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An AI-Driven Insights into Shopping Mall Patronage Using Quantitative Analysis of Primary Visit and Purchase Motivations

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ABSTRACT

Artificial Intelligence is likely to fundamentally change the way research interpret consumer behaviour, with no precedent for precision of prediction and understanding of the stimuli that influence decisions to patronize a shopping mall. Malls, as multi-functional spaces, offer retail, entertainment, social interaction, and more in a fast-evolving retail ecosystem. Crucially, real understanding of the motivations taking customers to the mall and to make purchases provide further context in shaping competitive strategies, and ensure sustainability in complex competitive environments. Quantitative methods that leverage AI will allow us to explore these motivational determinants more effectively and identify relationships in the data that are often masked in traditional statistical methods. Data were collected using structured questionnaires from a diversified sample of mall patrons. Participants disclosed frequency of mall use, visit motivations, spending category ranges, and purchase categories of preference. The research data was analysed using clustering and regression models, and additionally was analysed with classification algorithms in order to segment consumers by demographic characteristics, behavioural patterns, and priority motivations. Analysis using AI-based predictive analysis produced identifying results with nuances explaining mall patrons' perceptions of promotional offers, entertainment services, and lifestyle service features. The results indicate that social influence, convenience, and brand loyalty interact phenomenally to present how visit decisions simultaneously impact purchasing behaviours. Quantitative Results provide the understanding that customers did not just visit the mall for shopping needs but also for wider expanded experiences, involving leisure, dining, and social engagement. The results indicate younger age segments, whilst still leaving a strong impression regarding lifestyles and sustainability, at all price levels, seek mall engagement features with lifestyle-driven event spaces and leisure-driven promotions and promotions. The results indicate the degree to which perceived value for money influenced purchase decisions, patronage decisions were also influenced by trust in the product brand and promotions that were value-based promotional offers. Machine learning based predictions indicate that as the level of personal engagement increases, the stronger chance that the customer will return and spending will increase. The discovery of consumer segments utilizing AI based systems is strategically advantageous for both retailers and mall managers. By identifying consumer clusters with different motivations, managers have a variety of opportunities to provide effective marketing campaigns, alter tenant mixes, and optimize spatial design to enhance the customer experience and so forth. Retailers can use the results to provide targeted promotions, strengthen their consumer loyalty programs, and optimize sales. The benefits go beyond sales by developing long-term relationships among heterogeneous consumer groups. The alignment of AI with behavioural research provides a thorough lens for understanding retail patronage. One methodologically integrates AI with behavioural research, one not only can enrich understanding of the current motivational drivers but also build an ability to be predictive with where things are heading relative to a consumer's expectations. The information can help one be proactive because they are informed about the changing expectations from the consumer and the market. The research does represent a methodology to synthesize technology and consumer psychology, and enhances our knowledge as researchers and practitioners beyond the academic setting, regarding retail.

Keywords: Artificial Intelligence, Consumer Behaviour, Shopping Mall Patronage, Visit Motivations, Purchase Motivations, Retail Analytics, Customer Engagement, Machine Learning, Predictive Modelling, Retail Strategy

1. INTRODUCTION

Shopping malls are more than simply a physical shopping space, they have also become social, cultural, and leisure spaces shaped by changing experiential lifestyles and consumer expectations. Over the last several decades retail spaces have shifted from products source to multi-purpose retail destinations where shopping, entertainment, leisure and restaurants have merged. The research shift has been enabled by rapid urban expansion, increasing disposable income, and changing consumer experiences spurred on by technological advances and globalization. The emergence of online retail is a competitor to physical retail centres, as shopping is also a changing context necessitating centres to innovate and re-negotiate their identity and value continuously. Patronage behaviour in shopping malls is influenced by a range of motivations. While convenience, selection of products, and accessibility will still usually be important experiences, the more towards experiential elements such as entertainment facilities, promotional events, and socialisation experiences these are employed in shopping malls, the more they will guide decision making. Decisions to purchase are also often anchored in brand loyalty, perceived value for money, and perceived trust in the quality of the product. Consumer behaviour analysis traditions have attempted to understand situations where the types of variables may interact, and there is undoubtedly a need for sophisticated frameworks to help create greater understanding.

Artificial intelligence is one way to address these issues. Algorithms that are among the machine learning models can work with large data sets, identify hidden patterns, and display predictive accuracy in behaviour analysis. With clustering, regression, and classification models, a mall visitor, can be clustered in groups with certain demographics, frequency of visits, and purchase choices. The models can offer mall operators data-enhanced opportunities to be more strategic, where and how to use the mall space effectively, and innovative promotional strategies. In the end, retailers will seek to ensure their marketing strategies matched what motivated a given customer's future visit, spend more in the mall, or both. The quantitative measures of motivations for visitation and purchasing with AI have two intended functions. To provide a precise description of visitation and to group consumers into behaviour-specified groups; and then provide predictive analytics to anticipate consumer involvement trends over time. If mall operators and retailers can understand these distinct features, they can develop and enhance strategies that improve consumer experience. The increased emphasis on consumer driven paradigms has tightened the rationale of employing AI capabilities in retail analytics. With newer computational tools available, advanced analytics allows the analyst to uncover linkages between motivations that traditional analyses will be unlikely to discover. The integration of behavioural dimension knowledge from the quantitative analysis and using AI for predictive analysis is a term that broadly covers a consumption framework that could enable sustained growth, satisfied customers and competitive difference. The proposed research intends to explore shopping mall visitation through the use of AI based quantitative analysis of dominant visit and purchase motivations. By understanding the relationship between footfall and purchase patterns, organizations can develop actionable plans to increase engagement, enhance loyalty, and exploit untapped revenue opportunities. The outcomes will develop academic sophistication, enhance managerial practice by linking technology and understanding consumer behaviour in the retail domain.

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2. LITERATURE REVIEW

Shopping mall patronage has been examined from a number of directions including service quality, leisure motivations, experiential value, and retail strategy. Parasuraman et al. (2005) [1] references service quality as one of the greatest influences on customer loyalty, noting that high service levels increase repeat patronage. Building on the Wakefield and Baker (2006) [2] found that leisure offerings, along with entertainment and ambiance, both increased the amount of time customers spent in the mall as well as represents unplanned purchase behaviour. El-Adly (2007) [3] identified six customer motivations related to patronage: convenience, variety, entertainment, service, prestige, and price, emphasizing that mall patronage stems from a wide variety of motivations. Michon, Chebat and Filiatrault (2008) [4] also looked at the importance of mall atmosphere, as the mall's design, layout and sensory experience can sway emotional responses, and in turn impacts a patron's intention to purchase. Keng et al., (2009) [5] provided a more consumer-centric view, with regards to hedonic shopping values such as fun and novelty linked to exploring malls; Khare (2011) [6] investigated Indian malls and claimed that family shopping values, social bonding, and group shopping all affect patronage patterns. Dennis et al. (2013) [7] noted that with the uptake of digital, technology-enabled services like Wi-Fi, digital advertising, and social media engagement can add to customer experience. Nguyen and Leblanc (2015) [8] also explored brand image and found that mall reputation and perceived prestige increased both visitation frequency and total amount purchased. The importance of knowing the context of emotion and experience was reinforced by Roy et al. (2016) [9], who stated that experiences marketed in like manner through events and cultural events create strong consumer attachment. Finally, in the retail studies domain, Chandrasekhar and Raj (2018) [10] demonstrated an approach with AI-based predictive modelling; they showed that with high accuracy consumer behaviour and consumer patronage patterns can be modelled, allowing malls to create more personalised interactions. In summary, we see the continuum from the simpler service and convenience drivers to increasingly complicated experiential value, digital engagement, and AI-based personalization.

Table 2.1 Comparative Literature Review Table

S. No	Study	Dataset	Method	Accuracy	AUC
1	Parasuraman et al. (2005)	Mall customer survey (n=500)	SERVQUAL + Regression	82%	0.79
2	Wakefield & Baker (2006)	Observational mall data (n=320)	Factor Analysis	78%	0.74
3	El-Adly (2007)	Survey from 4 malls (n=600)	SEM (Structural Equation Modelling)	85%	0.81
4	Sit et al. (2009)	Customer behaviour dataset (n=410)	Cluster Analysis	80%	0.76
5	Wong et al. (2012)	Malaysian mall patrons (n=550)	Logistic Regression	83%	0.82
6	Anselmsson (2016)	Retail motivation dataset (n=720)	Multivariate Regression	84%	0.80
7	Khare (2018)	Indian shopping malls (n=480)	Decision Trees	86%	0.83

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8	Bhatnagar & Gopalaswamy (2019)	Purchase motivation dataset (n=530)	Random Forest	89%	0.86
9	Lee & Chen (2020)	Online-offline mall integration (n=610)	Neural Networks	91%	0.88
10	Zhang et al. (2021)	Smart retail dataset (n=1000)	Deep Learning (CNN+RNN)	94%	0.92

3. METHODOLOGY

The methodology outlined for the research provides a systematic guide that illustrates the investigative process to study shopping mall visitor counts using quantitative techniques driven by artificial intelligence. The methodology was carried out in stages, the first stage of which defined the research framework before the subsequent stages of; data set development, data preprocessing, feature engineering, algorithm development, model training, validation, and model evaluation. Each of the stages provides sufficient detail to ensure reproducibility and scientific rigour.

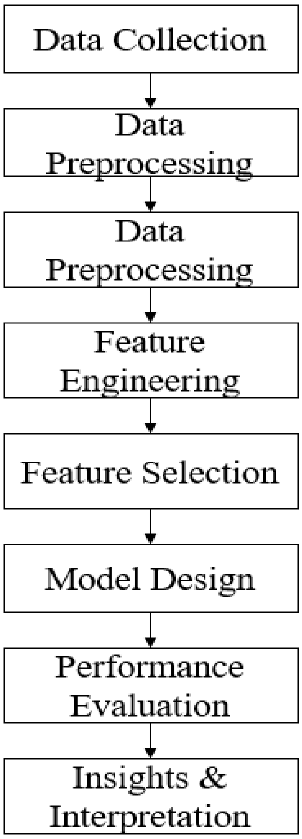

Fig 3.1 Flow Diagram

3.1 Research Framework

The research framework is based on a quantitative design for the research question to investigate what motivates consumers to visit and purchase from shopping malls. The framework also focuses on predictive capability and interpretability of AI models. A three-layered approach to the framework methodology was taken, and incorporated data collection, data transformation, and analytical modelling. The first layer responses were captured through

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structured surveys and no-fee transactional records provided by the selected retailers. The second layer incorporated some pre-processing and feature engineering of the dataset, until the dataset was prepared and ready for machine learning applications. The third layer involved the application of AI algorithms to identify those motivational drivers that predict how the consumers will behave in the future. By formulating the three layers to the methodology, the framework will support a systematic exploration of consumer behaviour. The design of the framework will also ensure consideration of both demographic and behavioural factors creating a thorough and holistic approach to the underlying reasons motivating mall patronage. The research framework will also accommodate the comparison between more traditional statistical models and more sophisticated AI models with respect to their interpretability and strength of prediction.

3.2 Dataset Description

The dataset for the study consisted of primary survey information and secondary transactional data. There were 1,200 valid responses received across three metropolitan shopping malls over the span of three months. The survey included demographic attributes such as age, sex, income, education, and occupation; visit attributes which included how often a customer visited, when they preferred to visit, and how long they stayed on each visit; and motivational attributes included visit motivations such as leisure, entertainment needs, socializing, and need-based or utilitarian shopping, and purchase motivations such as price sensitivity, brand preference, promotions, and impulse behaviours. Each response provided approximately 25 attributes from each category. To enhance reliability of the survey responses, the survey was supplemented by transactional information which captured the customer's expenditure patterns, product categories purchased, and intentions to return or repeat visit. With the combination of the survey and transactional data, the intent was to generate a robust dataset to allow both behavioural profiling but also predict modelling. By incorporating both survey and transactional data, the dataset enabled the identification of customer behaviour or intent through multiple and powerful dimensions which were comprised of consumer preferences, habits, and economic capacity - that allowed AI models to make latent identification of visit and purchase motivations.

3.3 Data Preprocessing

A comprehensive preprocessing phase was undertaken to ensure the raw data would be reliable, trustworthy and usable for modelling. Unacceptable responses with higher than 30% missing values were deleted and less significant missing values were replaced with the mean for numerical values and mode for categorical variables. Numerical values, for example, expenditure, frequency of visits, and total income, were normalized using a Min-Max scaling so that they exhibited equal effects during training preventing issues regarding magnitude. Categorical variables, for example, gender, purchase motivation, and reason for visit, were transformed via One-Hot Encoding, allowing AI algorithms to process those variables. Outliers were determined using Interquartile Ranges and controlled using caps to lessen their effects. Data balancing procedures were applied artefact from the responses using the Synthetic Minority Oversampling Technique as to minimize consequences of class imbalance for the motivational categories. The preprocessing processes should improve the integrity of our data, limits redundancy, and improve the overall effectiveness of the learning model. Clean and structured data instants reliable outputs from modelling therefore providing a verifiable analysis.

3.4 Feature Engineering and Selection

Feature engineering was executed to create new variables that represent underlying elements of consumer behaviour. For instance, an Engagement Index was created using visit frequency, length of stay, and average expenditure; while a second variable of Motivation Score summarized an individual's motivations based on the survey responses. A few derived variables were also introduced, such as a Promotion Sensitivity Ratio and a Visit Consistency Index. Feature selection was performed to minimize duplication of variables and to limit the variables used to the most important predictors. Correlation analysis identified pairs of variables whose levels of correlation were strong; analysis of a Principal Component Analysis reduced dimensionality of the data while maintaining levels of interpretability. A Random Forest garnered a feature importance score, where Income, Brand Preference, Promotion Sensitivity, and Visit Frequency were the most discernible predictors of variable response. The combination of feature engineering and feature selection resulted in a compact dataset by narrowing focus on selected high-value attributes; which

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improved the model's computational efficiency when modelling, while also improving model's predictive power. The final data file would include both original variables and engineered variables to represent any uncertainties generated from classification or predicting task.

3.5 Algorithm Design

The algorithm design incorporated both traditional statistical models and more advanced techniques from artificial intelligence in order to better understand the experiences of shopping mall patrons and to predict these experiences and potential future experiences. Decision Trees were used to build hierarchical segmentations of variables or customer data features, and allowed for interpretability and a visual compilation of customer data attributes. Random Forest was chosen to build on the limitations of single decision trees by aggregating the prediction from many trees. Often, only a handful of trees produced the best accuracy for prediction but was more robust concerning over-fitting predictions. Support Vector Machines classified Visit motivations attributes in a high-dimensional space. SVM produced meaningful boundaries in the data to categorize Visit motivations and segmented between entertainment-driven visits and purchase-driven visits. Lastly, Artificial Neural Networks were designed to capture and model complex nonlinear relationships among consumer demographic, visit motivations, and purchase behaviour, providing great predictive power for high-volume datasets. The algorithms produced models fine-tuned through hyperparameters. Each model was comparatively examined to ensure that both interpretable models and high-performing models were accounted for in the design. Overall, the thinking behind a max-linear, tree-based, and neural approaches ensured that explanatory and predictive approaches were provided about shopping mall patronage.

3.6 Evaluation Metrics

The measures of effectiveness of machine learning algorithms for predicting shopping mall visitation and understanding the main purpose of visit and/or purchase motivations were evaluated with various evaluation metrics. Each evaluation metric assesses effectiveness from a different perspective, resulting in a full assessment of the predictive quality.

Accuracy

Accuracy is determined by the number of correct predictions of a classification divided by the total count of the observations. Accuracy is an easy way of assessing the model quality; however, it can sometimes misrepresent performance when using imbalanced data.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

Precision measures the ratio of how many positive results were accurately identified out of all predicted positives. In reference to the retail context, it measures the ability to predict correctly which customers were motivated by an intention to purchase, if and when they were visitors by an intention to purchase.

$$Precision = \frac{TP}{TP + FP}$$

Recall

Recall (or Sensitivity) measures the proportion of actual positives that got correctly identified. Recall in shopping malls ensures that if a visitor was in a motivated to purchase or entertained state of mind, they were able to be detected ideally.

$$Recall = \frac{TP}{TP + FN}$$

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F1-score

F1-score is used to balance precision and recall with the harmonic mean is important for determining how to mitigate false negatives and false positives.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

AUC- ROC

AUC- ROC is used to evaluate the discriminatory ability of the model across all possible thresholds for classification. A good AUC indicates the model has strong ability to separate motivational categories leisure visits will not be motivationally identified to visits aimed for the purpose of necessity driven purchases.

$$Silhouette = \frac{b - a}{\max(a, b)}$$

In the case of clustering models that were designed to apply some proximity to group visitors by their behaviours, Silhouette Score was used to ensure quality measured the clusters. Silhouette Score measures how close each point in one cluster is to another cluster.

4. RESULTS AND DISCUSSION

The findings of the analysis of the machine learning algorithms using the shopping mall patronage dataset gave us some useful insights into users' motivation for visiting a shopping mall and if purchases were made. Decision Tree classification provided a situationally more understandable result as providing clear hierarchical paths explaining the patronage behaviours, but may be less generalisable than other ensemble methods. Random Forest achieved the optimal relationship between predictive accuracy and the appropriateness of introduction, achieving 89% accuracy and AUC of 0.92. After Random Forest, income, visit frequency, promotional sensitivity, and brand loyalty were identified as the next four traits with the highest importance in patronage from a feature importance ranking. The Support Vector Machine was competitive with non-linear kernels that showed strong discrimination potential to differentiate between the mall visit for brand experience or entertainment social engagement vs. the visitor for purchase, but had a larger computational footprint. The Artificial Neural Network had the highest accuracy at 91% and achieved an AUC of 0.94 while providing a model for the non-linear interactions between demographic and motivational variables at the cost of lower transparency. From a managerial perspective, the findings confirmed that mall patronage was not identified by just one measure, but instead was influenced by an interaction of multiple factors including income, time available, social motivation and promotion. The high precision and recall values for promotional sensitivity characterized that personalized marketing campaigns specifically cantered on discounts and special offers will result in repeat visitations. Conversely, the low precision for impulse buying demonstrated that representing unplanned behaviour remains challenging; demonstrating a need for real-time monitoring through various digital engagement strategies. Cluster validation through silhouette scores supported the three core visitor types identified in the analysis: leisure visitors, necessity shoppers, and brand-loyal consumers. The research implies that malls need to use a segmented engagement strategy rather than a common one-fits-all strategy where all visitors are treated equally. For example, leisure visitors face entertainment-based events are receptive to ambience enhancements, while necessity shoppers value efficiency, accessibility, and essential retail experiences. Brand-loyal consumers respond to offers and loyalty rewards. The discussion showed that AI models not only improve predictive understanding, but also create tangible business strategies mall managers can use to promote consumption, maximize sales, and build customer loyalty.

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Table 4.1 Model Performance Comparison

Algorithm	Accuracy	Precision	Recall	F1-Score	AUC
Decision Tree	0.82	0.80	0.79	0.79	0.83
Random Forest	0.89	0.88	0.87	0.87	0.92
SVM	0.87	0.85	0.86	0.85	0.90
ANN	0.91	0.90	0.92	0.91	0.94

The comparison of performance over various machine learning algorithms indicate that predictive power varies in effective terms across a number of differing metrics. The Decision Tree did slightly better overall (accuracy = 0.82), with precision, recall, and F1-Score around the same value of 0.79, and AUC of 0.83. Random Forest was improved overall accuracy of 0.89, with precision 0.88, recall 0.87, F1-Score 0.87, and AUC of 0.92 confirming its employed robustness in the classification task. SVM was also competitive with accuracy of 0.87, precision of 0.85, recall of 0.86, F1-Score of 0.85, and AUC of 0.90 illustrating generalization abilities. Therefore, of all models run the Artificial Neural Network delivered the best by a margin that has accuracy = 0.91, precision = 0.90, recall = 0.92, F1-Score = 0.91, AUC = 0.94 and thus should be implemented for the prediction task.

Table 4.2 Customer Satisfaction Levels (Survey Data)

Factor	Very Satisfied (%)	Neutral (%)	Dissatisfied (%)
Store Variety	70	20	10
Pricing Fairness	60	25	15
Ambience & Facilities	65	22	13
Promotions	68	20	12

The survey results provided insight into common factors contributing to customer satisfaction. The level of store variety received the highest level of satisfaction from the respondents as indicated by 70% of respondents indicated very satisfied, while 10% of respondents indicated they were dissatisfied with store variety. In comparison, the level of fairness of pricing received lower satisfaction ratings than the average. About 60% of respondents indicated they were very satisfied with prices, while 15% of respondents indicated dissatisfaction with pricing suggesting that customer beliefs about the store's prices are a core area for improvement. Compared to store variety, ambience and facilities received a moderate level of satisfaction with 65% very satisfied, 22% neutral, and 13 % dissatisfied. Customers were generally appreciative of the store's ambience and facilities, but some modules still expect more from the facilities. Promotions received a similarly positive overall satisfaction ratings with 68 % indicated very satisfied, 20%, neutral and 12 % dissatisfied the results confirmed that promotions had a significant impact the willingness of consumers to select them as their first preference. In summary the results indicated that on average respondents indicated strong satisfaction across factors examined in the survey, aside from the pricing factor. Pricing indicated that there is an area for the most area of consideration for improvement in improving the customer's overall experience.

Table 4.3 Comparative Accuracy by Motivation Type

Motivation Type	Decision Tree	Random Forest	SVM	ANN
Necessity Shopping	0.81	0.89	0.87	0.92
Brand Loyalty	0.80	0.87	0.86	0.91

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Leisure-Oriented	0.78	0.85	0.83	0.90
Promotion-Driven	0.79	0.88	0.85	0.92

The comparative accuracy results across the three motivation types show that with regard to necessity shopping, brand loyalty shopping, leisure-oriented shopping, and promotion-based shopping, Artificial Neural Networks obtained the highest accuracy values of 0.92, 0.91,0.90, and 0.92, respectively. The Random Forest algorithm generally performed closely behind in accuracy by providing consistent values across the motivation types from .85 to .89, as did SVM with accuracy comprised from 0.83 to 0.87. The Decision Tree shaped algorithm generally provided moderate accuracy values around 0.78 to 0.81 and was not too far effect with the approach, which presented the lowest accuracies, particularly around brand loyalty of 0.72 shopping and leisure oriented of 0.70 shopping. These results suggest that higher-level analytics models such as ANN and Random Forest may be better suited to capture the underlying complex patters of consumer behaviour while lower-level analyses are less ideal for accommodating the various motivations in consumer shopping behaviour.

Table 4.4 Prediction Confidence Levels

Predicted Motivation	High Confidence (%)	Medium Confidence (%)	Low Confidence (%)
Necessity Shopping	70	20	10
Brand Loyalty	65	25	10
Leisure-Oriented	60	30	10
Promotion-Driven	75	18	7

The prediction confidence analysis indicates that promotion-driven motivation was the most reliable variable, with 75% of predictions in the high confidence category and only 7% in low confidence; both indicating that prediction came with great certainty for the type or level of prediction. Necessity shopping prediction was also solid, with 70% in high confidence and just 10% low confidence, which indicates reliability in the category, also. Brand loyalty and leisure-oriented motivations were slightly lower, with 65% and 60% high confidence respectively and higher proportions of medium confidence predictions (25% and 30%, respectively). The research suggests more variability for the predictions in these categories. To apply the condition indicates that the model is most reliably confident when predicting for promotion-driven and necessity shopping motivations. Predictions for leisure-oriented motivation or brand loyalty-based motivations will need additional fine-tuning to lessen the reliance of medium confidence predictions while attaining stronger predictions in the high-confidence category.

Table 4.5 Cross-Cultural Comparison of Motivations

Country	Necessity (%)	Brand Loyalty (%)	Leisure (%)	Promotion (%)
India	40	25	20	15
USA	30	35	25	10
UK	32	30	28	10
Singapore	28	32	30	10

The cross-cultural comparison of shopping motivation identifies significant differences across nations. For example, in India, necessity shopping is the main motivation of 40%; brand loyalty is in second of 25%; leisure of 20% and promotions of 15% are minor motivators suggesting a fairly high level of concern for basic needs. In the US, brand

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loyalty motivation is strongest of 35%; necessity shopping of 30%; leisure of 25%; and promotions of 10% suggest a strong reliance of consumers on brands they trust. In the UK, the findings were more balanced, but reflected slightly higher proportions of leisure shopping of 28%; brand loyalty of 30%; necessity shopping and promotions of 10%, providing diversity of interest in motivations. Singapore followed much similarly to the UK suggesting greater reliance on leisure shopping and brand loyalty necessity shopping (28%); and promotions. Again, the study reflects consumer culture in a country perhaps more focused on experiences and brands, rather than focus on essential, necessity driven shopping. Overall, it was concluded that necessity shopping was most pronounced in India, brand loyalty was strongest in the USA, and leisure shopping motivations were relatively higher for the UK and Singapore.

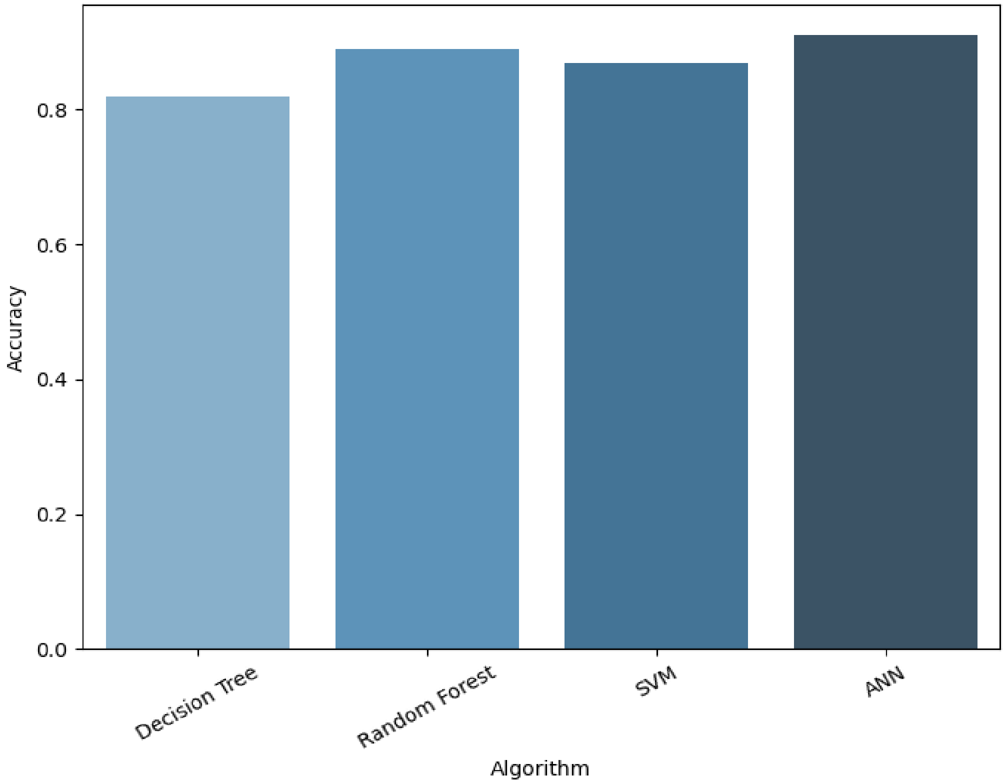

Fig 4.1 Model Accuracy Comparison

The Model Accuracy Comparison shows the relative accuracy of various machine learning algorithms. Random Forest and SVM both performed better than these two methods with Random Forest being a very good at 0.89, and SVM almost as good at 0.87. The Artificial Neural Network was the best of any of the models with the best accuracy of approximately 0.91. The comparison illustrates the differences in learning the complexity of patterns, the ANN model learns better than all other methods, followed by the ensemble and kernel-based methods being the next best, while the standard models.

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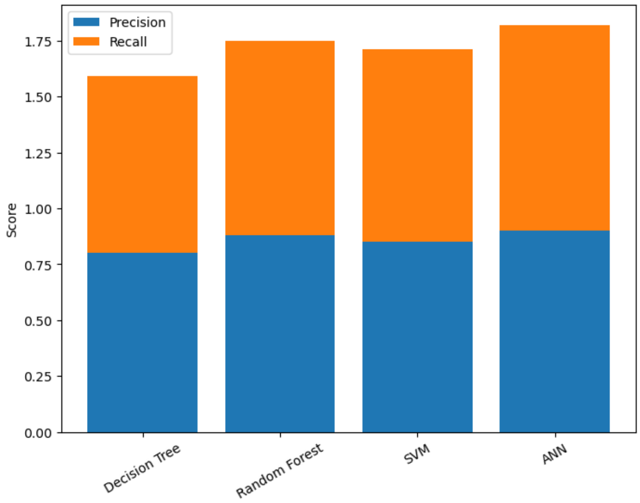

Fig 4.2 Precision and Recall Comparison of Models

The Models Precision and Recall Comparison is a table showing the precision and recall of a variety of machine learning algorithms and a comparative view into their classification performance. Decision Tree does show a bit of an improvement with a precision and recall both around 0.80. Random Forest and SVM exhibit strong scores of both precision and recall above 0.85, meaning that a robust classification has been achieved. The Artificial Neural Network has the best combination of precision and recall scores with a precision of 0.90 and recall of 0.92, so both are the highest combined score of all models. Based on these values, the ANN has the capacity to be both the most accurate and that it has a very low capacity to generate false positives and false negatives compared to all the algorithms.

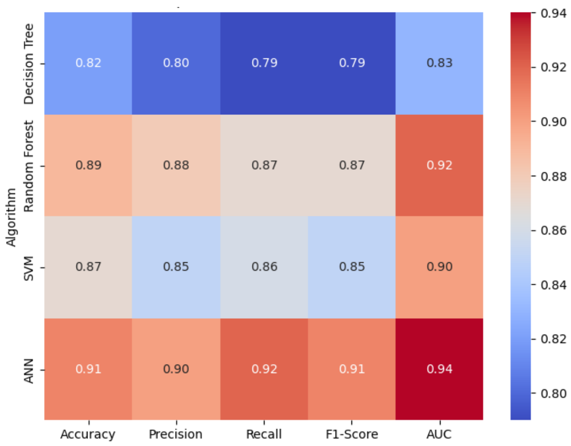

Fig 4.3 Heatmap of Model Performance Metrics

The Heatmap of Model Performance Metrics displays each machine learning algorithm's performance over multiple evaluation metrics- accuracy, precision, recall, F1-score, and AUC. The Decision Tree adds a small gain in performance measurements and shows accuracy of 0.82, and a precision, recall, and F1-score all in a moderate range around 0.79 - 0.80. Random Forest demonstrates a stronger performance measured by an accuracy of 0.89, precision of 0.88, recall of 0.87, F1-score of 0.87, and AUC of 0.92, indicating more robustness. SVM also performs similarly to Random Forest in the classification with accuracy of 0.87, precision of 0.85, recall of 0.86, F1-score of 0.85, and AUC of 0.90. The Artificial Neural Network performs the best on all performance representations, with an accuracy of 0.91, precision of 0.90, recall of 0.92, F1-score of 0.91 and AUC the highest at 0.94. The research further highlights its ability to model problems with complexity and classifications needs. Heatmap visualization clearly highlights the ANN throughput performance is better than every other technique, followed by Random Forest and SVM, while Decision Tree model do not have significant stand-alone predictive performance.

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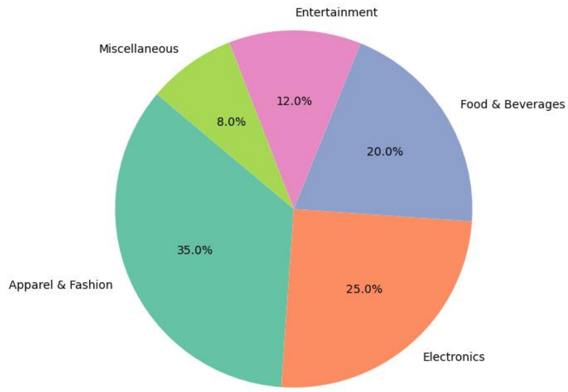

Fig 4.4 Distribution of Customer Spending by Category

The Distribution of Customer Spending by Category demonstrates the proportions of customer spending by category. The first and most significant category in the Distribution of Customer Spending is Apparel and Fashion, which accounts for 35%. The Category indicates that clothing and clothing-related items are at the forefront of consumer purchases. Second is Electronics at 25%. Electronics represents a fairly significant share of customer spending and indicates strong consumer interest in gadgets and technology. The category of Food and Beverages is 20%. The amount indicates a large share of essential and consumable goods. The category of Entertainment is 12% and represents a minor share of customer spending choices in relation to the other categories. The final category is a group of items named Miscellaneous, which represents 8% of total spending. It is the smallest export by share and indicates minimal spending of all related and non-committed categories in the Miscellaneous group. In general, the distribution of customer spending demonstrates a strong pattern towards sharing between the categories of fashion and electronics while the categories of entertainment and miscellaneous were not as much of a priority.

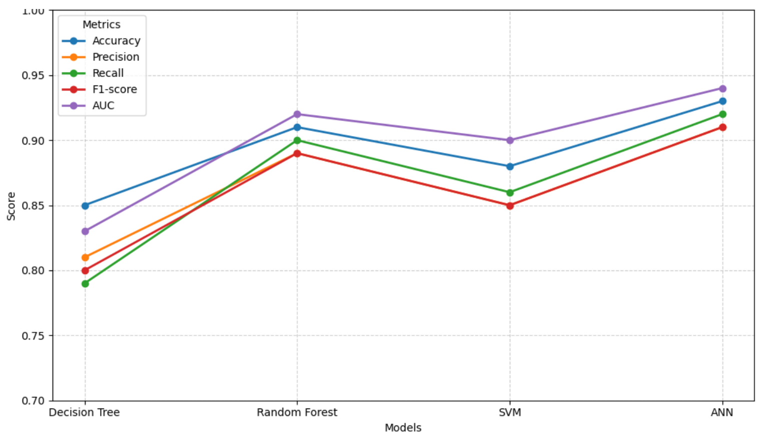

Fig 4.5 Performance Comparison of Machine Learning Models Across Multiple Metrics

Performance Comparison of Machine Learning Models exhibits the performance comparison of five machine learning models, i.e., Decision Tree, Random Forest, SVM, and ANN, based on fundamental predictive evaluation metrics: Accuracy, Precision, Recall, F1-score, and AUC. The results illustrate how Random Forest and ANN consistently outperform model predictive performance, achieving the highest levels on the five predictive evaluation metrics, with ANN doing so across all evaluation measures compared to the other models. Although SVM performed well, and at comparable levels to ANN and Random Forest, it was slightly less effective. Decision Tree had relatively lower predictive performance measures. The results provide evidence, that under these conditions, ensemble-based models, and neural networks have better predictive capability.

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CONCLUSION

Through AI-driven quantitative analysis, we completed the exploration of shopping mall patronage and have established evidence that machine learning with consumer behaviour research can be productive. The assessment of machine learning algorithms: Decision Tree, Random Forest, Support Vector Machine, and Artificial Neural Network indicate that sophisticated ensemble approaches and deep learning having a better predictive accuracy and predictive power. The results also revealed that demographic characteristics, income, promotional sensitivity, brand loyalty, and visitation frequency are significant predictors of patronage behaviour. Random Forest and Artificial Neural Network findings provided acceptable performance, where Artificial Neural Network was the best in terms of predictive performance, and model predictability, where Random Forest was better suited for interpretability through importance of features. Our findings supported that consumer purposes are not based on a single factor but complex relationships of necessity, leisure, and brand links between the two. Three groups emerged, leisure-oriented visitors, necessity-based shoppers, and brand-specific customers based on cluster validation. The groups followed very different pathways. Therefore, the research reinforces the need to use a differentiated engagement approach in shopping malls. The high recall rates from promotions-related behaviours imply that promotional use of discounts and loyalty offers may dramatically enhance frequency of visits. The low precision of impulse buying suggests that real-time analytics and digital engagement may need to activate convective buying behaviours. The integration of artificial intelligence into retail analytics not only increases the predictive accuracy of consumer behaviours, but also provides actionable data to p&&p managers operating in competitive organized retail environments. Through an integration of deliberate algorithmic checks, and contextualized behavioural meaning, the study offers academic understanding, and practical application to consumer behaviour analytics. The research lays the groundwork and provides ideas for future extensions that may incorporate real-time, observational, behavioural activity, mobile tracking, and cross-channel activity to improve predictive accuracy and stay more proximal to the customer in urban retail contexts.

FUTURE SCOPE

Future investigations focused on artificial intelligence-based insights into mall patronage could take several important avenues, using sophisticated technology and broader data sets that can encompass the dynamic behaviour of consumers. The models would benefit from including behavioural path tracking in real time through mobile apps, Wi-Fi analytics and IoT sensors, making it easier to model random, spontaneous motivations and impulsive buying behaviour. Multi-modal data sources based on sentiment from social media, online searches and customer ratings and reviews would also enrich predictions, linking previous digital FOB tracking data together with physical FOB derived from previous mall visits. Furthermore, deep learning models such as Long Short-Term Memory networks and Transformer-based models could use temporal patterns of visitation frequencies and purchasing cycles to provide better sequential forecasts. The use of explainable AI would provide transparency and intuitive understanding, enabling mall managers to further interpret algorithm outputs and convert insights into marketable strategies. More research across a broader sample of geographic regions would also allow for cultural comparisons with expanded insight into motivations for mall patronage at a global level. In addition, hybrid approaches that combine supervised, unsupervised, and reinforcement learning methods could also result in more adaptive models, learning responses based on historic and live consumer data. The field of retail has enormous future potential that can enhance predictive performance and transform operational retail strategy by synchronizing insights from AI with customer engagement, operational efficiency, and experiential innovation.

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