demographic Factors

Age

In Table4 the variable Age_capped shows that the mean age of customer is 44 years old, with the youngest customer being 22 years and oldest at 60 years old. This age range is to incorporate the wider customer groups shopping from the retail industry to cover as much population as possible. Table5 shows that, the average customer age for the coupons that were redeemed is the same as the average age of those not redeemed at 44 years, this could indicate that age does not play a role in influencing redemptions.

Gender

Table 6: Redemptions statistics by gender

gender	Female	Male	No_Gender
Volume	229,813	61,142	1,347
% of total volume	79%	21%	0%
redemption	0.52	0.42	0.14

79% of the sample targeted with coupons were female while 21% were male. On average the females show higher redemptions than males which could imply that being female have an influence on redemption.

Race

Table 7: Redemption statistics by Race

Race	African	No_race	Other (Indian/Asian)	White
Volume	81,645	56,889	44,711	109,057
% of Total	28%	19%	15%	37%
redemption	0.46	0.45	0.59	0.52

The population is mainly skewed towards Whites at 37% followed by African at 28%. The Indian/Asian group is the smallest of the population (19%); however, it shows the highest average redemptions with Whites coming second.

Income

Table 8: Redemptions statistics by Income

household_income_band	Less than R10,000	None	R10,000-R19,999	R100,000 or more	R20,000-R49,999	R50,000-R99,999
Volumes	18,066	3,338	35,903	40,831	112,808	81,356
% of total volume	6%	1%	12%	14%	39%	28%
redemption	0.60	0.28	0.45	0.52	0.50	0.50

The population is mainly made of medium to high income earners with more than 80% of the population having a household income more than R20,000. Surprisingly, the small population of the lower income group (less than R10,000) have the highest redemptions on average. The highest income group of R100,000 or more shows the second highest redemptions. The two extremes (high- and low-income groups) showing the highest redemptions when compared to other income groups, leaves the question of whether income has an influence on redemptions.

4.2.2 Coupon design factors

4.2.2.1 Face value

As seen in Table4 in variable name face_value_as_percentage_capped, on average the discount that consumers were offered is 15%, with discounts ranging from as low as 5% up to 40% of the threshold. Furthermore Table5, shows that those coupons that are redeemed generally have a higher percentage discount at 18% vs 13% for those not redeemed, indicating that there is a possible relationship between redemptions and a higher discount.

4.2.2.2 Threshold

On average the threshold of the coupons is R272 as seen in Table4. Most coupons have a lower threshold as seen with the 50th percentile at R125 while the 75th and the max thresholds are at R500 and R1000 respectively, indicating that very few coupons have higher thresholds amongst the coupons that formed part of the analysis for the redemption duration (Jan 2022 to June 2022).Table5 shows that coupons that are redeemed generally have a higher threshold.

4.2.2.3 Duration

Table4 shows that on average coupons in the dataset were valid for 19 days, with the least validity date being 3 days and the highest validity date at 38 days. However, majority have 16 days or less duration as seen with the 75th percentile of 16. This implies that generally the coupons do not have a longer validity period.Table5 further shows that coupons that are redeemed generally have a higher duration at 21 days vs 16 days for those not redeemed. This could indicate that duration has a relationship or an influence on coupon redemption.

4.2.2.4 Framing

Table 9: Redemption statistics when framing is in percentage

framing_is_percentage	No (0)	Yes (1)
redemption	0.55	0.42
Volumes	181,862	110,440
discount	R82	R9
threshold_capped	R376	R102

Table9 shows that 38% (110,440) of the coupons in the sample are framed as a percentage while 62% are framed in ZAR. The average redemptions for those framed as ZAR is 33% higher than those framed as a percentage indicating that framing in percentage results in lower redemptions than framing in ZAR. Furthermore, the threshold is lower for the coupons framed as a percentage when compared to those framed as rand off.

4.2.2.5 Categories where coupon can be redeemed

Table 10: Redemption statistics by product group where coupons are redeemable

Multicategory	Beauty	FBH	Fashion	Foods	Home	Total	% Split	Foods/Total
Yes	149	90,919	5,471	17,183	69	113,791	39%	15%
No	-	12,085	681	165,745	-	178,511	61%	93%
Total Volume	149	103,004	6,152	182,928	69	292,302		
Average redemptions per business unit	0.92	0.65	0.55	0.41	0.89			

Note*: FBH stands for Fashion, Beauty, Home. It indicates coupons that were opened for redemptions across the three business units.*

Table10 shows that 39% of the coupons in the sample are redeemable in multiple categories while 61% are redeemable in a single category. 93% of the single category coupons are from foods business unit indicating that the food products coupons for this sample are mainly done as single category while the other products such as fashion, beauty or home have multicategory coupons. As a result, the beauty and home coupons have shown higher redemptions on average while food products show the lowest redemptions on average. This indicates that coupons that are opened to be redeemed in broader product categories are redeemed more than those in single category.

Furthermore, variable multi_category_coupon in Table5 shows that the multicategory coupons are redeemed more on average than the single category.

These insights highlight that a potential relationship between the categories where coupons can be redeemed, and the business units may exist. This implies that either of these variables can represent multicategory redeemable coupons in the inferential analysis.

4.2.3 Behavioural factors

4.2.3.1 Previous redemption behaviour

Table4 shows that on average customers get 3 coupons in one campaign. Since there are more than 1 coupon campaigns being run at the same time this result to an average of 4 coupons per customer per month from a single retailer. As a result, over a rolling 6-month period customers receive on average 16 coupons, however they only redeem 1 of these over the same 6-month period on average. This highlight that even though customers are consistently given several coupons on an ongoing basis they do not turn to redeem most of these.

Furthermore, Table5 shows that those who have shown a behaviour of redeeming over the past 6 months turns to redeem more on average when they are sent a coupon again. Indicating that proneness may have an influence on future redemptions.

4.2.3.2 Previous purchasing behaviour

Table 11: Previous purchasing / engagement behaviour on targeted products

Prior_spending_on_targeted_product	High	Medium	Low	No_Prior_spend
Volumes	154,951	40,747	62,794	33,810
% of total volume	53%	14%	21%	12%
Average redemptions	0.67	0.40	0.31	0.19

Most (53%) of the coupons in the sample are sent to a category that a customer would have spent the highest over the preceding 6 months before the campaign. While only 12% are sent to customers where there was no previous engagement on the specific product. This indicates that coupons are sent more to drive already

highly engaged customers to engage more. Furthermore, the average redemptions for those who are already spending high on the product where they are given a coupon is higher than those who either spend less or do not spend at all. This indicates that sending a coupon to a customer on a product where they are already spending will likely result in higher redemptions than in a product where customers do not spend or have a lower spending engagement.

4.3 Correlational Analysis

4.3.1 Introduction

This subsection explains the results of the correlation analysis. A brief overview of how the correlation analysis was done is outlined. Followed by the correlation analysis results explanation per construct to see which variables in each construct (i.e., demographics, coupon design and consumer behaviour) have a relationship with coupon redemption.

4.3.2 Analysis

The Spearman correlation method was used to analyse relationships between the independent variables in demographics, coupon design and consumer behaviour with the dichotomous dependent variable (coupon redemption). Multiple iterations of correlation were run with the first iteration including all the variables from the three constructs see Table14 in the appendix, then variables with a correlation coefficient lower than 0.1 were removed as they indicate a weaker relationship with redemption while those above a correlation coefficient of 0.1 were included in the subsequent phase of the analysis as they showed a relatively stronger relationship with redemption.

As shown in Table15 in the appendix, there were 17 variables that showed a relationship with redemption with coefficients of +/- 0.1 or more. A multicollinearity check was done. As seen in Figure6 in the appendix, there were independent variables that had correlation coefficients of 0.7 or more with other independent variables which implied the existence of multicollinearity.

To treat the multicollinearity, the Variance Inflation Factor (VIF) method was used where variables with a VIF greater than 10 were removed from the analysis as this was an indication that the variable cause multicollinearity. The initial view of the variables that were causing multicollinearity is shown in Table15 in the appendix. Table13 below shows the final VIF outcome and Figure1 below shows the final correlation amongst variables after some variables were removed due to weak relationship or due to them causing multicollinearity.

Table 12: Variance Inflation Factor for variables with factor less than 10

Final VIP after interative treatment of multicolinerit	feature	VIF
0	redemption	3.6
1	Coupon_redemptions_past_6months_Capped	1.9
2	face_value_as_percentage_capped	9.1
3	Prior_spending_on_targeted_product_High	4.2
4	Multi_Category_coupon	3.2
5	duration_capped	5.6
6	gender_F	4.2
7	race_Other	1.5
8	Prior_spending_on_targeted_product_Low	2.3
9	Prior_spending_on_targeted_product_No_Prior_spend	1.7
10	framing_is_percentage	2.1
11	Coupons_per_month_capped	4.1

Figure 1: Final correlation matrix after removing multicollinearity

	redemption	Coupon_redemptions_past_6months_Capped	face_value_as_percentage_capped	Prior_spending_on_targeted_product_High	Multi_Category_coupon	duration_capped	gender_F	race_Other	Prior_spending_on_targeted_product_Low	Prior_spending_on_targeted_product_No_Prior_spend	framing_is_percentage	Coupons_per_month_capped
redemption	1.00											
Coupon_redemptions_past_6months_Capped	0.49	1.00										
face_value_as_percentage_capped	0.36	-0.01	1.00									
Prior_spending_on_targeted_product_High	0.36	0.32	0.03	1.00								
Multi_Category_coupon	0.35	0.01	0.64	0.02	1.00							
duration_capped	0.24	-0.41	0.52	0.07	0.41	1.00						
gender_F	0.17	0.12	0.06	0.12	0.08	0.05	1.00					
race_Other	0.12	0.12	0.04	0.04	0.03	0.02	0.30	1.00				
Prior_spending_on_targeted_product_Low	-0.20	-0.20	0.05	-0.56	-0.01	0.05	-0.06	-0.02	1.00			
Prior_spending_on_targeted_product_No_Prior_spend	-0.22	-0.16	0.09	-0.38	0.05	-0.15	-0.09	-0.05	-0.19	1.00		
framing_is_percentage	-0.1	0.09	-0.6	0.01	-0.4	-0.4	-0	-0	-0.1	0.10	1.00	
Coupons_per_month_capped	-0.3	-0.02	-0.5	-0.1	-0.5	-0.3	-0	0.02	0.07	-0.20	0.24	1.00

4.3.3 Explanation of correlation results by construct

As shown in Table13 and Figure1 above the variables that have a stronger relationship with redemption after treating for multicollinearity per construct are.

1. **Demographic factors**

   Gender – when gender is female there is a positive relationship with redemptions as seen with a coefficient of 0.17

   Race – When race is Other (i.e., Indian, Coloured, or Asian) there exists a positive relationship with redemption. However, there was a negligible correlation of -0.05 between race being African and coupon redemption see Table14 in appendix.

2. **Coupon Design factors**

   Face value – As the face value or discount of the coupon increases/decrease redemptions also changes in the same direction as shown by the positive correlation coefficient of 0.36 in Figure1

   Multi_category_coupon – the number of categories where the coupon can be redeemed has a positive relationship with redemptions as shown with correlation coefficient of 0.35 in Figure1 , indicating that a change in this variable will result in redemptions to change in the same direction.

   Duration – there is a positive relationship between duration and redemption indicating that as the time to redeem changes redemptions also changes in the same direction.

   Framing as percentage – There is a negative correlation of -0.13 between framing and redemption. This indicated that as more coupons are framed in percentage, redemption will change towards the opposite direction.

3. **Behavioural factors**

   Previous redemption behaviour – If a consumer is given more coupons within the same period (i.e., same campaign or same month) redemptions will likely reduce as shown by the negative correlation of -0.26 between the coupons_per_month_capped variable and redemption. However, if a

consumer has shown a high/low previous redemption behaviour over the preceding 6 months the redemptions will also be high/low, changing in the same direction as the previous redemptions. Furthermore, the previous redemption behaviour with variable coupon_redemptions_past_6months_capped shows the highest positive relationship with redemption at coefficient of 0.49, see Figure1.

Previous purchasing behaviour – If a consumer is targeted with a coupon that can be redeemed in a product that they have shown a high spending behaviour over the preceding 6 months period the redemption will increase as shown by the positive correlation of 0.36 with redemptions for the variable "prior_spending_on_targeted_product_high". Furthermore, if the consumer has shown a low or have never spent into the product they are targeted for, the redemption will likely decrease as seen with the negative correlation between redemptions and the variables "prior_spending_on_targeted_product_low" and ""prior_spending_on_targeted_product_no_prior_spend" in Figure1.

4.4 Inferential Analysis

4.4.1: Introduction

In the previous subsection correctional analysis results have been explained with variables such as face value, framing, duration, multi_category_coupon, previous purchasing behaviour (prior_spending_on_targeted_product), previous redemptions behaviour (coupon_redemptions_past_6months_capped), gender and race showing as those with a higher relationship with redemption. However, correlation does not necessarily mean causation. The purpose of this subsection is therefore, to assess which of those variables that are highly correlated with redemption, will cause redemption to increase or decrease.

As mentioned in the methodology section, logistic regression model is used to find which variables are likely to explain coupon redemption. The regression

model is presented in the following section. The model was implemented using python programming language as outlined in the introduction of section 4.

Logit(p) = Intercept + a_1x_1 + a_2x_2 +… + a_nx_n,

, where a_i for $_i$ in ($_1$ … $_n$) are the coefficients and x_i…x_n are the independent variables. Logit(p) is the log-odds ratio. For the ease of interpretation of the coefficients, an exponent of the coefficients of the logit function will be taken to convert them into odds ratios then a number 1 will be subtracted from the odds ratio with the result multiplied by 100 to convert to the percentage increase in odds of a redemption happening.

This model was used since the dependent variable(redemption) is dichotomous with the independent variables having numerical variables. Thus, making this a classification problem due to the dichotomous dependent variable (0=not redeemed and 1= redeemed). The model predicts whether a coupon will be redeemed or not redeemed.

4.4.2 Model results and findings

Figure 2: Logistic Regression Model output

Initial Iteration

```
Optimization terminated successfully.
         Current function value: 0.427061
         Iterations 7
                                        Results: Logit
==============================================================================================
Model:                        Logit                      Pseudo R-squared:            0.384
Dependent Variable:           redemption                 AIC:                         249683.3408
Date:                         2023-01-29 10:20           BIC:                         249799.7817
No. Observations:             292302                     Log-Likelihood:              -1.2483e+05
Df Model:                     10                         LL-Null:                     -2.0261e+05
Df Residuals:                 292291                     LLR p-value:                 0.0000
Converged:                    1.0000                     Scale:                       1.0000
No. Iterations:               7.0000
----------------------------------------------------------------------------------------------
                                                  Coef.  Std.Err.     z     P>|z|   [0.025  0.975]
----------------------------------------------------------------------------------------------
Coupon_redemptions_past_6months_Capped            1.2133   0.0069  175.1176 0.0000  1.1997  1.2269
face_value_as_percentage_capped                   0.0349   0.0008   41.0768 0.0000  0.0332  0.0366
Prior_spending_on_targeted_product_High          -0.0015   0.0130   -0.1161 0.9076 -0.0269  0.0239
Multi_Category_coupon                             1.2818   0.0135   94.6892 0.0000  1.2553  1.3083
duration_capped                                  -0.0100   0.0005  -18.2854 0.0000 -0.0110 -0.0089
gender_F                                         -0.0183   0.0115   -1.5940 0.1109 -0.0409  0.0042
race_Other                                        0.3202   0.0125   25.5653 0.0000  0.2957  0.3448
Prior_spending_on_targeted_product_Low           -1.2538   0.0160  -78.4803 0.0000 -1.2851 -1.2225
Prior_spending_on_targeted_product_No_Prior_spend -2.1270   0.0210 -101.4574 0.0000 -2.1681 -2.0859
framing_is_percentage                            -0.1520   0.0118  -12.9161 0.0000 -0.1751 -0.1290
Coupons_per_month_capped                         -0.2136   0.0019 -113.7811 0.0000 -0.2173 -0.2099
==============================================================================================
```

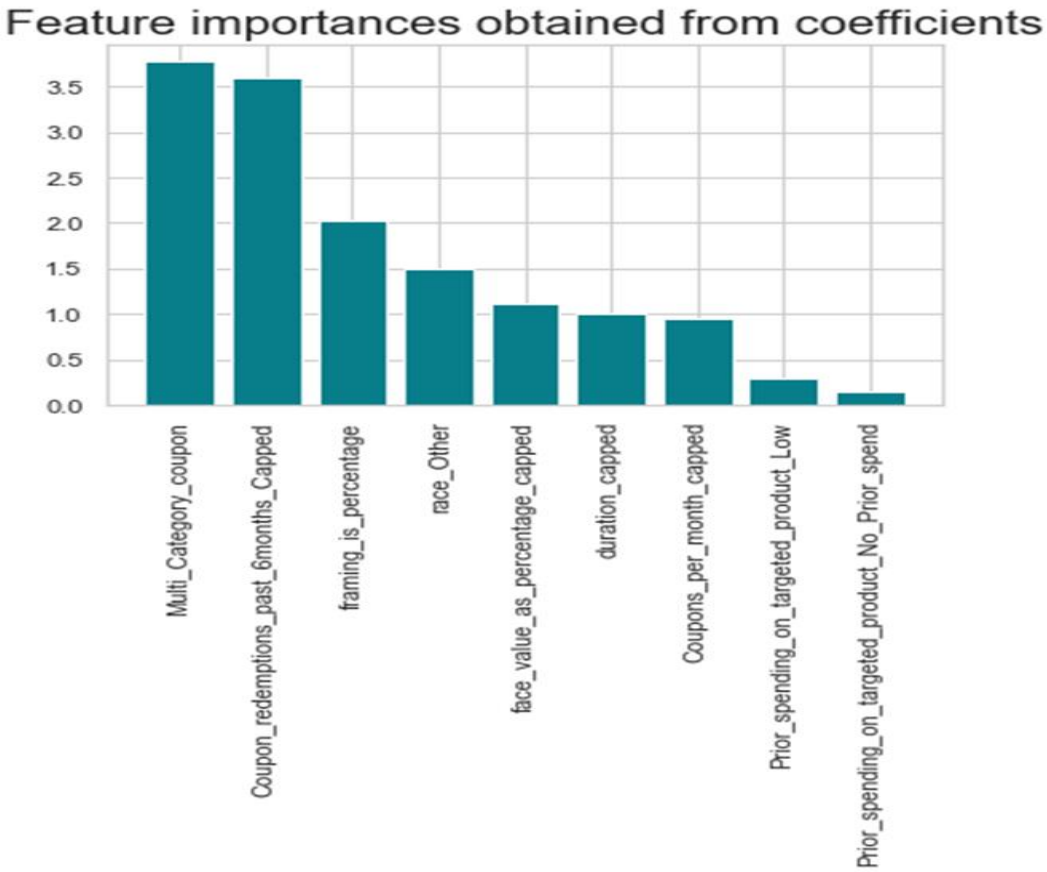
Final Iteration

```
Optimization terminated successfully.
         Current function value: 0.427065
         Iterations 7
                                        Results: Logit
==============================================================================================
Model:                        Logit                      Pseudo R-squared:            0.384
Dependent Variable:           redemption                 AIC:                         249682.0263
Date:                         2023-01-29 10:20           BIC:                         249777.2961
No. Observations:             292302                     Log-Likelihood:              -1.2483e+05
Df Model:                     8                          LL-Null:                     -2.0261e+05
Df Residuals:                 292293                     LLR p-value:                 0.0000
Converged:                    1.0000                     Scale:                       1.0000
No. Iterations:               7.0000
----------------------------------------------------------------------------------------------
                                                 Coef.  Std.Err.     z     P>|z|   [0.025  0.975]
----------------------------------------------------------------------------------------------
Coupon_redemptions_past_6months_Capped            1.2125   0.0069  176.1470 0.0000  1.1990  1.2260
face_value_as_percentage_capped                   0.0346   0.0008   43.2563 0.0000  0.0330  0.0361
Multi_Category_coupon                             1.2807   0.0135   94.7308 0.0000  1.2542  1.3072
duration_capped                                  -0.0101   0.0005  -18.7628 0.0000 -0.0111 -0.0090
race_Other                                        0.3143   0.0120   26.2741 0.0000  0.2908  0.3377
Prior_spending_on_targeted_product_Low           -1.2519   0.0128  -97.9209 0.0000 -1.2770 -1.2268
Prior_spending_on_targeted_product_No_Prior_spend -2.1255   0.0189 -112.4394 0.0000 -2.1625 -2.0884
framing_is_percentage                            -0.1564   0.0110  -14.2705 0.0000 -0.1779 -0.1349
Coupons_per_month_capped                         -0.2144   0.0018 -120.5834 0.0000 -0.2179 -0.2109
==============================================================================================
```

Figure 3: Feature importance for predictors of redemption

The feature importance shows how much a variable has an influence in explaining coupon redemption when compared to the other variables in the final model. This importance is derived from the coefficients of the variables in the final model as seen in Figure2. For example, the below figure indicates that the multi_category_coupon has the highest influence on coupon redemption followed by the variable coupon_redemptions_past_6months_capped while the prior_spending_on_targeted_product_no_prior_spend variable shows that giving coupons on products where consumer has no previous spending has the least

influence on coupon redemption when compared to the other variables in the model.



4.4.2.1 Demographic factors

During the initial iteration of the model building gender showed a p-value > 0.05 implying that it was not a significant predictor of coupon redemption, see first iteration of model building in Figure2. This implies that though the descriptive analysis found that females show a higher redemption than male, being female does not necessarily cause a consumer to redeem their coupon, hence gender does not influence coupon redemption. However, there is an influence on redemption when race is Indian or Coloured. A significant coefficient of 0.3143 for when race is Indian or Coloured was found which implies that increasing the population targeted for a coupon by 1 Indian/Coloured consumer will increase the odds ratio of coupon being redeemed by exp (0.3143) = 1.3692 which is approximately 37% increase in the odds of redemption over when consumer is African or White.

4.4.2.2 Coupon Design Factors

As shown in Figure2 , variables such as face value, framing, duration and whether a coupon can be redeemed in a single or multiple category all came up as significant predictors of redemptions with p-value < 0.05. Face value produced a coefficient of 0.0346 which implies that an increase of 1% in the discount offered will increase the odds of redemption by 4% (exp (0.0346) =1.0352 ≈ 4% increase). Surprisingly, the variable of whether a coupon can be redeemed in single or multiple categories came up as the highest predictor of redemption as seen with the highest coefficient of 1.2807 implying an increase of 1 unit in the coupons that can be redeemed in multiple categories over the single category will increase the odds of redemption by 260% (exp (1.2807) = 3.5992 ≈ 260% increase).

In addition, while duration and framing of coupon discounts as percentages are also important predictors of redemption, they however have a negative impact on redemption. Increasing the duration of coupon validity by 1 more day slightly reduces the odds of redemption by 1% (exp (-0.0101) = 0.9900 ≈ -1% increase). Similarly, framing the coupon discount as a percentage vs. a rand value decreases the odds of redeeming by 14% (exp (-0.1564) =08552 ≈ -14% increase).

4.4.2.3 Behavioural Factors

Previous redemption behaviour

The number of coupons given in one month and the previous redemption behaviour came up as significant predictors of redemption with p-values < 0.05, see Figure2 with variables “coupon_volume_redemptions6monthbefore” and “coupon_volume_permonth”. The previous redemption behaviour came up as the second highest predictor of redemption, see variable importance Figure3, indicating that the more consumers are familiar with redeeming the higher is the chance of redeeming again in future. With a coefficient of 1.2125 it implies that previous redemption behaviour will increase the odds of redeeming again by 236% if the number of previous redemptions is increased by 1.

On the contrary, if a consumer is given more coupons in one month it will have a negative impact on redemption. With a coefficient of -0.2144 it implies that increasing the number of coupons offered by 1 more coupon within a month will reduce the odds of redeeming by 19%.

Previous purchasing behaviour

A consumer's previous spending behaviour in the product that a coupon is offered is a significant predictor for redemptions. Offering a coupon in a product where a consumer has never spent or has a low spending behaviour will have a negative impact on redemptions. With the coefficient of -2.1255 for when there is no previous spending behaviour and a coefficient of -1.2519 for when the level of spending is low it implies that the odd of redemption reduces by 88% and 71% respectively for when coupons offered in the low engaged products is increased by 1 vs the medium to high engaged. Which inversely implies that increasing coupons in the medium and high engaged products will increase the odds of redemption.

4.4.3 Model fit statistics

Figure 4: Model fit statistics

	precision	recall	f1-score	support
0.0	0.81	0.85	0.83	43815
1.0	0.84	0.81	0.82	43876
accuracy			0.83	87691
macro avg	0.83	0.83	0.83	87691
weighted avg	0.83	0.83	0.83	87691

The accuracy of the model came out as 0.83 = 83% which implies that the model can correctly classify 83% of the coupons as redeemed or not redeemed. The precision for redemption (1) is 0.84 = 84% implying that 84% of the observations that the model predicts as redemptions are redemptions while the recall of 1 is 81% implying that the model can correctly classify 81% of the actual redemptions. The model shows that though it can correctly classify 81% of redemptions, 84%

of those that are predicted as redemptions will be redemptions. Furthermore, the overall F1-score which balances the model precision and recall is 83%. As a result, with these statistics of precision, recall and F1 score being as close to 100% it implies that the model is a good classifier/predictor of redemption.

Which in turn implies that the predictors that were found as significant predictors of redemption are valid as they result in more redemptions or non-redemptions being correctly classified.

Furthermore, the area under the receiver operating characteristic (ROC) curve is 0.83 which is very to 1 which further validates that the model is a good classifier of redemption.

Figure 5: The model's Receiver Operating Characteristic (ROC) Curve



4.4.4 Conclusion

The analysis finds that factors such as face value, multicategory coupons, duration, race, purchasing behaviour, framing coupons as percentage and the number of coupons received and redeemed in the past has an influence on redemptions. Offering coupons that are redeemable in multiple products as well as offering to consumers who have past redemption behaviour have the highest impact on increasing redemption. While offering coupons on products where consumers spent low or have never spent before have the highest impact on reducing redemption. These findings are further validated by the p-values < 0.05 of these variables in the logistic regression model as well as the model fit statistics

that gave an accuracy of 83%, as well as Precision, recall and F1-score of the same amount 83%.

5. Discussions, Implications and Conclusion

5.1 Introduction

The purpose of this research was to identify the factors influencing coupon redemptions. A literature review was conducted to identify what previous work has found, followed by a rigorous analysis as seen in the previous section to identify the factors that influence coupon redemption in the South African retail industry context. This section aims to triangulate the previous findings as per literature review with the findings of the above analysis to deduce if the previous findings that were mainly from outside of South Africa are also applicable in the South African retail industry and subsequently answer the questions.

1. What factors are encouraging coupon redemption in the South African retail industry?
2. What factors are discouraging coupon redemption in the South African retail industry?
3. How can South African retail companies increase coupon redemptions?

5.2. Demographic Factors

Several studies found that demographic variables such as age, gender, income, and race have an influence on coupon redemption (Clark et al. ,2013; Danaher et al., 2015; Wang & Lalwani, 2018). These views have been collaborated by many, however most of these studies were not conducted within the South African retail industry. Contrary to the popular believe, most of the demographic factors did not come up as key predictors of redemption within the South African retail industry. The descriptive analysis showed that the average age of consumers who did not redeem their coupons is the same as the average age of consumers who redeemed their coupons at 44 years old, implying that there is no difference in the age of consumers who redeem their coupons vs those who do not redeem their coupons.

Furthermore, the correlation of age with coupon redemption was found to be 0 as shown with variable age_capped in table14 in the appendix thus implying that there is no relationship between age and coupon redemption. Hence leading to the conclusion that age has no influence on coupon redemption. Disagreeing with the hypothesis that age has a positive influence on coupon redemption such that older customers are more likely to redeem their coupons. The reason age did not come up as an influencer for coupon redemption could be linked to the fact that the data used in this study was heavily skewed towards older customers, with 75% of the population being older than 35. Having a fair representation of the age younger than 35 could result in different findings since there will be a reasonable comparison of the different age groups. The retailer used to collect the data for this study is mainly popular in the relatively older population.

With regards to gender the analysis showed that females had high coupon redemptions when compared to males. Furthermore, the correlation between gender_f and coupon redemption is relatively high with a coefficient of 0.17 indicating that there is a positive relationship between gender being female and coupon redemption. However, from the inferential analysis the variable gender_f came up as a weak predictor or influencer of coupon redemption as seen in the first iteration of the model building in **Figure2** in the appendix where the p-value was 0.1109 which is above the limit of a p-value of 0.05 that is considered the acceptable p-value to deem an independent variable a predictor of a dependent variable.

This, therefore, contradicts the hypothesis that gender has an influence on coupon redemption such that males are more likely to redeem their coupons than females. The reason this hypothesis was not met could be linked to the low representation of males in the data which was at 21% while female represented 79% of the population used in the study. This could imply that future research must consider collecting data that represents the gender split of the South African population.

Similarly, with income, the descriptive analysis showed that consumers with income less than R10,000 had the highest average redemption, followed by consumers with income R100,000 or more. However, the income groups

between R10,000 to R99,999 had a lower average redemption than income group less than R10,000. Furthermore, when considering the correlation of the different income groups the group less than R10,000 shows the highest positive correlation of 5% when compared to all the other income groups (see table14 in the appendix) implying that low-income consumers redeem their coupons more than higher income consumers. This contradicts the hypothesis that higher income result in higher coupon redemption. However, after further investigating with the retailer it was found that the income variable is not updated frequently, and that it relies only on information provided by a customer when they joined the company's rewards program. Thus, there is a possibility that those customers who are flagged as less than R10,000 are misclassified since their income would have changed overtime. To effectively assess the influence that income has on coupon redemption, it might be useful to use primary data with the income collected directly from the consumers to ensure it is relevant and up to date.

On the other hand, when race was other which constitutes Indian, Coloured or Asian , the descriptive analysis showed that this group of consumers had the highest average redemption when compared to Africans and Whites though they were the smallest of the population .Furthermore, this variable had a relatively high correlation with coupon redemption when compared to Africans and Whites with the inferential analysis also showing that being other (Indian or Asian) will increase the odds of redeeming a coupon by 37%. This finding agrees with Wang and Lalwani (2018) who found that South and East Asian redeem more due to their interdependence culture. However, when race was African there was no influence on coupon redemption due to the negligible correlation between race_African and coupon redemption. Therefore, disagreeing with the hypothesis that Africans are more likely to redeem their coupons than other races, while proving the hypotheses that those with a collective culture are more likely to redeem as found in the small population of Asians in the dataset.

The hypothesis that Africans are more likely to redeem their coupons than other races was derived on the basis that the population used in this study was mainly Africans since the study took place in South Africa. However, the findings contradict the hypothesis and agrees with the previous studies that found that

Africans have a lower likelihood to redeem coupons when compared to other races.

5.3 Coupon Design Factors

Studies conducted by Zhang et al. (2019) and many others have found that the discount or face value offered is a key driver of redemptions. This has been confirmed to be the same in the findings of this study. Thus, proving the hypothesis that a higher face value will increase coupon redemption. Though face value is found to be a driver of redemption in the South African retail industry, it did not come as the strongest when compared to other factors in the model as many may have found outside the South African context.

Montazeri et al. (2021) found that framing as percentage off is more effective than cents off, while Yin and Dubinsky (2004) previously argued that the effect that framing has will vary based on price, with higher prices working well with cents-off and lower prices being more effective with percentage off. However, contrary to these findings the average redemptions were found to be lower where the discount is framed as percentage despite the prices also being lower than when the discount is in rand off. Furthermore, the inferential analysis of this study finds that framing the discount in percentages reduces redemption when compared to framing as rand-off. This contradicts the hypothesis that framing coupons in percentage-off will increase coupon redemption. This could be linked to the fact that the previous studies used to derive this hypothesis were mainly done outside of the South African context. This study instead finds that framing as rand-off result in higher redemptions than framing as percentage-off within the South African context. Thus, implying that the way in which consumers relate to how coupons are framed will vary in different geographies.

The study finds duration to have an influence on redemption. The descriptive analysis finds that on average the duration of coupons that were redeemed is higher than those not redeemed. In a similar vein, the correlational analysis shows that there is a positive correlation between duration and redemption. This coincide with previous studies which found that there is a direct correlation

between duration and redemption. However, the inferential analysis (the model) finds that as duration increases slightly there is a slight decrease in redemption. This indicates that though duration have an influence on redemption if it is set to be too long there will eventually be a negative effect on redemption. Highlighting that business must set just an adequate number of days (i.e.,14 days) for duration, such that the duration is not too long as this will eventually result in diminishing returns on redemption. This finding contradicts the hypothesis that a longer duration will result in higher redemptions. This could be because of people forgetting about the coupon if the duration is too long. Whereas, making the duration shorter helps drive urgency for consumers to redeem. An alternative could be that if a coupon is made to be valid for a period more than 14 days, the retailer must send frequent reminders to ensure coupon remains top of mind for the customer.

Surprisingly, multi_category_coupons appear to be the highest influencer of redemption when compared to the discount offered. Thus, proving the hypothesis that offering a coupon that is open in a wider product range will increase redemption. Most of similar studies previously found that opening a coupon to a wide product range will increase redemptions. It is however surprising since many studies have previously highlighted the discount offered as the key/highest factor that drives redemption and not necessary the number of products where redemption can be done.

5.4 Behavioural Factors

In a study conducted by Mills and Zamudio (2018) it was found that offering consumers many coupons at the same time will have a negative effect on redemptions. The study highlights that this is due to the costs associated with the choice since consumers generally do not like to engage in too much thinking when making decisions or choice. The findings of this study confirm this view, where it finds that offering more than one coupon in one month reduces the chance of coupons being redeemed. Thus, proving the hypothesis that offering more coupons to consumers will decrease coupon redemption. However, if a consumer has a previous redemption behaviour, the study finds that their chance

of redeeming again will be higher and this variable came up as the second highest influencer of redemption. This proves the hypothesis that consumers who have shown a previous redemption behaviour will have a higher chance of redeeming future coupons.

Like previous findings that offering coupons on products where consumers are already spending will increase redemptions, this study also finds that if a consumer have never spent or is spending low on the product where a coupon is offered the chances of redeeming will decrease. Which conversely implies that, if a coupon is offered in a product where consumer has a medium or high spending behaviour the redemption will increase, indicating that previous purchasing behaviour has an influence on redemption. Thus, proving the hypothesis that offering coupons on products a consumer purchases frequently will increase the redemption of such coupons.

5.5 Managerial Implications

The findings of this study provide key implications for managers to increase coupon redemptions and realise the return on their marketing investments for coupon campaigns. Firstly, managers must target coupon campaigns to consumers who have shown a previous redemption behaviour, since these consumers have a high likelihood to redeem their coupons in future campaigns as they have an experience of redeeming and engaging with coupons from the past. Secondly, managers must refrain from offering coupons that are redeemable on a single category product (i.e., on Apples only) since consumers do not engage much with coupons that do not give them the freedom to choose where to use the coupon. They must set up coupons that are redeemable in a wide range of products (i.e., the whole Foods department) to realise high coupon redemptions. Thirdly, they must offer coupons to consumers in line with their previous spending behaviour since the study finds that if consumers are given a coupon that is redeemable on a product where they have shown a high spending behaviour in the past, those consumers will have a high coupon redemption.

Furthermore, Managers must refrain from giving coupons to consumers on products where the consumer does not show a past spending behaviour since the likelihood of them engaging with such coupons is small. In addition, when managers want to drive acquisitions into new products, they must first drive awareness campaigns and get consumers to first engage with the product and later follow with coupon campaigns to drive more spending. This will increase coupon redemption when targeting products where consumers do not show high spending behaviour. Furthermore, managers must offer coupons with deeper discounts to drive more redemptions particularly in cases where they want to use coupons as a marketing leaver to drive acquisitions into a new product.

Fourthly, managers must frame the offer in rand-off, as consumers turn to redeem their coupons more when they can see the exact amount they will save compared to when it is framed as percentage since it requires them to do calculations to get to the saving. The study shows that those coupons that are framed in percentages result in lower coupon redemption. Finally, managers must refrain from giving too many coupons to consumers at the same time as this will negatively affect coupon redemption as consumers struggle with the cost associated with having to redeem more coupons at the same time. It will be useful to have sophisticated algorithms that managers use to inform which coupon a consumer is more likely to redeem at a given point in time and use this to send few and targeted coupons to consumers to realise higher coupon redemption.

5.6 Conclusion and recommendations

As outlined in detail in the previous sections, this study finds that factors such as previous purchasing and redemption behaviour, the discount or face value offered, opening redemption to a wide range of products and race being Asian cause redemption to increase. However, the race factor cannot be considered since this population is small in the South African market. Furthermore, when race was African the study finds no influence on coupon redemption due to the negligible correlation between this variable and coupon redemption. On a different note, factors such as giving too many coupons at the same time, giving

coupons on products that shows low or no previous spending behaviour and framing as a percentage discourages or decreases redemptions.

These findings suggest that if business wants to increase redemptions, they must target consumers who have shown a previous redemption behaviour while ensuring that the coupon being offered is redeemable in a wide range of products. Moreover, the products where the coupon is offered must be those where consumers showed a high spending behaviour in the past. The offer must be framed in rand-off as consumers turn to redeem their coupons more when they can see the exact amount they will save compared to when it is framed as percentage-off, since it requires them to do calculations to get to the saving. Furthermore, as many businesses have a need to acquire consumers into product lines where they do not have previous engagement, they can still offer coupons in these however, it is important that the coupon is targeted to consumers that do show some history of previous redemption behaviour and that it is redeemable in a wider range of products than a single category product. Furthermore, offering a deeper discount will also drive more redemptions particularly in cases where a business wants to use coupons as a marketing leaver to drive acquisitions into a new product.

Finally, the findings of this study show that though there are similarities in the findings done in the previous studies outside of South Africa there are also differences. These differences will mainly be introduced by the varying geopolitical environments, interests, and habits, with most of the influencing factors coming from a previous consumer behaviour and the attractiveness of the coupon being offered.

5.6.1 Limitations and future research

While the study provides several insightful findings on the factors affecting coupon redemption in the South African context and what retailers can do to increase coupon redemptions, there were however some limitations. Firstly, the data was collected from a single retailer which resulted in data not being a 100% representation of the South African population. This is evident with the data being

skewed towards the White customers that showed the highest (37%) percentage contribution in the population. Age representation being skewed towards older customers with 75% of the population being older than 35 years. The gender imbalance in the data with female 79% and male 21%. Furthermore, the income group of the population was mainly high-income earners with 39% having a household income between R20,000 to R49,999 and 42% with a household income of R50,000 or more per month. This is mainly because the specific retailer used in the study is known for servicing more affluent customers. Added to this was the fact that the income data that the retailer has may be outdated as it is not updated frequently. Moreover, the data from the retailer did not have the education variable which presented another limitation to assess or evaluate the influence that education has on coupon redemption. Despite these limitations the study does provide insights into the factors affecting coupon redemption in South Africa.

However, there is an opportunity for future research to consider a different data selection approach, by considering selecting the data from more than one retailer to get a better representation of the South African population, or alternatively by using primary data. Furthermore, with hypothesis on age, gender and income not supported with the data used in this study due to the skewness towards one gender, older age or the income information that is not frequently updated, there is merit in considering a different data selection process for future research. When considering variables such as income, it is recommended that primary data is collected for future research to ensure the income used is up to date since it will be directly from the customers.

Education is another factor that was not assessed in this study since the retailer's data does not contain this variable. Thus, a consideration of using primary data for future research can give researchers the opportunity to collect such variables directly from the target population. Having a dataset that has a fair representation of the demographic's variables may unlock new findings and insights for future research.

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6. Appendix

Table 13: First iteration of correlation analysis for all variables

Variable	Correlation to redemption
redemption	100%
Coupon_redemptions_past_6months_Capped	54%
Discount_int	39%
face_value_as_percentage_capped	37%
Prior_spending_on_targeted_product_High	36%
threshold_capped	35%
Multi_Category_coupon	35%
duration_capped	27%
business_unit_name_FBH	23%
gender_F	17%
race_Other	12%
Coupons_received_past_6months_capped	6%
household_income_band_Less than R10,000	5%
macrosegment_Habituals	4%
province_Western Cape	3%
business_unit_name_Fashion	2%
province_KwaZulu-Natal	2%
business_unit_name_Beauty	2%
province_Gauteng	2%
macrosegment_Aspirers	2%
channel_SMS	1%
household_income_band_R100,000 or more	1%
business_unit_name_Home	1%
macrosegment_Shopaholics	1%
Age_capped	0%
household_income_band_R50,000-R99,999	0%
province_Eastern Cape	0%
household_income_band_R20,000-R49,999	0%
macrosegment_Trendspotters	-1%
macrosegment_Dealhunters	-1%
channel_EMAIL	-1%
province_Limpopo	-2%
macrosegment_Savvys	-2%
province_Northern Cape	-2%
province_North West	-2%
race_White	-2%
macrosegment_No_segment	-2%
household_income_band_R10,000-R19,999	-3%
province_Free State	-3%
province_Mpumalanga	-3%
household_income_band_None	-5%
race_African	-5%
race_No_race	-5%
Prior_spending_on_targeted_product_Medium	-8%
gender_M	-10%
province_No_province	-11%
framing_is_percentage	-13%
gender_No_Gender	-16%
Prior_spending_on_targeted_product_Low	-20%
Prior_spending_on_targeted_product_No_Prior_spend	-22%
business_unit_name_Foods	-24%
Coupons_per_month_capped	-26%
Coupons_per_campaign_capped	-40%

Figure 6: Correlation matrix between all variables

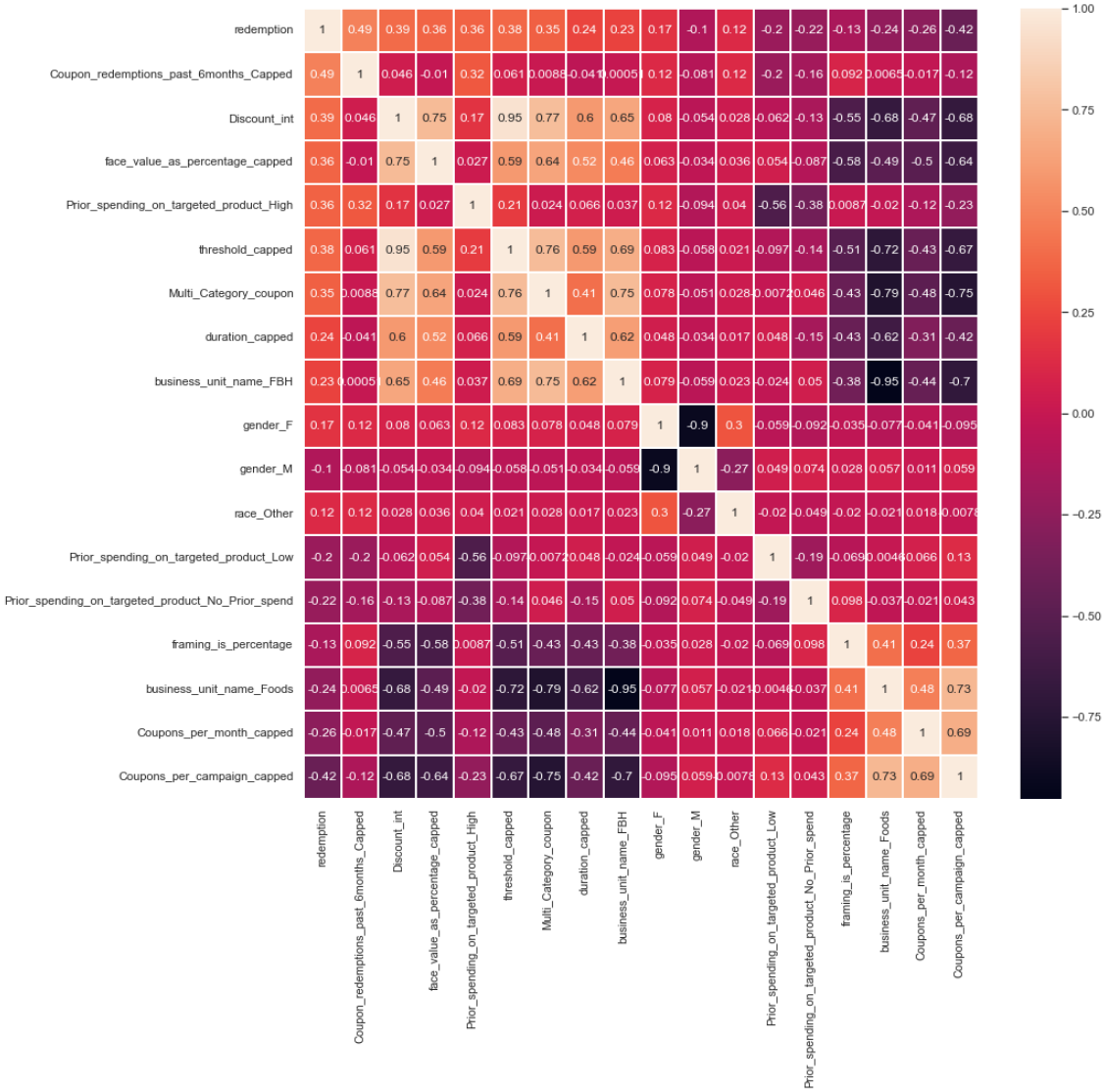

Table 14: First iteration of variance inflation factor (VIF) analysis

First view of VIF after considering only those that are correlated	feature	VIF
0	redemption	4
1	Coupon_redemptions_past_6months_Capped	2
2	Discount_int	42
3	face_value_as_percentage_capped	27
4	Prior_spending_on_targeted_product_High	5
5	threshold_capped	43
6	Multi_Category_coupon	8
7	duration_capped	11
8	business_unit_name_FBH	12
9	gender_F	18
10	gender_M	6
11	race_Other	1
12	Prior_spending_on_targeted_product_Low	2
13	Prior_spending_on_targeted_product_No_Prior_spend	2
14	framing_is_percentage	3
15	business_unit_name_Foods	27
16	Coupons_per_month_capped	10
17	Coupons_per_campaign_capped	14