# Factors Affecting the Effectiveness of Promotional SMS Communication in the Sri-Lankan Fashion Retail Sector



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**Abstract**

This study was undertaken to explore the determinants that can influence effective targeted promotional SMS communication in the Sri-Lankan fashion retail sector. The objective of this study is to examine the current context of targeted promotional SMS communication in Sri-Lankan fashion retail sector. This study is also aimed at examining the relationship between dynamic customer segmentation via transactional and loyalty-card data utilization for targeted promotional SMS communication and provide relevant recommendations to improve effectiveness of SMS promotional communication. This study uses a deductive research approach. Hypothesis were generated and tested via a survey in Colombo, Sri-Lanka with 347 responses. Based on the regression analysis, all the independent variables of loyalty-card data utilization, past purchase data utilization and dynamic customer segmentation had a strong positive relationship and a positive relationship towards the independent variable of effectiveness of SMS Communication and all the hypothesis were accepted along with the conceptual framework that 72% represents towards (Impact on) Effectiveness of SMS Communication by all the independent variables considered. Research was limited to the fashion retailing sector and only the retail customers were surveyed and new customers are excluded from the study benefits. As a research implication, adoption of big data and business-intelligence practices are highly recommended. Most of the prior literature is on the USA and Europe region and some are biased to eCommerce whereas this study focusses on the Sri-Lankan region and use of offline data sources for targeted SMS promotions.

**Keywords:** SMS Promotional communication, Targeting, Loyalty-Programs (Lps), Past purchase behavior, Data utilization

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**Introduction**

The Sri-Lankan retail sector contributes to around 34% of the country's GDP (Daily FT, 2019) and a major portion of it is comprised of the fashion retailing sector. 60% of Sri-Lankan fashion-retail customers are loyal to a retailer (Samarasinghe, 2016) and since, the true value of an organization relies on its loyal customers (Alshurideh, 2019), and effective promotional communication to the loyal fashion-retail customers has become very significant. Promotions and discounts adoption is higher in fashion-retail compared to other sectors due to its competitive nature (Ford , 2016) and there is an expectation within the sector to continuously refresh their communications and stay connected with customers (Sharma and Sahni, 2018).

Monthly, more than 350 billion texts are sent globally and more than 15% of them are promotional communications (Ahmed, 2018). As per Malamidou, Spyropoulos and Rotsios (2018), retailers reach the consumers via promotional short-messaging-service (SMS) by utilizing their loyalty-programmes (LP) details. Sri-Lanka utilizes LP collected data for SMS promotional communication (Weeraratne, 2015). However, at present, customers have become reluctant to share their details with LP as discount savings are not worth the spam promotions (Nguyen and Klaus, 2013). Thus, the need for deeper analysis into Customer-Relationship-Management (CRM) information and transactional databases for personalized promotional SMS has become important (Malamidou, et al., 2018).

## *Research Problem Identification*

With reference to the fashion retailing sector of Sri-Lanka, what are the factors that influence the effectiveness of SMS promotion?

Even-though data-driven personalized promotional communications have increased engagements by 800% (Stalidis and Diamantaras, 2019), retailers still send generic promotions to the entire customer-base which has resulted in consumers receiving irrelevant promotions (Malamidou, et al., 2018). These unwanted and annoying messages have negatively influenced customer attitude (Ahmed, 2018). Therefore, this can be seen as an aspect which requires attention with regard to the Sri-Lankan fashion retailing promotional communication (Samarasinghe, Suwandaarachchi and Ekanayaka, 2016).

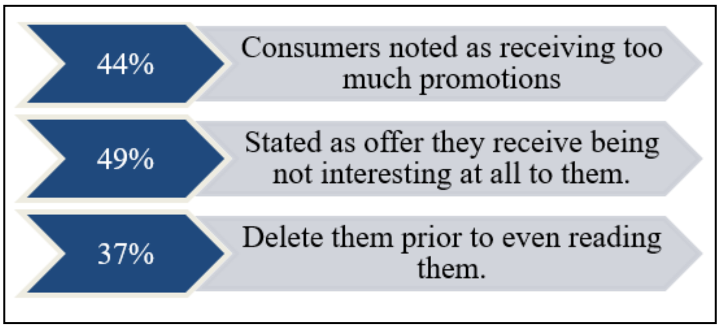


**Figure 1.** Message Bombarding

(Adopted from SAP Hybris, 2015)

As shown in Figure 1 , consumers are irritated by spammy promotional SMS bombarding (Smita, 2018). Communication frequency and message fatigue were noted as the key-challenges in promotional communication (Adobe, 2014). Sri-Lankan consumers have also become victims of message bombarding (Perera, 2010) and should move towards targeted promotions (Daniel, 2015). Ultimately, in loyalty-based messaging, SMS incrementality of repeated messages have resulted decreased returns (Bies, Bronnenberg and Gijsbrechts, 2021).

The success of SMS-marketing is based on its capacity to be highly target-oriented (Smita, 2018). However, 90% of the customers mention that the promotional SMS they receive have nothing to do with their interests (Adobe, 2014) and that they are irrelevantly bombarded (Nandi and Mittal, 2013) with messages. Too much information has confused and annoyed customers resulting in a negative attitude towards SMS-marketing campaigns (Ahmed, 2018).

**Litreature Review**

## *Loyalty Programs (LPs)*

In retailing, LPs are card-based which are scanner-readable or swiped at the checkout. They provide benefits to the user such as exclusive deals, cost-savings, rebates and even redeemable points (Allaway et al., 2006). 90% of the transactions were noted as having loyalty-cards (Byrom, 2001). In a global survey 72% responders have agreed that, all other factors equal, they would purchase from a retailer with a LP (Kumar, 2019). LPs encourage repeat purchases while exchanging incentives (Ramaboa and Das, 2015, Malamidou, et al., 2018). The core purpose of the LPs were seen as retaining loyal customers as acquiring new customers are difficult and cost-ineffective (Ramaboa and Das, 2015). As noted by Yapaa and Kennedy (2020), LPs were developed for rewarding the customers as well as generating information about them to manipulate their behavior by providing personalized offerings. Ultimately, “the plastic card becomes the mechanism for the exchange of information and rewards to take place" (Byrom, 2001). Finally, as noted by Stathopoulou and Balabanis (2016), for 2020 LP memberships were expected to be at 419 million and its importance continues especially for the luxury fashion brands.

## *Sri-Lankan Fashion Retail Promotional Communication*

Communication was interpreted as “who says what (message), in which channel to who (audience), with what effect” (Lasswell, 1948, as cited in Danaher and Rossiter, 2011). Sri-Lankan retailers are reaching out to customers for promotional communications by utilizing the data collected through LPs as a step in CRM (Weeraratne, 2015). Yet, as per Samarasinghe, Suwandaarachchi and Ekanayaka, (2016), many inefficiencies exist in Sri-Lankan fashion retailers’ promotional communication as they are not targeted. Consequently, discovering shopping trends were seen as the fashion retail sector’s lifeline which ultimately shall get molded into a personalized shopping experience (Silva, Hassani and Madsen, 2019).

*Short Message Service (SMS)*

SMS marketing was identified as one of the main such methods for brand communication in Sri-Lanka (Dilan, 2016). As per Smita (2018), text messages were seen as a very common method used for brand communication by world-renewed brands. As per a survey conducted by Mbuthia (2016), 80% of the respondents have agreed that sending text messages is the most adopted marketing strategy of fashion brands. However, on the other hand, SMS marketing was seen as an invasive method of communicating with the customers which is an aggressive push that doesn't influence shopping behavior but impacts negatively on the brand opinion (Gilani and Twiss, 2018). Furthermore, SMS spamming was seen as a major concern in Sri-Lanka as per the "Top Spammers in Sri Lanka in 2017" report by Truecaller revealed a 92% increase in spamming (Laymont, 2017). Thus, the need of SMS personalization has emerged and it is greatly-beneficial as depicted in Figure 2.

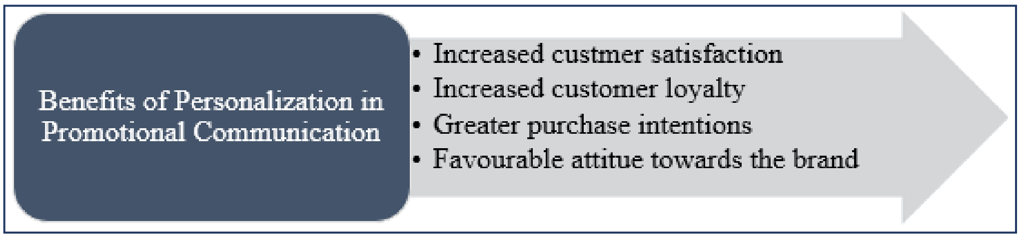


**Figure 2.** Personalization Benefits

(Adopted from Schreiner, Rese and Baier, 2019)

## *Related Theories*

*RFM (Recency, Frequency, Monitory) Analysis*

RFM was introduced by Bult and Wansbeek (1995) (Cited in Birant, 2011) and it is noted as the second most-used marketing method (McCarty and Hastak, 2007). Three attributes denoted under RFM are Recency, Frequency and Monitory values of the transactions made by the customers (Kohavi and Parekh, 2004). RFM variables that represent purchase history, frequency and total purchase value are derived using the transactional records (Chiu et al., 2009) which makes the RFM model extremely effective in customer segmentation (Cheng and Chen, 2009). RFM was discussed as most app;icable when sending promotional communications to customer databases in order to identify most probable customers that would respond to a given campaign (McCarty and Hastak, 2007). However, the RFM model was criticized as it fails to provide insights regarding new customers (McCarty and Hastak, 2007) and because it is less predictive since the three variables are isolated from the customer's geo-demographic data (Yang, 2004). Yet, RFM has dwelled over 50 years targeting customers and reducing promotional communication costs (Kohavi and Parekh, 2004).

*Market Basket Analysis (MBA)*

MBA or the Affinity Analysis is an unsupervised learning method which runs on transaction-type databases to identify "what goes with what" (Shmueli et al., 2018). MBA is a data mining technique which relies on the customer cart to identify recurring patterns in purchasing by extracting associations from transactional data, mainly for promotional campaigns (Zamil, Adwan and Vasista, 2020). When point-of-sale (POS) scanning data are collected with personally identifiable information (loyalty data), it can be analyzed to identify purchase patterns via MBA for targeting segments for cross and up-selling (Zamil, Adwan and Vasista, 2020).

*Customer Lifetime Value (CLV)*

CLV is noted as a key CRM concept similar to database-marketing and loyalty. It is denoted as the "Present value of all the future cash flows attributed to a customer relationship" (Pfeifer et al., 2005 as Cited in Blattberg, Malthouse and Neslin, 2009). Many consumer-centric organizations are utilizing CLV as a consumer-profitability metric to enhance the LP performance (Kumar, 2019). Utilizing customer purchase history, CLV is derived and evaluated (Woo, Bae and Park, 2005).

## ***Selection of Variables and Hypothesis Generation through the Literature***

*Loyalty Card Data Utilization*

Marketing Intelligence is oriented around loyalty-cards with large data warehouses. This highlights the real potential of loyalty-cards as the data collected through LPs can be used for targeted marketing rather than increasing traditional loyalty (Donnelly et al., 2012). Similarly, LPs are seen as a vehicle to track purchase patterns of individual preferences. (Ramaboa and Das, 2015). Also, as noted by Byrom (2001), LPs have provided immense data to understand consumers and their behavior.

Therefore, LPs were seen as data-rich environments to explore relational outcomes and when the loyalty-cards are scanned at checkout, they catalogue consumers automatically by day, time, product purchased, value, variety of other products etc. that can be analyzed for pattern behavior and targeted promotional communication (Allaway et al., 2006). Transforming loyalty-card data into customer knowledge would allow retailers to increase ROI of the promotional communications while utilizing the marketing resources at its best to maximize profitability (Hutchinson et al., 2015). Thus, the retailer is better informed when LPs are used to understand consumer interests and provide personalized offerings (Malamidou et al., 2018).

Silva et al., (2019), argues that as 85% of the fashion brand sales originated from customers registered in the databases, using big data analytics to individualize the consumer through LP data is the key to targeting When cardholder transitions are combined with geo-demographic details captured from the loyalty-card it gives a holistic view of the customer in the areas of products preferences, visit frequency and recency, life-style, visited stores and times and offer proneness (Byrom, 2001).

Even Sri-Lankan retailers have constructed databases with loyalty card data to be able to reach out for promotional communications (Pieris and Udunuwara, 2012). Yet, comparatively, Sri-Lanka has not made use of the loyalty-data to its true potential (Ragulan, 2013). But the LP members greatly expect promotional message personalization (Ramaboa and Das, 2015). As noted by Stone et al. (2003), customers experience just a card but a huge potential lies behind the data generated from it which ultimately requires optimizations in card and database management along with campaigns and promotional communication. A classic real-world example is the fashion brand H&M which is trying to reduce markdowns via big data analytics on store receipts and loyalty-card data instead of relying on designer intuitions (Silva et al., 2019).

Hence, it's expected that,

H1: There is a relationship between loyalty card data utilization and the effectiveness of the promotional communication.

*Past Purchase Data Utilization*

As noted by Donnelly et al. (2015), consumers appeared distant due to the lack of data utilizations for marketing intelligence. Likewise, when it comes to personalizing the promotional communication in brick-and-mortar stores, they have struggled a lot to personalize it compared to the online world. However, the best way forward is to start analyzing the past purchase data (Dekimpe, Geyskens and Gielens, 2019). Personalization in promotional communication demands extensive data collection and these data mainly refers to the past in-store behavior (Riegger et al., 2021).

Traditionally, customer insights can be derived from many sources, but most prominently it is the offline databases which hold purchase records and invoices (Kadir and Achyar, 2019). Various data source utilizations for personalized promotional communications were discussed in the literature out of which geo-demographic data are collected from the loyalty programs whereas, personally identifiable shopping behavior is achieved by utilizing past purchase data (Schreiner, Rese and Baier, 2019). There are many data types available in the in-store environment and the main focus of this study is on loyalty-card data and the purchase records as shown in Figure 3.

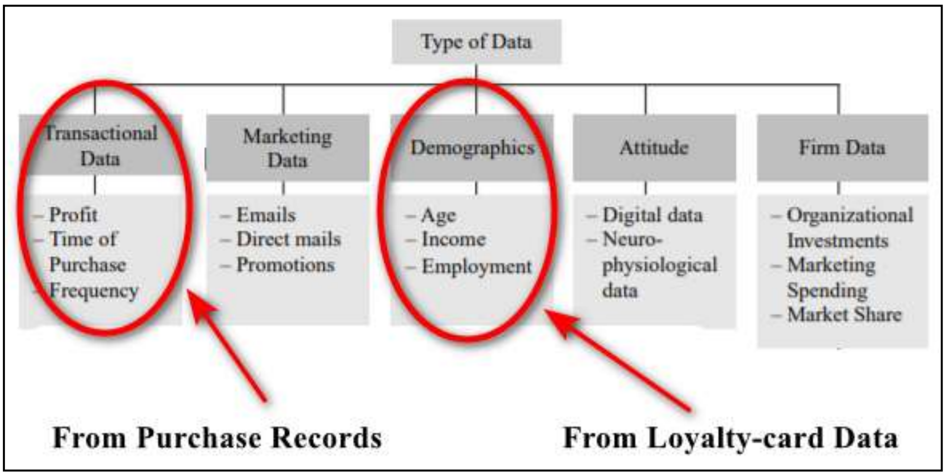


**Figure 3.** In-Store Data Types

(Adopted from Kumar et al., 2013)

Past purchase data utilization is also referred as basket data utilization and basket information collects data such as products purchased, time of the day, offers taken-up and which items are purchased together etc. which allows to personalize offerings (Byrom, 2001).

Daniel (2015), elaborates an example on a 'Levi's Jean Deal', where he explains that promotional messages related to the respective deal shall reach the consumers who are most-likely to purchase Levi's by highlighting the fact that, Sri-Lankan retailers must analyze loyalty data on individual-user level along with past purchase data-points to cross and up-sell.

Hence, it's expected that,

H2: There is a relationship between past purchase data utilization and the effectiveness of the promotional communication.

*Dynamic Customer Segmentation*

As per Hutchinson et al. (2015), marketers have refused to segment customers via the loyalty data collected, even by age or geo-locations and continued to treat them as a homogeneous group without acknowledging their differences. But the customers are expecting recommendations which reflects their buying behavior (Riegger et al., 2021) and "One size will no longer fit all" (Ferguson and Hlavinka, 2008). The retailers are having all the required opportunities to collect data and customize promotions for minor segments (Beeck and Toporowski, 2017). Largely undifferentiated promotions mean very little to LP customers (Ferguson and Hlavinka, 2008). Also, as LPs have entered a highly saturated market, promotional communication with highly segmented customers is the salvation (Ferguson and Hlavinka, 2008).

Even though, customers opt to join a LP does not mean that they behave equally (Allaway et al., 2006). Yet, Wijesiri (2016) noted Sri-Lankan marketers have ignored how a single product can be perceived differently by various groups as customers fluctuate among different segments more frequently (Kimari, 2016) where noticeable behavior patterns can be noted in small customer segments as well (Lind et al., 2016).

Traditional demographic segmentation in LPs has a very limited impact as they consider very minimal parameters such as age, family-size, education, etc. (Malamidou et al., 2018). Each customer segment comprises of different attributes and engage in a unique way and is completely separated from other segments (Ferguson and Hlavinka, 2008). Therefore, the future of LPs was seen as diversifying promotional communications into micro-groups rather larger segments (Cedrola and Memmo, 2010).

Hence, it's expected that,

H3: There is a relationship between dynamic customer segmentation and the effectiveness of the promotional communication

## Methodology

### *Research Design*

A deductive research approach was taken where the theories understood on literature such as MBA, CLV and RFM are tested through data collection. Surveys were used as the strategy to generate and test hypothesis. Since the hypothesis were generated and tested survey was utilized as the strategy.

*Population and Sampling Design*

The focus of the research is the fashion retailers in Colombo, Sri-Lanka. As per the Department of Economic and Social Affairs (2008), international standard industrial classification, Class '4771-retail sales of readymade garments' were selected for the respective scope which is under the Group of '477- retail sale of clothing, footwear and leather articles in specialized stores. (Refer Appendix A1).

The main reason for the above industry selection can be noted as the potential of having an established up-and-running loyalty program and an IT infrastructure which is vital for the study. Even among the aforementioned category, scope was further filtered to the following fashion retailers in Colombo Sri-Lanka (Table 1).

**Table 1. Selected Fashion Retailers**

| Fashion Retailer | Number of Outlets in Colombo | LPs | SMS Promotional Communication |
|---|---|---|---|
| Odel | 12 | Yes | Yes |
| Nolimit/Glitz | 09 | Yes | Yes |
| CIB | 10 | Yes | Yes |

Source: Author's illustration

As shown in Figure 4, since fashion-retailers and the loyalty-customers-base of the respective retailers become the primary stakeholders of the study's population, considering factors such as accessibility, timeliness, ability to collect a large number of responses, only the loyalty-customer-base of the respective fashion retailers are selected.

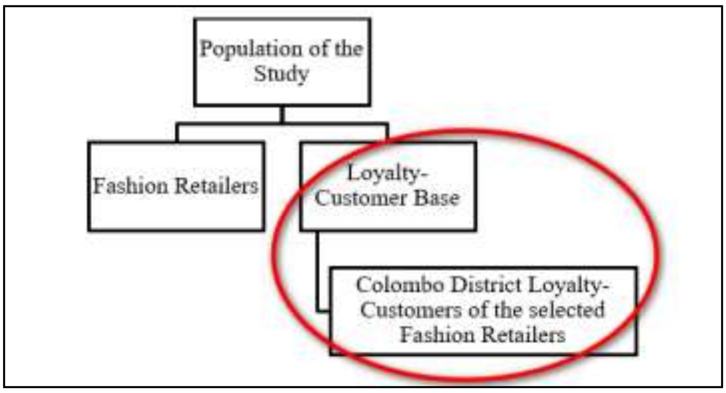


**Figure 4.** Population Filtering

Source: Author's work

However, the exact population volume identification for the study is challenging as the Colombo district loyalty customer-base of the selected retailers are not readily available.

Therefore, since the study is a quantitative study and the population is fairly large the Morgan table will be utilized to derive the sample size. As per the Krejcie and Morgan (1970) method induced Survey Systems (2022) sample calculation, the sample size is derived as follows,

Sample Size = 384.

Refer Appendix 2 for the questionnaire operationalization.

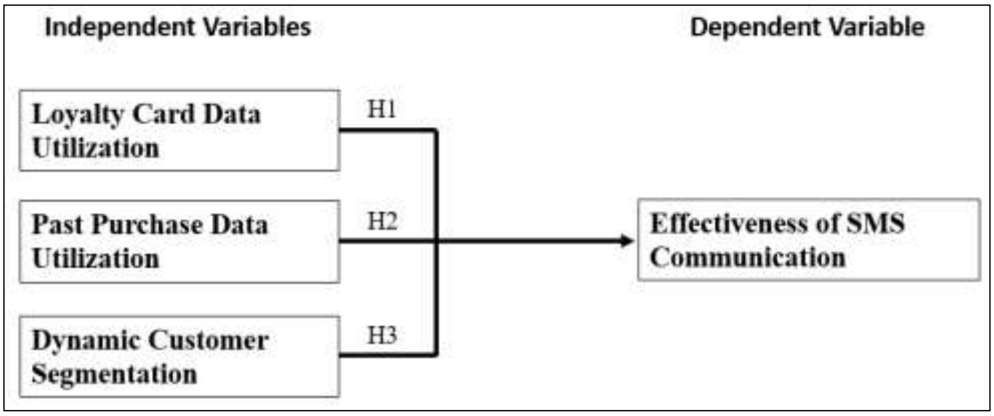


**Figure 5.** Conceptual Framework

**Data Analysis**

***Reliability Analysis***

As per the Statistics Solutions (2022a) construct reliability can be calculated by the Cronbach alpha and the variables above 0.7 are considered as reliable. Thus, as shown in Table 2, Cronbach alpha of the variables EC, LU, PU and DS are all above 0.7 which indicates a high internal consistency resulting a acceptable reliability.

**Table 2 - Reliability Analysis**

| Variable | Indicators | Reliability | |
|---|---|---|---|
| | | Cronbach's Alpha | N of Items |
| Effectiveness of SMS Communication (EC) | Relevance<br>Personalization<br>Fatigue | 0.702 | 3 |
| Loyalty-card Data Utilization (LU) | Availability<br>Usage<br>Utilization<br>Potential | 0.841 | 4 |
| Past-purchase Data Utilization (PU) | Gap<br>Utilization<br>Potential | 0.829 | 3 |
| Dynamic Customer Segmentation (DS) | Differentiation<br>Granularity<br>Timeliness | 0.817 | 3 |

### *Hypothesis Validation*

*Loyalty-card Data Utilization (LU)*

H1: There is a relationship between loyalty card data utilization and the effectiveness of the promotional communication.

**Table 3. LU Regression-Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .835a | .697 | .696 | .30435 |

Note: a.Predictors: (Constant), Loyalty_Card_Data_Utilization

As per Statistics Solutions (2022b), In a linear regression R Square denotes the degree of variance depicted by the dependent variable. Therefore, R Square value being 0.697 explains that 69.7% of the variances in dependent variable of 'Effectiveness of SMS Communication' is explained by the independent variable of 'Loyalty-card data utilization.

**Table 4. LU EC Pearson Correlation Analysis**

| Correlations | | | |
|---|---|---|---|
| | | Effective Targeted SMS Promotional Communication | Loyalty Card Data Utilization |
| Effective Targeted SMS Promotional Communication | Pearson Correlation | 1 | .835** |
| | Sig. (2-tailed) | | .000 |
| | N | 347 | 347 |
| Loyalty Card Data Utilization | Pearson Correlation | .835** | 1 |
| | Sig. (2-tailed) | .000 | |
| | N | 347 | 347 |

Note: **. Correlation is significant at the 0.01 level (2-tailed).

As Table 4 depicts, the Pearson correlation on loyalty-card data utilization to effective targeted promotional communication is a strong positive relationship as indicated by R = 0.835.

Hypothesis acceptance was done based on the 2-tailed significance considering the correlation theory where the p value shall be less than 0.05 to accept the alternate hypothesis. Thus, H1 is accepted since the significance is at 0.000 which is < 0.05 at the level of 99%.

*Past Purchase Data Utilization (PU)*

H2: There is a relationship between past purchase data utilization and the effectiveness of the promotional communication.

**Table 5. PU Regression-Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .660[a] | .436 | .434 | .41528 |

Note: a. Predictors: (Constant), Past_Purchase_Data_Utilization

As per Statistics Solutions (2022b), In a linear regression R Square denotes the degree of variance depicted by the dependent variable. Therefore, R Square value being 0.436 explains that 43.6% of the variances in dependent variable of 'Effectiveness of SMS Communication' is explained by the independent variable of 'Past purchase data utilization'

**Table 6. PU Regression-Summary**

| Correlations | | | |
|---|---|---|---|
| | | Effective Targeted SMS Promotional Communication | Past Purchase Data Utilization |
| Effective Targeted SMS Promotional Communication | Pearson Correlation | 1 | .660** |
| | Sig. (2-tailed) | | .000 |
| | N | 347 | 347 |
| Past Purchase Data Utilization | Pearson Correlation | .660** | 1 |
| | Sig. (2-tailed) | .000 | |
| | N | 347 | 347 |

Note:**. Correlation is significant at the 0.01 level (2-tailed).

As Table 6 depicts, the Pearson correlation on past purchase data utilization to effective targeted promotional communication is a strong positive relationship when R = 0.660

Hypothesis acceptance was done based on the 2-tailed significance considering the correlation theory where the p value shall be less than 0.05 to accept the alternate hypothesis. Therefore, H2 is accepted since the significance is at 0.000 which is < 0.05 at the level of 99%.

*Dynamic Customer Segmentation (DS)*

H3: There is a relationship between dynamic customer segmentation and the effectiveness of the promotional communication.

**Table 7. DS Regression-Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .595[a] | .354 | .352 | .44456 |

Note: a. Predictors: (Constant), Dynamic_Customer_Segmentation

As per Statistics Solutions (2022b), In a linear regression R Square denotes the degree of variance depicted by the dependent variable. Therefore, R Square value being 0.354 explains that 35% of the variances in dependent variable of 'Effectiveness of SMS Communication' is explained by the independent variable of 'Dynamic customer segmentation'

**Table 8. DS EC Pearson Correlation Analysis**

| Correlations | | | |
|---|---|---|---|
| | | Effective Targeted SMS Promotional Communication | Dynamic Customer Segmentation |
| Effective Targeted SMS Promotional | Pearson Correlation | 1 | .595** |
| | Sig. (2-tailed) | | .000 |

| | | | |
|---|---|---|---|
| Communication | N | 347 | 347 |
| Dynamic Customer Segmentation | Pearson Correlation | .595** | 1 |
| | Sig. (2-tailed) | .000 | |
| | N | 347 | 347 |

Note:**. Correlation is significant at the 0.01 level (2-tailed).

As Table 8 depicts, the Pearson correlation on past purchase data utilization to effective targeted promotional communication is a positive relationship when R = 0.595.

Hypothesis acceptance was done based on the 2-tailed significance considering the correlation theory where the p value shall be less than 0.05 to accept the alternate hypothesis. H3 is accepted since the significance is at 0.000 which is < 0.05 at the level of 99%.

**Table 9. Hypothesis Validation Summary**

| Hypothesis | Significance | Pearson Correlation | Relationship | Validity |
|---|---|---|---|---|
| H1 | 0.000 | 0.835 | Strong Positive | Accepted |
| H2 | 0.000 | 0.660 | Strong Positive | Accepted |
| H3 | 0.000 | 0.595 | Positive | Accepted |

Accordingly, since all the variables have a higher correlation (Table 9), all are used for the regression analysis.

### *Multiple Regression Analysis*

As Table 10 represents, the adjusted R square value is 0.72 which means 72% represents (impact on) the effectiveness of SMS communication by all the independent variables considered. In other words, 72% of the variations of the effectiveness of SMS communication is explained by this model.

**Table 10. Multiple Regression – Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .850[a] | .722 | .720 | .29235 |

Notes:
a. Predictors: (Constant), Dynamic_Customer_Segmentation, Loyalty_Card_Data_Utilization, Past_Purchase_Data_Utilizatio

**Table 11. Multiple Regression – ANOVA**

| Model | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Regression | 76.162 | 3 | 25.387 | 297.036 | .000[b] |
| Residual | 29.316 | 343 | .085 | | |
| Total | 105.477 | 346 | | | |

Notes: a. Dependent Variable: Effective_Targeted_SMS_Promotional_communication, b. Predictors: (Constant), Dynamic_Customer_Segmentation, Loyalty_Card_Data_Utilization, Past_Purchase_Data_Utilization

Also, considering Table 11, the total conceptual framework can be accepted since the significance is 0.000 where the p value shall be less than 0.05.

## Discussion and Implications

## *Discussion*

As per literature, LPs were seen as a vehicle to track purchase patterns of individual preferences. (Ramaboa and Das, 2015). According to Byrom (2001), LPs have provided an immense amount of data to understand consumers and their behavior in aggregate basis as well as at an individual level. When the loyalty-cards are scanned at checkout, they catalogue consumers automatically by day, time, product purchased, value, variety of other products etc. that can be analyzed for pattern behavior and targeted promotions (Allaway et al., 2006). As per the study, Pearson Correlation value being 0.835 and significance being 0.000, H1 was accepted by the researcher and LU has a strong positive relationship with the EC. Also, as the R2 value is 0.697, it confirms that LU contributes 69.7% to EC. Accordingly, based on literature and research findings, it can be concluded that LU can drastically improve the EC.

In accordance with literature, traditionally, customer insights can be derived from offline databases which hold purchase records and invoices (Kadir and Achyar, 2019). Personally identifiable shopping behavior is achieved by utilizing past purchase data (Schreiner, Rese and Baier, 2019). Past purchase data utilization is also referred as Basket data utilization and basket information collects data such as products purchased, time of the day, offers taken-up and which items are purchased together etc. which allows to personalize offerings (Byrom, 2001). As per the study, as the Pearson Correlation value is 0.660 and significance is 0.000, H2 was accepted by the researcher and PU has a strong positive relationship with the EC. Furthermore, R2 value being is 0.436, it confirms that PU contributes 43.6% to EC. Accordingly, based on literature and research findings, it can be concluded that PU can drastically improve the EC.

According to literature, traditional demographic segmentation in LPs has very limited impact as they consider very minimal parameters such as age, family-size, education, etc. (Malamidou, Spyropoulos and Rotsios, 2018). Each customer segment comprises of different attributes and engage in a unique way and is completely separated from other segments (Ferguson and Hlavinka, 2008). "One size will no longer fit all" (Ferguson and Hlavinka, 2008). Customers fluctuate among different segments more frequently (Kimari, 2016) where noticeable behavior patterns can be noted in small customer segments as well (Lind et al., 2016). As per the study, Pearson Correlation value being 0.595 and significance being 0.000, H3 was accepted by the researcher and DS has a positive relationship with the EC. Furthermore, R2 value being is 0.354, it confirms that DS contributes 35.4% to EC. Accordingly, based on literature and research findings, it's concluded that DS can drastically improve the EC.

Ultimately, considering all the variables, the significance being 0.000 and the adjusted R square value being 0.72 in the regression analysis,the proposed conceptual framework can be accepted where a 72% of the variations of the effectiveness of SMS communication is being explained by the proposed conceptual framework of the study.

## *Implications*

The data availability and its potential shall be understood first to implement utilization. It is more suitable to evaluate existing global solutions rather developing the capabilities from scratch. Prior to any implementations major BI tools such as Tableu or PowerBI can be utilized to visualize data and its potential. Ultimately, the consumers' geo-demographic variables shall be reflected in promotions.

Big data solutions shall be evaluated for this purpose and ultimately the omni-channel shopping experience avenue must be looked at to provide a balanced shopping experience in different platforms. Existing methods such as MBA, RFM can be used to ultimately reflect the buying behavior on the promotions.

More updated dynamic customer segments should be maintained for the promotional communication. Static segmentation methods should be discarded and minor behavioral changes must be tracked. When effectively utilized, LU, PU and DS can be achieved automatically and evaluations should occur more frequently as users fluctuate segments.

Further research can be done on the omni-channel shopping experience and big data utilization as most of the retailers are moving to online selling platforms as well. Therefore, connecting online and offline shopping experiences together would be the way forward. Furthermore, the research area can be expanded to include more fashion retailers and increase the sample size to further validate the study. Integrating other promotional types such as push notifications, email marketing, social media marketing for a more universal targeted promotional campaign can be further discussed.

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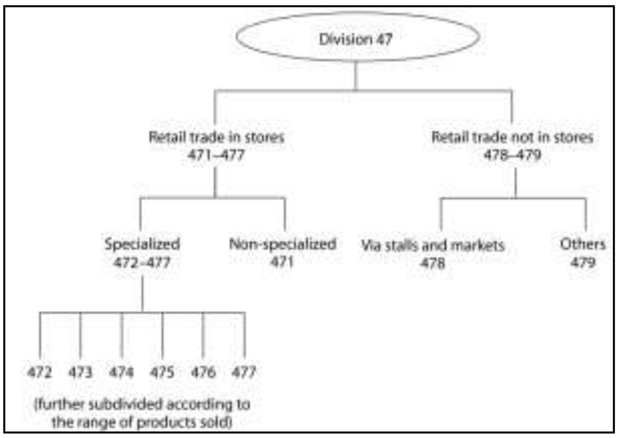
## Appendix

### *Appendix 1. Scope: Industry Classification*

As per the international standard industrial classification, Class '4771-Retail sales of readymade garments' were selected for the respective scope which is under the group of '477-Retail sale of clothing, footwear and leather articles in specialized stores. However, other classes under the same group such 4772, 4773 and 4774 were excluded as depicted below,



| Division | Group | Class | Description |
|---|---|---|---|
| | | 4763 | Retail sale of sporting equipment in specialized stores |
| | | 4764 | Retail sale of games and toys in specialized stores |
| | 477 | | Retail sale of other goods in specialized stores |
| | | 4771 | Retail sale of clothing, footwear and leather articles in specialized stores |
| | | 4772 | Retail sale of pharmaceutical and medical goods, cosmetic and toilet articles in specialized stores |
| | Out of Scope | 4773 | Other retail sale of new goods in specialized stores |
| | | 4774 | Retail sale of second-hand goods |

In Scope

Figure 6. Scope: Industry Classification

Furthermore, other related groups and classes such as the followings were excluded,

- 4641 - Wholesale of textiles, clothing and footwear
- 4751 - Retail sale of textiles in specialized stores: This class includes retail sale of fabrics, knitting yarn, basic materials for rug, tapestry or embroidery making, retail sale of textiles, retail sale of haberdashery (needles, sewing thread etc.
- 4782 - Retail sale via stalls and markets of textiles, clothing and footwear

(Source: Department of Economic and Social Affairs, 2008)

## Appendix 2. Operationalization

**Table 12. Operationalization**

| Concept | Variable | Indicator | Source(s) | Measure | Questions |
|---|---|---|---|---|---|
| Dependent Variable | Effectiveness of the promotional communication | Relevance | (Ferguson and Hlavinka, 2008), (Hutchinson et al., 2015), (Kimari, 2016), (Nandi and Mittal, 2013), (Ramaboa and Das, 2015) | 1-5 Likert Scale | 9 |
| | | Personaliz -ation | (Dekimpe, Geyskens and Gielens, 2019), (Silva, Hassani and Madsen, 2019), (Riegger et al., 2021) | | 10 |
| | | Fatigue | (Ahmed, 2018), (Bies, Bronnenberg and Gijsbrechts, 2021), (Daniel, 2015), (Nandi and Mittal, 2013), (Perera, 2010), (Silva, Hassani and Madsen, 2019), (Smita, 2018) | | 11 |
| | | Availability | (Allaway et al., 2006), (Byrom, 2001), (Ferguson and Hlavinka, 2008), (Yapaa and Kennedy, | | 12 |

| | | | | | |
|---|---|---|---|---|---|
| | | | 2020) | | |
| | Loyalty-card data utilization | Usage | (Allaway et al., 2006), (Byrom, 2001), (Hassani and Madsen, 2019), (Kumar, 2019), (Malamidou, Spyropoulos and Rotsios, 2018), (Pieris and Udunuwara, 2012), (Ramaboa and Das, 2015) | 1-5 Likert Scale | 13 |
| | | Utilization | (Malamidou, Spyropoulos and Rotsios, 2018), (Ramaboa and Das, 2015), (Silva, Hassani and Madsen, 2019) | | 14 |
| | | Potential | (Alshurideh, 2019), (Byrom, 2001), (Donnelly et al., 2012), (Ferguson and Hlavinka, 2008), (Hutchinson et al., 2015), (Ramaboa and Das, 2015), (Smita, 2018), (Stalidis and Diamantaras, 2019), (Stathopoulou and Balabanis 2016), (Stone et al., 2003), (Yapaa and Kennedy, 2020). | | 15 |
| Independent Variable | | Gap | (Daniel, 2015), (Dekimpe, Geyskens and Gielens, 2019), (Hutchinson et al., 2015), | | 16 |

| | | | | | |
|---|---|---|---|---|---|
| | Past Purchase Data Utilization | | (Kim, Kim and Park, 2010), (Nandi and Mittal, 2013), (Riegger et al., 2021), (Tera Data, 2015). | 1-5 Likert Scale | |
| | | Utilization | (Dekimpe, Geyskens and Gielens, 2019), (Donnelly et al., 2015), (Hutchinson et al., 2015), (Nandi and Mittal, 2013). | | 17 |
| | | Potential | (Allaway et al., 2006), (Byrom, 2001), (Ferguson and Hlavinka, 2008), (Kadir and Achyar, 2019), (Kumar et al., 2013), (Malamidou, Spyropoulos and Rotsios, 2018), (Schreiner, Rese and Baier, 2019), (Silva, Hassani and Madsen, 2019). | | 18 |
| | Dynamic Customer Segmentation | Differentiation | (Allaway et al., 2006), (Cedrola and Memmo, 2010), (Donnelly et al., 2015), (Ferguson and Hlavinka, 2008), (Hutchinson et al., 2015), (Kimar, 2016), (Lind et al., 2016), (Malamidou, Spyropoulos and Rotsios, 2018). | 1-5 Likert Scale | 19 |
| | | Granularity | | | |

| | | | | | |
|---|---|---|---|---|---|
| | | | (Beeck and Toporowski, 2017), (Cedrola and Memmo, 2010), (Donnelly et al., 2015), (Kadir and Achyar, 2019), (Kimar, 2016), (Lind et al., 2016), (Malamidou, Spyropoulos and Rotsios, 2018). (SAP Hybris, 2015), (Ramaboa and Das, 2015), (Riegger et al., 2021) | | 20 |
| | | Timeliness | (Allaway et al., 2006), (Donnelly et al., 2015), (Kimar, 2016), (Lind et al., 2016), (Nandi and Mittal, 2013), (Riegger et al., 2021). | | 21 |