Consumer Behaviour: Analysing Marketing Campaigns through Recommender Systems and Statistical Techniques

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Abstract: This article examines consumer behaviour’s impact on marketing campaigns' effectiveness using a recommender system and statistical analysis methods. Understanding consumer behaviour is essential in today's fiercely competitive and constantly evolving market. Our study aims to highlight the significant impact of consumer behaviour on marketing data through the innovative application of recommender systems supported by state-of-the-art machine learning and data analysis techniques. This approach addresses the formidable challenges of accurately predicting consumer behaviour. We provide a detailed introduction to recommendation systems, emphasizing their vital role in the modern marketing landscape. We then outline our theories, laying the groundwork for a deeper understanding of the relationship between marketing data and consumer behaviour. Additionally, we present a rigorous data analysis process that begins with data cleaning and progresses through univariate and bivariate analysis, culminating in advanced techniques such as the Apriori algorithm to discover association rules and thoroughly explore this symbiotic relationship. Our findings demonstrate the applicability and effectiveness of our methodology for interpreting the complex interplay between consumer behaviour and marketing data. Our conclusions highlight essential trends and offer practical recommendations for enhancing marketing strategies significantly. By elucidating the dynamic relationships between consumer behaviour and marketing outcomes, our study contributes to a more sophisticated understanding of consumer dynamics in the contemporary business environment. Furthermore, this paper underscores the importance of understanding consumer behaviour and the benefits of employing innovative data analysis methods. By decoding consumption trends, businesses can optimize their marketing strategies and improve customer satisfaction, strengthening their competitive edge in a constantly shifting market. Finally, incorporating recommender systems with artificial intelligence and machine learning tools for collaborative filtering can further refine these strategies, substantially boosting marketing efficacy.

Keywords: apriori; decision analytics; machine learning; marketing data; recommendation system.

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1. Introduction. Companies must deeply understand their customers in today's fiercely competitive and rapidly evolving business landscape. With the advent of globalization, market positions have become increasingly unstable, and businesses must strive to stay ahead of their rivals. In this context, comprehending consumer behaviour becomes paramount. Customers' behaviours, attitudes, and expectations are shaped by a complex interplay between their characteristics, the products or services offered by businesses, and the specific situations in which they find themselves. To effectively navigate this intricate landscape, companies must consider their marketing strategies, product offerings, promotional activities, and the environmental, cultural, and technological contexts in which they operate. Behavioural analysis allows them to know precisely how their consumers interact with their product. This knowledge helps to develop, adapt, and shape their services to meet their consumers' expectations. Accordingly, several previous studies have focused on this topic (Arndt, 1986; Battalio et al., 1974; Solomon et al., 2013).

Although various methods and studies exist to analyse consumer behaviour, accurately predicting specific consumer actions remains an ongoing challenge. The elusive nature of consumer behaviour necessitates innovative approaches to gain deeper insights into the driving forces behind consumer decision-making. In this study, we aim to address this challenge by investigating the impact of comportment behaviour on marketing data collected through a cutting-edge recommender system based on machine learning and data analysis. By leveraging fundamental concepts, disciplined areas, and theoretical foundations, we seek to enhance our understanding of consumption acts and illuminate the underlying factors influencing customer choices. Our research question is as follows: How can recommender systems and statistical analysis techniques be used to analyse consumer behaviour and improve marketing campaign effectiveness?

To provide a comprehensive exploration of this topic, the subsequent sections of this paper will outline the introduction in Section 1. Section 2 will present this background, encompassing the evolution of recommendation systems and highlighting their significance in unravelling consumer preferences and behaviours. Examining the historical development of recommendation systems can contextualize this study's current advancements and methodologies. Then, in section 3, we explain our approach by presenting the hypotheses formulated to elucidate the relationship between consumer behaviour and the data collected through our recommender system. These hypotheses serve as guiding principles for our research methodology and analysis. By establishing explicit assumptions, we systematically investigate the impact of consumer behaviour on marketing data and generate meaningful insights.

Additionally, this section outlines our proposed analytical approach. Section 4 presents the results and discussion during the analysis of the collected data, focusing on integrating machine learning techniques and data analysis. This approach will allow us to discover hidden patterns, correlations, and dependencies in the data to comprehensively understand consumer behaviour and preferences. We use advanced data analysis methods to generate actionable insights to support a company's marketing strategy and decision-making process. Finally, in Section V, we present conclusions and perspectives. By analysing the data in detail and applying our recommended methods, we interpret the results and illuminate the impact of customer behaviour on marketing data. By presenting these results, we aim to contribute to the existing body of knowledge about consumer behaviour and provide valuable insights for companies seeking to refine their marketing strategies, improve customer satisfaction, and drive growth.

In addition, this study recognizes companies' legitimate interest in understanding their customers, particularly in the context of a fiercely competitive and rapidly changing business environment (Handri & Idrissi, 2020a; Handri & Idrissi, 2020b). By utilizing a novel recommender system based on machine learning and data analysis, we seek to overcome the challenges associated with accurately predicting consumer behaviour. Through our comprehensive analysis, we aim to deepen the understanding of the impact of consumer behaviour on marketing data and provide practical recommendations for businesses to optimize their marketing efforts. By tailoring their strategies and offerings to align with consumer preferences, companies can enhance their competitive position and foster long-term success in the market.

2. Literature Review. To accurately present the state of the art in this field, we will conduct a comprehensive literature review on recommendation systems related to personal behaviour; we would like to stress the principal era of research associated with this project that needs to be to enable the most understanding of our approach:

2.1. Personal behaviour and its principal importance in marketing

Personal behaviour refers to the patterns of actions and decisions an individual makes in response to various stimuli, such as products, advertisements, or marketing strategies. Understanding personal behaviour is paramount in marketing, as it enables businesses to tailor their products and services to meet their target customers' specific needs and preferences. By analysing consumer behaviour, companies can develop effective marketing strategies and make informed decisions about product development, pricing, and promotion.

According to Tamuliene & Pilipavicius (2017), understanding customer preferences is crucial for selecting services such as insurance. This highlights how tailored strategies can significantly impact customer satisfaction and business success in specific markets such as Lithuania. Similarly, Zaki & Shared (2023) emphasize the importance of sustainable marketing in the MENA region, demonstrating that consumer purchasing intentions are significantly influenced by tailored marketing strategies that address sustainability concerns.

Various methods, such as surveys, focus groups, and data analysis, can be used to study personal behaviour. These methods provide valuable insights into customers' motivations and desires, helping businesses better understand what drives their purchasing decisions. Therefore, we observe a dynamic interaction between customer choices and marketing strategies. If marketing strategies influence consumer choices, analysing these choices to understand their motivations allows marketing strategies to be refined and improved.

2.2. Useful statistical methods for personal behaviour and knowledge extraction

Several statistical methods can be used to analyse personal behaviour and extract knowledge from consumer data (Ogiemwonyi & Jan 2023). One such method is regression analysis, which can identify relationships between variables and predict future behaviour based on historical data. Cluster analysis is another proper method that can be used to group consumers based on shared characteristics or behaviour patterns (Idrissi et al., 2016; Hadri & Idrissi, 2022; Tran & Huh, 2023). Data mining techniques, such as association rules and decision trees, can also extract knowledge from consumer data and identify trends and patterns. Additionally, machine learning algorithms, such as neural networks and support vector machines, can predict and classify consumers based on their behaviour. These statistical methods can provide valuable insights into personal behaviour and help businesses make informed decisions about marketing strategies and product development. Statistics can be considered depending on the objective. In general, statistical methods, called exploratory statistics, are used to explore data. Or to predict behaviour, called predictive or delusional statistics or inferential statistics). Our study will focus on experimental statistics based on descriptive and graphical techniques (Hegland, 2007; Idrissi et al., 2016; Tran & Huh, 2023). It is generally described by descriptive statistics, which include simple one- or two-dimensional exploratory methods (mean, moments, quantifies, variance, correlation, etc.). Currently, data analysis methods are used in many challenging fields (Al-Maolegi & Arkok, 2014). Currently, these methods are commonly used in marketing, for example, for managing customers based on their behaviour and characteristics to propose new targeted offers. They also analyse surveys by interpreting polls where extensive data analysis must be considered.

2.3. Recommender Systems and Comportment Behaviour

Recommender systems are machine learning algorithms used in e-commerce and other domains to suggest items or products in which a user might be interested. These systems use various techniques, such as colorimetric filtering, content-based filtering, and hybrid approaches, to generate personalized user recommendations. The impact of comportment behaviour on recommender systems has become an increasingly important area of research in recent years (Ben Ticha, 2015; El Handri & Idrissi, 2019; El Handri & Idrissi, 2022; El Handri et al., 2023a,b). Comportment behaviour refers to users' actions, attitudes, and beliefs as they interact with a system. By analysing the behaviour of users, recommender systems can generate more accurate and relevant recommendations. One approach to incorporating comportment behaviour into recommender systems is to use contextual information, such as the time of day or location, to better understand the user's needs and preferences (Aaker & Moorman, 2023). For example, a recommender system might suggest different products based on whether a user is shopping for groceries during the day or browsing for entertainment products at night. Another approach is to incorporate social information into the recommender system. By analysing social networks and user profiles, recommender systems can generate recommendations based on the behaviour and preferences of the user's social network. This approach is known as social filtering and has been used in various applications, such as movie and music recommendations. (Trinquecoste, 1999)

3. Methodology and research methods. The proposed approach builds upon the background of data analysis and recommendation systems, utilizing AI techniques to enhance the process. Data analysis has long been recognized as crucial for understanding patterns, trends, and relationships within datasets. Leveraging statistical techniques and exploratory analysis can extract valuable insights from raw data.

In the context of recommendation systems, the objective is to provide personalized and relevant suggestions to users based on their preferences and behaviours. Traditional approaches have relied on collaborative filtering or content-based filtering techniques. However, with advancements in AI, there is an opportunity to leverage more sophisticated algorithms and methods for knowledge extraction and recommendation generation.

Our approach begins by emphasizing the importance of data cleaning and preparation. By ensuring the quality and reliability of the data, we laid a strong foundation for subsequent analysis. Rigorous data cleaning and preparation are crucial for eliminating inaccuracies and inconsistencies. Following the data preparation, univariate and bivariate analysis techniques allowed us to explore the dataset's characteristics and unveil relationships between variables. This step provides a comprehensive understanding of the data, revealing patterns and correlations essential for the subsequent analysis stage.

Next, we leverage the power of the Apriori algorithm to extract knowledge and associations from transactional data. By identifying frequent item sets and generating association rules, we uncover meaningful connections among items, enabling us to make informed recommendations.

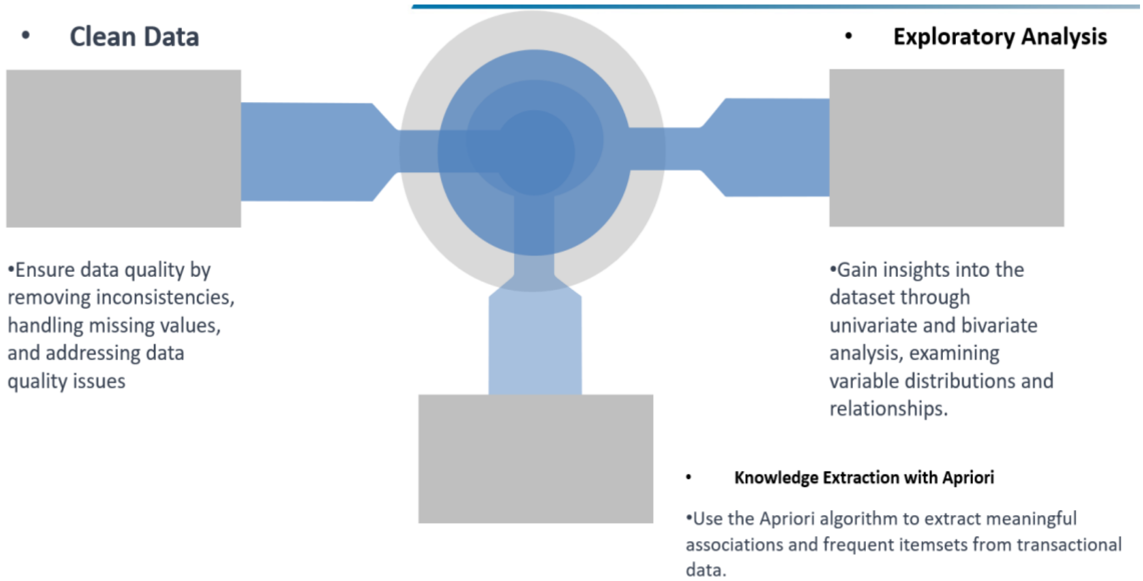

Figure 1. Preprocessing steps for recommendation
Sources: developed by the authors.

3.1. Step 1: Data Cleaning and Preparation

In the first step of our proposed approach, we focus on data cleaning and preparation, followed by univariate and bivariate analysis to gain insights into the dataset. Data cleaning involves removing inconsistencies, handling missing values, and addressing data quality issues. This part of the processing ensures that the data are reliable and suitable for further analysis.

The primary objective of this process in our proposed work is to reduce noise and eliminate uninformative content. The following steps were undertaken:

1. Data Understanding: A comprehensive understanding of the dataset’s structure and attributes was achieved, providing insights into the meaning and interpretability of each column.
2. Data Cleaning: Systematic handling of missing values, outliers, and inconsistencies in the dataset was performed. Missing values were imputed, or outliers removed and appropriately treated, and inconsistencies or errors were rectified. We did not find any empty lines during the analysis of the selected dataset.
3. Feature Selection: Relevant features were meticulously selected, discarding unnecessary or redundant attributes that did not contribute to the course selection algorithm's objectives. This step facilitated dataset simplification and improved computational efficiency.
4. Data Splitting: The dataset was divided into training and testing sets. The training set was used for algorithm training, while the testing set facilitated evaluating the algorithm’s performance on unseen data and assessing its generalization capability (Er-Rafyg et al., 2023)
5. Data Validation: Validation checks were performed to ensure the integrity and quality of the dataset. Additionally, we ensured the absence of duplicate data.

Following these steps, the dataset was appropriately prepared, establishing the groundwork for the subsequent approach application.

3.2. Step 2: Exploratory analysis

Building upon the cleaned and prepared dataset, the second step of our approach involves data exploration with univariate/bivariate methods. Once the data were cleaned, we performed univariate analysis to explore the distribution, central tendency, and variability of the individual variables. The pattern recognition step helps us understand the characteristics and patterns within each variable. Additionally, bivariate analysis allows us to examine relationships between pairs of variables (Idrissi et al., 2016; Handri & Idrissi 2022.; Tran & Huh, 2023). We utilize correlation analysis to measure the strength and direction of associations between variables, providing valuable insights into their interdependencies.

3.3. Step 3: Knowledge extraction and association rule generation using the Apriori algorithm

The third step of our approach involves knowledge extraction and association using the Apriori algorithm. The Apriori algorithm is well suited for discovering frequent itemset and generating association rules from transactional data. By identifying frequently occurring patterns, we can uncover meaningful associations among items. In the experiments, we evaluated our approach on a real dataset. These data include 2240 observations (customers) with 28 variables related to marketing data. More specifically, the variables provide insights into customer profiles, products purchased, campaign success (or failure) and channel performance. Thorough data preparation is essential before applying our proposed approach to the chosen dataset. The primary objective of this process in our proposed work is to reduce noise and eliminate uninformative content.

4. Results and discussion.

4.1. Results and discussion of Steps 1 and 2 (Data Cleaning, Preparation, and Univariate/Bivariate Analysis).

In this section, we present the results of our study by performing a graphical analysis and discussing the results. For example, Figure 2 visually represents the mustache box plots, revealing asymmetrical distributions within the data. By analysing the plot, we can gain insights into the characteristics of specific variables, such as MntFishProducts and MntSweetProducts.

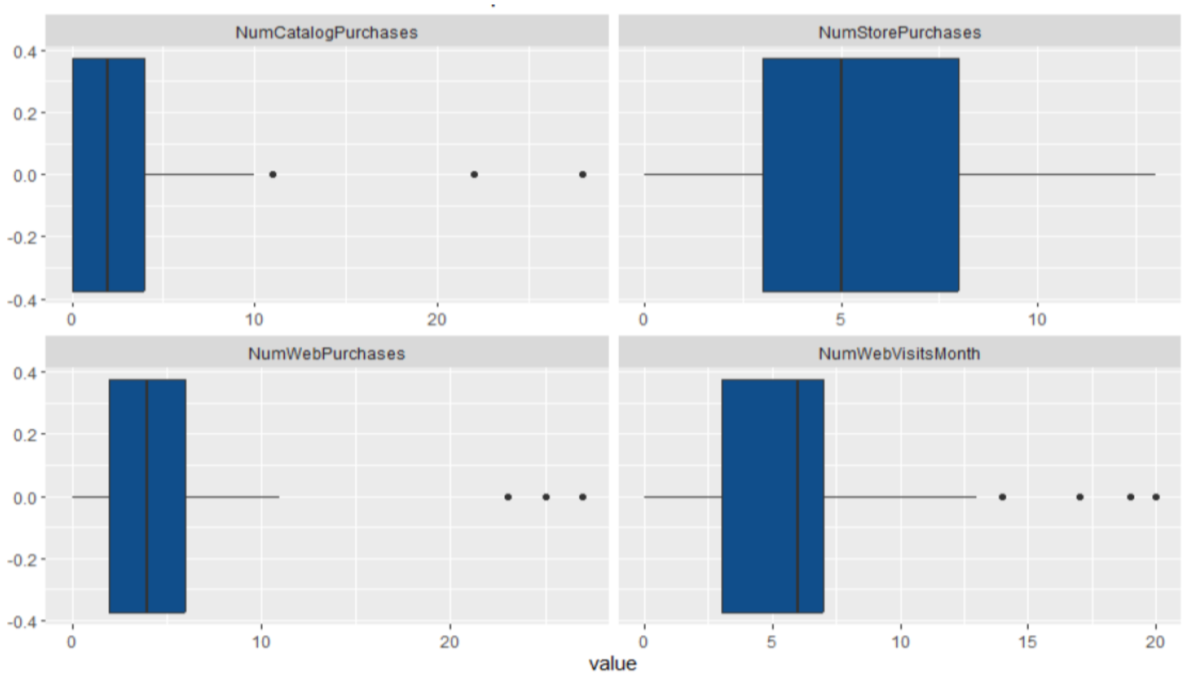

Figure 2. Symmetrical and Asymmetrical Data in Orders by Channel
Sources: developed by the authors.

In the case of MntFishProducts, the box plot demonstrates a higher price range, surpassing 100 and even 200. The continuous nature of the data is evident from the spread of points. This suggests that some customers purchase higher-priced fish products, potentially indicating a preference for premium or specialty items within this category. Similarly, when examining MntSweetProducts, the box plot illustrates a broader range of purchase amounts, from approximately 80 to 200. However, it is noteworthy that a small subset of customers made purchases exceeding 200. This finding implies that while most customers fall within a specific spending range for sweet products, a segment exhibits greater purchasing behaviour, potentially driven by specific preferences or circumstances.

Observing the asymmetrical nature of these mustache box plots allows us to discern patterns and tendencies within the data. These insights can be valuable for businesses seeking to understand customer preferences and optimize their product offerings and pricing strategies.

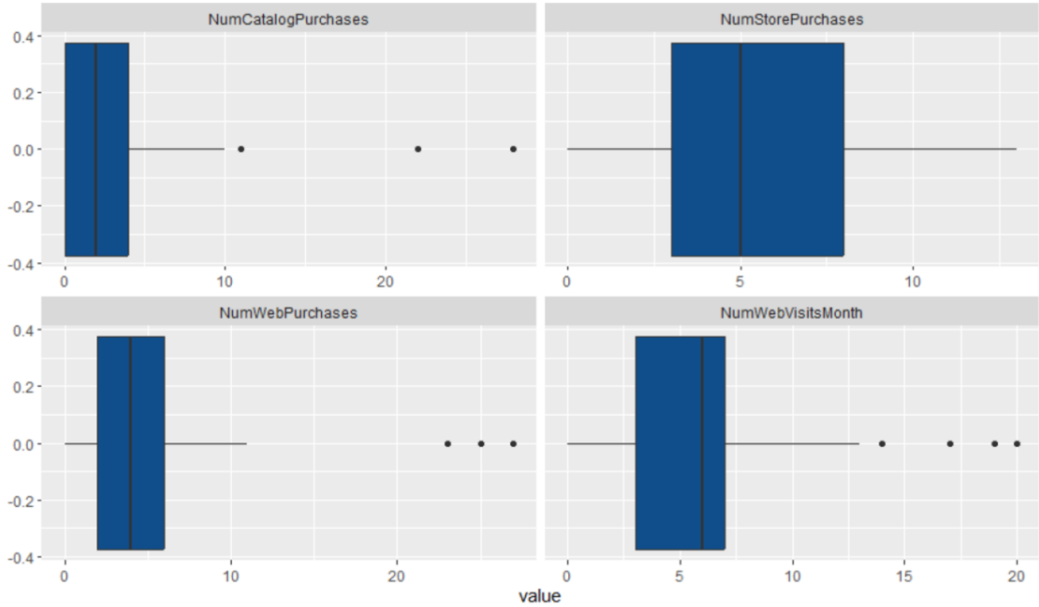

Figure 3. Symmetrical and Asymmetrical Data in Orders by Channel
Sources: developed by the authors.

Figure 3 depicts the distribution of orders by channel, highlighting both symmetrical and asymmetrical data patterns. The graph differentiates between orders made through catalogues and websites in stores. In the case of orders through catalogues and websites, the data exhibit a symmetrical distribution. This symmetry suggests that customers tend to place orders through these channels with a consistent frequency, indicating a stable demand for products or services offered via catalogues and websites.

However, the data related to in-store orders and website visits by the author demonstrate asymmetrical distributions. This asymmetry implies that there may be variations in the frequency or volume of orders made in physical stores and visits to the website. Factors such as store locations, marketing campaigns, or specific customer behaviours might contribute to these differences.

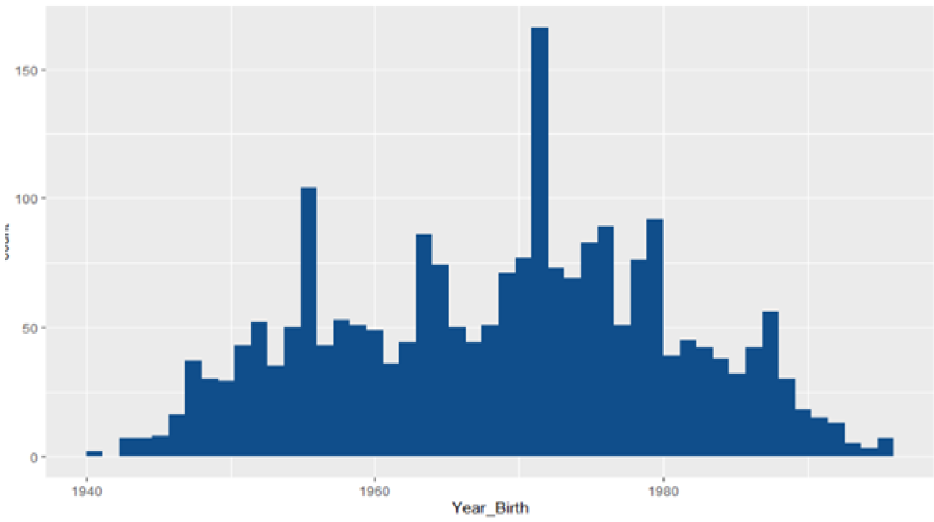

Figure 4. Histogram of Client Age
Sources: developed by the authors.

Understanding the symmetrical and asymmetrical characteristics of data in different channels provides valuable insights for businesses. By identifying patterns and discrepancies across channels, companies can tailor their marketing strategies and channel-specific offerings to target and engage customers effectively.

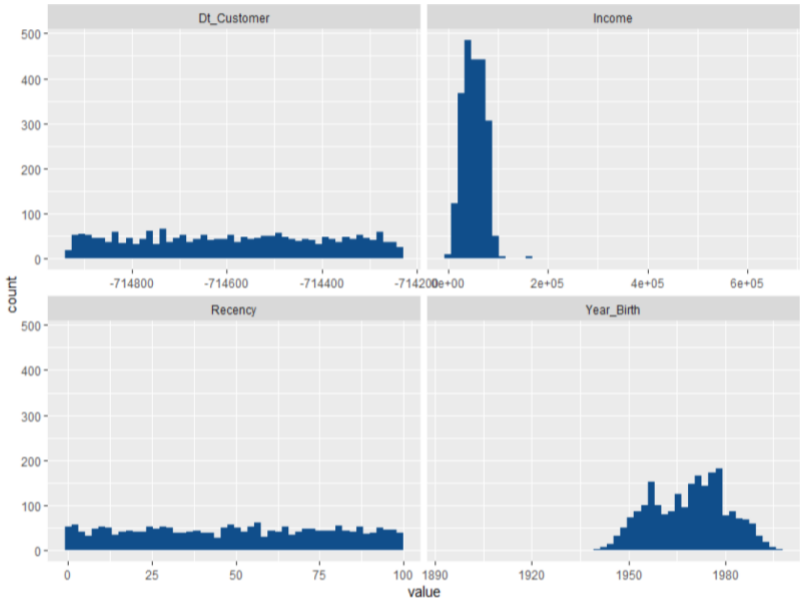

Figure 5. Client age and data analysis considerations
Sources: developed by the authors.

Figures 4 and 5 showcase the age distribution of customers and highlight the need for careful data analysis considerations, mainly when dealing with extreme values. The diagram presents the customers' birth years, offering insights into the age demographics of the dataset. Notably, one data point represents a customer born in 1940, making them 82 years old at the time of data collection. This finding prompts a critical analysis of the relevance and impact of this particular data point on the overall analysis. Given the advanced age of this customer, their preferences, behaviours, and purchasing patterns might significantly differ from those of most of the customer base.

Consequently, it is crucial to exercise caution when interpreting the insights derived from these data points, as they may not accurately represent the broader customer population. To mitigate the potential skewing effect of extreme age values, it is advisable to focus the analysis on continuous variables related to individuals. This allows for a more comprehensive understanding of consumer behaviour, ensuring that insights and recommendations apply to a broader range of customers. Additionally, creating an "age" field enables more targeted analysis and segmentation based on age groups, providing further granularity in understanding consumer preferences and behaviours. Therefore, by considering age distribution and implementing appropriate analysis strategies, businesses can derive more accurate and actionable insights, ultimately leading to more effective marketing strategies and customer-centric decision-making. We further examine the dataset using correlation analysis to conduct a comprehensive bivariate study.

Correlation represents the relationship between two concepts (El Handri et al., 2023b), where one is inseparable from the other. This signifies a necessary dependence between interconnected facts. When measuring an association's strength and direction, the correlation coefficient ranges from -1 to +1. A coefficient of 0 indicates no association, while values closer to -1 or +1 indicate stronger associations, potentially reaching a perfect correlation.

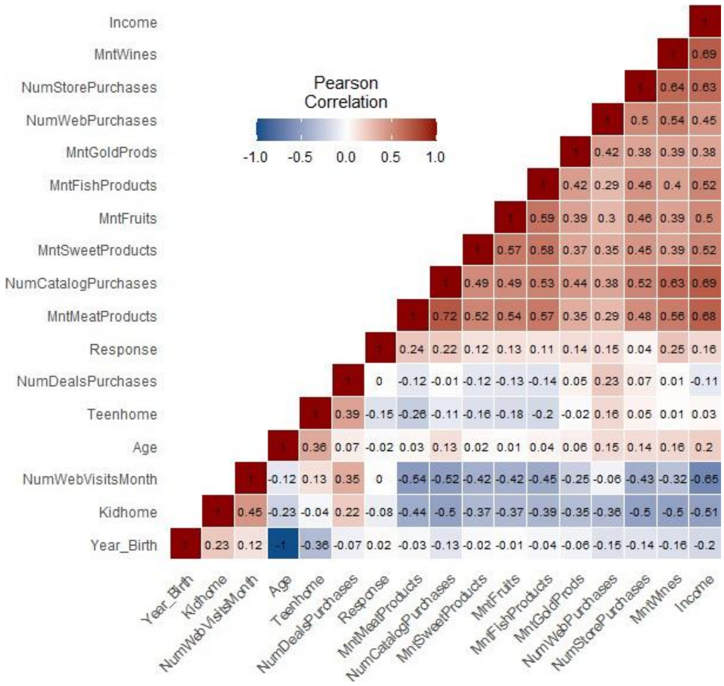

Figure 6. Correlation Analysis of Variables within the Dataset
Sources: developed by the authors.

In our analysis, we identified several strong correlations within the dataset, as shown in Figure 6. For instance, a strong correlation of 0.72 exists between MntMeatProducts and NumCatalogPurchases. Additionally, we observe a strong correlation of 0.69 between NumCatalogPurchases and income and between MntWines and income. The coefficient of 0.63 signifies a strong correlation between NumStorePurchases and MntWines, among others. These strong correlations provide insights into the interrelationships between variables. By examining these associations, businesses can uncover valuable patterns and dependencies, allowing for more informed decision-making and the development of effective marketing strategies. Variables with strong correlations indicate a significant relationship between them. These findings suggest that there are meaningful connections and dependencies between these variables.

By analysing correlations, we gain insights into the interrelationships and dependencies within the dataset. These correlations help us understand how different variables are related and can guide further analysis and decision-making processes in data analysis.

4.2. Results and discussion of Step 3 (Knowledge Extraction through "Association Rules": APRIORI Algorithm).

Several algorithms for extracting association rules exist, including Eclat, the GUHA ASSOC procedure, and OPUS, but the most widely used algorithm is APriori. It is extensively employed for analysing customer shopping baskets, making it the most suitable choice for our study context.

The Apriori algorithm is a data mining algorithm designed for extracting association rules. It aims to identify frequently occurring patterns in a dataset and deduce categorizations or provide recommendations based on those patterns.

The Apriori algorithm (Hegland, 2007) is implemented step by step as follows:

– Algorithm 1. Discovering Interesting Relationships: The Apriori Algorithm for Association Rule Mining

– Purpose: To discover frequent item sets and generate association rules from transactional databases.

– Inputs:

- A transactional database D, where each transaction T is a set of items.
- The minimum support threshold, minsup, is a user-defined parameter specifying the minimum frequency of itemsets to be considered frequent.

– Outputs:

- A set of frequent itemsets L, representing items frequently occurring together in transactions.
- The set of association rules R represents the implications among items in the database.

Steps:

1. Initialization:

- Set L1 = {frequent itemsets of size 1}. This involves scanning the database once to count the occurrences of individual items and selecting those with frequencies greater than or equal to minsup.

2. Iteration:

- For k = 2 to k_max (where k_max is the maximum size of the itemsets to be considered):
- The candidate itemsets Ck are generated by joining frequent itemsets in Lk-1. This involves combining itemsets of size k-1 that share a common prefix of k-2 items.
- Prune infrequent candidate itemsets from Ck by checking their support against minsup. This involves counting the occurrences of candidate itemsets in the database and discarding those that do not meet the minimum support threshold.
- Lk = frequent itemsets in Ck.

3. Association Rule Generation:

- For each frequent itemset l in L:
- Generate all possible nonempty subsets of l.
- For each subset s of l:
- The confidence of the rule "s -> (l - s)" is calculated as the support of l divided by the support of s.
- If the rule's confidence is greater than or equal to a user-defined minimum confidence threshold minconf, the rule is added to the set of association rules R.

4. Evaluation:

- The generated association rules in R are evaluated based on user-defined metrics such as support, confidence, lift, and other relevant measures to assess their relevance and significance.
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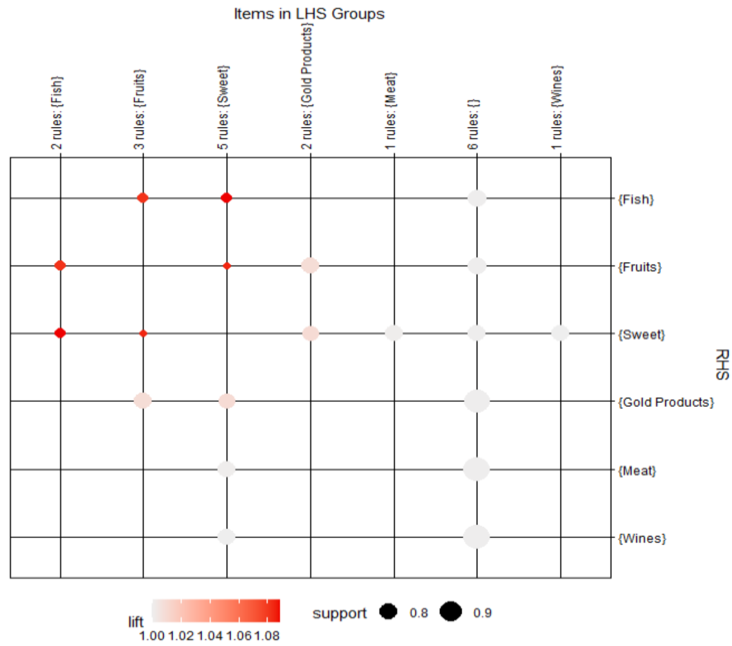

Figure 7. Association Rules Analysis: Insights and Recommendations from Transactional Datails
Sources: developed by the authors.

Using Apriori Algorithm 1, we can store these data in a CSV file to transform it into transactional data, which is the final step before extracting association rules. After applying and inspecting the top 20 most relevant association rules, we obtained the following output, as shown in Figure 7, with indicators such as lift, support, and confidence. We make the following observations: Sweet products, for example, are the most frequent in shopping baskets, followed by wines and gold products. Sweet products are associated with almost all other products, unlike wines, which are often purchased alone or occasionally with sweets but rarely with different products. Therefore, Sweets and fruits products are seldom purchased alone; they are frequently associated with other company products. Based on these findings, we can make the following recommendations: Disperse the Sweet products throughout the store as they are associated with almost all products. Certain products are arranged in the store and on the company's website based on the confidence and support values of the rules that link them together to promote cross-selling.

To further enhance this process, we propose the integration of principal component analysis (PCA) and feature extraction. PCA allows us to reduce the dimensionality of the dataset while retaining most of the information. By extracting relevant features, we can focus on the most influential variables and improve the efficiency of subsequent analysis. In addition to knowledge extraction, we can leverage our work on recommendation systems. Our new algorithm, Topk, builds upon the extracted associations to provide personalized recommendations. By considering user preferences and the identified associations, the Topk algorithm aims to offer accurate and relevant suggestions to users. Our extended approach encompasses data cleaning, univariate/bivariate analysis, and knowledge extraction using the Apriori algorithm (Al-Maolegi & Arkok, 2014).

5. Conclusions. In conclusion, combining data cleaning, univariate/bivariate analysis, knowledge extraction using the Apriori algorithm, and the integration of artificial intelligence (AI) techniques is promising for obtaining valuable insights and providing enhanced recommendations. By following these steps, we improved the quality and reliability of the data, gained a deeper understanding of individual variables and their relationships, and extracted meaningful associations among items. Indeed, analysing these associations has proven to be a simple and effective way to establish links between objects, items and articles in a shopping basket, for example. The frequency of appearance of the different combinations is determined. This method is particularly suitable for purchasing studies as part of basket analysis to improve marketing tactics such as cross-selling.

The use of AI can further enhance our approach. For instance, advanced machine learning algorithms can automate data cleaning and preparation, saving time and reducing manual effort. NLP techniques can be applied to analyse textual data, enabling us to extract valuable information from customer reviews or feedback (El Handri et al., 2023a).

Additionally, deep learning models can improve the accuracy and precision of association rule mining, allowing for more sophisticated pattern recognition and rule generation. Reinforcement learning can be integrated to continuously refine and optimize recommendation algorithms, adapting to changing user preferences and market dynamics (Ez-Zahraouy, 2023; Idrissi et al., 2016).

Furthermore, incorporating AI techniques such as image recognition or sensor data analysis can expand the scope of our approach to domains such as e-commerce, healthcare, or IoT applications [8-9], where diverse types of data are available for study.

Author Contributions: conceptualization, K. E. and Y. Y.; methodology, K. E. and M. D; software, M. D.; validation, N. C., Y. E. and K. E.; formal analysis, A. E.; investigation, M. D.; resources, K. E; supervision, K. E.; project administration, K. E. and N. C; funding acquisition, A. E. and M. D.

Conflicts of interest: The authors declare no conflicts of interest.

Data Availability Statement: The dataset marketing_data.csv available at https://www.kaggle.com/code/prasadiw/marketing-campaign-analysis consists of 2,240 customers of the company with data on the following:

- Campaign successes/failures
- Product preferences.
- Channel performances.
- Customer profiles based on spending habits.

Observations: There are a total of 27 columns and 2,240 observations in the dataset.

Informed Consent Statement: Not applicable.

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Поведінка споживачів: аналіз маркетингових кампаній за допомогою систем рекомендацій та статистичних методів

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Ця стаття досліджує вплив поведінки споживачів на ефективність маркетингових кампаній, використовуючи систему рекомендацій та методи статистичного аналізу. Розуміння поведінки споживачів є надзвичайно важливим у сучасному жорстко конкурентному та постійно мінливому ринку. Це дослідження має на меті підкреслити значний вплив поведінки споживачів на ефективність маркетингових кампаній через інноваційне застосування систем рекомендацій, підтриманих сучасними методами машинного навчання та аналізу даних. Цей підхід вирішує складні завдання точного прогнозування поведінки споживачів. Авторами узагальнено особливості систем рекомендацій, підкреслюючи їхню важливу роль у сучасному маркетинговому середовищі. У статті теоретично обґрунтовано взаємозв'язок між маркетинговими даними та поведінкою споживачів. Крім того, авторами описано процес аналізу даних, що починається з фільтрації даних через одновимірний та двовимірний аналіз, завершуючи передовими методами, такими як алгоритм Apriori для виявлення правил асоціації та ретельного дослідження цього симбіотичного зв'язку. Результати дослідження демонструють ефективність авторської методології для інтерпретації складної взаємодії між поведінкою споживачів та маркетинговими кампаніями. Отримані висновки підкреслюють важливі тенденції та обґрунтовують практичні рекомендації для підвищення ефективності маркетингових стратегій. Розкриваючи динамічні взаємозв'язки між поведінкою споживачів та маркетинговими результатами. Крім того, у статті підкреслено важливість розуміння поведінки споживачів та переваги використання інноваційних методів аналізу даних. Розшифровуючи тенденції споживання, бізнес може оптимізувати свої маркетингові стратегії та покращити задоволеність клієнтів, зміцнюючи свою конкурентну перевагу на постійно змінюваному ринку. Нарешті, впровадження систем рекомендацій з інструментами штучного інтелекту та машинного навчання для колаборативної фільтрації може ще більше вдосконалити ці стратегії, значно підвищуючи ефективність маркетингових кампаній.

Ключові слова: аналітика рішень; машинне навчання; маркетингові дані; система рекомендацій.