Managing the retail operations in the COVID-19 pandemic: Evidence from Morocco

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Novel coronavirus disease (COVID-19) and resulting lockdowns have contributed to major retail operational disturbances around the globe, forcing retail organizations to manage their operations effectively. The impact can be measured as a black swan event (BSE). Therefore, to understand its impact on retail operations and enhance operational performance, the study attempts to evaluate retail operations and develop a decision-making model for disruptive events in Morocco. The study develops a three-phase evaluation approach. The approach involves fuzzy logic (to measure the current performance of retail operations), graph theory (to develop an exit strategy for retail operations based on different scenarios), and ANN and random forest-based prediction model with K-cross validation (to predict customer retention for retail operations). This methodology is preferred to develop a unique decision-making model for BSE. From the analysis, the current retail performance index has been computed as “Average” level and the graph-theoretic approach highlighted the critical attributes of retail operations. Further, the study identified triggering attributes for customer retention using machine learning-based prediction models (MLBPM) and develops a contactless payment system for customers’ safety and hygiene. The framework can be used on a periodic basis to help retail managers to improve their operational performance level for disruptive events.

1 | INTRODUCTION

At the beginning of the current pandemic period (early 2020), an average citizen certainly would not have answered the pandemic-related question. Today, everyone in the world knows about COVID-19 as it has been impacting businesses in its way. In March 2020, the COVID-19 outbreak became a public health emergency of international concern (PHEIC). This time, unlike the past, the virus spread was rapid. Governments had to adopt mandatory measures to control its spread (Abdel-Basset et al., 2020; WHO, 2020). As a result, they prepared contingency plans and designed aid packages to support their economies. More so, the lockdown and closed borders have a significant impact on consumption and production (Lal et al., 2021; Vannucci & Pantano, 2020). It is widely recognized as a swan event that forces businesses to design measures for their operational sustainability.

Accordingly, Taleb (2008), disruptive events can take the form as white swan events (WSE) and black swan events (BSE). Here, WSEs are predictable; certain and its impact can be estimated. On the other hand, BSE are highly disruptive and highly unpredictable and cannot be estimated easily. Moreover, in such events, humans are influenced by poor understanding, which leads to ambiguous decisions and ripples, creating more chaos and entropy in a system (Manimuthu, Dharshini, et al., 2021). Therefore, COVID-19 has created disruption in many businesses, and retail sectors are one of the highly affected sectors.

The retail domain is significant to our everyday life as it plays a key role in consumption; besides, retailers at the bottom of supply chains are the significant contributors to the economic growth of developing nations (Kavilal et al., 2018; Lee & Lee, 2021). Moreover, shopping centers are becoming more of touristic attractions in many
countries. As a result, tourism sector is a key catalyst to support the retail sector (Devarajan et al., 2021; Gholipour et al., 2021). These two sectors intertwine and play a critical role in emergent markets. While sectorial studies on COVID’s impact are topical, the present study identifies scope for exploring its impact on the retail industry from a developing nation perspective through a unique approach. The study takes the perspectives of Morocco, which is ranked 12th in 2019 of emerging markets at the global level and the third in the African region (Kearney, 2019). It is recognized a strategic hub for trade and investment between Europe and Africa (Azzoulay & Al-Maghribi, 2019; Bai et al., 2021). Besides, the trend recognizes that Morocco as a vital tourist location (Ahmed et al., 2020). In the above background, the study attempts to address the following research question:

RQ: How to manage retail operations in the COVID-19 outbreak effectively and safer for the consumer? By answering the above research question, this study fulfills the following objectives: The study develops a three-phase evaluation approach. The approach involves fuzzy logic (to measure the current performance of retail operations), graph theory (GT) (to develop an exit strategy for retail operations based on different scenarios), and artificial neural network (ANN) and random forest-based prediction model with K-cross validation (to predict customer retention retail operations). This methodology is preferred to develop a unique decision-making model for BSE. The study offers key contributions to risk management and business sustainability literature. First, to our best knowledge, it is the pioneering study that analyzes the retail industry for essential items of any developing nation by adopting a modeling approach. Second, it offers insights into how the retail sector is sustaining during the COVID-19 pandemic by extending the deliberations of the impact from global and domestic retail perspectives. Even the COVID-19 pandemic is seen as WSE. The impact of COVID-19 outbreaks and restriction created a lot of uncertainty and ambiguity among the business leaders. Third, the present work evaluates the transformation of swan events, which are improbable events triggering innovative avenues of enterprise risk management. It also deliberates the impact of a white swan on the retail industry, a notable contribution to the sustainability literature. Finally, the study develops a contactless payment system for customers’ safety and hygiene.

The remainder of this paper is structured as follows: Section 2 reviews about swan events and theoretical tenet attached to them. Section 3 describes methodology used in the paper. Section 4 discusses the finding. Section 5 deliberates contributions, limitations, and future scope of the present study.

2 | BACKGROUND WORKS

2.1 | Understanding the swan events

In general, WSE is a highly probable event that is predictable; it creates a considerable impact and appears less random and more predictable (Taleb, 2008), for example, the effect of electrical vehicles on fossil fuels. Then, BSEs are challenging to estimate due to their state of randomness and sudden occurrence, for example, financial crisis in 2008 and shuttle explosion in space exploration. There is no predefined response mechanism for such events and challenging to anticipate outcomes due to a poor understanding of the events by humans (Alsaad & Al-Okaily, 2021).

Similarly, COVID-19 is a WSE as was expected in terms of its impact. However, one can argue that COVID-19 has become more infectious and evolved as a global pandemic; its influence on business operations became unforeseeable. Later, International Labor Organization (2020) suggested that the pandemic has affected around 232 million wholesale and retail trade, providing 70% of the global employment (Pandey & Litoriya, 2021). Therefore, the COVID-19 pandemic, which is viewed initially as a WSE, turned out to be BSE, as firms were unable to assess the impact of COVID-19 on their operations. Further, with the illusion of understanding, many functions faced highly disruptive and highly unpredicted challenges, making the COVID-19 impact on retail operations as BSE (Griva et al., 2021; Luo, 2021). Moreover, the element of surprise in BSE and how it disrupted the retail sector and forced shops to shut their doors for customers. So, it can be argued that COVID-19 was perceived as WSE due to poor understanding with limited information on the outbreak, which later evolved into a BSE. Moreover, to explore features of BSE study explored it is tenets. For any BSE, there are five tenets. However, the present study focuses on exploring the three principles: (1) absence of reference model or framework for the given problem, (2) understanding issues that are likely to occur that are ambiguous to predict, and (3) developing a decision-making model for a “hard to foresee” scenario.

Further, black swan theory (BST) explains that humans are prone to make convincing justifications that may look appropriate yet irrelevant, leading to disruptive events (Krupa & Jones, 2013). Similarly, in the retail industry, for example, many retailers tend to hold a different inventory level for future demand that is not constantly sound or optimal. Unlike some other sectors, in the retail industry, retailers do not create products. Instead, they purchase products from manufacturers and then sell it to final consumers. The industry is highly competitive, but it vastly includes various subsectors as food, electronics, fashion, and many more. The study can notice that retail is actively and solidly present in our everyday lives as consumers and constitutes an essential factor for the retail industry with wide range of choices for consumers (Cao et al., 2015; Mitchell, 2021). However, countries such as Singapore and Hong Kong1 were prepared for such an eventuality with a precise plan since as early as 2010. Yet, no such effective measures were proposed in Moroccan context. So, modeling and analyzing the impact of the COVID-19 on retail operations can be instrumental for economic recovery and resilience. It is more critical for developing countries such as Morocco. Therefore, present study evaluates the effect of the BS event in the retail operation for essential items such as groceries and medicines and develops a decision-making model for simple yet effective decision making for retail owners.

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1Singapore and Hong Kong efforts in stemming the COVID-19 spread. https://www.newyorker.com/news/news-desk/keeping-the-coronavirus-from-infecting-health-care-workers?itm_content=footer-recirc
2.2 Impact of COVID-19 on retail operations

First, most retail activities are classified based on the nature of the operations. They are based on the demand forecast, supply chain speed, inventory policy, and data availability (Fisher et al., 2000). Here, the challenge is understanding the early sales for better forecasting. Further, the organization must know the importance of forecasting (Cachon et al., 2007). However, the COVID-19 pandemic had a significant impact on business activities. It primarily affects consumers’ emotions and mental health (Chou & Shao, 2021). Further, individuals worldwide went through stress, anxiety, depressive symptoms, insomnia, denial, anger, and fear during and after the pandemic, which can modify and reshape their buying habits (Lund, 2007; Sebastiani et al., 2020).

In such events, early sales data were challenging, and most run businesses used an ad hoc forecasting approach. Second, speed is a significant factor in the retail sector because most consumer goods have a shorter life cycle (Gaur et al., 2005; Hardgrave et al., 2013). However, governments imposed the sudden lockdown, and social distancing was practiced by canceling events and gatherings and closing public places, stores, restaurants, schools, and universities. Even though supermarkets and stores that provide necessary products remain open amidst stringent guidelines, lockdown measures made the physical store experience tiring and unpleasant for customers, indirectly motivating them to shift toward online shopping (Van Donselaar et al., 2010). Further, no company could anticipate the demand spike due to COVID-19 and respond accordingly.

Third, inventory planning is critical for retail sellers because it facilitates product procurement based on the sales pattern (Ibidunni et al., 2020); however, it was disrupted by COVID-19. Then, this issue was pushed further due to product stockout. Also, the COVID-19 outbreak caused a significant global economic downturn, which negatively impacted product availability. Many products were out of stock in the stores. That leads to another factor, the financial health of customers and businesses (Liu et al., 2021). In other words, the purchasing power is expected to decrease, causing an economic recession.

Fourth, ambiguity in data availability because, in retail operations, the point-of-sale data can enhance the demand forecast, ensure shorter lead time and propose better inventory planning (Ibidunni et al., 2020; Johnson, 2001). Yet, all these activities are highly data driven, accompanied by data inaccuracy, affecting the sale volume and poor decision making in the retail operations. Furthermore, the travel restrictions and border closures impact the tourism sector and the retail industry, as the two sectors are connected, as the retail industry boosts the tourism domain (Patten et al., 2020). So, the absence of tourism hurts the retail industry during this pandemic period (Schleper et al., 2021). However, the BSE was coined by Taleb (2008). It is an event that has three unique characteristics such as:

- Outlining scenario with no relation to regular events
- Creates an extreme impact
- Illusion of understanding of the event leads to ambiguity. However, after the event’s occurrence, finding an explanation to justifies one’s action.

However, Taleb has not proposed COVID-19 as a pandemic (Avishai, 2020). Yet arguably, the planning for an unlikely event in the retail sector was negligible (Craighead et al., 2020; Gupta et al., 2022; Persis et al., 2021). From this context, the present work focuses on resource planning and analytical techniques to develop a decision-making model for retail operations. Therefore, it is clear from the above discussion that the retail operations were primarily affected by the COVID-19 outbreak. Further, it can be observed that the COVID-19 outbreak is initially seen as a WSE. However, its impact on the retail operations created ripples, leading to uncertainty and unpredictability, making it a BSE. Besides, the COVID-19 impact on retail operations was a surprise event as it did their business to a halt with no income, making it unpredictable and uncertain. So, the present work focuses on how retail operations in Morocco can operate in BSEs. The work develops a decision-making model using the three-phase approach that evaluates the status of retail operations followed, develops exit strategies for retail operations, and concludes with a prediction model for customer retention under the tenets of BST.

3 METHODS

An earlier study by Rynes et al. (2001) coined the word “Research-practices gap” highlighting the difference in perception between a management practitioner and an academician. Some studies suggest that such gaps exist due to the knowledge transfer problem, and this can be resolved by a more effective translation of management research question in academic publication (Shapiro et al., 2007, p. 249). However, the translation is instrumental, and the impact of translation relies on the articulation of presented paper. Therefore, paper should link the traditional practices with emerging techniques to overcome gap between practices (Corley & Gioia, 2011). Keeping this in mind, the study proposed a three-phase approach that used a traditional approach along with emerging techniques for retail operations for essential items. The approach involves fuzzy logic (to measure the current performance of retail operations), GT (to develop an exit strategy for retail operations based on different scenarios), and ANN and Random forest-based prediction model with K-cross validation (to predict customer retention for retail operations). This methodology is preferred to develop a unique decision-making model for BSE. The study has a three-phase approach, where each phase of the methodology leads to new findings as shown in Figure 1. Phase 1 involves fuzzy logic, which is used to assess the current level of retail operation. In the present study, fuzzy logic approach has been adopted from Lin, Chiu, and Chu (2006) and Narayananamurthy et al. (2018), which used fuzzy logic in manufacturing and service setting. Similarly, the study analyzes retail performance level and ranks attributes critical for retail operations for essential items (Foroudi et al., 2020). To achieve this, enabler, criteria, and attributes related to retail operations are identified from literature review and evaluated by collecting importance weight and performance rating to assess the current level of retail operation.
strategy for BS events. Moreover, GT will be helpful for analyzing interrelationship between these factors and select the appropriate factors to improve the performance of retail operations (Calafut et al., 2021; Duman et al., 2020; Manimuthu et al., 2019). Further, GT groups the factors that can be used as triggering variables in exit strategy. The third phase, machine learning (ML)-based prediction, is used to predict customer retention for retail shopping. To achieve this, ANN-based prediction model is developed. To conduct the prediction, all the factors are refined using feature reduction in random forest. Later, the remaining significant factors are used for ANN-based prediction model to promote customer retention for retail shopping. In parallel, authors drafted the different sections of paper based on the expert’s feedback, comments, and revisions. Several iterations led to emergence of final draft with no new aspect for presentation (Eisenhardt, 1989; Lee & Lee, 2021).

3.1 Research design

The present work consists of the three-phase approach: (1) using fuzzy approach to evaluate the present performance of retail operations, (2) classifying the factors using GT to develop an exit strategy, and (3) using machine learning-based prediction model (MLBPM) for customer retention.
As we are living under the social distancing obligation, the study used structured interview to collect data from respondents as a primary data source. The data are mainly quantitative, so they rely principally on convenient sampling. This research selects shoppers and retail shop owners as a main population to understand the factors that influence the retail operations for essential items and how to manage it efficiently during the COVID-19 pandemic. Also, using the 7-point scale collects importance weights and performance ratings for the retail performance factors. Using substantive validity, factors relevant for study were filtered. Here, every factor having a cutoff value >0.5 were retained. Out of the 145 attributes identified from literatures, 80 attributes related to retail operations were short-listed (Chen et al., 2021; Sreedharan et al., 2018). Similar approach was carried out for enablers and criteria, leading to seven enablers: 24 criteria and 80 attributes for final evaluation. Substantive validity was carried by team of professional consisting of PG student from Canada; two professors from Morocco; one retail merchandiser from Morocco; and one doctor from France.

Using enabler, criteria, and attributes, questionnaires were developed and sent to target population using modified total Dillman's approach (Persis et al., 2021; Sreedharan et al., 2018). The data collection focused on the following respondent’s profile:

- Full-time students from an international university. Most of them do not have a stable income and are working on their bachelor's graduating project. Their age range is between 20 and 25 years old. Study recorded their opinion as retail customers’ points of view because they all claim to be costumers of either physical or online retail shops (Ibidunni et al., 2020; Liu et al., 2021).
- Retail shop owners mainly focusing on essential items such as perishable products and medicines. These are people between 24 and 60 years old. They have a significant income for prime shopping location in Morocco. Their perspective and opinions are salient and relevant for research as they had firsthand experience with COVID-19 outbreak. Further, chosen members exhibited a significant knowledge about COVID-19 impact on Moroccan retail industry, which facilitated in developing decision-making model.
- As a matter of fact, it is necessary to target respondents with credible and relevant data for evaluating the retail operations. Therefore, 50 respondents were chosen as the target sample for the study, which was finalized using the Kendall coefficient (0.74).

#### 3.3 Data analysis

**3.3.1 Phase 1: Fuzzy evaluation model**

For the development of the evaluation model, seven enablers are identified, followed by 24 criteria and 80 attributes for retail operations in the COVID-19 outbreak (Fisher et al., 2000; Ibidunni et al., 2021; Sreedharan et al., 2019). Seven enablers have measured the retail performance index: consumer analysis, retail shops, government policy, luxury brands, financial performance, supply chain, and post-era COVID-19. These attributes are evaluated and rated by experts from retail operations in Morocco. To calculate the present performance of retail operations, a fuzzy logic model (refer to Appendix A.1) was used (Lin, Chiu, & Tseng, 2006; Vaishnavi & Suresh, 2020)

- Step 1: Identification of the enablers, criteria, and attributes of retail operations for essential items in COVID-19 pandemic done through experts' opinions (validated using substantive validity) to understand the factors that influences the retail operations for essential items and how to manage it efficiently during the COVID-19 pandemic. (Appendix A.1).

- Step 2: Assessment using fuzzy linguistic scale. The linguistic scale and corresponding fuzzy numbers represent the enablers’ importance; criteria and attributes are captured using fuzzy linguistic scale. The rating of the current retail operations is caught on a linguistic scale from target populations involved in the direct retailing in Morocco. The mode is used to combine the expert’s opinion for retail performance rating and weightage, and it is captured in Appendix A.2.

- Step 3: To calculate the fuzzy rating along with aggregated weights using the Equations (1) and (2), respectively (Vaishnavi & Suresh, 2020).

\[
M_{ij} = \sum_{k=1}^{K} \frac{(N_{ik} \otimes M_{ik})}{\sum_{k=1}^{K} N_{ik}} \tag{1}
\]

\[
M_{j} = \sqrt{\frac{\sum_{i=1}^{I} (N_{ij} \otimes M_{j})}{\sum_{i=1}^{I} N_{ij}}} \tag{2}
\]

Once criteria rating is obtained, next step is computing fuzzy retail performance index (FRPI) calculated by Equation (3).

\[
FRPI = \frac{\sum_{i=1}^{I} (N_{i} \otimes M_{i})}{\sum_{i=1}^{I} N_{i}} \tag{3}
\]

The FRPI is calculated using Equations (1-3) for retail operations in Morocco and its captured in Table 1.

- Step 4: Match the FRPI (refer to Appendix A.4) with the corresponding fuzzy interval, using a Euclidean distance method. The perceived closeness value of Euclidean distance is the appropriate fuzzy interval. Table 2 represents retail performance level in natural language expression and its respective fuzzy interval. The Euclidean distance is calculated by Equation (4).

\[
D(FRPI, RPL_{i}) = \sqrt{\sum_{i=1}^{I} (FRPI(x) - RPL_{i}(x))^{2}} \tag{4}
\]
The Euclidean distance method helps to convert FRPI into linguistic term and its computed using Equation (4). The steps of Euclidean distance computation are shown below.

\[
D(FRPI, E) = \sqrt{(4.49 - 7)^2 + (5.9 - 8.5)^2 + (7.27 - 10)^2} = 4.52
\]

\[
D(FRPI, H) = \sqrt{(4.22 - 5.5)^2 + (5.9 - 7)^2 + (7.27 - 8.5)^2} = 1.92
\]

\[
D(FRPI, A) = \sqrt{(4.16 - 3.5)^2 + (5.74 - 5)^2 + (7.27 - 6.5)^2} = 1.55
\]

\[
D(FRPI, L) = \sqrt{(4.12 - 1.5)^2 + (5.9 - 3)^2 + (7.27 - 4.5)^2} = 5.01
\]

\[
D(FRPI, P) = \sqrt{(4.49 - 0)^2 + (5.9 - 1.5)^2 + (7.27 - 3)^2} = 7.6
\]

Thus, linguistic label is matching with minimum of D value, the retail performance index of Morocco is known as “Average,” and its pictorial representation is shown in Figure 2.

From Step 4, the current retail performance index is found to be average. Also, many attributes have been found to be a poor contributor to retail performance (refer to Appendix A.3). Through, fuzzy ranking using crisp formula can be used. However, fuzzy-based ranking cannot compare the attributes pairwise to maximize the retail performance index, and setting thresholds is a subjectivity to the management (Sreedharan et al., 2018). Therefore, there exists an ambiguity in classifying attributes, criteria, and enablers as very weak, weaker, and stronger. In such a scenario, the graph-theoretic approach can be applied to pairwise comparisons and the unification of variables into
three distinct groups. Also, GT creates a better understanding of the ambiguous factors to predict and enables in developing an exit strategy for BSE.

3.3.2 | Phase 2: GT assessment model

GT method is a systematic and logical modeling approach to analyze interdependence among factors and rating of the assessment problem (Kaur et al., 2006; Rao & Gandhi, 2002). The GT provides the consolidated index for the entire assessment problem, that is, permanent value (Baykasoglu, 2014; Dev et al., 2014). The index value was obtained by calculating the permanent function of the input matrix (Anand & Kodali, 2010; Kavilal et al., 2018). This study analyzes the very weak attributes, weaker attributes, and vital attributes to identify triggering attributes using sensitivity analysis. To achieve this, there are four steps (refer to Appendix A.5).

**Very weak scenario**

Very weak (VW) attributes have been identified from the FPII. The objective of the GT application is to identify the triggering attributes among VW attributes to improve the overall retail performance level. The management can focus on these triggering attributes to enhance their performance. The current practice case of interrelationships among VW attributes and ratings of VW attributes are captured using Equation (A1). The ideal case of VW attributes is captured using Equation A2. The resultant relative index of the current practice case, relative sensitivity index, and ranking of triggering attributes are shown in Table 3.

Based on this, VW attributes result indicates that the most critical attribute are supermarkets as “high-risk” sites (A 222), subsequent domestic and international trade transactions changes (A 611), and then elimination and reduction of costs (A 513). If the management focuses on these VW attributes, they can improve their performance level. Similar approach was used to analysis other scenario. They are as follows.

| Case                                | Permanent index | Log10 of permanent | Relative index | Rank of RSI |
|-------------------------------------|-----------------|--------------------|----------------|-------------|
| Current practice case of VW attributes | 30288008177     | 10.48127           | 0.950896       | -           |
| Ideal case of VW attributes         | 105321583750    | 11.02252           | 1              | -           |
| Sensitivity analysis of attribute A 222 | 38524671097     | 10.58574           | 0.960374       | 1           |
| Sensitivity analysis of attribute A 511 | 34351937325     | 10.53595           | 0.955857       | 4           |
| Sensitivity analysis of attribute A 513 | 34909687873     | 10.54295           | 0.956492       | 3           |
| Sensitivity analysis of attribute A 532 | 33185736261     | 10.52095           | 0.954496       | 8           |
| Sensitivity analysis of attribute A 534 | 33587387232     | 10.52618           | 0.95497        | 6           |
| Sensitivity analysis of attribute A 611 | 35851554779     | 10.55451           | 0.957541       | 2           |
| Sensitivity analysis of attribute A 614 | 33183529781     | 10.52092           | 0.954494       | 9           |
| Sensitivity analysis of attribute A 622 | 33351509237     | 10.52312           | 0.954693       | 7           |
| Sensitivity analysis of attribute A 741 | 33831022297     | 10.52932           | 0.955255       | 5           |

**Weaker scenario**

Weaker (W) attributes have been identified from the FPII. The objective of the GT application is to identify the triggering attributes among W attributes to improve the overall outcome performance level. The management can focus on these triggering attributes to enhance their performance. The W attributes result indicates that the most critical attribute is an economic recovery (A 711), next financial recovery (A 742) and then buying patterns (A 115). If the management focuses on these W attributes, they can improve their performance level.

**Stronger scenario**

Strong (S) attributes have been identified from the FPII. The objective of the GT application is to identify the triggering attributes among S attributes to improve the overall outcome performance level. The management can focus on these triggering attributes to enhance their performance. The S attributes result indicates that the most triggering attribute is inventory value (A 634), subsequent mobile inventory management (A 633) and then age (A 111). If the management focuses on these S attributes, they can improve their performance level. Using the GT approach, the study has developed an exit strategy with three different scenarios to accommodate volatile decision making for BSE. However, to make the decision-making model more robust, the model needs to consider variability in decision making as well as to accommodate the “hard to foresee” scenario. Considering this, the study has employed ML-based prediction to make the model more robust and address variability in decision making.

3.3.3 | Phase 3: Developing an MLBPM

The study explored the current situation and developed different strategies for retail operations based on the above analysis. However, the research needs to examine the possibility of the retention of more customers (Al-Dhaen et al., 2021; Wang et al., 2020). To achieve this, the study needs to identify critical factors that can influence customer retention. Therefore, the study used MLBPM to consider variability
and nonlinearity in decision making for hard-to-predict scenarios. Among different algorithms widely used for intelligent predictive analytics, the study preferred random forest and ANN, as it is commonly adopted in decision-making models due to its minimum computing time with better accuracy for prediction model (Galli, 2020; Manimuthu, Venkatesh, et al., 2021; Persis et al., 2021). Using random forest, an ensemble technique that fits the regression line after generalizing with multiple decision trees developed from the subsamples drawn from the training dataset was used to obtain a reduced regression model. Further, random forest employs a nonparametric method of developing an ensemble of decision trees from a random selection of dimensions and bagged instances of the training dataset. Here, high dimensions in the model will reduce the performance of the ANN-based prediction method. Hence, it is essential to eliminate redundant and insignificant features from the model. Random forest algorithm computes the importance of parts based on variance reduction for every decision tree. The final significance of features will be the average values obtained from all trees (Ali et al., 2020). The importance of factors and the reduced model consisting of significant factors are listed in Appendix A.6.

The reduced regression model for customer retention in retail operation is further used to develop an ANN-based prediction model. This study used a resilient backpropagation neural network with a hyperbolic tangent function to predict customer retention. Resilient backpropagation learning follows an adaptive strategy to choose an appropriate learning rate by itself and helps develop faster convergence and develop an efficient regression model. The network has an input layer having nodes equal to the number of factors in the reduced model. Each instance from the training dataset has been given to the input layer, and the value activates certain nodes in the hidden layer. Here in this study, after repeated runs, one hidden layer with three nodes can develop a regression model with a high convergence rate (minimum steps) and high-performance measures. The output layer has one node to yield the predicted value (refer to Figure 3).

For every instance in the training dataset, the deviation of the expected value from the actual value is backpropagated locally to

![Figure 3 ANN-based classification for customer retention.](image-url)
update the weights between nodes between two adjacent layers. The resultant network topology is presented in Figure 3. The nodes in the hidden layers are activated based on the nonlinear fitness function evaluated to take a value between −1 and +1. The test datasets are used to validate the model and hence developed using ANN, and the deviation of values from the actual is used to calculate various performance measures (error statistics) such as MAE, MSE, RMSE, and MAPE values as follows:

| ANN-based prediction of consumer retention |
| MAE | MSE | RMSE | MAPE |
|-----|-----|------|------|
| 22  | 36  | 6    | 5.785714 |

Besides, resilient backpropagation network is validated using K-fold cross validation and cross-validation error (refer to Table 4). This method is used to select the prediction model that best generalizes to obtain customer retention values in the problem domain based on the cross-validation error obtained from the network.

4 | DISCUSSION OF FINDINGS

To determine the current and future situation of retail industry and its operations during COVID-19 outbreak, a fuzzy evaluation technique was developed based on enablers, criteria, and attributes. A similar study was proposed by Abdel-Basset et al. (2021) in the healthcare setting for disruptive events. However, the study focused on the process and did not evaluate the BST. So, the present study assessed the BST and was tested by retailers and millennials based mainly in Morocco.

Mainly, the study explored the dimension of retailing such as forecast; speed; inventory plan; and data accuracy in BSE. To achieve this, the study used an approach involving fuzzy logic (to measure the current performance of retail operations), GT (to develop an exit strategy for retail operations based on different scenarios), and ANN and random forest-based prediction model with K-cross validation (to predict customer retention for retail operations). Findings proved that during the COVID-19 crisis, the retail sector was operating in the average situation. Therefore, to improve the retail performance level, businesses should work on some specific attributes for retail operations. The FPII values highlight the relationship between all these factors. As a result, areas of improvement for retail operations are found. They are as follows:

- The first scenario shows that “supermarkets as ‘high-risk’ sites” “domestic and international trade transactions changes” and “Elimination and reduction of costs” are the most triggering very weak attributes.
- The second scenario indicates that “economic recovery,” “financial recovery,” and “buying patterns” are the most triggering weak attributes.
- The third scenario shows that “inventory value,” “mobile inventory management,” and “age” are the most triggering strong attributes.

Further, to minimize the absence of reference model, graph-theoretic approach was used to develop an exit strategy. All the factors were evaluated and categorized as very weak attributes, weak attributes, and strong attributes. Using these attributes, the study can predict the demand well and avoid phantom inventory. Further, early sales data can be captured using these exit strategies for better sales forecast. They are follows:

- First, the strong attributes are age, education, data privacy and data sharing, border lockdown, tackling misinformation and disinformation online, closing physical shops, moving events and sales online, donations, launching companies, fast service, mobile inventory management, and inventory value. All of these are favorable attributes, so retailers do not have much to do, expect keeping the same quality of work and the same way they deal with the circumstances and some of these attributes.
- Second, buying patterns, lockdown and social distancing, economic recovery, financial recovery, most bought items, developing new habits during the COVID-19 period, shift from physical to online shopping, ensuring core product availability to service demand, digital tools to enable public participation, and domestic suppliers are weak attributes that retail businesses should not neglect during and after the crises; they should take them into consideration in order to survive and overcome the critical situation caused by the pandemic.
- Lastly, retailers should priorities and capitalize on developing, improving, and sustaining the very weak attributes, which are domestic and international trade transactions changes, generating and maintaining liquidity, supermarkets as “high-risk” sites, purchase power of consumers and suppliers, elimination and reduction of costs, managing funds, inventory value, and an increased demand and purchasing power.

Here, the first and second scenarios manifest the poorly performing areas that should be improved for better sales forecast. Further, pandemic is significantly affecting the retail industry, especially in the following areas calling for better inventory planning:

4.1 | Supermarkets as “high-risk” sites

Supermarkets are the common and most popular retail shops because always, they are the destination of all kinds of customers. As a result, they are in general considered to be crowded spaces. Furthermore,
during the crisis, supermarkets are still playing a huge role and are still the principal stop for many buyers. However, because of the nature of the crises, the situation inside the markets is complicated, and the shopping experience can turn out to a nightmare. In addition, some customers do consider supermarkets as “high-site” sites that threaten their lives; as a result, they would either not shop at all in them or spend very short time inside them. That can cause a considerable loss for supermarkets as customers would not be exposed to all the choices provided by the retailers. Supermarket owners should focus on innovative ideas as the drive-through concept or move to online retailing to overcome this issue.

4.2 | Domestic and international trade transactions changes

At the beginning of the crises, there were plenty of transaction changes that negatively impacted the retail industry. Travel restrictions have had a significant impact on transactions, especially in the marketing phase, because marketers usually prefer face-to-face meetings to be able to build strong relationships with potential clients. For instance, in Morocco, there is a total ban for entering or leaving the country. Also, due to the uncertainty of the global industry’s future, numerous businesses lost some important international deals and clients. To overcome this matter, the business can refocus on the national transactions, improving the retailer’s situation and the whole country’s economy.

4.3 | Elimination and reduction of costs

Companies are struggling to adapt to the situation. For instance, some companies were obliged to lay off employees. Other companies started closing their international physical shops as the fast-fashion giant ZARA closing around 1200 stores around the world and is willing to pivot more aggressively toward selling online. So, once again, moving to sell online is the best possible option to overcome the negative impacts of the crises.

4.4 | Economic recovery

COVID-19 is having a crucial impact on economic activity and jobs and worser than past recession in the past. The recovery depends on whether the situation aggravates previous financial fragilities and vulnerabilities. The recovery can take either the “V,” “W,” “u,” or “L” shapes. “V” is the most optimistic one (Canuto, 2020). “How shaped will the post-coronavirus economic recovery be?” As we still are at the heart of the coronavirus crisis, it is still early to determine any specific shape of recovery as predominant anywhere; however, respondents assume that it will be negative, so it will probably take either the “w” or “L” shape.

4.5 | Financial recovery

A lot of businesses are experiencing financial downfall during the COVID-19 crisis. The go back to their previous economic level companies should put more efforts by adopting the following practices: to effectively communicate to stakeholders, to develop solid and robust business continuity plans, to understand government priorities and policies, to adopt incident management and scenario plans, and finally to map the economic impact.

4.6 | Buying patterns

All in all, necessities play an enormous role in consumers’ lives during the pandemic, so retailers should consider that. Retailers should keep the way they deal with the vital attributes. Respondents felt inventory value as a strong one. Inventory value has to do with the determination of the cost of unsold inventory. The own experience of the respondents can explain that in detail. However, to boost customer safety in retail operations and get accurate data, we needed to have better data collection using contactless mechanism. Nowadays, payment gateways are developed to ease the operations to both the consumers and the retail owners in real time. Many contactless payment modes are developed and deployed in the stores for smooth payment processes. Scalability and adaptability of these resources depends on the infrastructure support offered by the agencies. During the pandemic situations, these methods of payments have enhanced user access and provide solid customer engagement (Manimuthu, Venkatesh, et al., 2021). Most of the customized payment modes include their own application interfaces that provides offers, cash back discounts, and promotional vouchers to attract their consumers to use their application. There are few other contactless payment systems that use retail infrastructures with minimum customizations because of their modularity in operations. Data centers and local storages are also added as custom package when their subscription is requested for long term.

Some of the commonly available contactless payment systems use near-field communication (NFC), bar code, radio-frequency identification (RFID) tags, and holograms for their payment purposes. They provide unilateral consumer engagement and delivers instant payment response once the transactions are initiated/completed. Almost all the modern world transactions are done via digital platforms, and most of them use encryptions for safe payment. Bitcoins and various other cryptocurrencies are being accepted as payments, and their wallets are added in the cloud servers (Manimuthu et al., 2019). Almost many retail platforms accept touchless digital payment methods that help the customers to pay their bill on the go. From ticket bookings to patient’s health-care bills, all the transactions now transformed into digital payments, thereby making every movement accountable (refer to Figure 4).
CONCLUSION

The study focused on understanding the retail operations in the COVID-19 crisis and develop a decision-making model for BSE. Further, to test the theory of BSE, the study used a novel approach by integrating (1) fuzzy-based evaluation model, (2) a GT assessment model, and (3) ANN-based prediction model. The study chose the determining factors and operations that are linked directly or indirectly to retail operations. These factors are classified under the following enablers: consumers’ factor, retail stores, technology, brand image, and the COVID-19 era and post era. It is extremely important to have enough knowledge about these factors to perform effectively and efficiently in the retail industry during the pandemic crisis. This step helped build a basis for the following stage of the research: It is a major and determining one. The study aimed to determine the areas of improvement of the retail operations during the crisis. To do that, the study used fuzzy logic to see the current readiness and GT to see the relationship between the factors and prediction for customer retention through ANN-based modeling. The findings were interesting as we ended up with three significant enablers that formed a scope of growth for retail operations, which are supermarkets as high-risk sites, domestic and international trade transactions changes, and elimination and reduction of costs. Accordantly, the most common solutions to be adopted by retailers in the point of view of Moroccan respondents were focusing on e-commerce, the adoption of technologies, and keeping up with new trends as they drive-through concept or mobile inventory management. Luckily for the retail industry and thanks to its nature, it was not dramatically impacted by the COVID-19 crisis. Consumers always needed to buy different items even during the pandemic; however, the nature of their purchases has changed. Therefore, retailers responded to consumers’ demands and perform effectively in managing their retail operations. Consequently, it has become mandatory for business owners to be prepared for such BSE in the future.

5.1 Theoretical contribution

This study has the following theoretical contributions. Firstly, the study used an integrated approach of fuzzy logic, GT, and ANN for BSE to make it a unique contribution to management journals for the “hard to foresee” scenario. Secondly, the study proposed a framework for retail operations to faces the dynamics in retail operations during disruptive events and thereby contribute to the marketing journals. Thirdly, the deliberations define the actions that retailers should adopt to manage their operations in the COVID-19 crisis through the exit strategy. Fourth, the study used random forest and ANN for prediction modeling, where random forest identifies the best features and ANN predicts the impact on the dependent variable (customer retention), making its unique approach for measuring customer retention. Besides, the study serves as a reference model for retail operations literature during disruptive events, which is first of its nature. Moreover, the work explores three tenets of BST and evaluates them for retail operations. Further, the research serves as a reference model/framework for a given problem. It leads to the understanding issues that are likely to occur and ambiguous to predict for customer retention. Finally, the study put forth a decision-making model for “hard to foresee” scenario to model the uncertainty in retail operations, thereby addressing the tenets of BST.

5.2 Practical implication

The findings have notable practical implications for managers. Initially, the fuzzy evaluation technique enabled retail owners to spot areas of development regarding retail operations. Thanks to this technique, shop owners can deploy it with ease without the investment cost for measuring business excellence. Next, findings from GT suggest retailer’s road map to their operations in general to survive and
overcome the current crisis caused by the global pandemic. Further, the study developed a predictive model for customer retention in disruptive times, which can be adopted by any retail shop for business continuity during pandemic. Moreover, respondents consider supermarkets as high-risk sites where they can easily be contaminated. Therefore, retailers should take all the necessary precautions, such as imposing social distancing, wearing face masks, and using sanitizers more frequently. The second area of improvement and scope of growth is the elimination and reduction of costs. Respondents considered this attribute as a drag factor during the crisis. As a result, retail owners must reduce the costs as much as possible and consider some potential actions as licensing employees, closing physical shops, and moving to e-commerce. Regarding the negative aspect of international trading, the study found that retailers have started focusing more on national trading, which can positively impact the country.

5.3 | Societal implication

Thanks to this study, retail owners can deploy the decision-making model with ease without much of investment cost for measuring business excellence. Next, findings from GT suggest retailer’s road map to their operations in general to survive and overcome the current crisis caused by the global pandemic. Further, the study developed a predictive model for customer retention in disruptive times, which can be adopted by any retail shop for business continuity during pandemic. Finally, the study captures the best business practices of the shop owner who retained their customer during the pandemic. Also, the study developed a contactless payment system using NFC for customer safety and hygiene.

5.4 | Limitations and future scope

The study has a few limitations. The framework can only be used on a timely basis to help retail managers to improve their operational performance during a disruptive event. To enhance its capability, historical data along with a data repository are needed for frequent evaluation. Also, knowing very weak, weaker, and strong attributes in retail operations from COVID-19 perspective, the study can provide an exit strategy for retail managers for uncertain situation. However, the study was not classified into specific products segments. So, future studies on nonessential products to refine the proposed model. The proposed model focused on customer retention, which needs to be extended to constructs of operations such as supply disruptions risk mitigation and supplier liquidity and finance in the context of buyer-supplier collaboration. Besides, the study has developed an exit strategy for retail operations. If the data size can be increased for a particular industry, future work can develop “firefighting” strategies, which is need of the hour. Finally, shop owners’ sample was limited to privacy and data sharing-related issues. So, future studies can link Ethereum for data collection and analysis with blockchain for better data protection. For predicting customer retention, the study used ANN (MAPE = 5.785), which can be enhanced using XGB and deep learning to see the factors that influence the customer retention pattern. Also, the study proposed model for deployment in retail operations can be extended to develop customer dashboard and web hosting of the model as a decision-making model for retail operations. Finally, the research used GT to foresee an exit strategy that can be supplemented by more robust studies using game theory to classify scenarios accordingly. Finally, the issues related to phantom inventory are common due to data inaccuracy. So, contactless payment can be deployed to study these phenomena in detail in retail shops.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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# APPENDIX A

## A.1 Evaluation model for retail operations

| Enablers               | Criteria                        | Attributes                                                |
|------------------------|---------------------------------|-----------------------------------------------------------|
| Consumer analysis      | Consumers profile (A11)         | Age (A111)                                                |
|                        |                                 | Education (A112)                                          |
|                        |                                 | Lifestyle (A113)                                          |
|                        |                                 | Place of stay (A114)                                     |
|                        |                                 | Buying patterns (A115)                                    |
|                        |                                 | Creditworthiness (A116)                                   |
|                        |                                 | Purchase history (A117)                                   |
|                        | Preferences (A12)                | Most bought items (A121)                                  |
|                        |                                 | Preference in the retail channel (A122)                  |
|                        |                                 | Interest in new kind of products (A123)                  |
|                        | Consumer habits and trends (A13)| Developing new habits during the COVID-19 period (A131)  |
|                        |                                 | Shift from physical to online shopping (A132)            |
|                        |                                 | Major emotions during the period (A133)                  |
|                        | Consumer psychology (A14)       | Purchasing enthusiasm (A141)                               |
|                        |                                 | Concerns about the impact of the pandemic (A142)         |
|                        |                                 | Mental well-being (A143)                                  |
|                        |                                 | Vulnerability (A144)                                     |
| Retail shops (A2)      | E-commerce (A21)                | Rating of the online experience (A211)                    |
|                        |                                 | Data privacy and data sharing (A212)                     |
|                        |                                 | Data sharing and security (A213)                          |
|                        |                                 | The ease of finding products (A214)                      |
|                        | Physical retailing (A22)        | Rating of the physical retailing experience (A221)       |
|                        |                                 | Supermarkets as “high-risk” sites (A222)                 |
|                        |                                 | Management of store traffic (A223)                       |
|                        | Information sharing (A23)       | Safety measures (A224)                                    |
|                        |                                 | Store efficiency (A225)                                   |
|                        | Suppliers and clients (A24)     | Marketing tools and practices (A231)                     |
|                        |                                 | Delivering information through different channels (e.g., social medial, emails, or websites) (A232) |
|                        | Government policy (A3)          | Lockdown and social distancing (A311)                    |
|                        | Government assistance (A31)     | Travel and mobility restrictions (A312)                  |
|                        |                                 | Border lockdown (A313)                                    |
|                        |                                 | Governmental aid programs (A314)                         |
|                        | Transparency (A32)              | Building trust between government and citizens (A321)    |
|                        |                                 | Sharing proactive information (A322)                     |
|                        |                                 | Tackling misinformation and disinformation online (A323) |
|                        | Digital performance (A33)       | Digital tools to enable public participation (A331)       |
|                        |                                 | Offering open data and enabling public participation (A332)|

(Continues)
| Enablers                      | Criteria                | Attributes                                      |
|------------------------------|-------------------------|-------------------------------------------------|
| Branding (A4)                | Brand loyalty (A41)     | Customer retention (A411)                       |
|                              |                         | Product innovation (A412)                      |
|                              |                         | Closing physical shops (A413)                  |
| Corporate social responsibility (CSR) (A42) | Moving events and sales online (A421) | Donations (A422)                               |
|                              |                         | Launching campaigns (A423)                     |
| Communication (A43)          |                         | Convey positive brand image (A431)             |
|                              |                         | Keep in touch with customers (A432)            |
| Financial performance (A5)   | Financial health (A51)  | Purchase power of consumers and suppliers (A511) |
|                              |                         | Credit and financing (A512)                    |
|                              |                         | Elimination and reduction of costs (A513)      |
|                              | Managing profitability (A52) | Portfolio management (A521)                 |
|                              |                         | Domestic suppliers (A522)                      |
|                              | Funds (A53)             | Indebtedness (A531)                            |
|                              |                         | Managing funds (A532)                          |
|                              |                         | Generating and maintaining liquidity (A534)    |
| Supply chain (A6)            | Disruption (A61)        | Domestic and international trade transactions changes (A611) |
|                              |                         | Supply shock (A612)                            |
|                              |                         | Demand shock (A613)                            |
|                              |                         | Inventory depletion (A614)                     |
|                              |                         | Shipping capacity (A615)                       |
|                              | Shipping (A62)          | Shipping regulations (A621)                    |
|                              |                         | An increased demand (A622)                     |
|                              | Delivery (A63)          | Online delivery (A631)                         |
|                              |                         | Fast service (A632)                            |
|                              |                         | Mobile inventory management (A633)             |
|                              |                         | Inventory value (A634)                         |
| Post era COVID-19 (A7)       | Previsions (A71)        | Economic recovery (A711)                       |
|                              |                         | Sales previson (A712)                         |
|                              | Recommendations (A72)   | New trends and transition (A713)               |
|                              |                         | Adaptation to the future situation (A721)     |
|                              |                         | Breakthrough innovation (A722)                |
|                              |                         | IT and technology (A723)                       |
|                              |                         | Changing consumer habits (A724)                |
|                              | Consumer's perception (A73) | Valuing safety (A731)              |
|                              |                         | Essentialism (A732)                           |
|                              | Financial health (A74)  | Purchasing power (A741)                        |
|                              |                         | Financial recovery (A742)                      |
| Enablers | Criteria | Attributes | Fuzzy performance weight | Fuzzy performance rating |
|----------|----------|------------|--------------------------|-------------------------|
| A1       | A 11     | A 111      | (0.2,0.35,0.5)           | (3,5,7)                 |
|          |          | A 112      | (0.2,0.35,0.5)           | (3,5,7)                 |
|          |          | A 113      | (0.7,0.8,0.9)            | (3,5,7)                 |
|          |          | A 114      | (0.7,0.8,0.9)            | (3,5,7)                 |
|          |          | A 115      | (0.85,0.95,1)            | (3,5,7)                 |
|          |          | A 116      | (0.7,0.8,0.9)            | (3,5,7)                 |
|          |          | A 117      | (0.85,0.95,1)            | (8.5,9.5,10)            |
| A 12     |          | A 121      | (0.85,0.95,1)            | (5,6.5,8)               |
|          |          | A 122      | (0.85,0.95,1)            | (8.5,9.5,10)            |
|          |          | A 123      | (0.85,0.95,1)            | (7,8,9)                 |
|          |          | A 131      | (0.85,0.95,1)            | (5,6.5,8)               |
|          |          | A 132      | (0.85,0.95,1)            | (5,6.5,8)               |
|          |          | A 133      | (0.5,0.65,0.8)           | (2,3,5,5)               |
|          |          | A 141      | (0.5,0.65,0.8)           | (3,5,7)                 |
|          |          | A 142      | (0.5,0.65,0.8)           | (3,5,7)                 |
|          |          | A 143      | (0.7,0.8,0.9)            | (3,5,7)                 |
|          |          | A 144      | (0.7,0.8,0.9)            | (7,8,9)                 |
| A 21     |          | A 211      | (0.7,0.8,0.9)            | (7,8,9)                 |
|          |          | A 212      | (0.3,0.5,0.7)            | (5,6.5,8)               |
|          |          | A 213      | (0.5,0.65,0.8)           | (3,5,7)                 |
|          |          | A 214      | (0.5,0.65,0.8)           | (5,6.5,8)               |
| A 22     |          | A 221      | (0.7,0.8,0.9)            | (2,3,5,5)               |
|          |          | A 222      | (0.85,0.95,1)            | (2,3,5,5)               |
|          |          | A 223      | (0.7,0.8,0.9)            | (7,8,9)                 |
|          |          | A 224      | (0.85,0.95,1)            | (7,8,9)                 |
|          |          | A 225      | (0.7,0.8,0.9)            | (3,5,7)                 |
| A 23     |          | A 231      | (0.5,0.65,0.8)           | (5,6.5,8)               |
|          |          | A 232      | (0.85,0.95,1)            | (7,8,9)                 |
|          |          | A 233      | (0.7,0.8,0.9)            | (7,8,9)                 |
| A 24     |          | A 241      | (0.7,0.8,0.9)            | (7,8,9)                 |
|          |          | A 242      | (0.7,0.8,0.9)            | (7,8,9)                 |
|          |          | A 243      | (0.85,0.95,1)            | (5,6.5,8)               |
|          |          | A 244      | (0.7,0.8,0.9)            | (3,5,7)                 |
| A 31     |          | A 311      | (0.85,0.95,1)            | (3,5,7)                 |
|          |          | A 312      | (0.3,0.5,0.7)            | (3,5,7)                 |
|          |          | A 313      | (0.3,0.5,0.7)            | (7,8,9)                 |
|          |          | A 314      | (0.7,0.8,0.9)            | (7,8,9)                 |
| A 32     |          | A 321      | (0.5,0.65,0.8)           | (3,5,7)                 |
|          |          | A 322      | (0.5,0.65,0.8)           | (7,8,9)                 |
|          |          | A 323      | (0.3,0.5,0.7)            | (5,6.5,8)               |
| A 33     |          | A 331      | (0.85,0.95,1)            | (5,6.5,8)               |
|          |          | A 332      | (0.7,0.8,0.9)            | (5,6.5,8)               |
| A 41     |          | A 411      | (0.7,0.8,0.9)            | (2,3,5,5)               |
| Enablers | Criteria | Attributes | Fuzzy performance weight | Fuzzy performance rating |
|---------|----------|------------|--------------------------|-------------------------|
| A 41    | A 412    | (0.7,0.8,0.9) | (3,5,7) |
|         | A 413    | (0.3,0.5,0.7) | (7,8,9) |
| A 42    | A 421    | (0.5,0.65,0.8) | (8.5,9.5,10) |
|         | A 422    | (0.1,0.2,0.3) | (5,6.5,8) |
|         | A 423    | (0.2,0.35,0.5) | (5,6.5,8) |
| A 43    | A 431    | (0.7,0.8,0.9) | (5,6.5,8) |
|         | A 432    | (0.5,0.65,0.8) | (3,5,7) |
| A 5     | A 51     | (0.85,0.95,1) | (2,3,5,5) |
|         | A 512    | (0.7,0.8,0.9) | (3,5,7) |
|         | A 513    | (0.85,0.95,1) | (2,3,5,5) |
| A 52    | A 521    | (0.7,0.8,0.9) | (3,5,7) |
|         | A 522    | (0.85,0.95,1) | (5,6.5,8) |
| A 53    | A 531    | (0.7,0.8,0.9) | (2,3,5,5) |
|         | A 532    | (0.85,0.95,1) | (2,3,5,5) |
|         | A 534    | (0.85,0.95,1) | (1,2,3) |
| A 6     | A 61     | (0.85,0.95,1) | (0,0.5,1.5) |
|         | A 612    | (0.7,0.8,0.9) | (1,2,3) |
|         | A 613    | (0.7,0.8,0.9) | (1,2,3) |
|         | A 614    | (0.85,0.95,1) | (2,3,5,5) |
|         | A 615    | (0.5,0.65,0.8) | (2,3,5,5) |
| A 62    | A 621    | (0.5,0.65,0.8) | (7,8,9) |
|         | A 622    | (0.85,0.95,1) | (2,3,5,5) |
| A 63    | A 631    | (0.85,0.95,1) | (8.5,9.5,10) |
|         | A 632    | (0.3,0.5,0.7) | (5,6.5,8) |
|         | A 633    | (0.2,0.35,0.5) | (3,5,7) |
|         | A 634    | (0.2,0.35,0.5) | (3,5,7) |
| A 7     | A 71     | (0.85,0.95,1) | (3,5,7) |
|         | A 712    | (0.5,0.65,0.8) | (3,5,7) |
|         | A 713    | (0.85,0.95,1) | (7,8,9) |
| A 72    | A 721    | (0.5,0.65,0.8) | (3,5,7) |
|         | A 722    | (0.7,0.8,0.9) | (8.5,9.5,10) |
|         | A 723    | (0.85,0.95,1) | (8.5,9.5,10) |
|         | A 724    | (0.85,0.95,1) | (8.5,9.5,10) |
| A 73    | A 731    | (0.85,0.95,1) | (8.5,9.5,10) |
|         | A 732    | (0.2,0.35,0.5) | (2,3,5,5) |
| A 74    | A 741    | (0.85,0.95,1) | (2,3,5,5) |
|         | A 742    | (0.85,0.95,1) | (3,5,7) |
### A.3 | FPRI for retail performance attributes

Note: **Very weak attributes; *Weaker attributes; #Strong attributes.

| Attributes | Fuzzy performance rating $M_{ijk}$ | $W'_{ijk} = (1,1,1) - W_{ijk}$ | FPII | Crisp score |
|------------|----------------------------------|---------------------------------|------|------------|
| A 111      | (3, 5, 7)                        | (0.80, 0.65, 0.5)               | (2.4, 3.25, 3.5) | 3.15# |
| A 112      | (3, 5, 7)                        | (0.80, 0.65, 0.5)               | (2.4, 3.25, 3.5) | 3.15# |
| A 113      | (3, 5, 7)                        | (0.30, 0.20, 0.1)               | (0.9, 1.07)       | 0.933 |
| A 114      | (3, 5, 7)                        | (0.30, 0.20, 0.1)               | (0.9, 1.07)       | 0.933 |
| A 115      | (3, 5, 7)                        | (0.15, 0.05, 0)                 | (0.45, 0.25)      | 0.241* |
| A 116      | (3, 5, 7)                        | (0.30, 0.20, 0.1)               | (0.9, 1.07)       | 0.933 |
| A 117      | (8.5, 9.5, 10)                   | (0.15, 0.05, 0)                 | (1.275, 0.475)    | 0.529 |
| A 121      | (5, 6.5, 8)                      | (0.15, 0.05, 0)                 | (0.750, 0.325)    | 0.341* |
| A 122      | (8.5, 9.5, 10)                   | (0.15, 0.05, 0)                 | (1.275, 0.475)    | 0.529 |
| A 123      | (7, 8, 9)                        | (0.15, 0.05, 0)                 | (1.05, 0.40)      | 0.442 |
| A 131      | (5, 6.5, 8)                      | (0.15, 0.05, 0)                 | (0.750, 0.325)    | 0.341* |
| A 132      | (5, 6.5, 8)                      | (0.15, 0.05, 0)                 | (0.750, 0.325)    | 0.341* |
| A 133      | (2, 3.5, 5)                      | (0.50, 0.35, 0.2)               | (1.125, 1)        | 1.150 |
| A 141      | (3, 5, 7)                        | (0.50, 0.35, 0.2)               | (1.5175, 1.4)     | 1.650 |
| A 142      | (3, 5, 7)                        | (0.50, 0.35, 0.2)               | (1.5175, 1.4)     | 1.650 |
| A 143      | (3, 5, 7)                        | (0.30, 0.20, 0.1)               | (0.9, 1.07)       | 0.933 |
| A 144      | (7, 8, 9)                        | (0.30, 0.20, 0.1)               | (2.1, 1.6, 0.9)   | 1.567 |
| A 211      | (7, 8, 9)                        | (0.30, 0.20, 0.1)               | (2.1, 1.6, 0.9)   | 1.567 |
| A 212      | (5, 6.5, 8)                      | (0.70, 0.50, 0.3)               | (3.53, 2.5)       | 3.15# |
| A 213      | (3, 5, 7)                        | (0.50, 0.35, 0.2)               | (1.5175, 1.4)     | 1.650 |
| A 214      | (5, 6.5, 8)                      | (0.50, 0.35, 0.2)               | (2.52, 2.75, 1.6) | 2.200 |
| A 221      | (2, 3.5, 5)                      | (0.30, 0.20, 0.1)               | (0.60, 0.70, 0.5) | 0.650 |
| A 222      | (2, 3.5, 5)                      | (0.15, 0.05, 0)                 | (0.30, 0.175)     | 0.166** |
| A 223      | (7, 8, 9)                        | (0.30, 0.20, 0.1)               | (2.1, 1.6, 0.9)   | 1.567 |
| A 224      | (7, 8, 9)                        | (0.15, 0.05, 0)                 | (1.05, 0.40)      | 0.442 |
| A 225      | (3, 5, 7)                        | (0.30, 0.20, 0.1)               | (0.9, 1.07)       | 0.933 |
| A 231      | (5, 6.5, 8)                      | (0.50, 0.35, 0.2)               | (2.52, 2.75, 1.6) | 2.200 |
| A 232      | (7, 8, 9)                        | (0.15, 0.05, 0)                 | (1.05, 0.40)      | 0.442 |
| A 233      | (7, 8, 9)                        | (0.30, 0.20, 0.1)               | (2.1, 1.6, 0.9)   | 1.567 |
| A 241      | (7, 8, 9)                        | (0.30, 0.20, 0.1)               | (2.1, 1.6, 0.9)   | 1.567 |
| A 242      | (7, 8, 9)                        | (0.30, 0.20, 0.1)               | (2.1, 1.6, 0.9)   | 1.567 |
| A 243      | (5, 6.5, 8)                      | (0.15, 0.05, 0)                 | (0.750, 0.325)    | 0.341* |
| A 244      | (3, 5, 7)                        | (0.30, 0.20, 0.1)               | (0.9, 1.07)       | 0.933 |
| A 311      | (3, 5, 7)                        | (0.15, 0.05, 0)                 | (0.45, 0.25)      | 0.241* |
| A 312      | (3, 5, 7)                        | (0.70, 0.50, 0.3)               | (2.1, 2.5, 2.1)   | 2.367 |
| A 313      | (7, 8, 9)                        | (0.70, 0.50, 0.3)               | (4.94, 2.7)       | 3.933# |
| A 314      | (7, 8, 9)                        | (0.30, 0.20, 0.1)               | (2.1, 1.6, 0.9)   | 1.567 |
| A 321      | (3, 5, 7)                        | (0.50, 0.35, 0.2)               | (1.5175, 1.4)     | 1.650 |
| A 322      | (7, 8, 9)                        | (0.50, 0.35, 0.2)               | (3.52, 1.8)       | 2.750 |
| A 323      | (5, 6.5, 8)                      | (0.70, 0.50, 0.3)               | (3.53, 2.5)       | 3.15# |
| A 331      | (5, 6.5, 8)                      | (0.15, 0.05, 0)                 | (0.750, 0.325)    | 0.341* |
| A 332      | (5, 6.5, 8)                      | (0.30, 0.20, 0.1)               | (1.5, 1.3, 0.8)   | 1.250 |

(Continues)
| Attributes | Fuzzy performance rating $M_{ijk}$ | $W_{ijk} = (1,1,1)-W_{ijk}$ | FPII | Crisp score |
|------------|----------------------------------|----------------------------|-----|------------|
| A 411      | (2,3.5,5)                        | (0.3,0.2,0.1)              | (0.6,0.7,0.5) | 0.650      |
| A 412      | (3,5,7)                          | (0.3,0.2,0.1)              | (0.9,1,0.7)   | 0.933      |
| A 413      | (7,8,9)                          | (0.7,0.5,0.3)              | (4,9,4.2)     | 3.933#     |
| A 421      | (8,5,9,5,10)                     | (0.5,0.35,0.2)             | (4,25,3,325.2)| 3.258#     |
| A 422      | (5,6,5,8)                        | (0.9,0.8,0.7)              | (4,5,5,2.5,6) | 5.15#      |
| A 423      | (5,6,5,8)                        | (0.8,0.65,0.5)             | (4,4,22.5,4)  | 4.15#      |
| A 431      | (5,6,5,8)                        | (0.3,0.2,0.1)              | (1,5,1,3,0.8) | 1.250      |
| A 432      | (3,5,7)                          | (0.5,0.35,0.2)             | (1,5,1,75,1.4)| 1.650      |
| A 511      | (2,3.5,5)                        | (0.15,0.05,0)              | (0.3,0.175)   | 0.166**    |
| A 512      | (3,5,7)                          | (0.3,0.2,0.1)              | (0.9,1,0.7)   | 0.933      |
| A 513      | (2,3.5,5)                        | (0.15,0.05,0.5)            | (0.3,0.175)   | 0.166**    |
| A 521      | (3,5,7)                          | (0.3,0.2,0.1)              | (0.9,1,0.7)   | 0.933      |
| A 522      | (5,6,5,8)                        | (0.15,0.05,0)              | (0.3,0,325,0) | 0.341*     |
| A 531      | (2,3.5,5)                        | (0.3,0.2,0.1)              | (0.6,0,7,0.5) | 0.650      |
| A 532      | (2,3.5,5)                        | (0.15,0.05,0)              | (0.3,0,175,0) | 0.166**    |
| A 534      | (1,2,3)                          | (0.15,0.05,0)              | (0.1,0,1)     | 0.091**    |
| A 611      | (0,0.5,1,5)                      | (0.15,0.05,0)              | (0,0.025,0)   | 0.016**    |
| A 612      | (1,2,3)                          | (0.3,0.2,0.1)              | (0,0.4,0.3)   | 0.367      |
| A 613      | (1,2,3)                          | (0.3,0.2,0.1)              | (0,0.4,0.3)   | 0.367      |
| A 614      | (2,3.5,5)                        | (0.15,0.05,0)              | (0.3,0,175,0) | 0.166**    |
| A 615      | (2,3.5,5)                        | (0.5,0.35,0.2)             | (1,1,225,1)   | 1.150      |
| A 621      | (7,8,9)                          | (0.5,0.35,0.2)             | (1,5,2,8,1.8) | 2.750      |
| A 622      | (2,3.5,5)                        | (0.15,0.05,0)              | (0.3,0,175,0) | 0.166**    |
| A 631      | (8,5,9,5,10)                     | (0.15,0.05,0)              | (1,275,0,475,0)| 0.529      |
| A 632      | (5,6,5,8)                        | (0.7,0.5,0.3)              | (3,5,3,25,2.4)| 3.15#      |
| A 633      | (3,5,7)                          | (0.8,0.65,0.5)             | (2,4,3,25,3.5)| 3.15#      |
| A 634      | (3,5,7)                          | (0.8,0.65,0.5)             | (2,4,3,25,3.5)| 3.15#      |
| A 711      | (3,5,7)                          | (0.15,0.05,0)              | (0.45,0,25,0) | 0.241*     |
| A 712      | (3,5,7)                          | (0.5,0.35,0.2)             | (1,5,1,75,1.4)| 1.650      |
| A 713      | (7,8,9)                          | (0.15,0.05,0)              | (1,05,0,4)    | 0.442      |
| A 721      | (3,5,7)                          | (0.5,0.35,0.2)             | (1,5,1,75,1.4)| 1.650      |
| A 722      | (8,5,9,5,10)                     | (0.3,0.2,0.1)              | (2,5,5,1,9.1) | 1.858      |
| A 723      | (8,5,9,5,10)                     | (0.15,0.05,0)              | (1,275,0,475,0)| 0.529      |
| A 724      | (8,5,9,5,10)                     | (0.15,0.05,0)              | (1,275,0,475,0)| 0.529      |
| A 731      | (8,5,9,5,10)                     | (0.15,0.05,0)              | (1,275,0,475,0)| 0.529      |
| A 732      | (2,3.5,5)                        | (0.8,0.65,0.5)             | (1,6,2,75,2.5)| 2.200      |
| A 741      | (2,3.5,5)                        | (0.15,0.05,0)              | (0.3,0,175,0) | 0.166**    |
| A 742      | (3,5,7)                          | (0.15,0.05,0)              | (0.45,0,25,0) | 0.241*     |
A.4  | Notations used for fuzzy logic in retail readiness assessment model

| Indices         | Abbreviations                                      |
|----------------|---------------------------------------------------|
| $M_i$          | Fuzzy importance rating for retail performance of $i$th enabler |
| $M_j$          | Fuzzy importance rating for retail performance of $j$th criterion in $i$th enabler |
| $M_{jk}$       | Fuzzy importance rating for retail performance of $k$th attribute of $j$th criterion in $i$th enabler |
| $N_i$          | Fuzzy importance weight for retail performance of $i$th enabler |
| $N_j$          | Fuzzy importance weight for retail performance of $j$th criterion in $i$th enabler |
| $N_{jk}$       | Fuzzy importance weight for retail performance of $k$th attribute of $j$th criterion in $i$th enabler |
| FRPI           | Fuzzy retail performance index                     |
| $RPL_i$        | Fuzzy number of natural language expression set of retail performance level |
| $IFRPI(x)$     | Triangular fuzzy number of FRPI,                  |
| $IRPL(x)$      | Triangular fuzzy number of RPL,                   |

A.5  | Steps in graph theory

A.5.1  | Development of Matrix to capture respondents input for each factor

The diagonal elements are captured by the consensus of expert ratings of current practices of appropriate attributes. Appendix A.2 depicts the performance rating and weightage of the attributes. The off-diagonal elements represent interrelationships between characteristics and are captured through the consensus of the influence level by expert’s opinion. Then, interrelationships between the attributes depict the scale of the strength of interrelationship between the attributes. In Matrix B (Equation A1), B1 represents the attribute 1 rating in the current practice level. B2 represents the factor 2 rating in the status and so on. The off-diagonal element of Matrix B is the interrelationship between the factors (bij). The b1,2 represents the factor 1 influences in factor 2, and b2,3 represents the factor 2 influences in factor 3.

![Matrix B](image)

\[
\begin{bmatrix}
B_1 & b_{1,2} & b_{1,3} & b_{1,4} & b_{1,5} & b_{1,6} & b_{1,7} & b_{1,8} & b_{1,9} & b_{1,10} \\
b_{2,1} & B_2 & b_{2,3} & b_{2,4} & b_{2,5} & b_{2,6} & b_{2,7} & b_{2,8} & b_{2,9} & b_{2,10} \\
b_{3,1} & b_{3,2} & B_3 & b_{3,4} & b_{3,5} & b_{3,6} & b_{3,7} & b_{3,8} & b_{3,9} & b_{3,10} \\
b_{4,1} & b_{4,2} & b_{4,3} & B_4 & b_{4,5} & b_{4,6} & b_{4,7} & b_{4,8} & b_{4,9} & b_{4,10} \\
b_{5,1} & b_{5,2} & b_{5,3} & b_{5,4} & B_5 & b_{5,6} & b_{5,7} & b_{5,8} & b_{5,9} & b_{5,10} \\
b_{6,1} & b_{6,2} & b_{6,3} & b_{6,4} & b_{6,5} & B_6 & b_{6,7} & b_{6,8} & b_{6,9} & b_{6,10} \\
b_{7,1} & b_{7,2} & b_{7,3} & b_{7,4} & b_{7,5} & b_{7,6} & B_7 & b_{7,8} & b_{7,9} & b_{7,10} \\
b_{8,1} & b_{8,2} & b_{8,3} & b_{8,4} & b_{8,5} & b_{8,6} & b_{8,7} & B_8 & b_{8,9} & b_{8,10} \\
b_{9,1} & b_{9,2} & b_{9,3} & b_{9,4} & b_{9,5} & b_{9,6} & b_{9,7} & b_{9,8} & B_9 & b_{9,10} \\
b_{10,1} & b_{10,2} & b_{10,3} & b_{10,4} & b_{10,5} & b_{10,6} & b_{10,7} & b_{10,8} & b_{10,9} & B_{10,10}
\end{bmatrix}
\]

(A1)

A.5.2  | Interrelationships between the attributes

| Sl. no | Attribute i influencing attribute j | Qualitative measure of interdependencies | Strength of influence ($b_{ij}$) |
|--------|------------------------------------|-----------------------------------------|---------------------------------|
| 1      | Very low (VL)                     | 1                                       |
| 2      | Low (L)                           | 2                                       |
| 3      | Medium (M)                        | 3                                       |
| 4      | Strong (S)                        | 4                                       |
| 5      | Very strong (VS)                  | 5                                       |

A.5.3  | Computation of permanent value/Index

The permanent is a positive determinant of a developed matrix. Permanent computation is complex, and it takes probabilistic polynomial time. The permanent matrix calculation formula for any number of matrixes (Darvish et al., 2009; Kumar et al., 2017) is written as follows (Equation A2).

\[
\text{Per} B = \prod_{i=1}^{M} B_i + \sum_{i=1}^{M-1} \sum_{j=i+1}^{M} \sum_{k=1}^{M-1} \sum_{l=k+1}^{M} \sum_{m=1}^{M-1} \sum_{n=m+1}^{M} (B_{i,j} B_{j,k} B_{k,l} B_{l,m} B_{m,n} B_{n,o} B_{o,p} B_{p,q} + \text{All permutations})
\]

Attributes = $I_j$, ..., $M$, where, last attribute represent as $M$. 
A.5.4 | Relative index

The permanent value is converted in a logarithmic term as $\log_{10}$ (per B), for simple understanding and comparison purposes (Anand et al., 2016). The relative index value is calculated as

$$\text{Relative index value} = \frac{\log_{10} \text{Permanent index value}}{\text{Index ideal value}}$$  \hspace{1cm} (A2)

The ideal index is calculated in the developed matrix (in Step 1), all the diagonal attribute ratings are replaced by the ideal rating value given in Table 1, that is, the maximum/perfect value is 7. Then compute the ideal permanent value by using computation of permanent value.

A.5.5 | Sensitivity analysis

The sensitivity analysis has been conducted for each attribute to identify the triggering attributes. For example, for the first attribute, in the developed matrix, the first diagonal attributes’ actual rating is replaced by the maximum rating, that is, 7, and compute the permanent value of that matrix. Similarly, compute all other attributes for the relative sensitivity index. This relative sensitivity index value outcome is compared with the current level of retail operations relative index value. Then identify and rank the triggering attributes based on the highest relative sensitivity index (RSI) value to the current index value.

A.6 | Y—customer retention using random forest-based feature reduction

After eliminating insignificant features, A1 A5 A6 A8 A9 A11 A12 A14 A15 A16 B4 B5 B12 B13 B15 C2 C5 C7 C8 D3 D5 E1 E2 E3 E7 E8 F1 F2 F4 F5 F6 F7 G1 G2 G3 G4 G6 G7 G10 Y
| Attributes | % mean squared error |
|------------|---------------------|
| A1         | 3.4678              |
| A2         | 1.0680              |
| A3         | 1.9537              |
| A4         | 1.2638              |
| A5         | 2.1092              |
| A6         | 2.1166              |
| A7         | –0.8388             |
| A8         | 3.5398              |
| A9         | 3.3579              |
| A10        | –0.6948             |
| A11        | 3.8376              |
| A12        | 7.8358              |
| A13        | 0.5090              |
| A14        | 4.7837              |
| A15        | 2.7727              |
| A16        | 3.1332              |
| A17        | 1.1492              |
| B1         | 1.1743              |
| B2         | 1.7044              |
| B3         | 1.5726              |
| B4         | 2.0739              |
| B5         | 2.5673              |
| B6         | –1.2740             |
| B7         | –0.2923             |
| B8         | 1.2241              |
| B9         | 0.7926              |
| B10        | –0.7953             |
| B11        | –0.1383             |
| B12        | 3.2748              |
| B13        | 4.3820              |
| B14        | 0.4724              |
| B15        | 5.6320              |
| B16        | 0.8234              |
| C1         | –0.7643             |
| C2         | 5.1398              |
| C3         | –1.3054             |
| C4         | 1.3906              |
| C5         | 2.3588              |
| C6         | 0.4152              |
| C7         | 2.0465              |
| C8         | 0.0268              |
| C9         | 1.5911              |
| D2         | –0.5497             |
| D3         | 2.3108              |
| D4         | 0.9579              |
| D5         | 2.1163              |
| D6         | –0.3477              |

(Continues)
| Attributes | % mean squared error |
|-----------|---------------------|
| D7        | -0.4242             |
| D8        | -0.0317             |
| E1        | 5.5825              |
| E2        | 3.3252              |
| E3        | 4.3084              |
| E4        | 1.3576              |
| E5        | -1.1078             |
| E6        | -0.6209             |
| E7        | 13.7598             |
| E8        | 4.6504              |
| F1        | 3.5976              |
| F2        | 10.1912             |
| F3        | 1.9443              |
| F4        | 15.0677             |
| F5        | 3.4210              |
| F6        | 4.2618              |
| F7        | 4.7308              |
| F8        | 1.0281              |
| F9        | 1.0614              |
| F10       | 1.7776              |
| F11       | 1.7112              |
| G1        | 3.4926              |
| G2        | 2.0579              |
| G3        | 2.7718              |
| G4        | 6.5723              |
| G5        | 1.0809              |
| G6        | 4.2815              |
| G7        | 4.6483              |
| G8        | 0.2184              |
| G9        | 0.9136              |
| G10       | 3.1531              |
| G11       | -1.7422             |
| G12       | 0.4167              |