NBS8604 Marketing Analytics

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Segmenting and Predicting Customer Responses: A Marketing Analytics Study of Luna7's Promotional Strategy.

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1. Executive Summary

Luna7, a US-based online retailer of clothing and home goods, looks to enhance the effectiveness of its promotional campaigns by better targeting customers likely to respond to offers in key product categories. This report investigates whether lifestyle and shopping-related psychographic factors can segment Luna7's customers and assess whether these segments, along with past purchasing behaviour, predict responsiveness to category-specific promotions. Based on a dataset of 265 customer responses including demographics, psychographics, purchase history, and promotional outcomes, this report employs a combination of Factor Analysis, Cluster Analysis, RFM Analysis, and Logistic Regression. The findings reveal meaningful customer segments based on psychographic traits like mindfulness and digital engagement and demonstrate that segment membership and RFM behaviour significantly influence promotional response. The results provide Luna7 with a data-driven framework to personalise marketing, reduce campaign risk, and optimise ROI.

2. Introduction

Luna7 is a fictional US-based online retailer, comparable to Zara, offering clothing and home products through digital channels. As the company looks to expand into new service areas such as rentals and targeted promotions, it faces a crucial challenge, identifying which customers are most likely to respond to campaign efforts. This issue is heightened by the competitive retail environment, where ineffective targeting can result in low conversions and poor marketing ROI (Statista, 2024).

In response, Luna7 collected detailed data from a promotional survey involving 265 customers. The dataset includes variables on demographics, online/offline behaviour, promotional response, and psychographic traits such as mindfulness, social media use, and digital shopping engagement.

Prior research also shows that customer satisfaction is a strong predictor of cross-buying behaviour and new product trial (Verhoef, 2003); (Homburg et al., 2006)).

This report aims to answer two questions: (1) Can psychographic and lifestyle factors meaningfully segment Luna7's customers? (2) To what extent do these segments and past purchasing behaviour (RFM) predict responsiveness to key category promotions?

The goal is to deliver actionable insights that improve customer segmentation and campaign precision, ultimately enhancing Luna7's marketing impact.

3. Methodology

3.1. Data Selection and Preparation

The dataset provided by Luna7 comprises 265 customer records with over 130 variables spanning demographics, psychographics, digital behaviour, shopping preferences, purchase history, and promotional responses. For this report, variables were selectively used based on their alignment with the research aim i.e. to explore how lifestyle and behavioural factors can segment customers and predict category-specific promotional response.

Key variables:

- Psychographics: Items related to mindfulness (mindful1–15), online review preferences (Q33, Q37, Q40 series), and social media use.
- Behavioural Metrics: Variables capturing past purchase behaviour such as last_buy, freq_buy, and last_spend.
- Promotional Outcomes: Binary response variables such as res_cloth, res_home, and res_acce.

Many variables contained missing values.

- For 10 ordinal variables with missing data (e.g., last_buy, last_spend), missing values were replaced using the **median of nearby points** in SPSS.
- For 11 nominal variables, missing entries were imputed using the mode, i.e. with the most frequently occurring category.
- Binary promotion response variables (res_cloth, res_acce, res_home, res_ret) were recoded where necessary to reflect 0 = No and 1 = Yes. This step ensured the reliability of results and avoided biased estimates (Hair et al., 2014).

3.2. Analytical Procedures

A total of 43 psychographic and digital orientation variables including mindfulness scale items, review importance, social media engagement, rental intention, and shopping app use were selected for Exploratory Factor Analysis (EFA) to uncover latent dimensions driving Luna7 customers' behavioural and attitudinal tendencies. Prior to extraction, sampling adequacy and factorability of the correlation matrix were confirmed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity. The KMO score of 0.870 and a highly significant Bartlett's Test of Sphericity ($\chi^2 = 7577.807$, $p < .001$) as seen in Figure 6 indicated that the dataset was well-suited for factor analysis.

To segment Luna7's customers based on the underlying psychographic dimensions identified through factor analysis, a K-Means clustering technique was applied using the eight saved factor scores as input variables. Three, four, and five-cluster solutions were tested and evaluated based on interpretability, cluster size balance, and ANOVA significance.

RFM (Recency, Frequency, Monetary) analysis was used further to quantify and segment customer purchasing behaviour using three key metrics, how recently a customer made a purchase (Recency), how often they purchase (Frequency), and how much they spend (Monetary value). Scores from 1 (low) to 4 (high) were assigned to each Recency, Frequency, and Monetary dimension, based on distribution and quintile analysis. An RFM Index was created using the formula (Please see Figure 19), allowing a representation of customer value profiles.

A logistic regression model was used to predict customer response to Luna7's accessories promotion using psychographic cluster membership, factor scores, and RFM variables. To assess the extent to which lifestyle-based segments and past behaviour predict customer responses to Luna7 promotions, logistic regression was conducted across three key product categories**: clothing, accessories, and home** items. Each model included cluster membership (based on psychographic segmentation) and RFM scores (Recency, Frequency, Monetary) as independent variables. For each model, accuracy, Nagelkerke R^2, AUC (ROC), and Hosmer-Lemeshow test were used to assess performance.

Visualisation throughout the process included scree plots, component loading matrices, RFM frequency tables, ROC curves, and classification plots, providing interpretability and clarity of findings.

4. Analysis and Results

In this section, we detail the findings from each of the four analytical techniques, integrating visuals for clarity. Together, these results paint a comprehensive picture of who is likely to adopt Luna7's clothing rental service and why.

Factor Analysis

Following the Kaiser criterion (eigenvalues > 1) and scree plot inspection (see Figure 8), **eight components** were retained and rotated using Varimax rotation to achieve interpretability. As shown in the rotated component matrix (Figure 9), each factor exhibited strong loadings above 0.6 for several items, and communalities exceeded 0.5 in most cases, satisfying reliability thresholds. These 8 factors collectively explain 66.34% of the total variance, which is acceptable for behavioural data. These factors were interpreted as representing themes such as **Mindlessness**, **Rental Product Sensitivity**, **Omnichannel** Online Shopping Usage, **Offline Shopping Preference**, **Social & Visual Shopping Influence, Visual Review Trust**, **Reviewer Characteristics & Credibility**, **Review Type Scepticism**. The extracted factor scores were saved and subsequently used as inputs for cluster analysis and predictive modelling.

Cluster Analysis

To further improve the findings, customers were segmented into four clusters. The four-cluster solution was selected as the most appropriate as it offered clearly interpretable segments such as **Mindless Mobile Shoppers, Rental Rationalists, Social Validators**, and **In-Store Seekers**, that aligned well with the study's psychographic framework. Moreover, the ANOVA results for the four-cluster model showed significant differences ($p < .001$) (see Figures 13, 14 and 15) across seven of eight factors, indicating effective discrimination between segments. Compared to the three-cluster model (Figures 10, 11 and 12) which had an imbalanced distribution with over 58% in one group and the more fragmented five-cluster model (Figures 16, 17 and 18) which yielded some overlapping profiles. The four-cluster solution provided the best trade-off between statistical robustness and marketing relevance. Therefore, it was retained for further analysis and interpretation.

Using the final cluster centres, 4 customer segments were derived (Please see Table 1 and Figure 13). These latent dimensions capture nuanced attitudinal patterns, reducing complexity in further analyses. These segments offer targeted marketing personas for Luna7's campaigns.

RFM Analysis

From Figure 20 and 21, The frequency distribution of the RFM Index showed a concentration around mid-range scores such as 321 and 421, representing customers who are relatively recent purchasers but with lower spend and frequency. These two segments alone accounted for over 60% of respondents, indicating strong potential for re-engagement strategies. Higher-value groups like 431, 422, and 332 were also present and recommended for loyalty programs, while at-risk customers like RFM 112, 113, etc. were fewer in number but suitable for win-back campaigns. The RFM output provided a robust behavioural segmentation framework, suitable for integration with psychographic clusters derived earlier, and formed the basis for predictive modelling in the next stage of analysis.

Customers were segmented into high-potential, loyal, and churn-risk groups. (See Table 2) Strategic targeting recommendations included loyalty incentives for high scorers and win-back offers for low scorers.

Logistic Regression

Using insights from factor analysis, psychographic clusters, and past purchasing behaviour, three binary logistic regression models were developed to predict customer responsiveness to Luna7's promotions in clothing, accessories, and home product categories. The dependent variables (res_cloth, res_acce, res_home) captured whether a customer had responded positively to recent promotional campaigns. Independent variables included psychographic cluster membership (from K-Means on factor scores), RFM behavioural scores, and select factor scores.

The **accessories model** (See Figure 22 and 23) demonstrated the strongest performance, with a **Nagelkerke R^2 of 0.558**, **classification accuracy of 83%**, and **ROC-AUC of 0.90**. Significant predictors included trust in review visuals and reviewer credibility, along with Cluster 3 membership—socially influenced shoppers—who were over 5.5 times more likely to respond.

The **home category model** (See Figure 24 and 25) achieved **84.9% accuracy** and an **AUC of 0.89**, although a **significant Hosmer-Lemeshow test ($p = 0.019$)** indicated minor calibration issues. Digital shopping usage and monetary value positively influenced responsiveness.

The **clothing model** (See Figure 26 and 27) showed moderate predictive strength (**Nagelkerke $R^2 = 0.259$; accuracy = 68.7%; AUC = 0.76**). Factors such as mindlessness and mobile engagement had weaker but notable effects.

Significant predictors included online review engagement ($Exp(B) = 2.699$, $p < .001$), trust in review metrics ($Exp(B) = 1.812$, $p = .029$), and past purchase frequency ($Exp(B) = 2.499$, $p = .011$). Membership in Cluster 3, associated with socially influenced shoppers, increased odds of purchase by over 5.5 times ($p = .029$).

Amongst these, the **accessories model was chosen as the best predictive model** due to its superior model fit, explanatory power, and interpretability. It provided clear, statistically significant insights into how psychographic traits and behavioural variables combine to influence promotional responsiveness aligning directly with the research objective.

These results confirm that both psychographic profiles and purchasing history jointly influence promotional responsiveness. Luna7 can now tailor campaigns using predictive analytics, especially for accessories, where the model performed best.

5. Business Implications and Recommendations

The results of this report have clear implications for Luna7's promotional strategy. The integration of lifestyle-driven segmentation with behavioural purchase profiling enables the company to move from general promotional targeting to a personalized marketing approach.

Firstly, customer decision-making in the accessories category appears to be strongly influenced by visual validation and peer opinions. Luna7's most responsive segment (Cluster 3 - Social Validators) showed significantly higher likelihood of responding to accessories promotions (Logistic Regression AUC = 0.902). These customers are highly influenced by user reviews, images, and credibility of content. To capitalise on this, Luna7 should incorporate more visual elements like user-generated photos, influencer partnerships, video testimonials, product imagery and review highlights directly into promotional emails and app experience. Track open rates, click-throughs, and conversions for Cluster 3 specifically. Apparel brands like ASOS and Sephora have successfully used review-based marketing to boost click-through rates and conversions, especially among Gen Z.

Moreover, despite Luna7's strong digital presence, nearly half of its customers fell into mid-tier RFM codes like 211 and 321, indicating recent purchases but low frequency and spend. These are 'warm' leads that can be re-engaged through mobile-first promotions. For instance, push notifications, app-exclusive flash sales, or gamified loyalty programs can nudge customers toward repeat buying. Measure push notification open rates and session times on the app. Luna7 can introduce a mobile-exclusive loyalty tier that rewards repeat purchases within 30 days. Fashion brands such as SHEIN and H&M have seen measurable success using this kind of reactivation strategy Statista, 2023.

Finally, given that lifestyle and shopping psychographics proved significant predictors of promotional response, Luna7 should operationalise these insights by integrating psychographic cluster IDs and RFM scores into their CRM. This will enable real-time personalised targeting. For example, targeting Cluster 1 (Mindless Mobile Shoppers) with impulse-triggering notifications during peak app hours, or sending trust-building content to Cluster 3 (Social Validators) before a new product launch. Use CRM automation to adjust campaign tone, timing, and incentives based on cluster-specific behaviours. Also, conduct quarterly CRM audits to ensure segmentation accuracy and campaign performance.

These recommendations align directly with the segmentation and predictive findings and offer Luna7 a clear path to increase campaign ROI and long-term customer value.

6. Conclusion

This report set out to investigate how lifestyle and shopping-related psychographic factors, combined with past purchasing behaviour, can be used to segment Luna7's customer base and predict their responsiveness to promotional campaigns. Through application of Factor Analysis, K-Means Clustering, RFM Analysis, and Logistic

Regression, the report identified four distinct psychographic segments and behaviour-based purchasing profiles across 265 customers.

The results confirmed that Luna7's customers are not an inflexible group. Distinct patterns such as visual trust in reviews, impulsive app-based shopping, and offline store preferences emerged through psychographic segmentation. When combined with RFM-based insights, these segments enabled strong predictive modelling, particularly for accessory purchases where the logistic regression model achieved 83% accuracy and an AUC of 0.902.

By integrating psychographics with behavioural metrics, Luna7 now has a robust framework for more targeted, effective marketing. This data-driven strategy allows the company to engage high-potential segments while optimizing campaign spend, laying the groundwork for improved customer retention, increased frequency, and higher return on promotional investments.

7. References

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Appendix 1 - Snapshots of the Results and Tables

Statistics

		Months since last purchase	Expenditure (in US Dollar) of last purchase	number of purchases in the last year	When was the first purchase	Visit its offline stores	Visit its website using computer	Visit its website using smartphone	Buy at its offline stores	Buy from online using computer	Buy from online using smartphone
N	Valid	223	223	223	223	223	223	223	223	223	223
	Missing	42	42	42	42	42	42	42	42	42	42
Mean		3.24	3.04	2.28	5.27	2.81	3.18	2.87	2.79	3.12	2.73
Median		3.00	3.00	2.00	5.00	3.00	3.00	3.00	3.00	3.00	2.00
Mode		2	2	2	5	2	3	2	2	2	1

Figure 1 - Ordinal Variables before Data Cleaning Summary

Statistics

		response to luna7 promotion on clothing last month	response to luna7 promotion on accessories last month	response to luna7 promotion on home items last month	response to luna7 free returns on orders last month	Bought women's clothes last year	Bought men's clothes last year	Bought kids items last year	Bought shoes last year	Bought bag last year	Bought accessories last year	Bought home items last year
N	Valid	223	223	223	223	223	223	223	223	223	223	223
	Missing	42	42	42	42	42	42	42	42	42	42	42

Figure 2 - Nominal Variables before Data Cleaning Summary

Result Variables

	Result Variable	N of Replaced Missing Values	Case Number of Non-Missing Values First	Case Number of Non-Missing Values Last	N of Valid Cases	Creating Function
1	last_buy_1	42	1	265	265	MEDIAN (last_buy,2)
2	last_spend_1	42	1	265	265	MEDIAN (last_spend,2)
3	freq_buy_1	42	1	265	265	MEDIAN (freq_buy,2)
4	first_buy_1	42	1	265	265	MEDIAN (first_buy,2)
5	visitoffline_1	42	1	265	265	MEDIAN (visitoffline,2)
6	visitweb_1	42	1	265	265	MEDIAN (visitweb,2)
7	visitphone_1	42	1	265	265	MEDIAN (visitphone,2)
8	buyoffline_1	42	1	265	265	MEDIAN (buyoffline,2)
9	buyonline_1	42	1	265	265	MEDIAN (buyonline,2)
10	buyphone_1	42	1	265	265	MEDIAN (buyphone,2)

Figure 3 - Transforming using median imputation for ordinal variables

Statistics

		MEDIAN (last_buy,2)	MEDIAN (last_spend,2)	MEDIAN (freq_buy,2)	MEDIAN (first_buy,2)	MEDIAN (visitoffline,2)	MEDIAN (visitweb,2)	MEDIAN (visitphone,2)	MEDIAN (buyoffline,2)	MEDIAN (buyonline,2)	MEDIAN (buyphone,2)
N	Valid	265	265	265	265	265	265	265	265	265	265
	Missing	0	0	0	0	0	0	0	0	0	0

Figure 4 - Ordinal Variables After Data Cleaning Summary

Statistics

		response to luna7 promotion on clothing last month	response to luna7 promotion on accessories last month	response to luna7 promotion on home items last month	response to luna7 free returns on orders last month	Bought women's clothes last year	Bought men's clothes last year	Bought kids items last year	Bought shoes last year	Bought bag last year	Bought accessories last year	Bought home items last year
N	Valid	265	265	265	265	265	265	265	265	265	265	265
	Missing	0	0	0	0	0	0	0	0	0	0	0

Figure 5 - Nominal Variables After Data Cleaning Summary

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.870
Bartlett's Test of Sphericity	Approx. Chi-Square	7577.807
	df	903
	Sig.	<.001

Figure 6 - KMO and Bartlett's Test Results

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.372	21.795	21.795	9.372	21.795	21.795	9.058	21.065	21.065
2	8.219	19.113	40.908	8.219	19.113	40.908	3.947	9.180	30.245
3	3.345	7.780	48.688	3.345	7.780	48.688	3.939	9.160	39.405
4	2.085	4.849	53.537	2.085	4.849	53.537	3.166	7.363	46.768
5	1.656	3.850	57.387	1.656	3.850	57.387	2.654	6.171	52.939
6	1.477	3.435	60.822	1.477	3.435	60.822	2.179	5.067	58.006
7	1.292	3.004	63.825	1.292	3.004	63.825	1.912	4.446	62.452
8	1.080	2.512	66.337	1.080	2.512	66.337	1.671	3.885	66.337
9	.992	2.307	68.644						
10	.946	2.200	70.844						
11	.891	2.072	72.917						
12	.775	1.803	74.720						
13	.711	1.654	76.373						
14	.692	1.609	77.982						
15	.626	1.456	79.438						
16	.589	1.370	80.808						
17	.575	1.336	82.144						
18	.567	1.320	83.464						
19	.539	1.253	84.717						
20	.498	1.158	85.875						
21	.463	1.076	86.951						
22	.446	1.037	87.988						
23	.429	.997	88.985						
24	.402	.934	89.920						
25	.395	.919	90.839						
26	.370	.860	91.699						
27	.365	.849	92.549						
28	.335	.780	93.329						
29	.300	.697	94.026						
30	.283	.658	94.684						
31	.271	.630	95.314						
32	.267	.620	95.934						
33	.250	.582	96.516						
34	.217	.504	97.020						
35	.201	.467	97.488						
36	.188	.437	97.925						
37	.181	.420	98.345						
38	.159	.370	98.715						
39	.141	.327	99.042						
40	.129	.301	99.343						
41	.117	.271	99.614						
42	.103	.240	99.855						
43	.063	.145	100.000						

Extraction Method: Principal Component Analysis.

Figure 7 - Total Variance Explained

Table 1 - Final Cluster Centres for 4 cluster solution

Cluster	Label	Key Traits	Dominant Factors
C1	Mindless Mobile Shoppers	App-driven, less conscious shopping, high impulsivity	High Factor1 (Mindlessness), High F6 (Mobile/App Usage)

C2	Rental Rationalists	Price- and policy-focused, cautious rental users	High Factor 2 (Rental Criteria), Moderate F3 (Digital usage)
C3	Social Validators	Strong reliance on reviews, peer opinions	High Factor 5 (Visual Review Trust), High Factor 7 (Reviewer Judgment)
C4	In-Store Seekers	Prefer physical stores, low digital reliance	High Factor 4 (Offline Shopping Preference), Low Factor 3/Factor 6

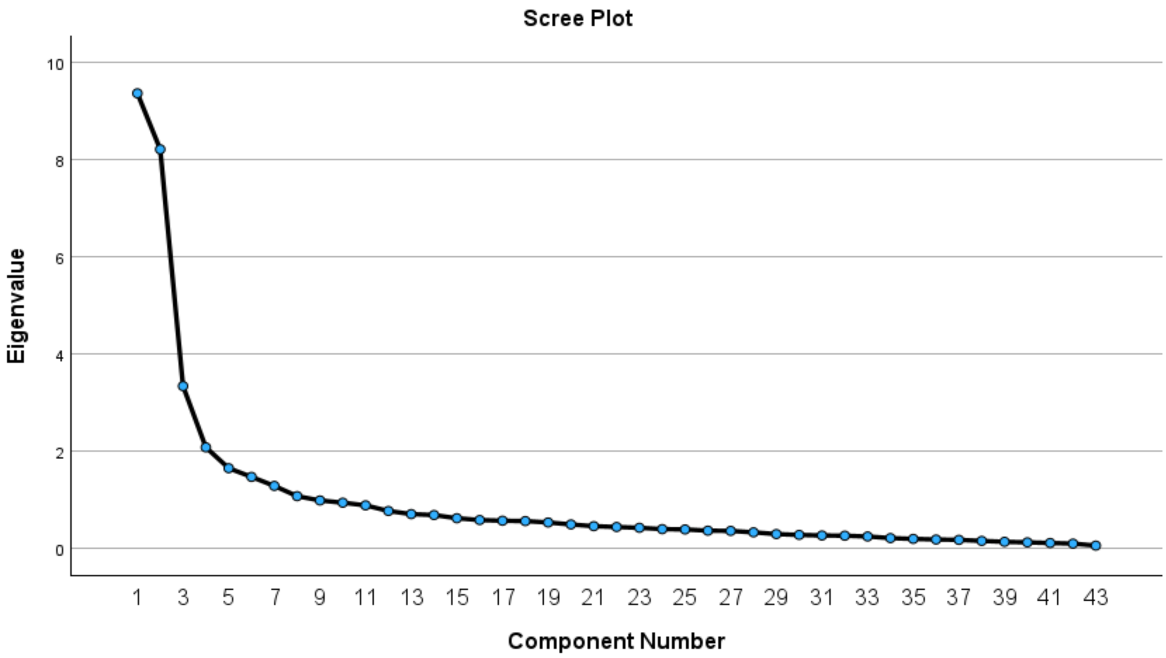

Figure 8 - Scree Plot for Factors Extraction

Rotated Component Matrix[a]

	Component							
	1	2	3	4	5	6	7	8
7. It seems I am "running on automatic" without much awareness of what I' m doing.	.881							
8. I rush through activities without being really attentive to them.	.875	.123						
10. I do jobs or tasks automatically, without being aware of what I'm doing.	.830	.200			.126			
3. I find it difficult to stay focused on what's happening in the present.	.827				-.121			.165
14. I find myself doing things without paying attention.	.817			-.131				-.106
12. I drive places on "automatic pilot" and then wonder why I went there.	.814			-.162		-.128		
2. I break or spill things because of carelessness, not paying attention, or thinking of something else.	.785					-.174		
4. I tend to walk quickly to get where I'm going without paying attention to what I experience along the way.	.769	.141		.169				-.127
6. I forget a person's name almost as soon as I've been told it for the first time.	.728	.103	.113	.205			-.130	
5. I tend not to notice feelings of physical tension or discomfort until they really grab my attention.	.725		-.129		-.212			.124

13. I find myself preoccupied with the future or the past.	.716	-.118	.100					
11. I find myself listening to someone with one ear, doing something else at the same time.	.704					.102		-.104
9. I get so focused on the goal I want to achieve that I lose touch with what I am doing right now to get there.	.702							
15. I snack without being aware that I'm eating.	.671		-.219	-.277				
1. I could be experiencing some emotion and not be conscious of it until sometime later.	.597	-.108	-.117		-.189	.114	.189	.225
What factors are important for you to rent a clothing? - Quality of the clothing		.852		.162				
What factors are important for you to rent a clothing? - Cleanness of the clothing	.174	.835					.108	
What factors are important for you to rent a clothing? - Rental price of the clothing		.801	-.103			.217	.133	.145
What factors are important for you to rent a clothing? - Delivery and drop-off policy		.751	.169	.229				
What factors are important for you to rent a clothing? - Regular sale price of the clothing		.679		.296	.221	.177		
MEDIAN(buyonline,2)			.878	.115				
MEDIAN(visitweb,2)			.859		-.114	.108		.165
MEDIAN(visitphone,2)			.822	.204	.306	.111		
MEDIAN(buyphone,2)			.801	.198	.328	.162		
How often do you use the following social media platform? - Snapchat			.469	.250	.367	.377		
Some websites provide both verified product reviews (i.e., by customers who bought the product at the website) and unverified reviews (i.e., by people who did not buy the product at the website, although they may have purchased it elsewhere). Please indicate your degree of agreement and disagreement on the following statements: - I do not trust any unverified reviews.	-.240		.299	.236	.170	.220	-.258	
How important is each part of online consumer review to your buying decision? - Customer images		.163	.142	.721	.193		.175	
How important is each part of online consumer review to your buying decision? - Reviewer characteristics		.114	.153	.672				.310
How important is each part of online consumer review to your buying decision? - Helpfulness votes		.160		.655	.216	.153		
How important is each part of online consumer review to your buying decision? - Photo of product contributed by the reviewer		.329	.183	.630		.114		

What factors are important for you to rent a clothing? - Characteristics of previous users of the clothing		.479	.175	.516	.244	.168		
MEDIAN(visitoffline,2)			.104	.258	.837			.105
MEDIAN(buyoffline,2)			.178	.281	.827			
How often do you use the following social media platform? - Instagram		.272	.297		.446	.334		.264
How often do you use the following social media platform? - Twitter	.101		.303		.140	.705		
How often do you use the following social media platform? - YouTube		.115		.175	-.188	.683	.148	.282
How often do you use the following social media platform? - Pinterest		.149	.372		.242	.609		.144
How likely are you to rent clothes in future?	-.247	.171	.222	.179	.348	.418	-.120	
Some websites provide both verified product reviews (i.e., by customers who bought the product at the website) and unverified reviews (i.e., by people who did not buy the product at the website, although they may have purchased it elsewhere). Please indicate your degree of agreement and disagreement on the following statements: - Unverified reviews can be useful.		.135					.882	
Some websites provide both verified product reviews (i.e., by customers who bought the product at the website) and unverified reviews (i.e., by people who did not buy the product at the website, although they may have purchased it elsewhere). Please indicate your degree of agreement and disagreement on the following statements: - I read the unverified reviews if they contain detailed product information.		.114				.166	.822	
How often do you use the following social media platform? - Facebook		.106	.319		.310	.121	-.157	.686
How important is each part of online consumer review to your buying decision? - Review text		.127		.403			.320	.596
How important is each part of online consumer review to your buying decision? - Review rating or score	.137	.315		.328		.120	.153	.537

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 8 iterations.

Figure 9 - Rotated Component Matrix

Final Cluster Centers

	Cluster 1	2	3
REGR factor score 1 for analysis 1	-.02777	.06184	-.12381
REGR factor score 2 for analysis 1	.04006	.49133	-1.14469
REGR factor score 3 for analysis 1	-.28107	.12556	-.11259
REGR factor score 4 for analysis 1	.52726	-.12438	-.04215
REGR factor score 5 for analysis 1	.60914	-.02190	-.32632
REGR factor score 6 for analysis 1	-1.36315	.36034	.02060
REGR factor score 7 for analysis 1	.09536	.10620	-.30097
REGR factor score 8 for analysis 1	.52384	.14948	-.66429

Figure 10 - Final Cluster Centres for 3 Clusters

ANOVA

	Cluster		Error			
	Mean Square	df	Mean Square	df	F	Sig.
REGR factor score 1 for analysis 1	.834	2	1.001	262	.833	.436
REGR factor score 2 for analysis 1	63.293	2	.524	262	120.677	<.001
REGR factor score 3 for analysis 1	3.312	2	.982	262	3.371	.036
REGR factor score 4 for analysis 1	7.097	2	.953	262	7.444	<.001
REGR factor score 5 for analysis 1	11.450	2	.920	262	12.442	<.001
REGR factor score 6 for analysis 1	49.099	2	.633	262	77.587	<.001
REGR factor score 7 for analysis 1	4.145	2	.976	262	4.247	.015
REGR factor score 8 for analysis 1	22.498	2	.836	262	26.915	<.001

The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

Figure 11 - ANOVA Table for Clustering (3 clusters)

Number of Cases in each Cluster

Cluster	1	42.000
	2	155.000
	3	68.000
Valid		265.000
Missing		.000

Figure 12 - Number of Cases in Each Cluster (3 cluster)

Final Cluster Centers

	Cluster 1	2	3	4
REGR factor score 1 for analysis 1	.05482	.19757	.05299	-.22437
REGR factor score 2 for analysis 1	.11400	.09095	.01995	-.17759
REGR factor score 3 for analysis 1	-.71827	-.12940	-.00616	.72431
REGR factor score 4 for analysis 1	.60303	.42674	-1.10390	.41676
REGR factor score 5 for analysis 1	-.32378	.28627	-.48683	.65144
REGR factor score 6 for analysis 1	.26729	-1.38589	-.02983	.61831
REGR factor score 7 for analysis 1	-.78262	.45265	.07249	.34952
REGR factor score 8 for analysis 1	.25885	.31434	-.04347	-.37019

Figure 13 - Final Cluster Centres for 4 Clusters

ANOVA

	Cluster		Error			
	Mean Square	df	Mean Square	df	F	Sig.
REGR factor score 1 for analysis 1	1.956	3	.989	261	1.978	.118
REGR factor score 2 for analysis 1	1.196	3	.998	261	1.199	.311
REGR factor score 3 for analysis 1	24.537	3	.729	261	33.638	<.001
REGR factor score 4 for analysis 1	47.857	3	.461	261	103.720	<.001
REGR factor score 5 for analysis 1	20.375	3	.777	261	26.213	<.001
REGR factor score 6 for analysis 1	39.196	3	.561	261	69.872	<.001
REGR factor score 7 for analysis 1	19.635	3	.786	261	24.988	<.001
REGR factor score 8 for analysis 1	6.355	3	.938	261	6.771	<.001

The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

Figure 14 - ANOVA Table for Clustering (4 clusters)

Number of Cases in each Cluster

Cluster	1	66.000
	2	44.000
	3	81.000
	4	74.000
Valid		265.000
Missing		.000

Figure 15 - Number of Cases in Each Cluster (4 cluster)

Final Cluster Centers

	Cluster 1	2	3	4	5
REGR factor score 1 for analysis 1	.10661	-.35523	.36845	.50411	.05706
REGR factor score 2 for analysis 1	.44997	.04338	.38628	.13802	-.80124
REGR factor score 3 for analysis 1	1.43421	.08682	-.17774	-.73027	-.42845
REGR factor score 4 for analysis 1	-.39763	.06520	.75391	.76406	-1.07055
REGR factor score 5 for analysis 1	-1.11668	.33155	.17842	-.22704	.03530
REGR factor score 6 for analysis 1	-.22307	.30005	-1.31774	.50864	.03614
REGR factor score 7 for analysis 1	-.41519	.13944	.47986	-1.01244	.41996
REGR factor score 8 for analysis 1	.30640	-.62853	.05409	.54254	.75474

Figure 16 - Final Cluster Centres for 5 Clusters

ANOVA

	Cluster		Error			
	Mean Square	df	Mean Square	df	F	Sig.
REGR factor score 1 for analysis 1	7.300	4	.903	260	8.083	<.001
REGR factor score 2 for analysis 1	10.904	4	.848	260	12.864	<.001
REGR factor score 3 for analysis 1	24.350	4	.641	260	38.001	<.001
REGR factor score 4 for analysis 1	25.942	4	.616	260	42.095	<.001
REGR factor score 5 for analysis 1	13.803	4	.803	260	17.188	<.001
REGR factor score 6 for analysis 1	21.040	4	.692	260	30.418	<.001
REGR factor score 7 for analysis 1	16.097	4	.768	260	20.966	<.001
REGR factor score 8 for analysis 1	21.347	4	.687	260	31.074	<.001

The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

Figure 17 - ANOVA Table for Clustering (5 clusters)

Number of Cases in each Cluster

Cluster	1	32.000
	2	110.000
	3	36.000
	4	39.000
	5	48.000
Valid		265.000
Missing		.000

Figure 18 - Number of Cases in Each Cluster (5 cluster)

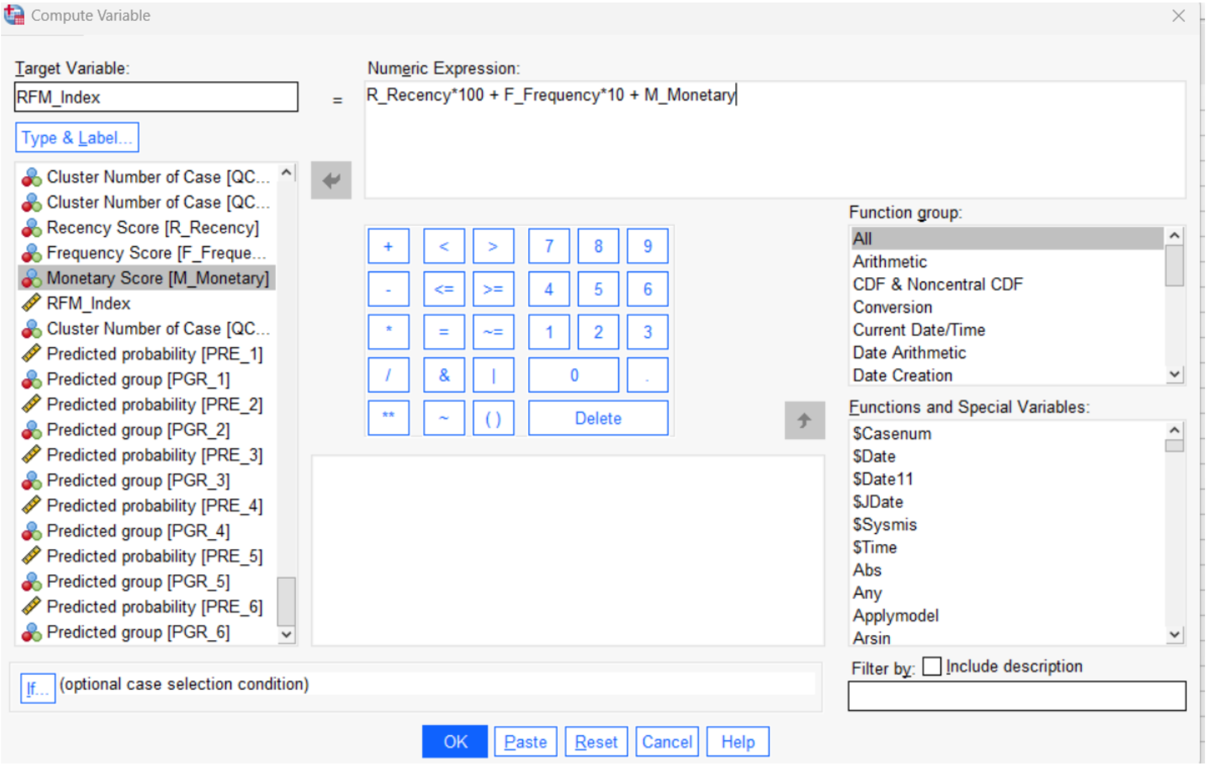

Figure 19 - RFM Index Calculation

RFM_Index

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	112.00	1	.4	.4	.4
	113.00	1	.4	.4	.8
	211.00	1	.4	.4	1.1
	221.00	9	3.4	3.4	4.5
	222.00	1	.4	.4	4.9
	231.00	2	.8	.8	5.7
	243.00	1	.4	.4	6.0
	321.00	84	31.7	31.7	37.7
	322.00	6	2.3	2.3	40.0
	331.00	4	1.5	1.5	41.5
	332.00	12	4.5	4.5	46.0
	333.00	1	.4	.4	46.4
	342.00	1	.4	.4	46.8
	421.00	74	27.9	27.9	74.7
	422.00	18	6.8	6.8	81.5
	423.00	2	.8	.8	82.3
	431.00	25	9.4	9.4	91.7
	432.00	14	5.3	5.3	97.0
	433.00	2	.8	.8	97.7
	441.00	3	1.1	1.1	98.9
	442.00	2	.8	.8	99.6
	443.00	1	.4	.4	100.0
	Total	265	100.0	100.0	

Figure 20 - RFM Index Frequencies

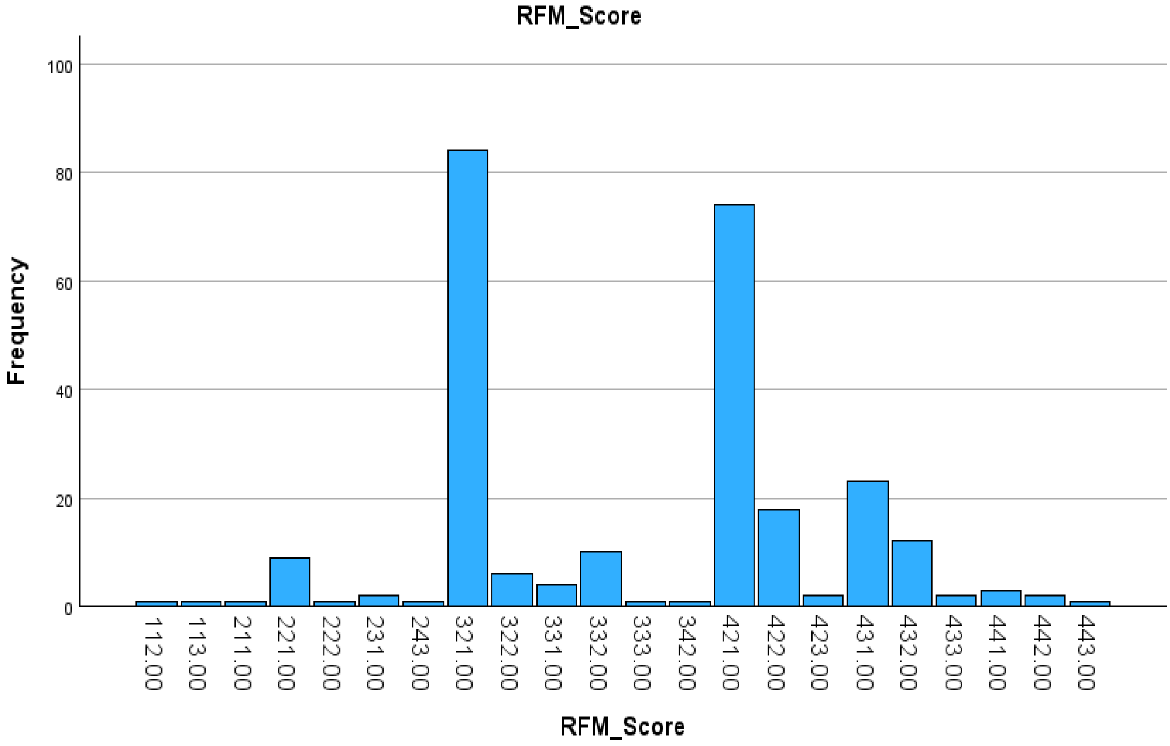

Figure 21 - RFM Score Distribution

Table 2 - RFM Customer Groups

RFM Code	Count (%)	Interpretation
111	14 (5.3%)	Inactive – old, rare, low-spend (churn risk)
211	131 (49.4%)	Recent but low frequency/spend (growth potential)
311	49 (18.5%)	Past loyalists – high frequency but not recent
321	32 (12.1%)	High potential – recent & frequent
331	5 (1.9%)	Top-tier – recent, frequent, high-spend

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	55.257	14	<.001
	Block	55.257	14	<.001
	Model	55.257	14	<.001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	288.198[a]	.188	.259

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	13.786	8	.088

Figure 22 - Logistic Regression Model Summary for res_cloth

Classification Table[a]

	Observed		Predicted: response to luna7 promotion on clothing last month — No	Predicted: response to luna7 promotion on clothing last month — Yes	Percentage Correct
Step 1	response to luna7 promotion on clothing last month	No	37	56	39.8
		Yes	27	145	84.3
	Overall Percentage				68.7

a. The cut value is .500

Figure 23 - Logistic Regression Classification Table for res_cloth

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	132.207	14	<.001
	Block	132.207	14	<.001
	Model	132.207	14	<.001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	190.699[a]	.393	.558

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6.486	8	.593

Figure 24 - Logistic Regression Model Summary for res_acce

Classification Table[a]

	Observed		Predicted: response to luna7 promotion on accessories last month: No	Predicted: response to luna7 promotion on accessories last month: Yes	Percentage Correct
Step 1	response to luna7 promotion on accessories last month	No	166	20	89.2
		Yes	25	54	68.4
	Overall Percentage				83.0

a. The cut value is .500

Figure 25 - Logistic Regression Classification Table for res_acce

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	109.202	14	<.001
	Block	109.202	14	<.001
	Model	109.202	14	<.001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	192.620[a]	.338	.497

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	18.306	8	.019

Figure 26 - Logistic Regression Model Summary for res_home

Classification Table[a]

Observed			Predicted: response to luna7 promotion on home items last month – No	Predicted: response to luna7 promotion on home items last month – Yes	Percentage Correct
Step 1	response to luna7 promotion on home items last month	No	184	13	93.4
		Yes	27	41	60.3
	Overall Percentage				84.9

a. The cut value is .500

Figure 27 - Logistic Regression Classification Table for res_home

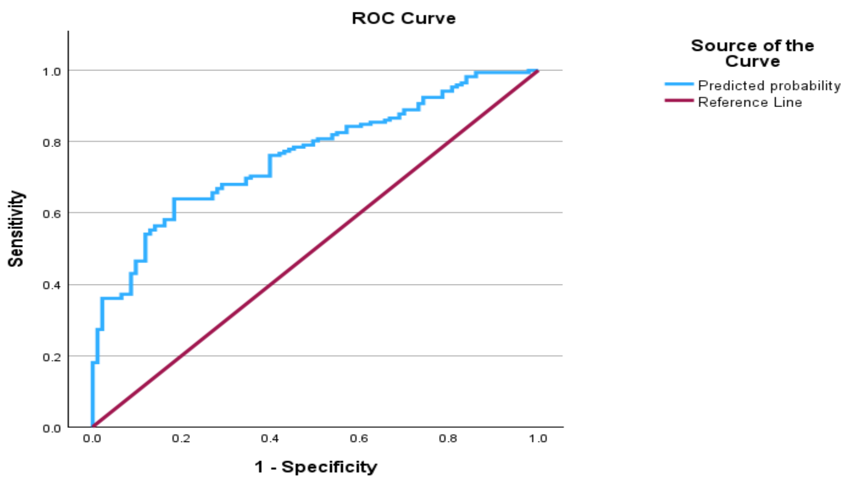

Figure 28 - ROC Curve for clothing

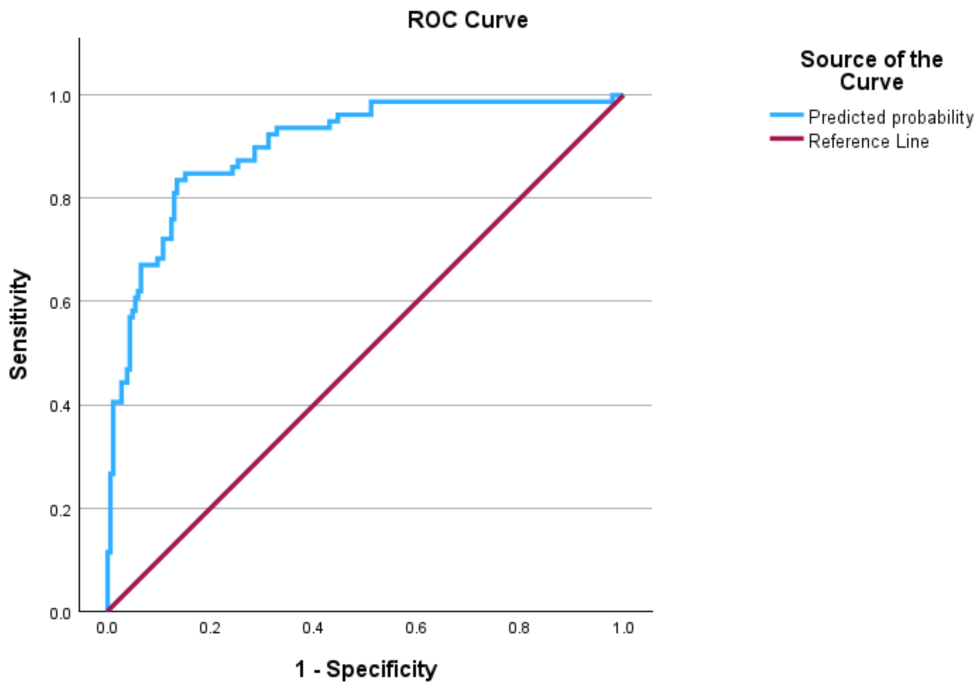

Figure 29 - ROC Curve for accessories

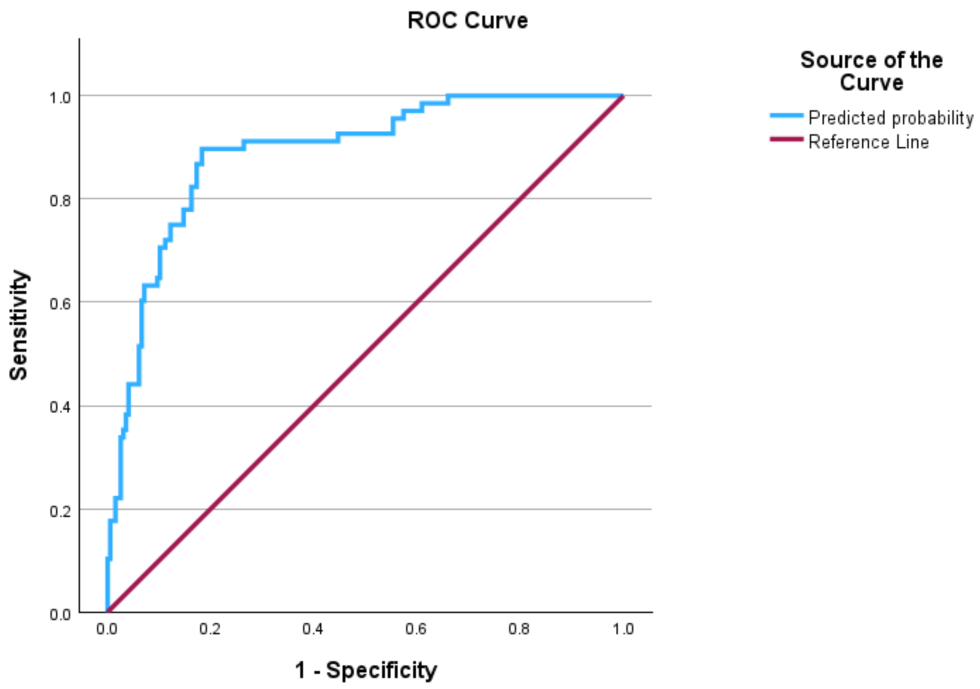

Figure 30 - ROC Curve for home