

The relative power of behavioural, demographic, and psychographic variables as predictors of systematic purchase behaviour

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Abstract

This study bridges a gap in existing research by fusing behavioural variables from historical transactional records with demographic and psychographic data, aiming to predict systematic purchase behaviour (SPB). The research also investigates to what extent each of the group of variables helps understand the anatomy of SPB.

Data from over 2,481 stores, covering January 2012 to November 2015, was obtained from a leading UK grocery and pharmacy chain. Pseudo-anonymized records merged from transactional and survey data resulted in a cohort of 12,137 participants meeting the inclusion criteria. A novel measure, Bundle Entropy, derived from transactional data, evaluates SPB. Machine learning models and techniques are employed for predictive and variable importance analysis.

Preliminary results show that all variables in combination have a robust performance over random choices at predicting SPB, with Random Forest and XGBoost being equally well-performing. Shapley Additive exPlanations and Model Class Reliance results also show that behavioural variables have a more dominant role than socio-demographic, personality and psychological variables when predicting SPB. For instance, the significance of *total visits* suggests that frequent customer engagement serves as a key determinant, while the nuanced roles of age and variety-seeking behaviour underscore the multifaceted nature of consumer SPB.

Future research will delve into machine learning models relying solely on demographic and psychographic variables to discern their distinct contributions to SPB prediction.

Track: Marketing and Retail

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INTRODUCTION

The examination of consumer purchasing behaviours through the utilisation of demographic and psychographic variables has been a longstanding tradition, as evidenced by various works in the field (Rich and Jain 1968; Slocum and Mathews 1970; Dubois and Duquesne 1993; Bellman et al. 1999; Baumeister 2002; Silvera et al. 2008; Islam et al. 2017). Despite the well-established practice of incorporating these traditional factors, there remains a notable gap in the literature regarding the significance of behavioural variables derived from transactional records in modelling different purchase behaviours, such as systematic product choices over time. This lacuna primarily arises from challenges associated with data accessibility, wherein obtaining comprehensive datasets encompassing diverse behavioural variables on a national scale proves more challenging than acquiring individual sets of data. Retailers routinely gather vast quantities of daily purchase records, constituting a valuable source of behavioural data. In contrast, survey data, employed predominantly for the collection of psychographic and demographic insights, is procured less frequently due to the inherent cost constraints associated with its administration.

This study aims to address this issue via unprecedented access to data sets from a leading UK retail chain that links consumer demographics, psychographics and purchase data for a sample of households/loyalty card holders who signed up to an incentivised consumer panel. Using these data sets, the study seeks to examine the relative power of behavioural, demographic, and psychographic variables as predictors of systematic purchase behaviour (SPB).

SPB was introduced in 2015 by Guidotti et al. (2015) to describe a person’s regular buying patterns. To better understand this behaviour, consider a hypothetical purchase sequence from Table 1. For instance, *Person 1* has a highly systematic buying behaviour, always buying products w , x , and y together in every purchase. In contrast, *Person 2* and *Person 4* follow different patterns of buying behaviour, changing one or more items on every visit to the store (See Table 1), raising the question of who is more systematic compared to *Person 1*?

While it may seem simple to evaluate the probability of each product or the repeat purchase rate for v , w , x , y , or z , assessing the evolution of combinations is more challenging. To address this, a measure called *bundle entropy* is used in this study. Mansilla et al. (2023) offers a technical explanation of *bundle entropy* and how it can be used to measure SPB.

Table 1: The predictability of different purchase scenarios assessed by *bundle entropy*.

Expected Predictability	Person	Set of Baskets	Bundle Entropy
Extremely high	Person 1	$[(wxy), (wxy), (wxy)]$	0.00
High	Person 2	$[(wxy), (wxz), (wxv)]$	0.23
Medium	Person 3	$[(wxy), (wxv), (xyz), (xyv)]$	0.50
Low	Person 4	$[(wx), (xy), (yz), (zv)]$	0.60
Extremely low	Person 5	$[(wxy), (abc), (stu)]$	1.00

BACKGROUND

Demographic variables have been used in attempts to predict consumer behaviour since the 1960s (e.g. [Mathews and Slocum Jr, 1969](#)). They remain powerful determinates of behaviour, but they are not a panacea. Psychographics can also be useful in predicting consumer purchases as they provide insights into consumers' personalities, attitudes, beliefs, values, interests, and other psychological factors that influence their buying behaviour. However, the effectiveness of psychographics (and demographics) in predicting consumer purchases can vary depending on various factors such as the industry, product category, and target audience. Several academic studies have explored the relationship between psychographics and consumer purchases, and the efforts go back to the 1970s (e.g. [Green, 1977](#)).

Efforts in the commercial realm to understand consumer behaviour have an equal long-standing history, dating back to the Values and Lifestyles (VALS) ([Mitchell 1984](#)) or List of Values (LOV) ([Kahle et al. 1986](#)) approaches. These methods garnered attention for their innovative attempt to categorise individuals into psychographic segments based on their values and lifestyles rather than just demographics.

More recently, personality traits, specifically the Big Five framework ([Costa and McCrae 1992](#)), have emerged as a popular means of analysing buying behaviour. Initial studies, such as [Verplanken and Herabadi \(2001\)](#), [Pirog and Roberts \(2007\)](#) and [Sun and Wu \(2014\)](#) suggested that conscientiousness and extroversion were negatively correlated with impulsive buying tendencies at the individual level. However, more recent research has challenged this view, indicating that while conscientiousness and extroversion may not have a significant relationship with impulsivity, they are positively linked to neuroticism, openness, and agreeableness ([Ali et al. 2022](#)).

However, the evidence for how effective these approaches can be is mixed at best; we don't always behave in a way that conforms to psychographic measures (e.g. [Barber et al., 2012](#), among many others). [Myers et al. \(1971\)](#) contend that psychographics provide a viable alternative to demographic metrics. [Sandy et al. \(2013\)](#) explicitly compares the effectiveness of demographics against psychographics and gets mixed results. In their study, demographics seemed better at predicting electronic device purchases, whilst psychographics were better at predicting TV show choice. This underscores the potential impact of both psychographic and demographic predictors under different contexts.

Further studies have delved into the relative impact of demographic and attitudinal variables on consumer behaviour. The evidence shows that incorporating both types of variables can greatly improve the accuracy of predictive models. For example, a study conducted by [Sorce et al. \(2006\)](#) demonstrated that the integration of these variables raised the proportion of variance explained by almost 50% in the realm of online shopping intentions. Additionally, [Rahim et al. \(2014\)](#) noted that the interaction between demographic factors and psychographic measures can be quite nuanced, highlighting the complexity of consumer decision-making processes.

Notably, both demographics and psychographics can be influenced by autonomic or synaptic decisions within a household ([Kirchler 1995, 1988](#)). Demographic information such as age, gender, income, and education level can provide insights into consumer behaviour but may not capture the full complexity of decision-making within a household. For instance, while age can indicate certain purchasing behaviours like having children, it does not

necessarily explain how decisions are made within a household.

On the other hand, psychographics delve deeper into the psychological and behavioural traits of individuals, offering insights into their attitudes, values, interests, and lifestyle preferences. These factors can greatly influence consumer choices, particularly in syncretic decision-making scenarios where multiple household members contribute to the decision-making process. However, even in cases where a lead decision-maker is apparent, psychographics may not always emerge as the dominant predictor of consumer buying behaviour (Sandy et al. 2013).

The issue of household versus individual dynamics further complicates the relationship between demographics and psychographics. While psychographics are inherently focused on individual decision-makers, demographics often exhibit a stronger association with household-level features. For example, demographic variables like household composition and marital status explicitly reflect characteristics of the household unit and can significantly impact purchasing decisions made for the entire household.

Taking into account both demographic and psychographic variables when studying buying behaviour can provide a more comprehensive understanding (Sorce et al. 2006; Asniar and Surendro 2019). Demographics offer insights into the structural aspects of consumer populations, while psychographics reveal the motivations and preferences that drive consumer choices. However, a natural question arises: what is the role of past behaviours in studying buying behaviour?

Behavioural data analysis based on transactional data is relatively new; however, various attempts have been made to derive determining features (e.g. habit tendency and various propensity scores) from transactional data like loyalty card data and online purchase data (Smith et al. 2004; Chu et al. 2010; Mansilla et al. 2023). A recent study found that although intentions are generally good predictors of behaviour, some people fail to carry out their intentions and instead revert to past patterns of behaviour (Asniar and Surendro 2019; Koll and Plank 2022). However, to the best of our knowledge, no studies have investigated the combined impact of behavioural, demographic and psychographic variables on systematic choices. Therefore, our research imperative is: *To explore the relative power of demographic, psychographic and behavioural variables in explaining systematic purchase behaviour at the household level.*

MATERIALS AND METHODS

Data Materials

The *transactional data set* was provided by a leading retailer with over 2,481 stores across the UK. This dataset comprises sales records made by more than 1 million loyalty card members covering from January 1st, 2012, to November 4th, 2015. Access to more recent data was not possible at this stage. Despite the data being somewhat dated, it still holds significant value for the research due to the connection between the transaction and survey data with individuals' authorisation. The data was subjected to confidential, privacy, and ethical protocols, and was pseudo-anonymized during processing.

The *survey data set* used in this study was initially created to explore the impact of personality and psychological factors on purchase behaviours. Although it was not specifically

designed to investigate SPB, it still provides valuable information on 12,968 participants, including their demographics, shopping behaviours and motivations, and psychological characteristics. we found matches for 12,835 individuals. However, 698 participants displayed negative spending values without a clear explanation. We considered the possibility of a storage error, but this could not be confirmed. Consequently, we removed these 698 participants from the dataset, resulting in 12,137 individuals for further analysis.

To ensure that our analysis includes only those customers who purchase regularly, we established a lower inclusion criterion of no less than 5 visits. Also, to prevent outliers from skewing our data, we set an upper inclusion criterion of up to 300 visits, resulting in a cohort of 10,978.

Measuring systematic purchase behaviour

Our research utilises the definition of SPB as provided by [Mansilla et al. \(2023\)](#). This definition characterises an individual’s buying behaviour as either systematic or unsystematic based on their shopping basket over time. To assess consumers’ SPB, we will be utilising a metric known as *bundle entropy*. The examples in Table 1 display some simple but illustrative purchase scenarios showcasing the accuracy of *bundle entropy* in predicting customer behaviour. The measure’s ability to match the expected predictability of each scenario supports our decision to use the measure. For a comprehensive explanation of how *bundle entropy* functions, please refer to [Mansilla et al. \(2023\)](#).

Machine learning model selection and interpretation

Our study aims to predict SPB by leveraging transactional and survey data through a regression task. We have incorporated 27 input variables from the merge data set, comprising both pre-existing and engineered variables (e.g., ‘Average gap between purchases’, ‘Average distinct items per basket’). A summary of all the variables, including the data source and a brief description, can be found in Table 2. While a diverse range of input variables can enhance the model’s performance, it can also increase complexity, making it harder to interpret. Nonetheless, this presents an opportunity to investigate a wider array of models that can effectively capture linear and non-linear connections between variables, which may have gone unnoticed in lower-dimensional spaces.

We compare three popular machine learning regressors: Linear Regression, XGBoost, and Random Forest. These algorithms are widely used due to their robust predictive power on real-world data. The comparison is conducted using *R-squared*, *Mean Absolute Percentage Error* (MAPE), and *Mean Absolute Error* (MAE).

After identifying the best-performing model, we use machine learning techniques to determine the most important variables and their extent of influence. To avoid biased interpretation towards the best-performing model ([Fisher et al. 2019](#)), we use Model Class Reliance (MCR) ([Smith et al. 2020](#)), evaluating all equally well-performing models. This way, it learns all the potential relationships between the input variables and the output from all the other well-performing models.

Additionally, we utilised the Shapley Additive exPlanations (SHAP) ([Lundberg et al. 2017](#)) method to improve the interpretability. This technique allowed us to determine the

direction of the association between input variables and the output.

Table 2: Description of the independent variables from the transaction and survey data.

	Independent Variable	Source	Description
1	Total visits	Transact.	Number of visits during the period covered
2	Inter-basket mean gap	Transact.	Average days between purchases
3	Total distinct items	Transact.	Total unique items across baskets
4	Average items per basket	Transact.	Average count of items per basket
5	Period covered days	Transact.	Total days between first and last basket
6	Total spend	Transact.	Total monetary value (£) across all baskets
7	Average basket spend	Transact.	Average monetary value (£) per basket
8	Median basket spend	Transact.	Median monetary value (£) per basket
9	Day time classification	Transact.	Preferred buy time (morning, evening, afternoon)
10	Age	Survey	Age of the participant
11	Income	Survey	Annual income in the household before taxes
12	Gender	Survey	Type of gender (0: man, 1: woman)
13	Household composition	Survey	Number of people leaving in the same place
14	Qualification	Survey	The highest level of education of the participant
15	Marital status	Survey	The marital status of the participant
16	Openness	Survey	Measures the openness to new experiences
17	Conscientiousness	Survey	Measures of disciplined and carefulness
18	Extroversion	Survey	Measures the level of sociability
19	Agreeableness	Survey	Measures the level of trusting
20	Emotional stability	Survey	Measures of anxiety/pessimism
21	Variety seeking	Survey	Measures the seek of variety
22	Self-control	Survey	Measures the level of self-control
23	Frugality	Survey	Measures general attitudes towards spending
24	Shopping impulsivity	Survey	Measures the level of impulsivity
25	Shopping mission	Survey	Number of product categories across purchases
26	Happiness	Survey	Measures the level of general happiness
27	BAS	Survey	Measures the level of impulsiveness

Methodology

Outcome variable

In order to determine the *Bundle Entropy* (BE) for each individual, we applied equation 1 to their complete basket of items. In this approach, each item in the basket is assigned a unique product identifier, where distinct product formats are treated as separate entities due to their function and value.

$$BE(\mathcal{B}) = \frac{1}{\log_2 |\mathcal{B}|} \times \sum_{b_k \in \mathcal{B}} p(b_k) R(b_k) \quad (1)$$

Unique baskets purchased by an individual are denoted by B , while the probability of observing a basket b_k is $p(b_k)$ and $R(b_k)$ represents the self-information measure that quantifies the loss associated with presuming the appearance of basket b_k .

Experimental procedure

We started by training our three machine learning algorithms to predict *bundle entropy* using the merged data set. The outcome variable, *bundle entropy*, ranges from zero to one. Zero indicates low SPB, and one indicates high SPB. Scores between zero and one suggest a more balanced SPB. To thoroughly evaluate the effectiveness of all models, the data is split into 80% for training and 20% for testing using stratified random sampling.

To fine-tune each model, the Grid search technique is employed to search through the hyper-parameters. Once the optimal model is identified, it's assessed on the test data. The models are evaluated on their *R-squared*, *MAPE* and *MAE*. Additionally, a Dummy Regressor is created to compare the models' performance with random chance. The best-performing model is further explored to understand the relative power of the behavioural, demographic, and psychographic variables. For this, we use SHAP values and MCR to ensure that our findings are consistent and not the cause of random fluctuations in a given model.

PRELIMINARY FINDINGS

The results of predicting SPB through different machine learning regressors are displayed in Table 3. All three models perform significantly better compared to a Dummy Regressor ($R^2 = -0.001$, $MAPE = 22.13\%$). Both tree-based models were the highest-performing models. While XGBoost showed an R^2 of 0.82 and a $MAPE$ of 7.78%, Random Forest results also on an R^2 of 0.82 but a slightly higher $MAPE$ of 7.86%. However, Random Forest exhibits a processing time of 15 seconds versus 7 minutes for XGBoost.

Table 3: Results of machine learning regressors for predicting SPB

Regressor Model	Results		
	R-Squared	MAPE	MAE
Dummy Regressor	-0.001	22.13%	0.70
Linear Regression	0.777	8.89%	0.29
XGBoost	0.82	7.78%	0.26
Random Forest	0.82	7.86%	0.26

We selected the Random Forest model to evaluate the impact of behavioural, demographic, and psychographic factors on SPB through SHAP values and MCR. Despite both

models having equal prediction performance, the Random Forest model’s favourable processing performance made it our top choice.

Figure 1 displays the SHAP summary plot for the Random Forest regressor predicting *bundle entropy*. The 27 predictor variables are ranked in order of importance, with behavioural variables making up the top seven. The most crucial feature is ‘Total visits’, indicating that higher levels of store visits are associated with high SPB. This suggests that shoppers who make more purchases in a given period tend to seek variety, making them less systematic in their choice combination. Of the demographic variables, only ‘Age’ appears to have some level of importance, with younger customers associated with higher SPB compared to older customers. Among the top variables, the most important psychographic variable is ‘Variety-seeking’, which aligns with the association between high SPB and higher levels of variety.

Figure 2 displays the MCR results for exploring SPB using all input variables. Each feature’s minimum importance is represented as MCR- and visually as a lollipop on the chart. Only a select few variables have a value above zero, with ‘Total visits’ being the most prominent, followed by ‘Total distinct items’ and ‘Average distinct items per basket.’ This indicates that these features are essential across all the top-performing models. Conversely, variables with MCR- values of zero lack relative predictive power and are thus not necessary in the set of best-performing models.

CONCLUSION

The findings from this study contribute to the body of evidence that demographic and psychographic variables predict and explain a small proportion of consumer purchase outcomes (e.g., Rich and Jain 1968, Bellman et al. 1999, Sorce et al. 2006). Moreover, it provides empirical evidence that behavioural variables can have a significant impact on predictive power. These contributions are timely as the extant literature lacks a truly parsimonious model that successfully predicts SPB. SPB is a unique behavioural outcome, assessed by *bundle entropy*, that reflects consistency in product choices over time, as opposed to static indicators, such as repeat purchases, frequencies, and repertoire size.

This study has responded to the research imperative and showed the potential of using machine learning models for reliable explanatory purposes. It also highlights the predictive variables of customers with high SPB: being male, being older, spending more but in fewer visits, buying fewer unique items per visit, seeking less variety, being less extroverted, and being less open and agreeable. Notably, many demographic and psychographic variables are irrelevant and may cause noise that harms the model’s performance. From an explanatory viewpoint, the study provides valuable insights into the relationship between personality traits and SPB. The findings show that personality traits hold similar significance levels as age and gender in predicting SPB. It further reveals that personality traits are more relevant than education and marital status in this aspect.

The ability to predict SPB has practical implications. By being able to identify individuals with low levels of SPB (high *bundle entropy*), companies can strategically target sales or promotions on alternative products, as these individuals tend to buy unsystematically. Furthermore, the findings have revealed that lower levels of SPB values are associated with

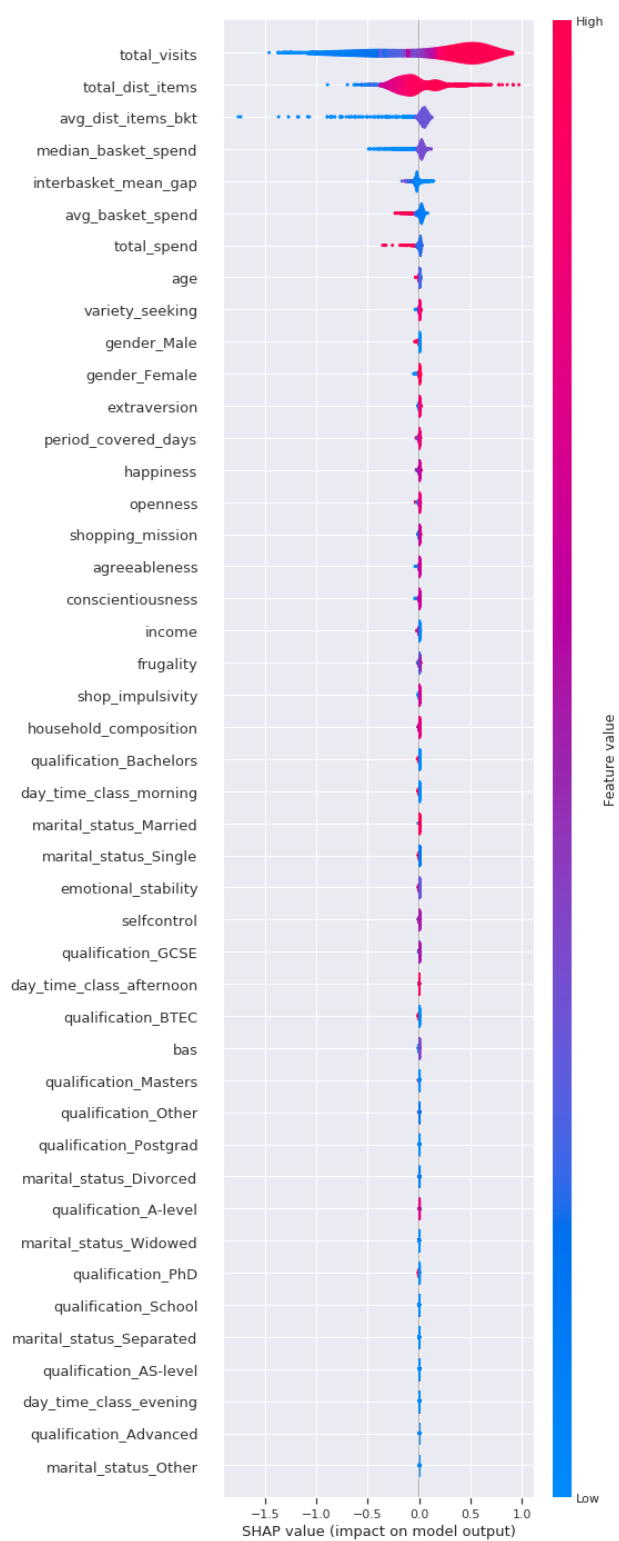


Figure 1: SHAP summary plot for Random Forest predicting SPB.

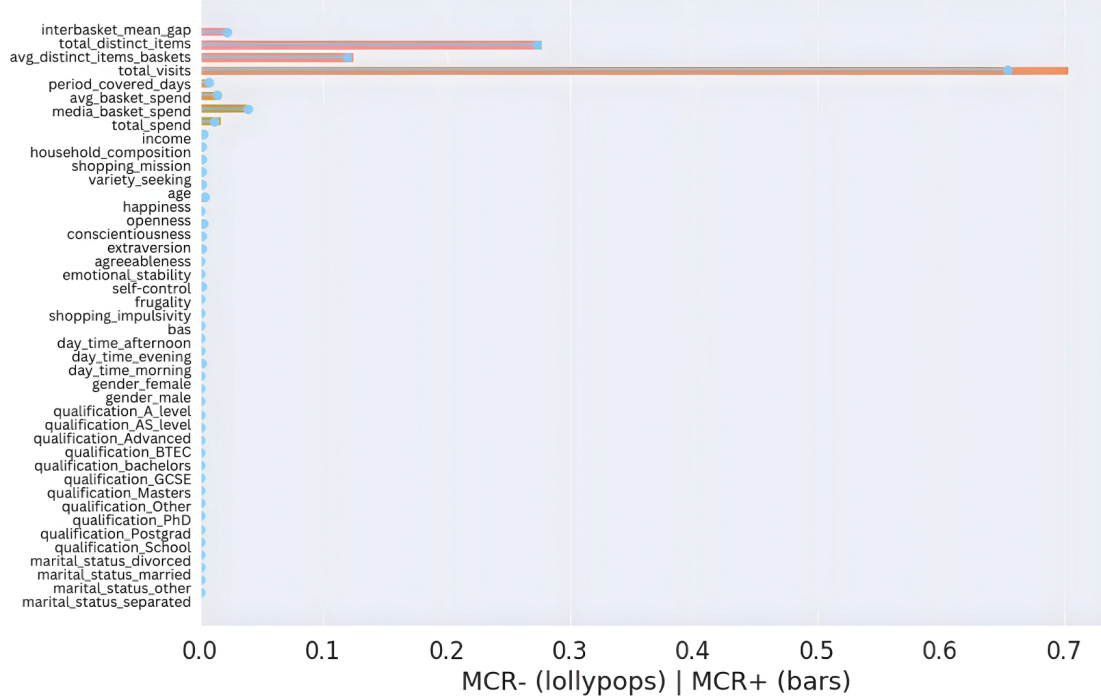


Figure 2: MCR chart illustrating feature importance across multiple Random Forest models for predicting SPB

young individuals and women. Therefore, businesses looking to promote new products or services should specifically target these groups in their marketing efforts. In contrast, individuals who exhibit high SPB tend to shop for the same products over time, making sales or promotions on alternative or new products pointless. Retailers should, therefore, focus on offering discounts and promotions on the products that these customers already purchase and trust. It was also found that men tend to have higher SPB than women. Hence, marketing efforts promoting repeat purchases should target them.

From a methodological perspective, the study demonstrates that the exploratory method of using ML regressor models to identify individuals with high or low SPB levels is an effective approach that can be extended to investigate other complex purchase behaviour outcomes over time. The results highlight the potential of utilising ML models, combined with techniques of variable importance, to gain valuable insights into various aspects of consumer behaviour.

FUTURE DIRECTIONS

As our research progresses, the next logical progression will be assessing machine learning models that exclusively rely on demographic and psychographic variables, both independently and in combination, for SPB prediction. This step aims to separate the impact of behavioural variables and clarify the distinct contributions of demographic and psychographic factors. By utilising SHAP and MCR analyses in this refined context, we can gain a more profound comprehension of the intricate connections between various predictor variables.

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