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Purchasing Pattern Exploration in Fashion Retail using Transaction Data

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ABSTRACT

Large volumes of fashion retail transaction data offer valuable insights into consumer purchasing behavior, yet extracting actionable knowledge remains challenging in a highly competitive market. This study analyzes an open-access fashion retail dataset containing product details, transaction values, review ratings, payment methods, and purchase dates to support management and marketing decisions. Consumer purchasing behavior is examined using predictive analytics and clustering techniques. The results show a high level of predictability in transactions, indicating that consumer purchases follow consistent patterns rather than random behavior. Clustering analysis further reveals the presence of distinct consumer segments, although the separation between these groups is relatively weak. Despite this overlap, the identified patterns provide meaningful insights into customer behavior. Overall, the findings demonstrate that transaction-level data can be effectively leveraged to support inventory planning, product assortment decisions, and segmentation-based marketing strategies. This research highlights the strategic value of fashion retail transaction data in enhancing data-driven decision-making and improving managerial effectiveness in the fashion retail sector.

Keywords: Fashion Retail, Transaction Data, Consumer Purchasing Behaviour, Predictive Analytics, Customer Behaviour
JEL Classifications: C55, D12, M31, L81

1. INTRODUCTION

The fashion retail industry has a fast-paced atmosphere; merchandise is typically only sold for a short period of time, trends change quickly, and the customer base shifts rapidly (Garcia, 2021; Roy et al., 2023; Rudniy et al., 2023). As a result, many retailers struggle to efficiently manage inventory, schedule and execute promotional events, and maintain profitability (Begum and Ali, 2024; Elwood, 2021; Sharma and Sharma, 2024). Because of these challenges, transaction data generated each day through retail sales are a critical source of information that help retailers to understand true purchasing habits and to base decisions on evidence-based data (Akram et al., 2022; Casciani et al., 2022; Gurnani and Gupta, 2024; Sagar, 2024). Unlike traditional reporting systems that provide aggregate level data about sales or category performance, transaction-level reporting provides greater detail about the actual products purchased, how the products purchased change over time, and how customers differ from one another in their purchasing habits (Benson-Emenike et al., 2023; Niaz, 2022).

The high volume and complexity of retail transaction records make it very difficult for retailers to derive actionable insights from the data using conventional descriptive analyses (Rana and Youn, 2024). Retailers may look at aggregate level statistics to review total sales or category performance, but usually do not identify the deeper relationships between the products purchased or other more detailed patterns or structures associated with purchasing behaviours (Samineni, 2022; Sokol and Holý, 2024). For example, retailers need to determine which products tend to be purchased together, how purchasing behaviour is impacted by other transaction variables (e.g. total purchase amount, rating of the products purchased, type of payment used) and whether retailers can identify unique customer segments based on their behaviours (Pardeshi et al., 2025; Wang, 2025). This information is essential for retailers to improve product assortment decisions, develop more effective marketing strategies, and optimise stock levels (Hossain, 2025; Yellanki, 2023; Yu et al., 2024).

Analyzing transaction data can give the fashion retail sector a better insight into its operations by providing two different kinds of data (Begum, 2024; Kholod et al., 2024). The first is pattern discovery, which helps you find patterns in your customers' buying habits and identify products that would be good candidates for bundling, cross-selling, and recommending to one customer during the purchasing cycle (Arivazhagan et al., 2022; Kwon, 2024). The second is customer grouping, which allows you to identify customers with similar purchasing habits and tailor your engagement strategies based on their similarities to enhance targeting effectiveness (Raza et al., 2023). The two types of information listed above are useful in transforming raw sales records into useful, actionable insights that can improve operational efficiency and aid in your strategic planning.

Additionally, this project has quantitatively analyzed the transaction data from a publicly available dataset focusing on extracting patterns of recurrent transactions and identifying groups of customers with similar purchasing patterns to provide a detailed view of how customers interact with fashion products in the retail industry. The value of this research lies in two contributions: (1) Providing tangible supporting evidence of previous research supporting the development of purchase structures from transaction data, and (2) Defining groups of customers who have exhibited different purchasing behaviors that can inform decision-making by retailers regarding inventory management and marketing activities.

2. METHODOLOGY

This study uses transaction level data from the fashion retail industry to analyze purchasing patterns and buyer behavior in relation to purchased items and sold goods. The transaction data represent a record of transactions containing information such as the purchase amount, rating reviews from consumers about their experience with a purchased product, and payment type. These components represent the basis for how consumers interact with a fashion retail product and allow for an appropriate analysis of consumer purchasing structures and consumer purchasing patterns. The data used for this research is found in publicly available sources, and has been selected so that there is a level of transparency and reproducibility within the analysis process.

To conduct the analysis, a complete analytical workflow was executed in Python because it is an extremely powerful computational tool that is able to perform data analysis and find patterns in the data very easily (Teimourzadeh et al., 2023). Python makes working with very large transaction datasets much easier and allows for all of the analyses to be completed within the same environment by way of integrating several different analyses into one environment. The analysis process starts with loading the data and performing some exploratory analysis on the data to get a good idea of what the structure, scale, and attribute characteristics of the data are. At this point in time, basic descriptive statistical analysis is conducted to identify potential anomalies in the data, complete the data, and ensure that the variables being examined in the study pertain to the study's goal of examining purchasing patterns.

Afterward, we carry out data preprocessing to get the purchase records ready for analysis. Data preprocessing includes cleaning up inconsistencies, dealing with missing information, and converting categorical variables into a format that can be easily understood by computers (Geasela et al., 2024; Lee et al., 2025; Tannady et al., 2025). The transaction attributes related to product purchases will be arranged so that you can see items that were purchased together in a single sale, allowing you to spot patterns in combination of purchases from our customers. Lastly, the numerical variables, such as the amount of money spent on a purchase or the review score given to a product, will be normalized or discretized wherever it makes sense to ensure we are able to conduct the same level of analysis across all transactions.

After data has been prepared, an exploration for patterns in retail purchase activity is performed to reveal regularities. The analysis will look for frequently occurring purchase structures that suggest how products or other characteristics of transactions tend to be associated with each other within sales records. At this stage, the exploration will help the analyst identify common tendencies in frequency and relationship between purchases and develop potential relationships to inform retail strategies like product bundling or targeted promotions. The analytical procedures analyze interpretability, so that the extracted patterns can be connected directly back to the types of decisions that retailers make in their operations.

The customer behavior section involves grouping analysis of customers based on their transaction characteristics. The purpose of this section is to find different segments within the dataset based on how many purchases are made, what types of products are purchased, or other characteristics of the transaction. Grouping is used to create a systematic way of differentiating customers from each other based on how they actually made their purchases. Grouping allows merchants to make informed decisions regarding inventory planning and personalized marketing.

For all aspects of the analysis, including data manipulation, calculations, and interpretation of results, Python libraries were used to assist with those tasks. Because we used Python to handle raw data through to the analysis of patterns or behaviour, the entire research process was able to be carried out in a transparent and replicable manner (Danchev, 2022). All of these methodological procedures are in line with the research objective of investigating fashion retail purchasing patterns, allowing for flexibility to expand upon in the future, and reducing the amount of overlapping methodology with like studies.

3. RESULTS

3.1. Dataset Description

The data used for this study contains 3,400 transactions from fashion retail stores. Each record consists of six major attributes: Customer Reference ID, Item Purchased, Purchase Amount (USD), Purchase Date, Review Rating, and Payment Method. Each record contains information relating to either the product or transaction.

An example of a record corresponding to the dataset has been provided in the results section to show how the data looks. The examples of purchased items in the sample (handbag, tunic, tank top, leggings, wallet), the diversity of the transaction amounts, the various ratings given to each item purchased, and the variety of payment methods used will provide evidence that the data collected is ample and varied enough to allow for the exploration of different design patterns and behaviours of customers who shop at fashion retailers. The report regarding the shape of the data being (3400, 6) demonstrates to the researcher that the amount of data they are working with is adequate for exploring patterns and behaviours associated with consumers who shop in these types of stores.

This structure of the data set shown on Table 1, provides a foundation for analyzing purchasing behaviors from both transactional and behavioral viewpoints that will lead into subsequent phases for pre-processing, visualizing, and modeling the data.

3.2. Preprocessing

The preprocessing phase of the dataset was completed to test the validity of the quality of the data and ascertain whether or not the data were suitable for further analysis. The results of the preprocessing phase indicate how the data set is structured with regards to the size (dimensions) of the dataset, name of the attributes, type of attributes and the missing value statistics from the data. The data set has a total of 649 records (size) and 31 variables (within each record) (size = 649 records and 31 variables). The attributes that are recorded include both demographic/contextual (such as school, sex, age, and address) and behavioral/outcome related variables (such as study time, internet access, health, number of absences from school, etc.) as well as Study time and G1 and G2.

The missing values analysis results show an empty table of missing values which indicates that no missing values were found within the data set and therefore, there is no need to impute missing values which further reduces any potential bias generated by not having complete observations. In addition, the summary results of the preprocessing phase states that the original dataset's shape (649 × 31) compared to the processed dataset's shape (649 × 31) are the same size, therefore, there were no records (instances) removed through the cleaning phase and the preprocessing was primarily used to ensure consistent formatting versus deleting records.

After reviewing the processed dataset, it has been confirmed that all of the variables are consistently arranged, and the input files were formatted correctly for use in analytics. The output from the preprocessing stage gives confidence that there will be no data inconsistency issues that affect the analytics downstream, and all of the variables are ready for use in either predictive or exploratory modelling.

3.3. Visualization

Before entering into the modeling phase, visualizations play an exploratory role in understanding a processed dataset. The most important visualizations should include a correlation heatmap. This heatmap (Figure 1) summarizes the linear relationships between numerical variables. This step helps verify variability across features, identify any redundancies or multicollinearity in the data, and give some indication as to which variables may prove more useful when it comes to prediction and creating groups of observations for further exploration.

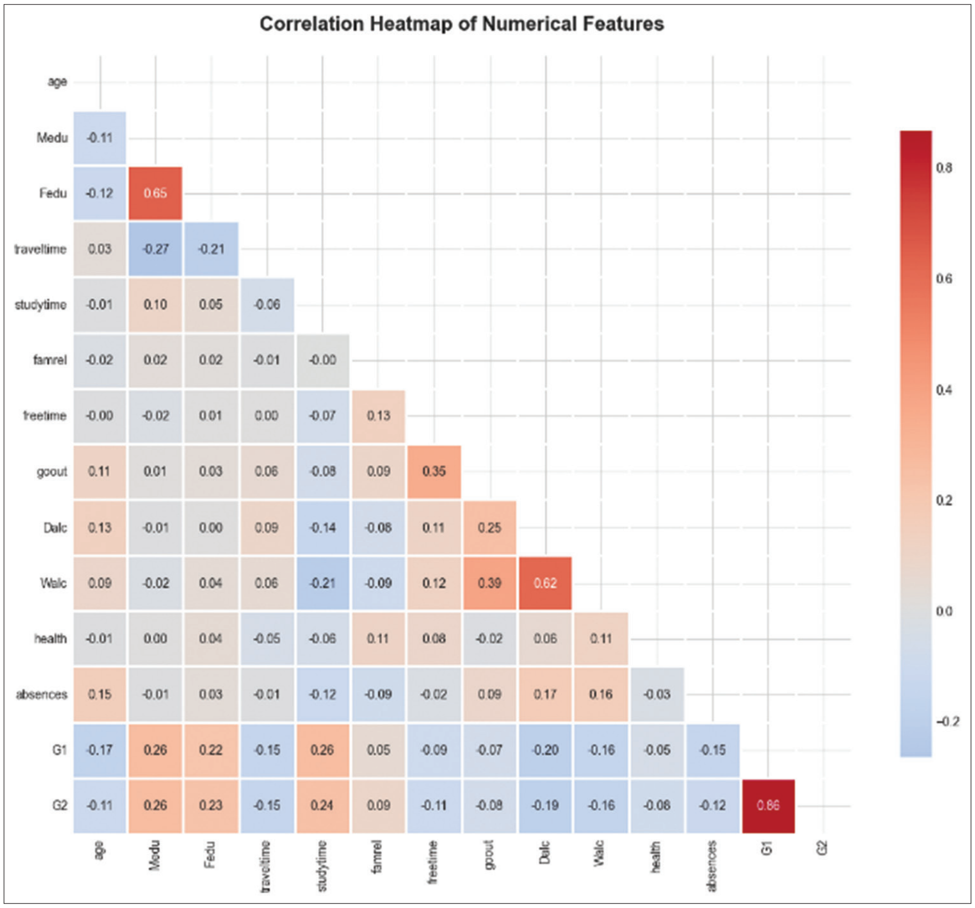
The figure's colour gradient demonstrates how negatively correlated G1 and G2 are (the dark blue sections), but since they have a high positive correlation ($r = 0.86$), it shows that the first and second grading periods should be heavily related to each other and likely capture the same signals for academic performance. In addition, parents education levels (Medu and Fedu) are positively related ($r = 0.65$) to one another, meaning if one of them is high then it would be likely that the other is as well. Moderate to high levels of correlation are seen with alcohol related variables such as Dalc and Walc ($r = 0.62$). This means that people typically have similar weekday and weekend drinking patterns. There are moderate levels of correlation behaviourally, between goout and Walc ($r = 0.39$) and between freetime and goout ($r = 0.35$). This suggests that if people have more leisure time, they will be socializing to a greater extent. When a person socializes more, they will also have increased consumption of alcohol on weekends.

Most of the other correlations show weak (near zero) correlations as indicated by the heatmap, demonstrating that each of the numerical variables adds unique information. Therefore, the findings can aid in the modeling stage by: (i) Pointing out potentially redundant feature pairs (for instance, G1 and G2), and (ii) Indicating groups of features that represent consistent behaviors (for example, alcohol and social behaviour) that can be

Table 1: Example dataset

No	Customer reference ID	Item purchased	Purchase amount (USD)	Date purchase	Review rating	Payment method
1	4018	Handbag	4619	February 5, 2023	NaN	Credit Card
2	4115	Tunic	2456	July 11, 2023	2	Credit Card
3	4019	Tank Top	2102	March 23, 2023	4.1	Cash
4	4097	Leggings	3126	March 15, 2023	3.2	Cash
5	3997	Wallet	3003	November 27, 2022	4.7	Cash

Figure 1: Correlation heatmap of numerical features



applied towards predictive analysis and customer grouping. The plot demonstrates the pairwise correlation coefficient between numerical variables with a red correlation indicating a positive correlation and a blue correlation indicating a negative correlation, and correlation coefficients that are nearer to +1 and −1 represent a stronger linear relationship.

3.4. Modelling

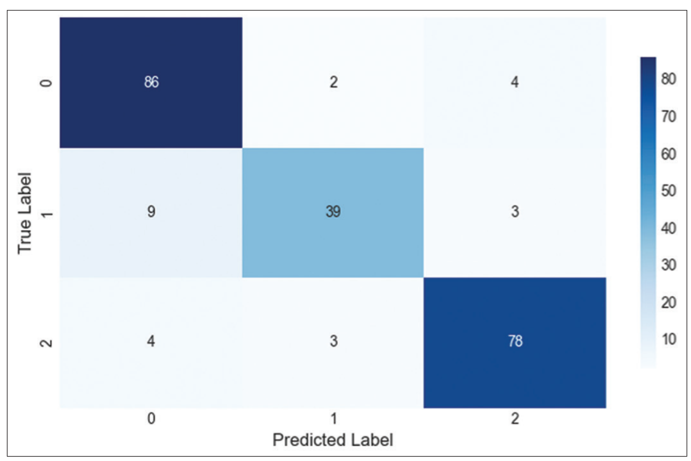
There are two analytic models in the modelling stage: Classification and clustering. Classification and clustering represent two distinct analytic objectives.

3.4.1. Classification

Classification Analysis: Conducts an analysis against all significant transaction-level and behavioral attributes to predict target outcomes in fashion retail. Overall classification is quite predictive and measurements include accuracy = 0.8904, precision = 0.8909, recall = 0.8904 and F1-score = 0.8891. The results demonstrate that the model captures meaningful, consistent patterns within the transaction data and can be relied upon to provide predictive analysis.

The classification results in the data are shown on the confusion matrix (Figure 2). From the confusion matrix, it is clear that a high level of correspondence exists with the true labels and predicted labels for all three classes as most instances are classified along the main diagonal of the confusion matrix. All but Class 0 show

Figure 2: Random forest confusion matrix for classification results



a particularly strong level of predictability with 86 accurate predictions for Class 0, 39 accurate predictions for Class 1 and 78 accurate predictions for Class 2. Misclassifications are minor for each of three classes, suggesting balanced behavior of the predictive model. In other words, this predictive model generalizes well for the different outcome categories.

According to the findings, the stable precision (0.87-0.92) and recall (0.87-0.92) values across classes are further indicative of the dataset's ability to have informative attributes that distinguish between the purchasing success of different transactions. Also, the strong diagonal dominances that are present in the confusion matrix help to support the conclusion that purchasing behaviour is structured into transaction attributes, rather than being random noise.

In summary, from a management perspective, the findings show that fashion retail transaction data can be used effectively for operational planning and decision-making, as high levels of predictive accuracy provide managers with the ability to predict the outcome of a transaction more reliably, therefore informing them as to how many products should be in their inventory, what products should be included as an assortment, and what resources are available to allocate towards each category or profile of transaction.

From a marketing perspective, the classification results provide fashion retailers with the basis for determining data-driven targeting and creating personalized campaigns. Accurate predictions of transaction outcomes allow fashion retailers to segment their customers based on their purchasing behaviours and to more effectively create tailored campaigns such as; personalized promotions, loyalty programs, and other recommendation strategies. By aligning marketing activities with the predicted purchasing behaviour of customers, fashion retailers will be able to improve the effectiveness of their campaigns and increase customer engagement.

The comparison of true labels against predicted labels across three classes is shown visually in this matrix by the degree of darkness of the diagonal cells. Cells that are dark indicate a high number of correct predictions; thus, the model performed well and had a balanced classification approach.

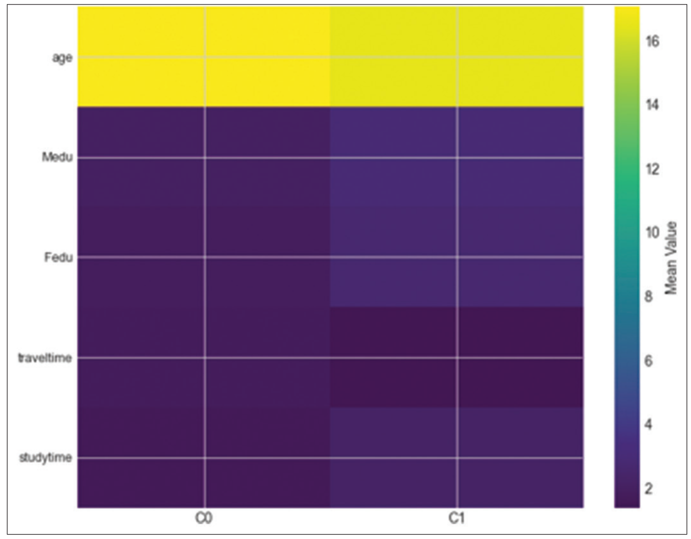
3.4.2. Clustering

The application of clustering analysis in addition to predictive modeling has been utilized to identify natural groupings within the transaction data. Results show two clusters exist within the dataset, each of which has a fairly balanced distribution (C0 = 47.30% of observations; C1 = 52.70% of observations). With this balanced distribution, it can be inferred that customer transactions in fashion retail can be grouped into two dominant behaviours rather than having a dominant single purchasing pattern.

The quality of clustering is assessed by the Silhouette score (0.1264) and Davies-Bouldin index (2.4890). These scores indicate that there is some degree of distinguishable grouping between customer transactions; however, the separation between the clusters is weak overall. This weak separation illustrates the fact that there is significant overlap in terms of the types of purchasing behaviours exhibited by customers in fashion retail. This is what many consumers experience, as they tend to have similar base needs but differing levels of intensity, preference and frequency in terms of how they shop for clothing and accessories.

In Figure 3, the average feature values of each cluster are represented. The average values of age demonstrate that neither cluster has an unusually high or low average age; thus, age is not a key differentiator between the clusters. In addition, cluster 1 has a higher average value for study time and parental education

Figure 3: Mean feature values by cluster (K-Means)



(Medu and Fedu), indicating that cluster 1 has a more defined behavioral and contextual profile than cluster 0, whose feature values are lower than those of cluster 1, meaning that the overall purchasing profile for cluster 0 is less intense and/or structured than cluster 1. While the differences between the two clusters are small, they indicate that there are measurable differences in how customers behave between the clusters.

Clustering can provide a level of initial segmentation that will support inventory planning and assortment strategies from a management perspective. Retailers can use the clustering results to inform product availability and stock levels by using the most significant features for each cluster. In other words, for example, if cluster 1 tends to buy a specific product a lot while cluster 0 does not buy that same product very often, retailers can make sure they have enough of that product available for each behavioral group. Even with only slight segmentations, retailers can help decrease inefficiencies in their business by avoiding utilizing uniform stocking strategies between heterogeneous customer groups.

Clustering analysis provides a foundation for segmentation based marketing efforts by identifying key characteristics of customer groups, which can be used to create unique promotional approaches. For example, on a much higher level than that of the average promotional effort developed through a clustered marketing effort, different segments could receive other types of promotions; thus, one segment might receive value-driven promotions while the other might be targeted for the experience or quality of the product. Although the distance separating clusters is quite minimal and, therefore, the segmentation could be more clearly defined by marketers to develop separate and distinct, targeted communications from a segmentation perspective by leaving traditional one-size-fits-all promotions behind.

Overall, as shown by the results of these clustering analyses and strong classification results, this clustering methodology complements the predictive insight gained from analyzing the transaction data, revealing how customers cluster together based on their behavior in the purchasing process within the fashion retail segment.

The heatmap shows the mean values for the various numerical characteristics chosen for each of the clusters and, based upon the color, indicates the relative magnitude of the different clustered values and the behavioral differences amongst customers within each of these two customer clusters.

4. DISCUSSION

The findings from our modeling demonstrate two complementary perspectives about the "Understanding Purchasing Behavior through Retail Transaction Data in Fashion:" (1) A predictive perspective that assesses how well transaction characteristics predict customer behavior, and (2) A grouping perspective that shows how transactions can form natural behavioral segments within fashion retailing. Throughout these analyses, transaction data offers actionable insights about managing and marketing fashion retail operations.

The predictive modeling results show that the classification performance is strong (accuracy $\approx$ 0.89), which means that transaction-level variables provide powerful signals that reliably differentiate the outcome categories. In other words, fashion retail transactions are not random. Fashion retail transactions have identifiable structures that can be predicted based upon transactional attributes such as the products that are selected by customers, when they make purchases, and other characteristics of the transaction. From a managerial perspective, this level of predictability is a critical factor in making operational decisions as it allows retailers to predict transaction outcomes and allocate resources accordingly. For example, a reliable prediction can help retailers plan inventory. Retailers can identify and stock high-demand product categories ahead of time, thus reducing the chances they will experience stockouts, and minimizing the chances of experiencing excess inventory. In addition, predictive patterns can assist with assortment optimization, allowing managers to determine which products to focus on during particular time frames based on the actual transactions that have occurred.

The clustering of customer segments is consistent with the predictive results in that they indicate that two dominant segments exist within the transaction dataset (with a fairly equal number of transactions in each segment). Despite the low silhouette score for cluster separation, the result still indicates that the database has significant differences in customer purchasing behavior. In a fashion retail context, this overlap is typical as customers generally share at least some common baseline needs (such as essential clothing), but they can also vary greatly in terms of style preferences, sensitivity to price, and frequency of purchases. From a management perspective, the identification of two broad customer segments can provide a foundation for implementing a segmentation-based approach to inventory management. Retailers can define their segments in terms of distinct purchasing characteristics, such as value (higher vs. lower value transactions) or frequency (frequent vs. occasional purchasers), and develop inventory allocation plans and replenishment cycles that meet the needs of those segments.

Modeling results can also be used in marketing to create better targeted and efficient strategies with the modeling results. In terms of demonstrating the value of transaction data as a means to support personalized targeting, the excellent classification performance shows that the use of transaction data can identify what transaction characteristics are associated with specific outcomes for customers. Thus, marketers will have a better chance of creating successful promotional campaigns by using data-driven offers as opposed to mass promotions. Clustering also supports audience segmentation in designing marketing campaigns. Marketers that separate their customers into two distinct but interpretable groups (even if moderate separation is achieved) will be able to design their campaign messaging, discount structures, and channel strategies in ways that are most effective for each customer group. For example, a campaign targeting a customer group that is more responsive to loyalty incentives and product recommendations will differ from a campaign targeting a customer group that is more sensitive to time-limited promotions or bundles of products.

Overall, modeling results can help fashion retailers to generate insights that will be important and actionable for their business. Predictive modeling can help fashion retailers to forecast their business operations; and group analysis can support fashion retailers with their customer segmentation efforts and personalization of their marketing. Together, these approaches will provide greater support for distinguishing between patterns in purchasing behaviour (or purchasing patterns) and how those patterns can be utilized by managers to make decisions. It is important to note, however, that the clustering results indicated moderately weak levels of separation among the customer groups that were formed during this modelling phase. Therefore, it is recommended that additional exploration to refine the clustering results (e.g., implementing consumer behaviourally based features with more detail or granularity; selecting a different form of data for clustering; or using a different time frame for data to cluster) should produce more unique and actionable customer groups.

5. CONCLUSIONS

By using both transaction data from the clothing retail industry and analyzing it through both predictive and grouping methods, this research looks at the purchasing patterns of consumers to provide retailers with actionable intelligence on how to make decisions based on purchase behavior. The transaction data consisted mainly of transaction data with information about items purchased, the amount paid for the items, review/rating, payment type, and date/time of purchase. This information serves as the most appropriate way to gain insight into the way that consumers behave based on actual sales history.

The modeling efforts demonstrate that transaction-level data have a strong ability to provide behavioral signals and predict future behavior, as demonstrated by high accuracy = \$.89. This indicates that there are recognizable and predictable patterns for purchasing in the fashion retail sector; these patterns may be exploited further in the development of operationally focused strategies, e.g., planning for when to buy more items into inventory, optimizing product variety in product assortments offered to shoppers, and determining how to allocate resources among retail stores. The grouping analysis provided further insights as to how consumers were purchasing in two major categories of shoppers represented relatively equally in number and volume of purchases; thus, these two segments provide an initial understanding into the differences between consumers in terms of their purchasing behaviors. Overall, while there was only moderate separation of the clusters formed, this segmentation analysis still provides a practical starting point for profiling customers and examining potential variations among purchasing behaviors.

The results indicate that transactional analysis has the potential to provide valuable insights to fashion retailers regarding their management and marketing. Management can use predictive analytics to enhance the overall efficiency and planning of the business as well as develop new methods for targeting customers using customer grouping techniques. Future research should aim to improve the quality of segmentation through additional behavioral variables, investigating new group configurations, and analysing temporal trends or seasonality to improve the accuracy of segmentation analyses.

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