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DESIGNING THE SMART WAREHOUSE: KEY AUTOMATION CRITERIA FOR SUSTAINABLE AND SCALABLE OPERATIONS

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ABSTRACT

Purpose- Warehouses face challenges due to rising demands for efficient, sustainable, large-scale operations, making automation essential for enhancing processes and reducing costs. This paper compares three automation models LSTM, Prophet, and Logistic Regression that can improve warehouse management, particularly in sales forecasting and reorder prediction.
Methodology- Using actual warehouse sales data from Kaggle, time-series models (LSTM and Prophet) were built for daily sales forecasting and Logistic Regression for reorder quantities on each item. The models evaluated each model's ability to project warehouse sales and determine replenishment timing.
Findings- Results suggest that LSTM provided better forecasting results than Prophet, with lower MSE, RMSE, and MAE values, modelling both short-term volatility and long-term trends. Logistic Regression showed high accuracy and decent precision, though low recall suggests it missed many reorder cases.
Conclusion- While LSTM models can improve decision-making in warehouse management, further development of classification models is essential to enhance reorder prediction accuracy, increase recall, and prevent stockouts.

Keywords: Warehouse management, automation, LSTM, reorder prediction, inventory management, smart warehouses
JEL Codes: M11, C53, O33, L91

1. INTRODUCTION

The rising nature of the operational complexity of supply chains has made it necessary to invest in smart warehouses built on automation (Coito et al., 2021). Smart warehouses are facilities with the purpose of organising work, minimising people's mistakes, and maximising productivity by employing different techniques and technologies, including for the organisation of goods flow and storage (Plakantara et al., 2024). Today, there is pressure for time, an increase in the volume of products transported, and a reduction in operational costs for modern logistics. Moreover, sustainability has emerged as a significant factor since organisations aim to minimise expenditure, rein in expenses, and reduce operating expenses such as wasting energy and increasing general impact on the environment (Khan et al., 2021). Another is scalability since as warehouses' operations scale up other systems, there must also be an increase in scale without compromising on effectiveness.

Technologies in automation, including robotics, IoT, AI, and machine learning, are making changes in conventional warehouses (Dhaliwal, 2020). Robots have specific uses in scaling up repetitive and manual tasks such as picking, packing, and moving goods. IoT facilitates monitoring and tracking of inventory and stock, machinery, and the conditions inside and outside the warehouse in real time (Khan et al., 2022). Machine learning (ML) and AI solutions are being applied to solve prediction of sales, equipment failure, and stock management problems (Khedr, 2024). These technologies combined make up the foundational need for smart warehouses as companies seek to increase efficiency and remain agile. Despite the advancements in automation, many warehouses still need help with three key issues: forecasting capability, stock management, and the effectiveness of reordering choices. Stock forecasting is the most sensitive aspect in order to avoid overstocking or lack of stock in future businesses (Kourentzes et al., 2020). Time management of stock facilitates the correct organisational placement of stocks so that they only take up a little space. Reorder decisions are so crucial in inventories that they can be achieved that they must stick out, but at the same time, they must not overstock (Upadhyay, 2024).

Most prior work has concerned itself with the universal application of automation technologies. Still, very little research has comparatively investigated the performance of various forecasting models to verify the effectiveness of some forecasting models for sales and inventory of warehouse products (Fildes et al., 2022). The majority of prior studies are more concerned with discussing and promoting the use of automation systems. To the authors' best knowledge, there is little research comparing multiple time series forecasting models (including LSTM and Prophet) or decision-making models (such as logistic regression) for reorder prediction (Ahmad et al., 2025). More studies are needed to compare and assess predictive models in regard to warehouse automation. Consequently, more research needs to be done that engages LSTM and Prophet in direct time-series forecasting of warehouse sales. In addition, as for the warehouse environment and prediction of guiding reorder points, logistic regression, usually used in classification tasks, needs to be given adequate attention in research (Liu, 2022). This has made it necessary to undertake a comprehensive comparative analysis of the forecasting and decision-making models in the warehouse environment.

The main focus of this paper is to fill this gap by comparing the LSTM and Prophet models for warehouse sales forecasting, as well as the logistic regression for the reorder point prediction. Warehouse data collected from Kaggle is used in this research to assess the efficiency and reliability of these models to automate primary warehouse functions. In other words, the paper's objectives are as follows: To establish which type of forecasting model, LSTM or Prophet, yields a more accurate sales forecast for warehouses and whether Logistic Regression is useful for anticipating reorder points. This study has important practical implications for companies managing smart warehouses. It becomes important for firms to know which of the models used in forecasting is more reliable in order to improve their decision-making in factors such as stock control, hence enhancing their operations while at the same time slicing costs (Tadayonrad & Ndiaye, 2023).

2. LITERATURE REVIEW

2.1. Automation in Warehousing

Technologies have infiltrated almost every aspect of warehousing and minimised human participation (Shozi, 2021). A key technology is ASRS, with robotics and IoT sensors also being significant (Jie et al., 2024). ASRS makes direct and random storage and access to stored items possible and more efficient, eliminating expatriate labour costs. It will be beneficial for managing extensive stock quantities across expansive warehouses where first accuracy and second speed are paramount. Robotics complement warehousing by automating some crucial tasks such as picking, sorting, and packaging (Merkert et al., 2023). Human employees can operate in partnership with robots like AGVs and robotic arms for different repetitive assignments (Grau et al., 2020), which are likely to be accomplished more efficiently by them.

Smart sensors, through the IoT (Internet of Things), have a crucial function in measuring inventory and monitoring the delivery process, as well as controlling the environment, including the temperature and humidity of stored products (Ding et al., 2021). In its essence, IoT does more than enable continuous collection and analysis of data, which in turn thus assists warehouse managers in the deployment of resources and optimal utilisation of equipment and other aspects related to operations (Kumar et al., 2022). These technologies, along with machine learning algorithms, are basic ones for constructing smart warehouses where technology plays a vital role in getting automated control and data analysis (Van Geest et al., 2021).

2.2. Sustainability in Warehousing

Due to increased awareness of the effect of the natural environment on executive decisions, sustainability issues have now gained significance in warehousing (Hao et al., 2020). The four principles of green and sustainable warehouse management include conserving energy and avoiding wastage while embracing environmental conservation measures. Warehouse lighting and climate control systems, lighting control systems, and other such energy-efficient systems decrease the levels of carbon emission (Füchtenhans et al., 2023). Also, the layout of warehouses and automated operational systems can be optimised to decrease energy use since distances of transport within warehouses can be minimised, thereby decreasing fuel usage and, therefore, emissions. Several measures are observed in the sustainability of a warehousing business; one of them is waste management. AI-driven tools also minimise overstocking, and fewer perishable items are wasted since the goods are moved through the supply chain faster (Şimşek, 2024).

2.3. Time-Series Forecasting in Warehousing

Forecasting plays a crucial role in warehousing since it reflects the prediction of the demand for a specific item (Irhami & Farizal, 2021). On this object, time series forecasting models have a vital role in predicting the sales rates for further periods, controlling the inventory, and devising manufacturing schedules (Tadayonrad & Ndiaye, 2023). Earlier well-known methods, such as ARIMA (Autoregressive Integrated Moving Average), have been used for forecasting using only past data (Rafferty, 2021). This makes ARIMA suitable for short-range forecasting, in particular, because it needs help modelling trends in the data over very long periods. To overcome this limitation of the above models, new models have been developed in recent years, such as Prophet and LSTM models. Obviously, Prophet, furthering from Facebook, can work well with customised data that contain seasonality and missing data that can be desirable in warehouse sales forecasting with cyclical trends (Güler et al., 2023). Certainly, the Prophet works best in cases where the fluctuations are typical for certain seasons, such as in the case of holiday sales; for instance, the model can include external factors, such as holidays and promotions (Tang et al., 2022).

Long short-term memory (LSTM), which is one of the RNNs, is designed to handle temporal data well and, therefore, is the best model for forecasting over longer periods (Vennerød et al., 2021). LSTM is particularly advantageous in dealing with a sequence of data, which is helpful in warehousing since the sequential record of sales is useful in modelling the pattern of demand (Joseph et al., 2022). It excels at this because of its convolution property, which takes into account patterns that span many time steps as opposed to other models such as ARIMA or Prophet.

2.4. Inventory Reordering and Optimisation Models

The assessment of the right time to order more stock is a very vital factor in warehouse management (Sugiarto & Suprayitno, 2023). Some of the popular forecasting algorithms include Logistic Regression, decision trees, and random forests when determining reorder points to improve stock replenishment (Seyedan, 2023). Logistic regression can be used for binary classifiers, for example, if it is or is not time to reorder a product through the evaluation of previous sales and current stock (Ntakolia et al., 2021). Even though straightforward, Logistic Regression remains a benchmark for other complex models, and it is easy to use.

Decision trees and random forests, on the other hand, have more complex models for inventory management undertaking since they can capture nonlinear relations between the variables (Supsermpol et al., 2023). As a form of predictive model, the decision trees sort the data with the help of if-then rules, which can be helpful in determining reordering decisions (Dhebar & Deb, 2020). Random forests, as an extension of decision trees used in the ensemble method, prevent overfitting and help to take into account other factors influencing the likelihood of reorders, including suppliers' performance, time required for delivery, or climate fluctuations (Svoboda & Minner, 2022).

The applied nature of these models in stock management is that they help to avoid overstock of products, situations when products are out of stock, and to determine the right time for restocking (Upadhyay, 2024). Compared to the conventional methods of decision-making, the ML tool helps in making better and more automated decisions by integrating real-time data and thereby improving the functionality of the warehouses against fluctuations in the demand load patterns (Hassan & Mhmood, 2021). When the new models are implemented into smart warehouses, they will help improve the efficiency as well as sustainability of the warehouses.

3. METHODOLOGY

3.1. Dataset

The data used in this work originates from Kaggle https://www.kaggle.com/datasets/kirbysasuke/retail-sales and consists of historical data of sales in a made, both at retail and in a warehouse. The data includes such attributes as item types, supplier details, and sales values by period. Retail sales refer to sales from the retail vendors, and warehouse sales depict the direct sales of the warehouse. Further, data on suppliers is included in the dataset, as well as the description of every item and its type, whether it is wine, beer, and so on – all this data is essential for analysing tendencies and forecasting further sales and subsequent reorders. The given set of data offers great opportunities for the creation of not only pure time series forecasting models but also for classification models to predict reorders.

3.2. Data Preprocessing

Before model development, the dataset was preprocessed to remove any unwanted data or data that was not fit for use. First, the observations with a lot of missing data were excluded, or if the data were records, the missing data were replaced with median values in continuous data. Subsequently, categorical features like the supplier names were converted into integers with Label Encoding to facilitate subsequent training of models. This step was crucial for the chosen Logistic Regression model as this model accepts numerical input only. Further, the normalisation of sales data was done to scale all features. This was vital in the LSTM and Prophet modelling since differences in scalas may significantly impact the results. In the end, again, the dataset was divided between training and testing data sets with a view to checking the performance of the models.

3.3. Model Development

Long Short-Term Memory (LSTM) neural network is a subcategory of Recurrent neural network tools (Muhuri et al., 2020). Recurrent neural networks specifically facilitate the processing of time series data by keeping track of the previous time step information (Wang et al., 2022). In this study, LSTM was used to forecast sales for the future warehouse using previous sales records. In the construction of the model, the input data were sequential, and the LSTM layers were tasked with processing the temporal data. In the process, each time step in the sequence gave a temporal dimension of sales data within the given period and enabled the model to learn from previous sales. Multiple layers were used to capture long-term dependencies in the LSTM architecture. Next, the model was developed, the results of future sales of the test set were determined, and patterns were searched to enhance the standards for future inventory and operation planning.

3.4. Prophet Model for Time-Series Forecasting

This work also used the Prophet model, a model developed by Facebook, to compare it with LSTM. Prophet is a tool developed for time series that includes seasonality, trends, and holidays (Stefenon et al., 2023). The premise of the method is that a given time-series data is decomposed into these components, and a separate model for each of them is applied. Prophet is most useful when data contains fluctuations accompanied by cycles, making it suitable for warehouse sales that may slightly differ with seasons or promotions. Credibly, two of Prophet's strengths include its capability to deal with missing observations and its capability to provide forecasts for models that possess uneven gaps within a time series (Rafferty, 2021). In this case, Prophet was trained on the same set of sales data, which was used to develop LSTM, and Prophet model performance was determined based on the forecast of future warehouse sales.

3.5. Logistic Regression for Reorder Predictions

Logistic regression was implemented as a binary classifier to determine when a reorder should be fier. The control variable was whether a reorder was required or not, depending on the level of sales and other comparable factors, such as the type of item and from which supplier. Logistic regression is a common technique used to predict binary data. In this case, logistic regression was used to determine if the stock levels had fallen below the required reorder point. These were the feeds used in the model: the warehouse sales feed, the retail sales feed, and the encoded supplier feed. Finally, the model predictions were tested on the test dataset to measure its efficiency in forecasting reorder points, which are valuable tools for determining the right inventory levels.

3.6. Evaluation Metrics

For LSTM and Prophet (Regression Models)

The performance of both forecasting models was evaluated using three key metrics:

Mean Squared Error (MSE) - Sums up the squared difference between the observed and the estimated values to realise the total amount of variance or error of the model used (Chicco et al., 2021).

Root Mean Squared Error (RMSE) - The square root of MSE provides an interpretation of the same scale as in the initial raw data measurement [40].

Mean Absolute Error (MAE) - Gives an idea of how well the model performed or how accurate the forecast was by averaging the absolute difference between a given model's estimate and the actual value (Chicco et al., 2021).

For Logistic Regression (Classification Model)

The classification model for reorder prediction was evaluated using the following metrics:

Accuracy - The proportion of all reorder decisions predicted out of all the total predictions.

Precision - The relative number of reorders that was given as positive, the ability of the model not to produce false positives.

Recall - The rate of actual reorders within the model, which is the capacity of the model to predict all needed reorder cases.

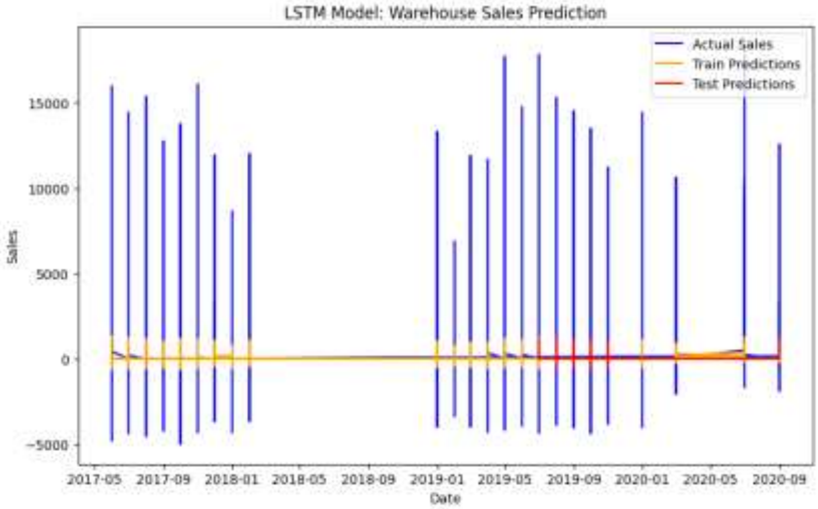
F1-Score - An average of the precision and recall measures, taking into consideration the importance of both false positives and false negatives, gives a high overall level of detail for the model.

4. RESULTS

4.1. LSTM

A line graph employed showing the actual sales and sales forecast from the LSTM model shows the extent of the forecast's accuracy. The plot also reveals that the model has been able to correctly estimate fundamental variations in the sales volumes, such as changes in rising trends or downward movements and fluctuations that are experienced seasonally.

Figure 1: LSTM Model: Warehouse Sales Prediction



The graph of the sales forecast from the LSTM model displays the model's competency in tracking the path of actual sales, which is extremely helpful in forecasting the demand for the warehouse's operation.

From the MSE, RMSE, and MAE, it is clear that the LSTM model achieves a fair level of predictability. Reducing the forecasting error of the LSTM makes it an efficient tool for sales forecasting, especially in warehouses, where the accurate prediction of sales is critical for strategy and inventory management, as shown in Table 1.

Table 1: LSTM Model

Model	MSE	RMSE	MAE
LSTM	71,107	266.66	36.02

Figure 2 shows a comparison of Prophet's customised forecast and the LSTM model, along with the sales that occurred from January 2017 to March 2020. Though Prophet performs well and is in line with the average trend, it sometimes falls short of LSTM in picking spikes or drops in sales. The analysis of the Prophet Sales Forecast Plot reveals that while Prophet serves to capture broad features, it fails to provide the same level of detail in short-term fluctuations in sales as provided by LSTM. Prophet's MSE, RMSE, and MAE indicate Prophet's lower accuracy than LSTM in this particular dataset. Prophet suits scenarios where large trends are more dominant. Still, when it comes to warehousing, where day-by-day or weekly fluctuations come into play since LSTM captures such short-term variations, it is the better model in this instance, as shown in Table 2.

Figure 2: Prophet Forecast for Warehouse Sales

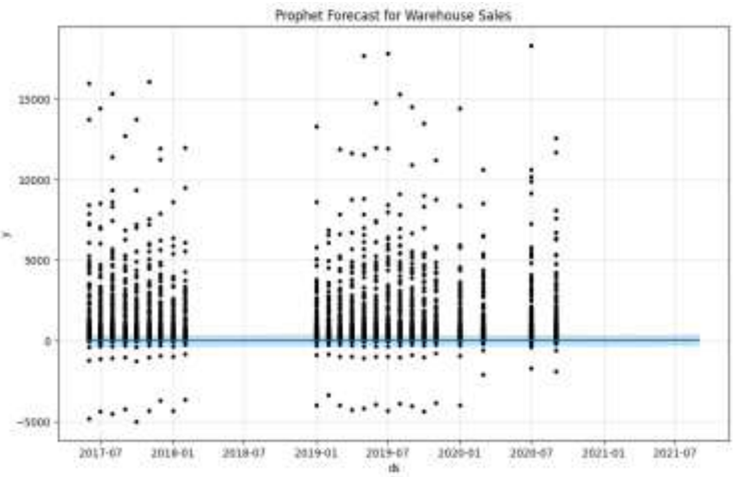


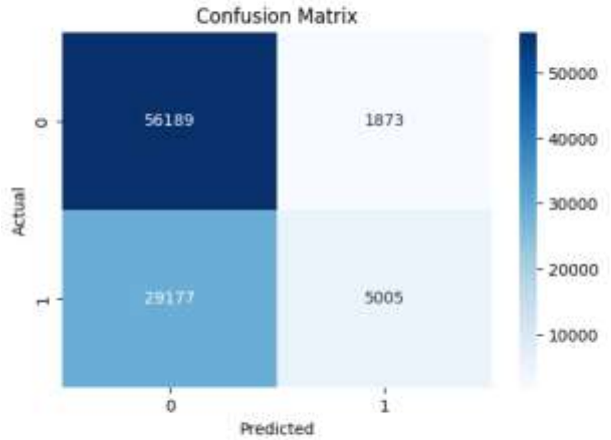
Table 2: Prophet Model

Model	MSE	RMSE	MAE
Prophet	73,687	271.45	46.45

4.2. Logistic Regression

Several binary Logistic Regression models were developed to determine if a reorder is needed with sales information and other variables like supplier details. Analysing the results of the work, the paper used the confusion matrix provided below to find out how many reorders were correctly and incorrectly predicted by the model. The matrix describes the true positive framework consisting of correct reorders while the false positive framework consists of over-reordering; the true negative framework is properly reordered, while the false negative framework is under-reordering.

Figure 3: Confusion Matrix



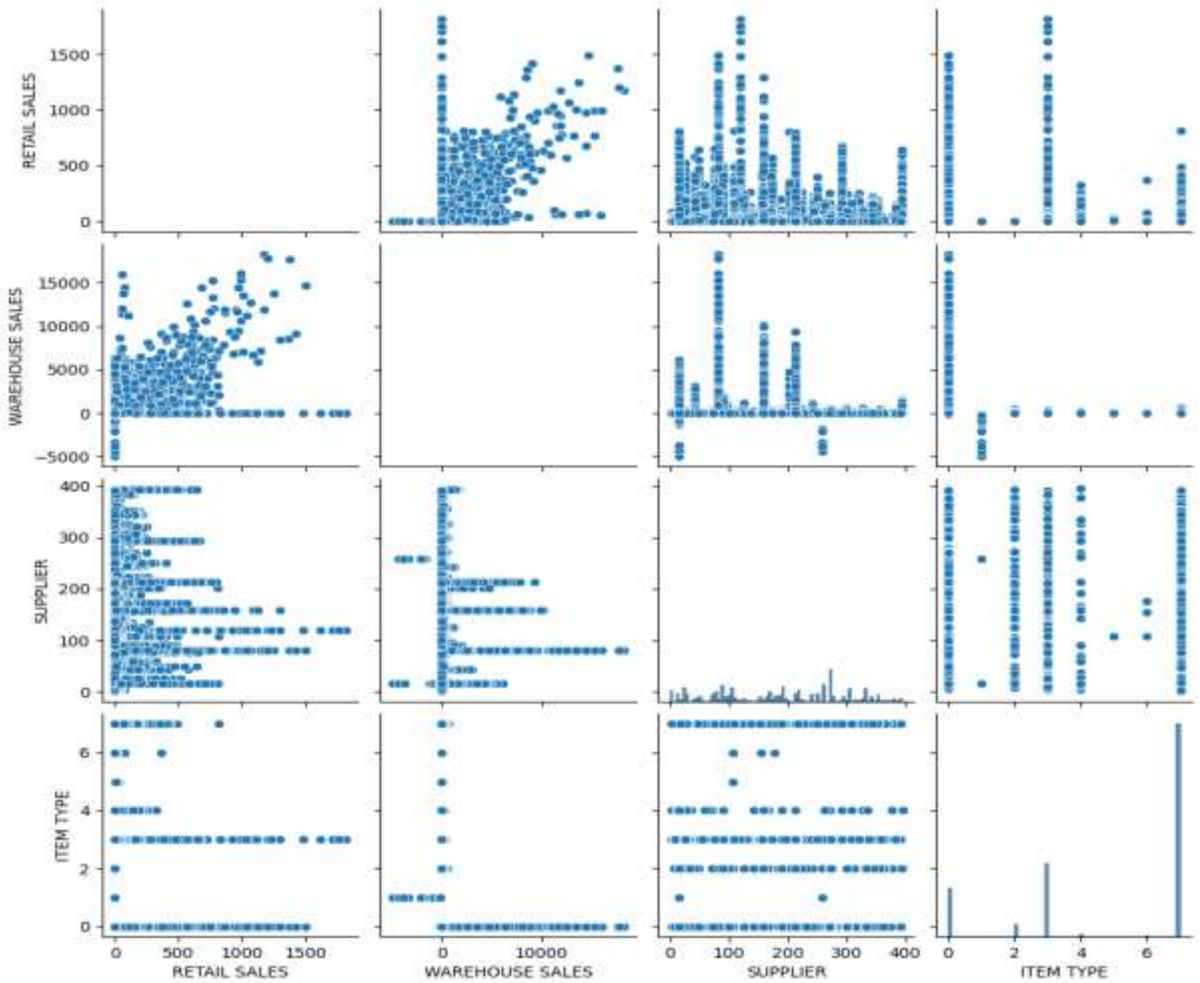
The Confusion Matrix for the Logistic Regression model shows high degrees of accuracy in cases where a reorder is not needed. Still, there are low values in cases where the reorder is needed, meaning the model has several false negatives. Relatively more error is seen in terms of low recall, 14.64%, which suggests here that many times, necessary reorders are being missed, hence acting as a false negative. This is a significant area for improvement in the model, especially in predicting reorders due to labour restrictions of the existing model. Precision indicates that if the model gives a reorder point, which in its case is often accurate, then it is helpful in providing the right time to reorder. However, this is hampered by the fact that the model needs to identify all reorders necessary to maintain optimal stocks, as shown in Table 3.

Table 3: Logistic Regression

Metric	Value
Accuracy	66.34%
Precision	72.77%
Recall	14.64%
F1-Score	24.38%

The logistic Regression model's low recall highlights a significant limitation: the shortcoming of the model is that it fails to identify that a reorder is needed in some cases, leading to stockouts. These results imply that there are other models that better estimate the shorthand to the curr logistic regressions model. In future work, decision trees or ensemble models are more suitable for this classification task. The overall pair plots is depict in Figure 4.

Figure 4: Pairplots



5. DISCUSSION

The LSTM model was more accurate in warehouse sales forecasting because it possessed architectural benefits over the Prophet model. LSTM stands for Long Short-Term Memory, and it is intended to work well with complex and nonlinear data by preserving the memory over length. This enables LSTM to capture both long and short-term patterns of sales, which are especially important when determining demand in a warehouse setting that is frequently influenced by short-term specials and seasonality, amongst other factors. LSTM is able to model the underlying patterns in the data over multiple steps of sales behaviour to learn from and store for the next forecast period, making LSTM a model that is superior to some of the simpler time-series models.

On the other hand, Prophet, while being good at capturing seasonality and trends, needs to capture short-term variations. Prophet works well to break time-series data down into trend, seasonality, and holiday features, which is most helpful when making long-term forecasts in situations with less volatility. However, its use of linear trends and additive components undermines its effectiveness at estimating disparities, especially where there is rapid non-linearity, which is a common factor in the sales of a warehouse. While Prophet is more appropriate when it comes to forecasting stable and rhythmic uplifts like seasonal variations, the fluctuation in the sales pattern is more complex than what Prophet can provide with LSTM.

It took a lot of work to implement the logistic regression used in the prediction of reordering points, too. While the first metric gave decent precision, the second value needed to be higher, meaning a lot of cases where a reorder should have occurred were missed. However, Logistic Regression, which falls under the class of linear classifiers, fails to model intermediate-level interactions between the multiple factors that come into play when reordering decisions are made, such as supplier delays, changes in sales, and lead times. Consequently, it had a lower accuracy in predicting all required reorders, which is crucial for efficient stock management to be performed in the warehouse.

Implications for Smart Warehousing

The findings emerging from the study have significant implications for the development of effective and efficient smart warehouses. As shown by the LSTM model above, the right sales forecasting can improve several management decision-making activities. In other words, warehouses are able to set and order stock in a manner that caters to demand without the pitfall of overstocking the warehouse. This not only dramatically cuts down on unnecessary inventory but also prevents a potential scenario of stockouts, a scenario which can severely inconvenience business operations and cost potential sales. In addition, it helps in efficiency through improved resource positioning or employment, such as labour and space for storage, thereby contributing to a successful and growing warehouse business.

The drawback in the reorder prediction made by Logistic Regression implies the prospects of other elaborate classifiers in smart warehouses. This paper also showed that the reordering point is essential for the continuous flow of resources and that wrong forecasting is likely to lead to stockouts or delayed and excessive inventory holding costs. Random forests or gradient boosting are two more complex models able to spot curvilinear relations between features, enhance the reorder point's accuracy, and enhance the procedures controlling inventory.

6. CONCLUSION

In this paper, LSTM, Prophet, and Logistic Regression models were used to analyse the warehouse sales prediction and reorder points. The study showed that LSTM gave better sales forecasting than Prophet, giving smaller errors and a better ability to track short-term oscillations. The fact that the LSTM model can perceive both long-term tendencies and much-sophisticated nonlinear dependencies gave it the upper hand and put it in the position of the best-perfecting model of sales forecasting in the context of dynamic warehouse conditions. Prophet is a good model for measuring cyclical patterns and trends, but it has low short-term forecasting errors. Regarding reorders, specifically Logistic Regression provided adequate accuracy; however, it had very low recall. That is, it omitted numerous critical reorder situations, which is detrimental to managing stock.

The study also has broad practical relevance to the design of smart warehouses. LSTM, as an operational AI tool, more specifically, can improve existing alternatives by raising the accuracy of sales predictions, which, in turn, makes the process of demand forecasting and stock control more effective. It also means less waste, appropriate stock management, and regular restocking, and it is helpful in sustaining and growing warehouse departments. Warehouses can enhance their service quality without creating negative environmental effects such as stockouts and excessive stock.

However, this study has some limitations. It only provide an idea about one that operates a single warehouse, which restricts the scope of the dataset heavily. Secondly, the recall of the Logistic Regression model is low, and this means that there is merit in the use of superior techniques in the classification of products that have to be reordered. Further studies aiming at extending outcomes using deep reinforcement learning to adapt inventory stock correspondingly and investigating additional accurate neural network models or population modes for enhancing the predictive performance in forecasting and classification are also suggested. These advanced models could give much better real-time approaches to handling stock within intelligent warehouses.

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TURNING INTEREST INTO ATTENDANCE: THE COMMUNICATION CHANNELS THAT INSPIRE EVENT PARTICIPATION IN OMAN

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ABSTRACT

Purpose - The main aim of this study was to assess the role of marketing communication channels in enhancing visitor participation in Oman's events. The study examines event companies' adoption of traditional and digital marketing communication channels, visitor expectations of these channels, and their link to increased attendance at events.

Methodology - This study used a quantitative research approach and exploratory research design. Random sampling was performed in this study. A questionnaire was used to collect data. The ethics form was completed, and after approval, data were collected from 195 respondents.

Findings - The findings of the study included the majority of respondents who attended the Muscat Nights event (n=86). A total of 56.4% of respondents obtained complete information on the events via communication channels. Friends and family are traditional channels of communication that visitors expect for event information (4.51). Visitors' expectations of digital communication platforms for events include social media influencers (4.41). On the other hand, event companies use digital communication methods to spread event information via radio and television news (4.21), while SMS to mobile phones is the most common digital communication mode used by event companies (4.53). The study revealed a strong association between traditional and digital communication channels, with traditional channels demonstrating a significant value of 0.034 and digital channels achieving a significant value of 0.032, indicating a strong link between these two channels and increased event visitor participation.

Conclusion - The study suggests that event planners and organizers should utilize both traditional and digital marketing channels to reach their target demographic, as both complement each other and increase attendance.

Keywords: Digital channels, tradiational channels, event participation, social media, communication gap.
JEL Codes: M31, D83, G14

1. INTRODUCTION

Marketing communication is critical for organizations, as their success is largely dependent on it (Kotler & Armstrong, 2018). This entails strategically disseminating details concerning products, services, or brands to trigger emotional responses and inspire action (Fitriana et al., 2021), defines brand identity, drive consumer behaviour, and propel organisational objectives (Harb et al., 2019). Moreover, it is critical for building relationships with clients, emphasising capabilities, and advancing offerings in an increasingly competitive market (Porcu et al., 2019). Marketing communication increasingly influences companies' communication strategies, enhancing brand appeal, equity, and performance (Luxton et al., 2017). Rehman et al. (2022) emphasized the shift from one-way to two-way communication in marketing, highlighting the effectiveness of social media in facilitating this shift. Likewise, Afridah & Lubis (2024) stated that companies that engage in marketing communication have reported significant increases of 20 to 30% in brand awareness and sales revenue. Fitriana et al. (2021) asserted that maintaining client involvement and satisfaction requires marketing communication methods, which are frequently less expensive than recruiting new ones. Understanding the target audience and their information sources is crucial for effective marketing, whether through digital marketing, advertising, or social media, ensuring targeted and effective advertising (Harb et al., 2019). Companies that conduct marketing campaigns with three or more channels have a 287% greater purchase rate than those with only one channel. Additionally, compared to single-channel strategies, multichannel marketing yields a 24% better return on investment (Allied Market Research, 2025).

Events are public celebrations with an annual theme that bring residents and visitors together to share their anecdotes (Getz, 2012). The global event industry, valued at USD 736.8 billion in 2021, is projected to reach USD 2517.7 billion by 2035 (Allied Market Research, 2025). Oman contributed USD 1.9 billion in total spending in 2023, implying that the event industry significantly contributes to the economy (Zawya, 2024). Events are being held more frequently in many cities and countries to improve the perception of the location, draw tourists, and offer leisure activities to locals and visitors (Garay 2017). Oman's events sector (trade shows, expos, conferences, and cultural festivals) is growing swiftly, with a focus on digitalisation through onsite technology, apps, ticketing, and hybrid events (Oman Observer, 2016). Technology is transforming event operations and attendee experience in Oman using various communications, such as mobile applications, digital displays, e-registration, and hybrid streaming (Tumati & Al Sulaimi, 2023). According to the Oman Observer (2016), the events industry is regarded as a significant source of revenue, jobs, international recognition, and foreign investment in Oman. Events are viewed as a key pillar for developing and improving the tourist industry in Oman’s prospective national tourism strategy until 2040 (Oxford Business Group, 2017). The Sultanate of Oman's capital city holds the Muscat Festival, recently renamed ‘Muscat Nights,’ which highlights Omani customs, culture, and legacy and includes workshops, fashion displays, exhibitions, and entertainment events. Oman's Vision 2040 promotes economic diversification, with the event sector enhancing investment opportunities, business tourism, MICE, and positioning Oman as a regional hub for international events (Al-Lawati, 2024).

Numerous studies have demonstrated the significance of marketing communication channels, such as those that shape customer expectations and build brand awareness (Kotler & Keller, 2016); create brand awareness, which forms the basis of long-term brand equity in the event industry (Fill & Turnbull, 2019); improve customer retention and loyalty through continuous communication (Grönroos, 2011); increase conversation and engagement rates (Żyminkowska, 2019); improve attendee satisfaction and post-event engagement (Schmitt, 2003); boost public confidence through coordinated and credible communication (Al-Rubai’ey, 2023); influence social media communication on consumer behavior and brand performance (Rehman et al., 2022); and improve the event attendant experience (Tumati & Al Sulaimi, 2023). Despite the growing importance of marketing communication channels for event success and organisational performance, no research has been conducted in Oman. As a result, several stakeholders in Oman will find great value in the current study on the role of marketing communication channels in enhancing visitor participation in events. In addition to providing much-needed information to the expanding body of literature, the study's findings will be extremely helpful to stakeholders such as the Ministry of Heritage and Tourism, Oman Convention and Exhibition Centre, event planners and organisers, students, and future researchers. The main objectives of this study are as follows; determine the current traditional and digital marketing communication channels adopted by event companies to reach their target audience, analyse visitor expectations of traditional and digital marketing communication channels to learn about events, and determine the relationship between traditional and digital marketing communication channels and enhance visitor participation in events.

2. LITERATURE REVIEW

Marketing communication is a focused activity that involves communicating information about products and services to consumers or potential consumers via different channels to persuade them to buy from organisations (Fill & Turnbull, 2016). Marketing communication is the process of delivering company information to consumers, including product images for decision-making (Kotler & Keller, 2016). Marketing communication aims to inform, persuade, or remind the target audience of a company's offerings (Kotler & Armstrong, 2018). Fill & Turnbull (2016) stressed that the goal of marketing communication is to influence the behaviours of the target market rather than simply informing, persuading, or reminding consumers.

2.1. Traditional Communication Channels

According to Keller (2016), almost everyone globally has been exposed to one or more forms of mass media, such as radio, newspapers, television, and outdoor media. Event organizers have extensively employed traditional marketing communication techniques, such as print and broadcast media, to promote events (Jackson & Angliss, 2017). Similarly, Geraghty & Conway (2016) argue that traditional communication methods, such as print, broadcast, and outdoor advertising, are still successful in reaching a large audience for events and activities. Kumar et al. (2017) stated that traditional communication channels, such as television, radio, and print media, remain effective in reaching customers. Traditional communication channels, such as radio, television, newspapers, and outdoor advertising, have a strong beneficial influence on consumers’ purchase decisions (Mustafa & Al-Abduallah, 2019). However, Danielsbacka et al. (2022) contend that these channels are losing their efficacy as more people move to digital channels. While Murtiasih et al. (2021) discovered that marketing messages are helpful in generating awareness of events, they also proposed that participants (i.e., customers) successfully market events through word-of-mouth referrals. Moreover, Tümer et al. (2019) stated that word-of-mouth is critical for attracting visitors to events because it makes potential guests feel excited and educated while competing for their attention. Furthermore, Morra et al. (2018) detailed that some of the most popular communication methods for event promotion are word-of-mouth and recommendations from family and friends. Additionally, Liu & Draper (2022) stated that family and friends play an important role in event communication, shaping opinions, participation, and support, thereby demonstrating the interconnectedness of event advertising and execution. Rentman (2025) stated that choosing the appropriate media for event communication is critical for connecting with and involving the audience. However, Hänninen & Karjaluoto (2017) argued that personalized communication tailored to clients' requirements, interests, and preferences has a greater influence on purchasing decisions than mass communication channels.

According to Todor (2016), television is the primary source of news for consumers, and higher engagement results in better advertisement recall. Television's ability to segment and target the right show or broadcasting channel based on consumer preferences makes it a valuable communication tool. According to Mair & Weber (2019), there is a considerable positive association between purchasing behaviour and seeing information on billboards regarding products, services, events, or other activities. Mustafa & Al-Abduallah (2019) indicated that outdoor advertisements have the greatest influence on consumer purchasing choices, followed by television, radio, and newspapers. According to Todor (2016), consumers who choose to purchase items that are not durable are more likely to be persuaded by television commercials than by the radio, newspapers, and magazines. In contrast, Habib et al. (2015) asserted that radio is a mode of communication that tends to affect long-term product and service consumers, with older consumers being more inclined to be influenced by radio advertisements. Mair & Weber (2019) discovered that communication via newspaper advertisements is more efficient than any other medium, as a significant proportion of the population still reads newspapers and is exposed to these messages. Traditional communication media include not only direct contact but also culture, tradition, local wisdom, and the core of community life (Danielsbacka et al., 2022). Kumar et al. (2017) indicated that the integration of traditional and digital communication channels can significantly increase client engagement with the organization, as traditional communication channels, such as flyers, brochures, newspapers, and radio, are one-way and limit customer interaction, hindering their ability to respond effectively.

2.2. Digital Communication Channels

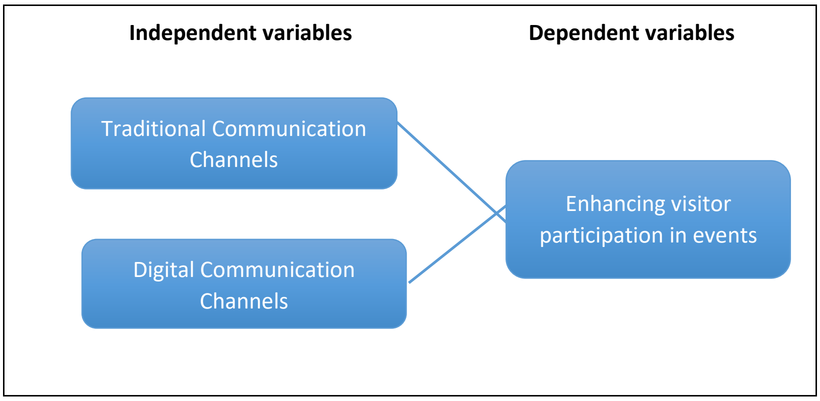
Fraccastoro et al. (2021) stated that new media advancements have significantly influenced media choices and tools, transforming traditional media such as print, television, and radio into interactive digital media such as websites, mobile applications, audio-visual techniques, and gaming, thereby enhancing message transmission. Putra et al. (2023) specified that digital communication methods have a huge impact on the promotion and exposure of events, as they use online platforms, interactive information, and real-time social media updates. Email, social networking sites, messaging applications, and webpages are ideal for providing extensive information and direct communication with visitors (Rehman et al., 2022). Geraghty & Conway (2016) stated that digital communication channels are creative and that technology-driven initiatives provide consumers with engaging and memorable experiences. However, Van Dijk (2020) claimed that digital communication channels face challenges such as information overload, which can make it difficult for customers to consume and comprehend large amounts of information.

Digital communication via social media, interactive exhibits during events, and personalized email marketing based on attendee preferences can have a long-term influence and persuade visitors to attend events. Communicating about events through an event website is an effective way to offer comprehensive information; however, an event website should be clean, simple to use, and easily accessible to potential guests (Simon, 2023). In addition, Fraccastoro et al. (2021) stated that effective search engine optimization increases event visibility, resulting in an indispensable tool for worldwide reach. A mobile event app can be an effective communication tool, allowing the audience to engage through polls, surveys, and group chats (Alwi et al., 2022). Rehman et al. (2022) investigated how customer needs and decisions have altered in the digital age, emphasizing the importance of more personalized and focused communication tactics, such as emails, immersive videos, and chatbots. Communication via email works well before and after events, but during the event, direct techniques such as text messaging, mobile apps, group conversations, or social media should be employed to keep attendees connected (Cvent Blog, 2025). Email marketing is an excellent way to reach a large number of people and is one of the most cost-effective communication platforms available (Simon, 2023). Social media sites such as Twitter, Facebook, and LinkedIn can be used to reach a broad audience (Dwivedi et al., 2015). Danielsbacka et al. (2022) stated that mobile marketing via smartphones employs digital platforms such as mobile applications, SMS, push alerts, and websites to provide personalized data-driven targeting through analytics, which is an important digital marketing feature.

Effective communication in marketing necessitates a thorough grasp of the target audience's wants and preferences, as well as a deliberate approach to conveying a consistent message through different platforms (Cizrelioğulları et al., 2019). Social media has transformed event communication, marketing, perception, and experience, enabling platforms such as Instagram to foster emotional anticipation, interactions, and storytelling (Jin et al., 2019). Social media is a vital instrument in the marketing and promotion of products and services, allowing brands to interact with customers in real time and generate memorable experiences (Butkouskaya et al., 2023). This promotes authentic and engaging interactions, boosting brand exposure, involvement and retention. Social media also has the capacity for viral sharing of content, which can increase the visibility of brand messages (Erkan & Evans, 2016). Social media sites such as Instagram, TikTok, and YouTube function as year-round promotional instruments, generating excitement and establishing an online community around festivals (Aljukhadar et al., 2020). Additionally, Al-Badi et al. (2017) noted that more than half of the respondents in Oman used social media for local travel, with recommendations from friends being the primary source of information. Others rely on their previous experiences and social media for advice. Technology platforms facilitated event participants in Oman to communicate more quickly and effectively by allowing them to post feedback, read information, and inquire about activities and events. Attendees also used technology to learn about the event's date, time, location, transportation, event activities, and how to find promo codes and discounted tickets (Tumati & Al Sulaimi, 2023).

Furthermore, Tumati et al. (2024) found that the information provided by social media influencers significantly impacted tourists' decisions to visit a destination in Oman, and credibility was also relevant. The research also shows that customers' decisions are influenced not only by influencers on social media platforms but also by the platforms. Facebook, YouTube, Instagram, WhatsApp, and TikTok are the most widely used social media platforms globally, with over four billion active users (Statista, 2025). These platforms share key features such as interactivity, user participation, and user-generated content publishing (Jin et al., 2019). Daskin & Tumati (2024) discovered that Omani Z tourists choose a tourist site because it was recommended by social media and influencers. Instagram, the third-largest global platform with over two billion active users (Statista, 2025), is a prominent visual communication channel and has become particularly influential in event marketing because of its attractiveness (Tumati et al., 2024). As a free app, users can share photos and videos, comment on content, and engage with their communities (Aljukhadar et al., 2020). Fake news, rumours, and modified materials are easily shared via social media and digital platforms, causing confusion among visitors and alarm among organizations (Lazer et al., 2018).

Figure 1: Theoretical Framework



3. METHODOLOGY

This study adopted a quantitative research approach. Creswell & Creswell (2018) specified that quantitative studies usually use large sample sizes to detect significant statistical findings and apply these findings to a larger population. The quantitative research approach helps standardize methodologies and numerical data to eliminate bias from research, ensuring the trustworthiness and authenticity of the findings for future studies (Claxton & Barthlow, 2024). This study used an exploratory research design. Bryman (2018) stated that exploratory research is essential when there is little past research on a specific issue, as it provides the necessary awareness and knowledge for a greater understanding. Additionally, the exploratory research design enables academics to investigate unanswered issues and explain previously unknown mechanisms (Creswell & Creswell, 2018). Random sampling was employed, which means that the respondents were selected randomly from Muscat and were willing to answer the questionnaires. Claxton & Barthlow (2024) stated that random sampling ensures that all possible participants are selected equally and fairly, thus reducing researcher bias. Samples were collected from 195 respondents; however, eight were removed because they were incomplete in certain sections of the questionnaire. Primary data were collected using questionnaires. Kothari (2023) revealed that questionnaires are an effective method for gathering information, saving resources and time compared to traditional methods like focus groups or interviews. They allow for honest responses without judgement, particularly for delicate subjects (Bryman, 2018).

This study employed the questionnaire developed by Vlachakis et al. (2018); however, it was modified to fit the requirements of this study's design. The instrument consists of several parts: Part 1 is a demographic profile of respondents; Part 2 is a multi-response checklist to identify their opinions on marketing communication channels and respondent satisfaction; Part 3 is to determine the marketing communication channels used by event companies to reach their target audience; and Part 4 is to examine the marketing communication channels that are most effective in maximizing guest event attendance based on consumer perspectives. Frequency distribution, percentages, ranks, and weighted means were used to analyze the data. The frequency distribution is a statistical tool used to determine the distribution of respondents and the frequency of respondents who fit a specified profile, such as gender, age, and marital status. Both the proportion of respondents and the percentage of respondents who fit a given profile were calculated using percentages. Other relevant statistical tools, such as correlation, were used to draw conclusions from the data collected.

4. RESULTS

Table 1 presents the respondents' profiles. Of the respondents, 76.5% were male and 23.5% were female. The majority of respondents (41.2%) were in the age range of 20–30 years, followed closely by those aged between 31 and 40 years (37.3%). Furthermore, 15.5% of the individuals were in the 41–50-year age group, and the remaining 5.9% were 50 years or older. Moreover, a significant proportion of respondents (87.7%) reported being in a marital relationship, while only 12.3% reported being unmarried. Furthermore, most respondents (59.9%) were Omanis, whereas the remaining 40.1% were non-Omani nationals. Regarding the employment status of the participants, 79.1% were employed, 20.9% were unemployed, and none were employed.

Table 1: Respondents Profile (n=187)

Category	Frequency	Percentage
Gender		
Male	143	76.5
Female	44	23.5
Age		
20-30 years	77	41.2
31-40 years	70	37.4
41-50 years	29	15.5
50 years old and above	11	5.9
Civil Status		
Single	23	12.3
Married	164	87.7
Nationality		
Omani	112	59.9
Non-Omani	75	40.1
Employment Status		
Employed	148	79.1
Unemployed	39	20.9
Retired	0	0

Table 2 shows the types of events that the respondents attended. Notably, Muscat Nights had the highest attendance rate (86%). This indicates a high level of interest in attending the event. Notably, this event is one of the most enduring events in Oman and is held annually between January and February each year. Previously known as the Muscat Festival, this event underwent a name change in 2023 to become Muscat Nights. In addition, COMEX Oman was rated as the second-most important event attended by respondents, with 78 percent. The COMEX technology exhibition in Oman fulfils the function of presents up-to-date trends and revolutionary technologies that significantly influence the daily lives, communication, occupational pursuits, and social connectivity of individuals. Over the course of 31 years, COMEX has played a vital role as a prominent sourcing and networking hub for the technology market in Oman and has consistently maintained its position as a premier platform for ICT procurement, product launches and technology demonstrations in the Gulf. In addition, the

Thailand Expo ranked third with 71%, and the Oman Dates Festival ranked fourth with 67 percent. A majority of the survey respondents, comprising 64 percent, participated in GHEDEX Oman, while 61 percent attended the Sultan Camel Race Cup event. Furthermore, 57 percent attended the Muscat International Book Fair, and 55% attended a multitude of other events, such as the IDF Oman and Oman Agro Food & Water Exhibition Conference. Finally, two events with comparatively lower attendance rates were the Muscat Market Fair (30%) and Oman Fire Safety and Security Event (24%), as reported by the survey respondents.

Table 2: The Type of Events Attended by Respondents

Types of Events	Percentage	Rank
Muscat Nights (before known as Muscat Festival)	86	1
COMEX Oman	78	2
Thailand Expo	71	3
Oman Dates Festival	67	4
GHEDEX Oman	64	5
Sultan Camel Race Cup	61	6
Muscat International Book Fair	57	7
Others (IDF Oman, Oman Agro Food & Water Exhibition Conference)	55	8
The Food and Hospitality Oman	53	9
Home and Building Expo Oman	52	10
Muscat International Jewellery Exhibition	49	11
Oman Health Exhibition	45	12
EduTrac	44	13
Muscat Market Fair	30	14
Oman Fire Safety & Security Event	24	15
Total		**15**

Figure 2 depicts whether the respondents received complete information about the events through the communication channels they used. According to 56.4% of the respondents (29.9% were fully informed and 26.5% were fairly informed), they received the required information about the vaccine. However, 43.6% of respondents (32% with limited information and 11.6% with incomplete information) reported not receiving the necessary information.

Figure 2: Did you receive the full details of the events through the communication channels?

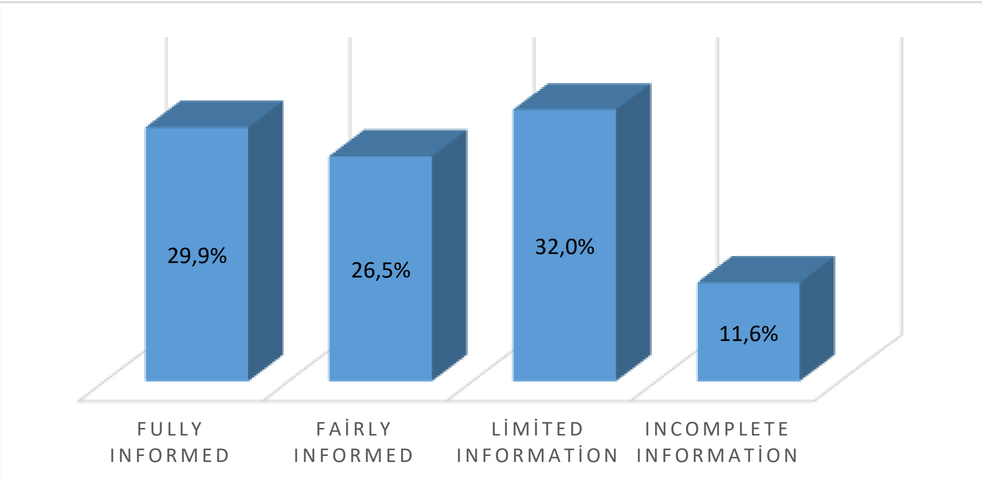


Figure 3 shows the respondents' satisfaction with the information they received about the events through various communication channels. Of the respondents, 53.1% were satisfied with the information they received about the events (28.6% were very satisfied, and 24.5% were satisfied). However, 25.1% were dissatisfied with the information they received (19% were dissatisfied, and 6.1% were very dissatisfied). Among the respondents, 21.8% were undecided.

Figure 3: Satisfaction with Event-Related Information Received through Various Communication Channels

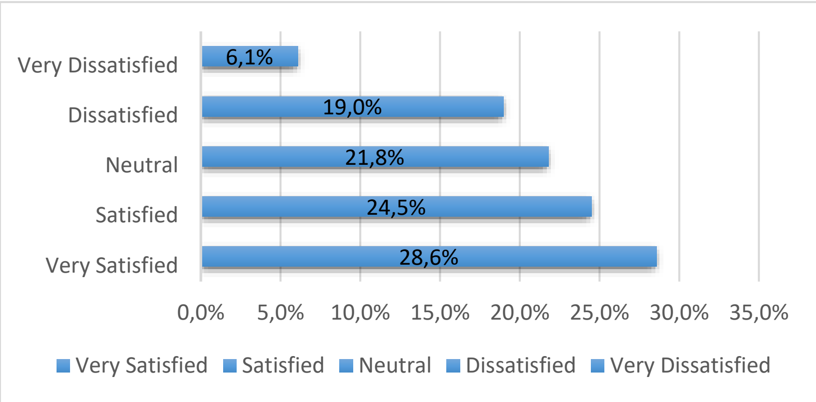


Table 3 outlines the marketing communication channels utilized by event companies to reach their target audience and the most effective channels for maximizing event attendance from the consumer perspective. Visitor expectations of traditional communication channels include friends and family, which received the highest mean score for visitor expectations of communication channels (4.51), followed closely by word-of-mouth (4.43). This means that most respondents obtained information about events through their friends, family, and word of mouth. Other communication avenues include newspapers, radio, and TV news (4.38), advertisements on radio and TV (4.22). This implies that event-related information was publicised through various media venues, including radio, television news, and radio and television commercials. On the other hand, the current practices of traditional communication channels include radio & TV news (4.21) and advertisements on radio & TV (4.15). This indicates that event companies are currently communicating with their target audience through radio and television news and advertisements. Other forms of communication included billboards and hoardings (4.01) and trade fairs, expos, and exhibitions (3.881). This means that attendees learned about events through advertisements from trade shows, expos, and exhibits, billboards, and hoardings.

Table 3: Visitor Communication Gap Analysis

Information Channels	Visitor expectation of communication channels		Current practice of communication channels by event companies		Visitor expectation Gap
	Mean	Standard Deviation	Mean	Standard Deviation	
Traditional Channels					
Friends & family	4.51	0.839	3.44	0.928	**1.07**
Word of mouth	4.43	1.025	3.57	1.119	**0.86**
Radio &TV news	4.38	1.127	4.21	0.831	**0.17**
Ads in Radio & TV	4.22	0.936	4.15	0.918	**0.07**
Ads in trade fairs & exhibitions	4.06	0.816	3.88	1.071	**0.18**
Billboards & hoardings	3.89	0.867	4.01	0.866	-0.12
Brochures, flyers & posters	3.32	0.891	3.72	1.118	-0.40
Signage & banners	2.79	1.212	3.37	0.880	-0.58
Newspapers & magazines news	2.65	1.101	3.28	0.865	-0.63
Ads in newspapers & Magazines	2.58	0.857	3.09	0.826	-0.51
Press conferences, interviews, and discussions	2.55	0.986	3.18	0.897	-0.63
Notices, circulars, and memos	2.26	1.113	2.79	0.868	-0.53
Digital Channels					
Social media influencers	4.41	0.988	3.87	0.983	**0.54**
Instagram	4.39	1.133	3.92	1.211	**0.47**
What's App	4.22	0.968	3.63	0.922	**0.59**
X (Twitter)	4.13	0.919	3.88	1.024	**0.25**
TikTok	4.05	0.833	3.43	1.121	**0.62**

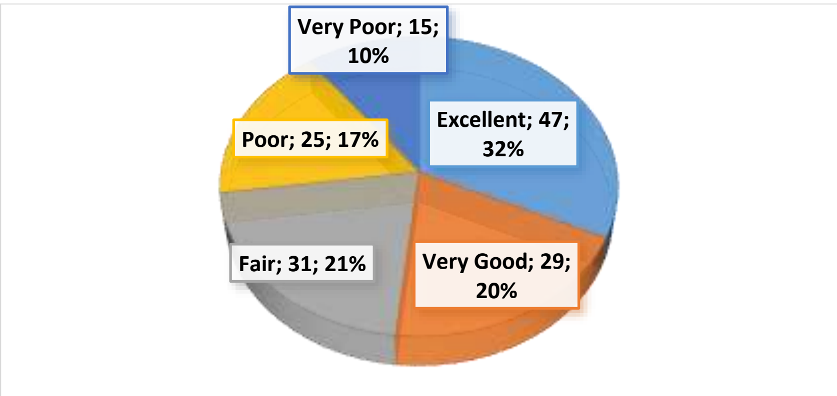
Snapchat	3.55	1.091	2.26	1.138	**1.29**
SMS to Mobile Phones	3.51	1.136	4.53	0.976	-1.02
Google Ads	3.42	0.856	3.42	0.826	0.00
LinkedIn	3.37	1.165	3.05	0.939	**0.32**
Event apps & website	3.16	1.110	2.18	0.979	**0.98**
Email Marketing	3.15	1.122	4.42	0.949	-1.27
Facebook	2.18	0.925	3.55	0.875	-1.37

Visitor expectations of digital communication channels had the highest mean score for social media influencers (4.41). This implies that most respondents expect event-related information from social media influencers. Other digital communication channels respondents expect to receive information about events from include Instagram (4.39), WhatsApp (4.22), X (Twitter) (4.13), TikTok (4.05), and Snapchat (3.55). Respondents wanted to obtain event-related information via numerous social media platforms, including Instagram, WhatsApp, X (Twitter), TikTok, and Snapchat. Similarly, contemporary practices for digital communication channels, such as SMS on mobile phones (4.53). This implies that event organisers are currently connecting with their target audience via SMS to clients' mobile phones. Other digital communication methods used were e-mail marketing (4.42) and Instagram (3.92). This suggests that organisations use email marketing and Instagram to communicate with event participants. Other digital communication platforms were X (Twitter) at 3.88, and social media influencers at 3.87. This indicates that companies employed X and social media influencers to inform respondents about events.

A visitor communication gap analysis was also conducted. Gap analysis = Visitor expectations for communication channels – the current communication channel practices of event companies. In traditional channels, friends, and family (1.07) had the most favourable visitor’s expectation gap. This implies that most respondents look forward to knowing information about events through friends and family. Other options included word of mouth (0.86), advertisements in trade fairs & exhibitions (0.18), radio and TV news (0.17) and advertisements in radio and TV news (0.07). The remaining have negative values: newspapers & magazines news (-0.63), press conferences, interviews and discussions (-0.63), signage and banners (-0.58), notices, circulars, and memos (-0.53), ads in newspapers & Magazines (-0.51), brochures, flyers & posters (-0.40), and finally, billboards & hoardings (-0.12). This means that companies are currently practicing them, but respondents were not expecting them as much as they were practiced by organisations.

Snapchat had the most favourable visitor-expectation gap (1.29). This suggests that visitors anticipate receiving more event-related communications on Snap Chat. Other options included event apps and websites (0.98), TikTok (0.62), and WhatsApp (0.59). This means that guests at events seek additional information from event apps and websites, TikTok, and WhatsApp. Additionally, Social media influencers (0.54), Instagram (0.47), LinkedIn (0.32), and X (Twitter) (0.25). This implies that organisations should communicate further information through various social media influencers and platforms such as Instagram, LinkedIn, and X. In contrast, Facebook had the largest negative visitor expectation gap (-1.37). This means that few respondents looked forward to obtaining information on Facebook. Other options included e-mail marketing (-1.27), and SMS to mobile phones (-1.02). This signifies that communication about the event via e-mail marketing and SMS to mobile phones should be kept to a minimum, as people do not expect much information from these channels. Finally, the only item with a value of 0.00 was Google Advertisements. This means that the visitors’ expectation of communication through Google Ads is 3.42, which is the current practice of communicating about events using Google Advertisements.

Figure 4: Overall Evaluation of the Communication Channels Used by Event Organizers



Respondents were asked to assess how well they thought the events were communicated to them in Muscat, Oman. Figure 4 demonstrates that 52% of respondents (excellent, 32%; and very good, 20%) were thoroughly satisfied with the communication channels. However, 21% of the participants considered the communication channels fair and equitable. However, the remaining 27% (17% and 10% of poor and very poor, respectively) were not satisfied with the communication methods. This suggests that, in the respondents' opinion, regardless of communication strategies, event organizers efforts to spread news of their events are ineffective.

Table 4: Correlation Analysis

		Enhancing visitor participation in events	Traditional Communication Channels	Digital Communication Channels
Enhancing visitor participation in events	Pearson Correlation	1	0.181*	0.182*
	Sig. (2-tailed)		0.034	0.032
	N	187	187	187
Traditional Communication Channels	Pearson Correlation	0.181*	1	0.708**
	Sig. (2-tailed)	0.034		0.00
	N	187	187	187
Digital Communication Channels	Pearson Correlation	0.182*	0.708**	1
	Sig. (2-tailed)	0.032	0.000	
	N	187	187	187

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 4 shows a connection of r=0.181 (p=0.034 < 0.05) between traditional communication channels and higher visitor involvement in events. This indicates that traditional communication channels have a significant value of 0.034, which is less than the 0.05 threshold value. Consequently, there is a strong association between traditional communication channels and increased visitor involvement in the events. The study found a correlation (r=0.182, p=0.032 < 0.05) between digital communication channels and increased visitor involvement in the events. This means that digital communication channels achieved a significant value of 0.032, which was less than 0.05. The results show a strong association between digital communication channels and increased visitor involvement in events.

5. DISCUSSION

Table 3 presents information on visitor expectations of traditional communication channels, such as friends and family (4.51) and word of mouth (4.43). The findings are consistent with Liu and Draper (2022), Murtiasih et al. (2021), Tümer et al. (2019), and Morra et al. (2018), who indicated that word of mouth and recommendations from family and friends are the most prevalent communication methods expected by event participants. Similarly, the current company communication channels include radio and television news (4.21) and radio and television advertisements (4.15). The findings coincide with Mustafa and Al-Abduallah (2019), Kumar et al. (2017), Todor (2016), Keller (2016), and Habib et al. (2015), who said that television and radio continue to be among the top communication channels for sending information about events, products, and services. On the other hand, event attendees expect digital communication channels such as social media influencers (4.41), Instagram (4.39), and WhatsApp (4.22). The findings are consistent with the findings of Statista (2025), Daskin & Tumati (2024), Tumati et al. (2024), Butkouskaya et al. (2023), Tumati & Al Sulaimi (2023), Aljukhadar et al. (2020), Jin et al. (2019), Al-Badi et al. (2017), and Erkan & Evans (2016), who stated that social media influencers and social media sites have the ability to directly communicate with people about events, tourism, and products and services in general. On the other hand, the digital communication platforms used by event companies include Instagram (3.92), X (Twitter) (3.88), and social media influencers (3.87). The findings concur with Statista (2025), Daskin & Tumati (2024), Tumati et al. (2024), Butkouskaya et al. (2023), Tumati & Al Sulaimi (2023), Aljukhadar et al. (2020), Jin et al. (2019), Al-Badi et al. (2017), and Erkan & Evans (2016), who stated that social media influencers and sites can engage with people directly regarding events, tourism, and products and services in general. Table 4 reveals a strong association between traditional and digital communication channels, with traditional channels demonstrating a significant value of 0.034 and digital channels achieving a significant value of 0.032, indicating a strong link between these two channels and increased event visitor participation. The findings are consistent with Cvent Blog (2025), Danielsbacka et al. (2023), Putra et al. (2023), Tumati & Al Sulaimi (2023), Rehman et al. (2022), Cizrelioğulları et al. (2019), Mustafa & Al-Abduallah (2019), Jackson & Angliss (2017) and Kumar et al. (2017) mentioned that both traditional and digital communication channels are equally crucial for informing the target audience about a company's products and services.

6. CONCLUSION AND RECOMMENDATIONS

Marketing communication channels are essential for organisations seeking to reach a wide range of people while maximising their return on investment. Choosing the right media platforms for event communication is a critical component of marketing strategy and has shifted from conventional media to a more comprehensive approach that incorporates digital platforms. Digital platforms, such as social networking sites, search engine optimization, and email marketing, prioritize personalization and engagement; however, understanding consumer behaviour is critical for effective communication. The study found that despite the rapid advancements in digital communication and modern technologies, traditional communication remains relevant to attendees. To guarantee that attendees are well informed, Oman's event planners, organisers, and other stakeholders involved in the event sector should use both conventional and digital communication techniques. Based on the findings, Muscat Nights, formerly known as the Muscat Festival, is the most popular event in Oman. Event companies utilise traditional channels such as radio, TV, and billboards for event information, while digital channels such as mobile messages, email marketing, Instagram, and social media influencers are used. A visitor communication gap analysis revealed that traditional channels, such as friends and family, have the most favourable communication methods, followed by word of mouth, trade fair advertisements, radio and TV news, and advertisements in trade fairs and exhibitions. This implies that organisations must increase communication through these channels. For digital channels, the findings reveal that Snapchat, event apps and websites, TikTok, WhatsApp, social media influencers, Instagram, and X were the most preferred communication channels. This implies that companies should increase their communication through digital channels. The study reveals a strong association between traditional and digital communication channels and enhanced visitor participation in events.

Based on the results, the following recommendations are proposed:

- ✓ Considering audience preferences and message type, as well as connecting media for a seamless experience, can help maximize reach and engagement, resulting in a successful event communication plan.
- ✓ Digital communication channels must be balanced with traditional methods to ensure effective communication and social interaction.
- ✓ Marketing communication enables businesses to interact with their target demographics by learning about their wants and needs. This helps them craft messages that build stronger bonds and increase brand loyalty.
- ✓ Most respondents preferred social media influencers for event-related information, suggesting that organisers should hire influencers with substantial followings to effectively communicate about events.
- ✓ Event companies should utilise popular social media platforms such as Instagram, WhatsApp, X, TikTok, and Snapchat to communicate their events effectively and efficiently.
- ✓ Respondents prefer to receive information through friends and family, word of mouth, and radio and TV ads, suggesting an increase in the event information flow.
- ✓ As respondents stated that they received either limited or incomplete information about events, it is important for event companies to communicate about events fully using various communication channels.
- ✓ Currently, satisfaction with event-related information received through various communication channels is not very high; therefore, it is important to communicate event-related information in full and in advance with all details.

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ABSTRACT

Purpose- The study explores the role of machine learning and reinforcement learning in optimising lean warehousing practices, focusing on demand forecasting, inventory optimisation, and stock prioritisation. Lean warehousing aims to reduce waste, cut costs, and maintain efficient stock levels through data-driven strategies.

Methodology- Three models were applied: Long Short-Term Memory (LSTM) for demand forecasting, reinforcement learning (RL) with placeholder costs for dynamic inventory management, and K-means clustering for inventory prioritisation. Performance metrics included RMSE, MAE, total reward, and Silhouette Score to evaluate effectiveness.

Findings- The LSTM model produced accurate demand forecasts with low RMSE (0.048) and MAE (0.025), aligning stock levels with actual demand. RL recorded a negative reward of −1511.83, highlighting the importance of integrating real-time cost data for better inventory decisions. K-means achieved a strong Silhouette Score (0.935), effectively supporting ABC inventory classification.

Conclusion- The study demonstrates that machine learning and reinforcement learning can significantly enhance lean warehousing by improving demand alignment, inventory prioritisation, and operational efficiency.

Keywords: Lean warehousing, machine learning, reinforcement learning, demand forecasting, inventory optimisation, LSTM model, ABC classification, data-driven inventory management
JEL Codes: M11, C53, O33, L91

1. INTRODUCTION

Some of the lean principles applicable in a warehouse include reducing costs associated with unnecessary operations, attaining optimal utilisation of the warehouse space, and staggering inventory storage (Rahman et al., 2023). These principles are implemented in the form of Just in Time (JIT) mechanisms, betterments ongoing, and efficiency measures to address needs with little waste (García-Cutrín & Rodríguez-García, 2024). When inventory is better aligned to demand, inventory density is optimised, labour and space utilisation is optimised, and overstocking and stockouts are minimised, lean warehousing improves customer satisfaction and operational costs (Narendran, 2023).

The application of new technologies such as machine learning, reinforcement learning, and clustering motivates new opportunities for lean warehousing. Predictive analytics systems such as the LSTM can accurately predict the demand for warehouses, therefore improving demand fulfilment for stock (Falatouri et al., 2022). Reinforcement learning provides an effective way of managing inventories in that the system only replenishes inventories by simulating costs and rewarding itself with the gains that come with increased demand (Du Plessis, 2020). Furthermore, using clustering, such as the K-means analytical tool, the inventory is grouped in a way that forms an ABC analysis, meaning it gives a priority list to inventory items so that management can allocate more resources to the items that are more influential according to lean thinking (Orelma, 2024).

The typical methodologies for lean implementation are largely pre-scripted, and they need to be more dynamic tools for tracking inventory. The best research in this field at the current period demonstrates only a few cases of reinforcement learning's use in adaptive inventory management and the primary application of machine learning in real-time demand forecasting within lean environments (Khedr, 2024). While clustering analysis is used in inventory management, its application in ABC analysis in lean warehousing is limited. These gaps are addressed in this research by bathing demand alignment, efficient, low-cost inventory management, and a prioritised ordering system to facilitate lean warehousing goals in a significant manner.

The main objective of the current research is to assess the effectiveness of using these technologies in the process of applying lean initiatives to warehousing activities. In this research, demand forecasting will be done with LSTM, inventory control using Reinforcement learning, and K-means clustering for inventory categorisation to establish these models' utility for lean warehousing.

2. LITERATURE REVIEW

Many companies have now embraced lean warehousing, where they aim at minimising waste while improving efficiency and manifold of inventories in relation to demand in warehouse operations. The simple and lean strategies of work organisation JIT, Kaizen, and the 5S method will perform significant functions in achieving these goals (Maryani et al., 2020). JIT pulls attention to low inventory keeping and manufacturing or procuring a component only when required so that overstock is eliminated and the supply chain adapts swiftly (De Martini, 2021). It links purchases and stocks effectively and delivers the goal of minimising wastage in an organisation. Kaizen means gradual, constant change to prevent the occurrence of various inefficiencies in the business processes (Suárez-Barraza et al., 2021). The other model, the 5S model, Sort, set in order, Shine, Standardize, and Sustain, is more about organising the workplace, which is a systematic method free from clutter and aims at reducing unnecessary movement and hence improving productivity (Rizky, 2023). Combined, these lean principles form the across-the-board approach to warehouse management since they ensure that resources do not surpass operational requirements.

Integrating modern innovations such as machine learning, reinforcement learning, clustering, etc, can enhance lean principles where the processes change dynamically depending on demand or the inventory level (Yan et al., 2022). There are, for example, the LSTM models that have demonstrated capability in demand forecasting that is central in JIT strategies (Jahin et al., 2024). LSTM is useful for learning patterns in chronological sequences and, therefore, is useful for demand forecasting since managers can make adjustments based on real demand instead of relying on arbitrary forecasts of inventory needs (Pacella & Papadia, 2021). This demand alignment can cut away unnecessary inventory generally and increase turnover, each of which will support lean objectives. Of the primary areas of Machine Learning, reinforcement learning is one of the most informative and flexible approaches to reinventing inventory management concerning actual conditions that arise with practitioners in stock controlling (Olaleye, 2024).

Thus, using Q-learning or other reinforcement techniques, models for choosing the best policy for replenishment or restocking can be obtained that adapt to fluctuations in demand (Shakya, 2024). This dynamic adaptability relates to some of the lean manufacturing principles, such as low inventory management and responsiveness to market changes. Moreover, clustering techniques, with no exceptions, such as K-means clustering, support the primary focus area, which is stock prioritisation in the inventory industry (Goncalves et al., 2021). It is possible to separate inventory into three groups: High priority items labelled "A," moderate importance labelled B, and low importance labelled C; this enables the appropriate allocation of resources to the most important items the outlets deal in, resulting in efficient use of space and employee time, promoting lean completely.

However, existing knowledge and research still need to be improved when it comes to integrating the tenets of both advanced machine learning and reinforcement learning to produce lean inventory management that would remain deeply dynamic in practice (Spreitzenbarth et al., 2024). In lean warehousing, conventional systems utilise averaged shelf-life standards and fixed inventory policies, which are often rigid and cannot adapt promptly to demands (Liljeqvist, 2021). These failures of response may result in overproduction or underproduction, which is counter to the lean goal. While no research has incorporated Reinforcement learning with placeholder or dynamic costs in lean models, models with these features could support real-time decision-making for work that is consistent with lean theory principles of minimising waste and improving inventory control (Mumani et al., 2021). Although, by now, various authors have already started exploring the applications of machine learning like LSTM in demand forecasting, more interrelation has yet to be conducted exploring its implementation into real-time lean practices where demand predictions produced are immediately useful in determining stocking levels and reordering policies.

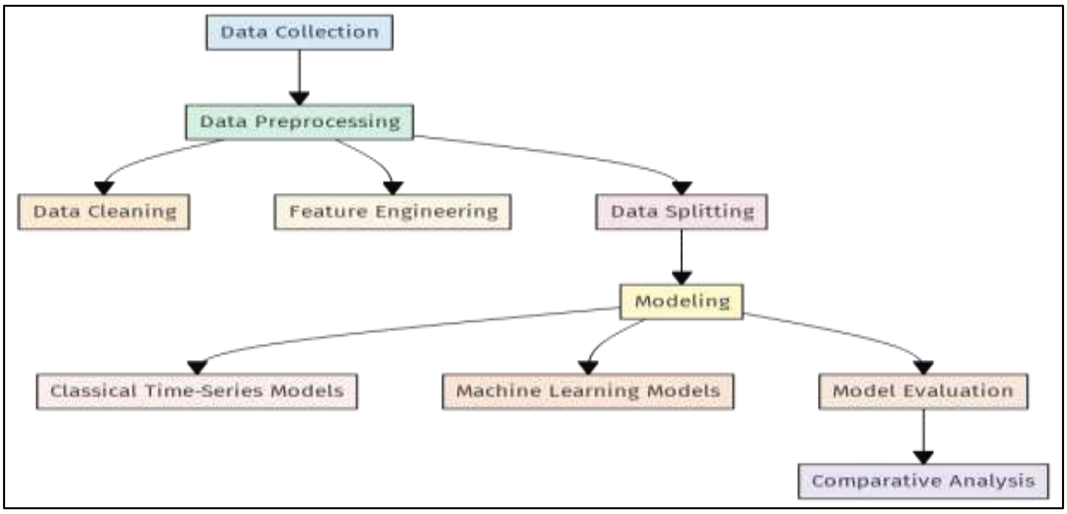
Likewise, although clustering is well-known in inventory management operations, its implementation within lean warehousing contexts is limited (Cagliano et al., 2022). Clustering can also help to prioritise items since items can be classified according to the frequency with which they are demanded, the turnover rate of the item, and the extent to which they weigh in the inventory management strategy (SCHIRO & RUBIN). Nevertheless, more research needs to be done regarding the ways clustering could be useful to lean objectives: For example, high-usage and low-usage items that can be ordered again and again and items that are only restocked on rare occasions, respectively. Also, clustering methods seldom integrate with other dynamic models that would allow for more flexible and responsive lean warehousing strategies like reinforcement learning (Hajdu, 2024).

These gaps are filled in this study through LSTM, which is used for demand forecasting; Reinforcement learning with dummy costs for inventory control; and K-means, which is used in ABC analysis (Arantes, 2020). These technologies present information that can be used effectively in managing stock with enhanced response to the lean objectives. Thus, while investigating the effects of these models in combination, the study hopes to illustrate the potential of technology to ensure lean warehousing is sustainable, efficient, and relevant to operating needs.

3. METHODOLOGY

The approach used in this research to study and enhance warehouse operations is through the preparation of models and lean. This section explains the characteristics of the used data, the EDA process conducted, and concrete settings of the LSTM, reinforcement learning, and clustering.

Figure 1: Methodology Flow Diagrams



3.1. Dataset Overview

The work employs a rich dataset that includes several important variables necessary for examining warehouses and demand characteristics. The data fields include Sales which shows daily or weekly sales numbers, which are used as the dependent variable in the demand forecasting of the LSTM model. Order Item Total refers to the overall amount within transactions or at a given time given by the clients to the business. Aids in determining the demand pattern as well as the level of stocks to be held. Benefit per Order is expressed as the profit or margin per order, and it offers information on the financial outcome of individual items and product groups. Current Stock indicates the present stock position of each of the inventories. This information is very useful when it comes to stock management and is also applied in reinforcement learning and clustering.

3.2. Models and Approaches

Exploratory Data Analysis (EDA) - Exploratory Data Analysis was done in a bid to identify trends or nature of the data set and the relationship, if any, that is likely to exist between variables (Nielsen, 2022). Planned analyses include:

Descriptive Statistics - Exploratory analysis is used to calculate moments such as mean, median, and standard deviation of all the variables to get a general view of data such as centrality and spread.

Distribution Plots - Histograms and density plots on variables such as Sales, Order Item Total, and Current Stock to know distribution to know whether the values are skewed or not and to look for more than one peak in the distribution.

Correlation Matrix - A correlation matrix was constructed to analyse the correlation between numeric variables and to determine what could affect sales and stock quantities. This insight points to points that some of the variables may be relevant when it comes to forecasting and inventory models.

Box Plots - Benefit per order and other fields related to profit benefit from the use of box plots since they allow the identification of outliers in profit data and comparison of the distribution of profit by category.

3.3. LSTM Model for Demand Forecasting

Using this LSTM model, demand patterns are predicted at this moment with a view of optimally stocking to actual requirements with little or no overstocking or stockout.

Objective - It requires precise future demand estimation derived from the company's previous sales data and detailed planning of necessary stocks in further Lean inventory management.

Configuration - The Sales data is first normalised and divided into sequential data segments for the LSTM model, where the sliding window technique is used to create input-output pairs.

Model Architecture - For the LSTM model, 64 entities are contained in the hidden layer, and a connected output layer will be used with a single output. The neural network is learned for twenty epochs, and mean squared error was used as the normal mean loss.

Optimisation - The parameters for learning rate and batch size were both optimised to achieve the lowest value of validation loss. To avoid over-fitting, early stopping was done by considering validation loss as the stopping parameter.

Evaluation Metrics - The model performance is assessed by root mean square error (RMSE) and mean absolute error (MAE), which provide an understanding of the closeness of the forecasted values with actual demand.

3.4. Reinforcement Learning for Inventory Optimisation

Reinforcement learning, and in particular Q-learning, is used to model and minimise holding and shortage costs of the inventories.

Setup - When holding and shortage costs are not available, a cost per unit per period of 0.01 is assumed so as to generate numeric values for the holding and shortage rewards that are the result of the actual inventory actions of the model. Q-learning architecture allows the agent to learn through trial and error because the agent will choose an appropriate action (e.g., ordering or holding inventory) that would maximise the cumulative reward.

State Representation - A state identifies one level of stock current, and actions include ordering or holding inventory. Incentive signals provide the directions to make decisions relating to inventory status and the potential costs as calculated by simulation.

3.5. Learning Parameters

The training is carried out for over 100 iterations, and the rate of learning, along with the discounting factor, is chosen to improve the overall reward earned. Total reward, which measures the model's effectiveness in reducing the costs involved in decision-making, is the chosen key performance indicator. The higher the cumulative reward, the better the lean inventory optimisation signals from holding costs and stockout penalties.

3.6. K-means Clustering for ABC Analysis

K-means clustering is used to sort inventory into priority levels, A, B, and C, enabling managers to concentrate on products that have a high impact on the firm's operations.

Features - Key features include Current Stock, Average Lead Time, and Max Order Quantity. These variables offer information concerning demand frequency, demand urgency, and the rate of turnover that various items make; hence, they are useful in ABC categorisation. Inventory items are segmented based on their importance, with "A" items receiving the highest priority due to higher demand or turnover rates.

Evaluation Metric - The performance of clustering is assessed by silhouette score, which depicts the degree of conformity of an item to the given cluster. A silhouette score of 0.8 or higher indicates that the items have high intergroup dissimilarity and, therefore, are well grouped for ABC classification to prioritise inventory based on lean. All of these models, LSTM for demand forecasting and, K-means for ABC categorisation, reinforcement learning for inventory optimisation, are consistent with the lean principle as they eliminate waste, increase efficiency, and identify high and consequential inventory resources. This work gives a framework of how a scientific management approach may be accomplished in the warehousing sector to support lean goals through the rational use of technology.

4. RESULTS

4.1. Exploratory Data Analysis (EDA)

The EDA was commenced by estimating the mean, median, and standard deviation to investigate important EDA figures such as 'Sales,' 'Order Item Total,' and 'Current Stock.' Analysing the sales variable on sensitivity, it was possible to see high volatility, which means that the demand force during different periods can greatly vary. The mean was used to give the average sales value, while the standard deviation was used to indicate the variation necessary for determining core business times or slow business periods. Likewise, there was fluctuation in the Order Item Total that shed light on the number of items ordered per customer and its implications on the order of inventory. Current stock helped to define the stock positions of the various products, and this showed us that some products tend to be stocked more because of high demand or slow turnover.

Distribution and Correlation Analysis

Some of the distributions generated for variables include the Sales, Order Item Total, and Benefit per Order as shown in Figure 2, 3, 4, and 5. These plots help to illustrate data spread and skewness, which patterns like peak sales in specific periods or with items of higher profit margin. Thus, Sales and Order Item Total distribution provided an idea about high and low-frequency sales patterns or frequent order changes to stock more seasonally.

Figure 2: Sales Distributions

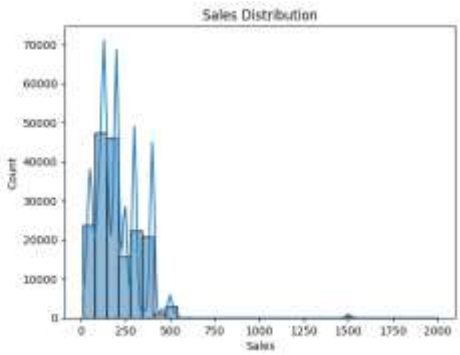


Figure 3: Order Item Total Distribution

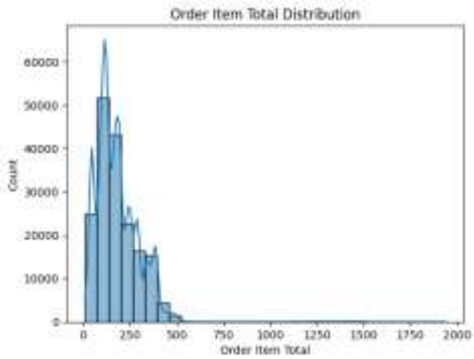


Figure 4: Benefit per order Distribution

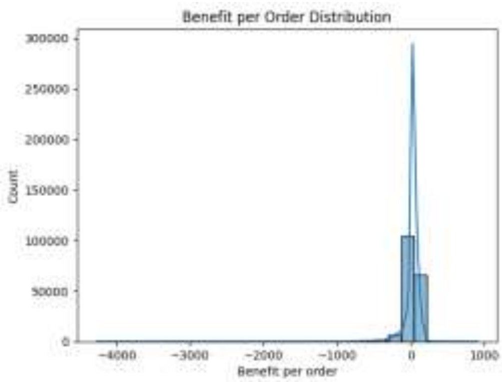
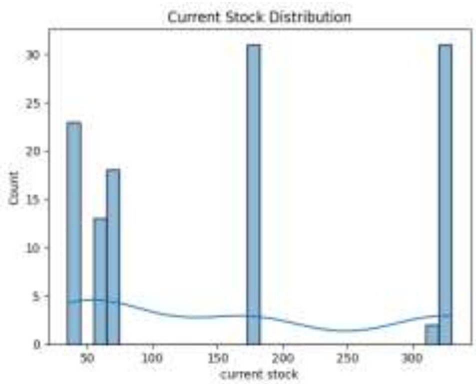
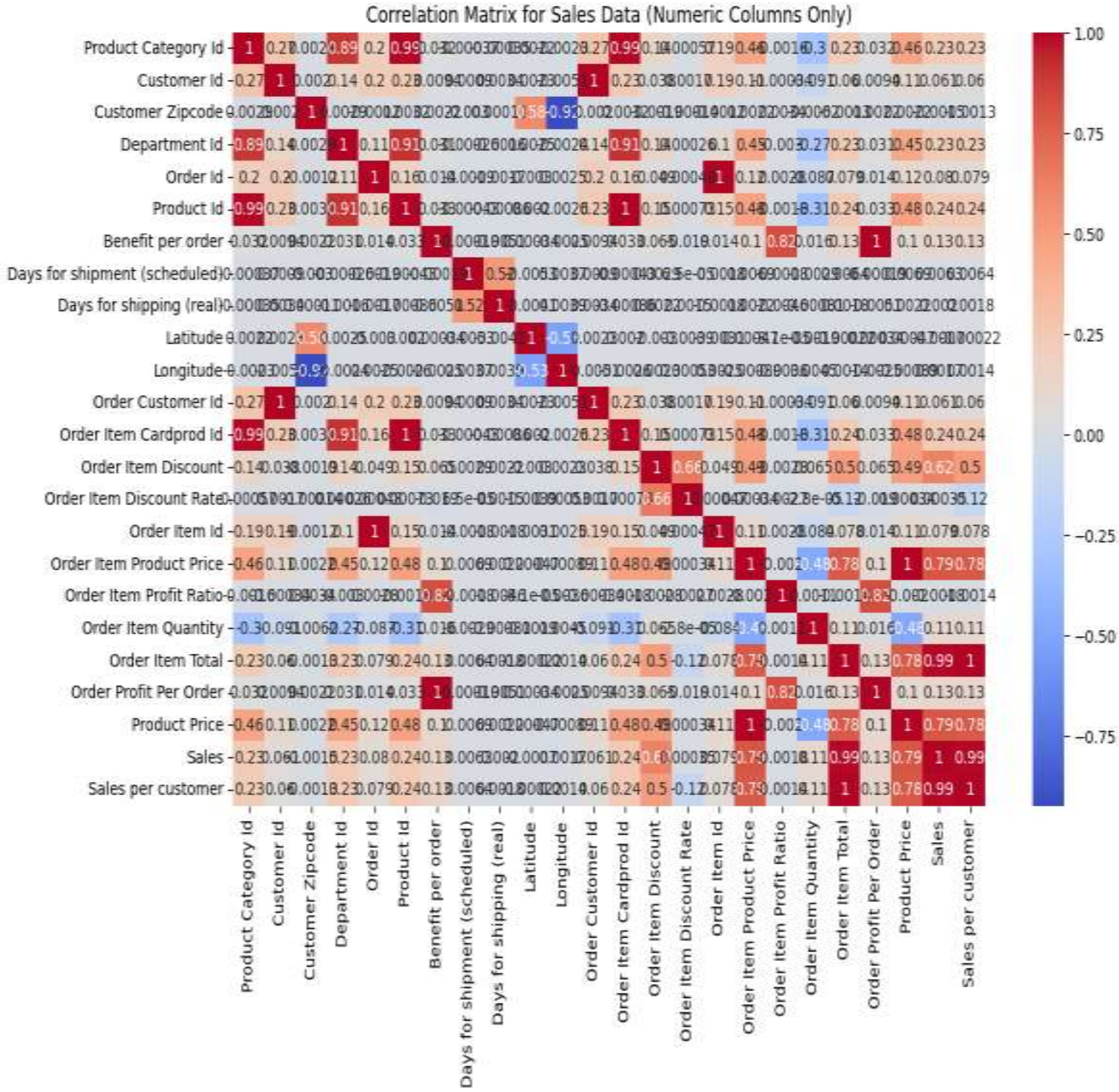


Figure 3: Current Stock Distribution



The correlation matrix showed in Figure 6 the existence of positional links between the factors, thus enabling one to determine variables that could affect Sales or Current Stock. For instance, we even had a moderate positive correlation with sales, implying that when the totals of the order items increase, the sales value also increases. The correlation matrix was thus used to determine inputs to serve in the model by identifying disclosed variables governing demand and inventory control.

Figure 4: Correlation Matrix



4.2. LSTM Model for Demand Forecasting

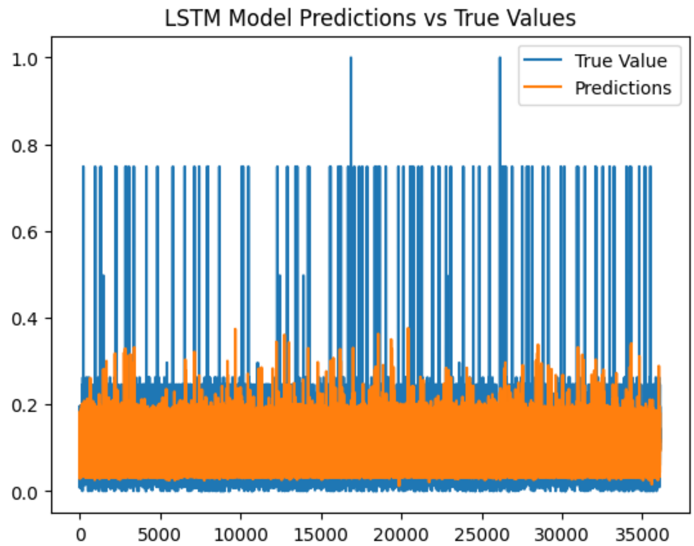
This sales data was used to train the LSTM model to predict demand patterns. Key performance metrics included:

```
1129/1129 ━━━━━━━━━━━━━━━━━━━━ 11s 9ms/step
LSTM RMSE: 0.048436146027012406
LSTM MAE: 0.025603224240329594
```

The explicative low error metrics affirm utility demand patterns and lean objectives by forecasting accurate stock levels. Low RMSE and MAE values indicate our predicted sales were nearly accurate, and thus, there are small chances of overstock or stockouts.

A line chart **(in Figure 7)** that maps actual and predicted sales values confirmed the result and further validated the model. Here, the plot demonstrated that the predicted demand was almost consistent with the actual values during various periods, suggesting that the proposed LSTM-based model could identify the seasonal trends and fluctuations in the demand patterns. This visualisation supports another strength of the model for predictive stock control in lean warehouse contexts, specifically in avoiding both stock out and excess stock.

Figure 5: LSTM Model



4.3. Reinforcement Learning for Inventory Optimisation

The reinforcement learning model employed was Q-learning, and the holding and shortage costs were replaced by placeholders in order to test inventory management. The total reward that was attained was -1511.83, which reveals that the current cost placeholders resulted in a bad reward, signifying that the simulated costs exerted a large influence over the model.

```
Total Reward Collected by RL Model: -1511.8334380533656
```

The negative reward implies that the placeholder costs need to envision the cost structure in a lean warehouse environment accurately. Therefore, better optimisation or incorporation of real-time cost data might increase the model's efficiency. In the context of inventory, what has been dubbed as reinforcement learning models, such as Q-learning, need real cost signals. Here, the placeholders offered only restricted flexibility, which may have exacerbated the firms' suboptimal inventory outcomes. Of course, more work could be done to incorporate holding and shortage costs more realistically and dynamically into the model. This would be very similar to lean warehousing since it cuts holding costs during periods of low consumption and, conversely, does not cause stockouts during periods of high consumption.

4.4. K-means Clustering for ABC Analysis

For ABC analysis, the K-means clustering model was used to segment items into three categories: A, B, and C, with respect to priority. Taking inputs such as the Current Stock, Average Lead Time, and Max Order Quantity, the Silhouette Score has come out to be equal to 0.935. This high value suggests that the OLS method produced clusters where items in a given cluster have similar demand and stock attributes. The high clustering accuracy found at this level is conducive to prioritisation because the high-priority items (A) are separated from lower ones (C), making it easier for warehouse managers to concentrate on important items for demand satisfaction.

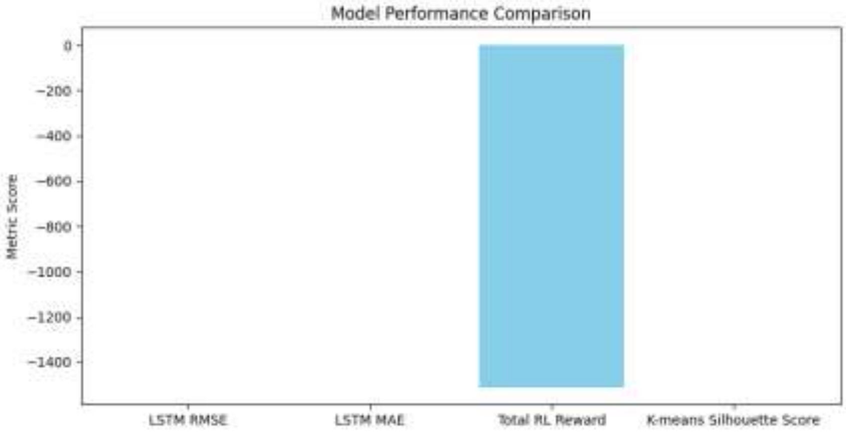
```
Silhouette Score for K-means clustering: 0.9353315131597475
```

A consolidated table summarises the performance metrics across all models, highlighting key results as shown in Table 1.

Table 1: Comparison Models

Model	Metric	Accuracy/Score
LSTM (Demand Forecasting)	RMSE	0.048
LSTM (Demand Forecasting)	MAE	0.025
Reinforcement Learning (Inventory Optimisation)	Total Reward	-1511.83
K-means Clustering (ABC Analysis)	Silhouette Score	0.935

Figure 6: Model Performance Comparison



The Figure 6 presents a Model Performance Comparison across different metrics for various models or approaches. It includes LSTM RMSE and LSTM MAE (measuring prediction error for the LSTM model), Total RL Reward (possibly for a reinforcement learning model, indicating the cumulative reward achieved), and K-means Silhouette Score (assessing the quality of clustering). The bar heights suggest negative or low scores for the LSTM metrics, potentially due to high error. At the same time, Total RL Reward has a prominent positive value, indicating strong performance in achieving rewards. The absence of a bar for the Silhouette Score could imply poor clustering performance or a lack of data for comparison.

5. DISCUSSION

Both LSTM and reinforcement learning and K-means clusterisation point to the importance of technology in implementing lean warehousing principles to allow demand-focused inventory replenishment, cost control, and proper stock prioritisation.

The proposed LSTM model, therefore, presents a relatively small RMSE of 0.048 and an MAE of 0.025, indicating high model accuracy in terms of demand pattern forecasting. This level of forecasting is important in lean warehousing since it enables the warehousing systems to balance inventory with the actual usage needs without compromising on either excess or shortage. Thus, depending on arrival and turnover, Just-in-Time (JIT) principles are applicable, which allows optimal stock levels for the warehouse in response to forecasted demand, thereby decreasing holding costs and increasing overall performance. The high accuracy also contributes to lean objectives as ordered and stocked items are retrieved and replenished only when needed, hence eliminating the issue of excess due to excess.

Q-learning withholding and shortage costs as the placeholder led to the reinforcement learning model with a total reward of -1511.83. This result can be explained by the fact that variable cost build-ups should have used context-sensitive values instead of fixed-holding cost coefficients. The negative reward implies that the model was often rebuked for inventory decisions that could well be acceptable for the real cost structure of the system. This suggests the value of incorporating current realistic cost information – the model proposed could then provide even more flexible solutions while achieving the best cost/benefit ratios. Specifically for a lean warehousing environment in which the inventory decisions are directly linked with cost efficiency goals, a reinforcement learning model with real cost inputs may substantially improve the supply point inventory's capability to adjust to demand volatilities, thus supporting lean objectives.

In the K-means clustering, the Silhouette Score was found to be 0.935, which means the model properly categorised the items on the basis of inventory control priority, a priority-wise grouping of items, also known as ABC analysis. This categorisation aids lean principles by directing resource utilisation to high-priority goods: these are in Category A, and they are restocked more frequently than goods in Categories B and C. It also gives the ability to manage many aspects of a project at a single location, which is precisely the purpose of the lean approach, which emphasises minimising the consumption of resources in the environment. This high silhouette score means the quality of clusters that will be selected as items within the same category will have similar demand and stocking characteristics, hence making ABC analysis consistent and useful.

The adaptation of these models in the real-life warehousing system is beneficial, but there are distinct issues as well. Better demand forecasts, inventory mobility, and priority assignment contribute positively to the aspect of warehouse productivity. In real-time implementation, quality data is used, and there should be strong IT support, and the model has to be tuned consistently. Deriving the cost automatically creates more data limitations for the model as records become incomplete or disparate stock levels become outdated, which is especially detrimental for reinforcement learning as costs need to be reactive and constant. Additionally, these models need practical analysis of cost-benefit to realise when such technology investment is equal to operational efficiencies.

6. CONCLUSION

These findings indicated that lean warehousing could be well performed by using machine learning and reinforcement learning. By receiving low RMSE and MAE, the LSTM model was proved effective in demand prediction, contributing to lean principles that avoid holding stock beyond actual demand. The reinforcement learning model finding also emphasised how the cost store required dynamic numbers only; using placeholder values would cost a negative reward. Nevertheless, the model evidences the flexibility that reinforcement learning provides for inventory management within lean warehousing, including the real-time cost component. The model deployed for clustering using K-means resulted in a high Silhouette Score and, as such, further enhances inventory prioritisation for targeted stocking appropriation to ensure space and labour resources are maximised for items with high demand.

The incorporation of such technologies in lean warehousing makes it more effective because demand status can be forecasted easily, and inventory can be managed sustainably while resources are properly deployed. Some prospects could be followed up in the future, such as the use of real-time cost data in reinforcement learning for dynamic inventory management. Furthermore, new clustering methods or any combination of the models could enhance the process of inventory classification and contribute to the achievement of lean warehousing. This research provides a foundation for implementing data-driven lean warehousing with great potential for enhancing the application of technology.

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ASSESSMENT OF MARITIME LOGISTICS EFFICIENCY IN COASTAL STATES THROUGH DATA ENVELOPMENT ANALYSIS

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ABSTRACT

Purpose- Coastal countries are in an advantageous position compared with landlocked countries in terms of logistics costs and transit times. However, for both the efficient functioning of global transport systems and the competitiveness of coastal countries, it is also important to consider whether this geographical advantage is being effectively exploited. Accordingly, this study analyses the relative efficiency of coastal countries in translating their logistics infrastructure and their logistics competence and service quality into maritime connectivity.

Methodology- The study employs a constant returns to scale Data Envelopment Analysis (CCR-DEA) model configured for output maximization. The Infrastructure Score and the Logistics Competence and Quality Score, which are components of the Logistics Performance Index (LPI), are used as model inputs. The Liner Shipping Connectivity Index (LSCI), representing maritime connectivity, is used as the model output.

Findings- The findings indicate that, within the sample, China has the highest efficiency and that East and South Asian countries exhibit higher efficiency levels compared with other regions. The relatively low maritime connectivity efficiency of the Nordic and Baltic countries can be explained by the fact that their hinterlands are very well connected to the major Northern European hubs. Moreover, deep-sea liner services avoid additional sea legs and prefer ports in the Le Havre-Hamburg range.

Conclusion- The study evaluates the relative efficiency of 92 coastal countries within the framework of an output-oriented DEA model configured with LSCI as the output. East and South Asian countries exhibit higher efficiency levels compared with other countries. Sri Lanka, in particular, attains a high level of maritime connectivity despite having below-average input levels. The findings indicate that maritime connectivity is influenced by factors such as geographical location, beyond logistics infrastructure and logistics competence and service quality.

Keywords: LPI, LSCI, logistics infrastructure, logistics performance, maritime logistics
JEL Codes: C61, L91, R41

1. INTRODUCTION

Maritime transport constitutes the backbone of international trade (Gu & Liu, 2023), and enables the movement of large volumes of goods at lower costs compared with other modes of transport. Thanks to the advantages provided by containerization and advances in shipbuilding, the cargo capacities of commercial ships have increased, allowing maritime transport to benefit more from economies of scale through reducing transport costs (Haralambides, 2019). By contrast, the logistics costs of the landlocked countries are about 50% higher than those of coastal countries (Kashiha et al., 2016; Limao & Venables, 2001). In this context, maritime logistics performance is of critical importance for countries to be able to connect seamlessly and efficiently to global supply chains and to exploit as fully as possible the geographical advantage provided by access to the sea. In particular, for coastal countries, the extent to which their logistics infrastructure and service capabilities translate into access to overseas markets through effective liner connectivity is crucial for exploiting this potential efficiently.

Maritime connectivity is a concept that refers to the access of firms operating in a port's hinterland to overseas country markets; higher levels of connectivity are generally associated with lower freight rates and higher trade volumes (Mishra et al., 2021). One of the commonly used measures of maritime connectivity, the Liner Shipping Connectivity Index (LSCI), expresses the degree to which a country is integrated into the global maritime system (United Nations Conference on Trade and Development (UNCTAD), 2025). In the global transport system, ports function as an interface between the interdependent foreland and hinterland (Rodrigue & Notteboom, 2010), and it is more appropriate to conceptualize this system as a complex and multidimensional network ratem than as a set of isolated processes. In this complex and interdependent structure, the efficiency of maritime transport depends not only on ship/port elements but also on port–

hinterland linkages. In this context, the following research question arises: to what extent are coastal countries able to transform their existing level of logistics infrastructure and quality into accessibility to overseas markets (i.e., maritime connectivity)?

To measure this multidimensional performance and to answer the research question, this study proposes a model that uses Infrastructure Score (INFRA) and the Logistics Competence and Quality Score (COMP) metrics from the World Bank's Logistics Performance Index (LPI) as model inputs (World Bank Group, 2023). Furthermore, the suggested model considers LSCI as model output (United Nations Conference on Trade and Development (UNCTAD), 2025). In line with the research aim, the model is based on Data Envelopment Analysis (DEA) with constant returns to scale (CCR) assumption and configured for output maximization (Charnes et al., 1978). DEA is a reliable non-parametric quantitative analysis method that is frequently employed in studies on logistics efficiency (Cavaignac et al., 2021; Gan et al., 2022), maritime transport efficiency (Nguyen et al., 2022), and port efficiency (Krmac & Mansouri Kaleibar, 2023).

The research question and model aim to contribute to the scholarly literature by moving beyond the traditional focus on operational performance and cost efficiency, and instead investigating the extent to which existing logistics infrastructure and service quality can be transformed into maritime connectivity. Furthermore, despite their importance and potential in world trade, South Asian ports have received limited attention in the academic literature (Vinod & Prakash, 2024). However, the decision-making units (DMUs) of the current study comprise all coastal countries included in the LPI dataset provided by the World Bank, except for the exclusions specified in the methodology section. The remainder of this paper is structured as follows: Section 2 presents the research methodology. Section 3 reports the empirical findings. Section 4 is devoted to the discussion, and Section 5 presents the conclusions

2. METHODOLOGY

This research employs DEA as a non-parametric approach that is frequently used in efficiency measurement (Charnes et al., 1978). A DEA model can be designed under assumptions of constant or variable returns to scale (Banker et al., 2004). In line with the purpose of the current research, DEA is considered with an assumption of constant returns to scale, and the formulation is adopted from Ragsdale (2007) to ensure clarity and ease of application for business managers. The model aims to calculate the relative efficiency of decision-making units (DMUs) in translating their INFRA and COMP into the LSCI. The analysis is based solely on secondary data obtained from publicly available sources (United Nations Conference on Trade and Development (UNCTAD), 2025; World Bank Group, 2023). The research protocol is shown in Table 1.

Table 1: Research Protocol

Metric	Source/Detail
Input 1: LPI infrastructure score (INFRA)	World Bank Group (2023)
Input 2: LPI logistics competence & quality score (COMP)	World Bank Group (2023)
Output: LSCI	United Nations Conference on Trade and Development (UNCTAD) (2025)
DMU	92 coastal countries
Exclusion criteria	Micro island states, Caribbean Island states, very small coastal or riverine countries, landlocked countries, and war-affected economies. In addition, countries for which 2023 LSCI data were not available were also excluded from the sample.

As shown in Table 1, the output-oriented DEA model is configured for two inputs (INFRA, COMP) and one output (LSCI) to assess the relative efficiency of 92 DMUs (see Eq. 1) and is solved using linear programming. Microsoft Excel's solver module is used for this purpose, and the formulation is based on Ragsdale (2007). The configuration aims to maximize output (see Eq. 2) considering model constraints as shown in Eqs. (3) and (4). In formulation:

i indexes DMUs (i.e., coastal countries) in the model
j indexes the input and output variables in the model
w_j = weight coefficient for output j; where $w_j \geq 0$
v_j = weight coefficient for input j; where $v_j \geq 0$
n_O = total number of outputs
n_I = total number of inputs
O_{ij} = value of output j for DMU i
I_{ij} = value of input j for DMU i

$$Efficiency\ of\ DMU\ "i"=\frac{\sum_{j=1}^{n_O} O_{ij}w_j}{\sum_{j=1}^{n_I} I_{ij}v_j} \tag{1}$$

$$MAX: \sum_{j=1}^{n_O} O_{ij}w_j \tag{2}$$

$$\sum_{j=1}^{n_o} O_{kj}w_j \leq \sum_{j=1}^{n_I} I_{kj}v_j\,, \qquad \forall\, k\ =\ 1, \dots, 92 \tag{3}$$

$$\sum_{j=1}^{n_I} I_{ij}v_j\ =1 \tag{4}$$

3. FINDINGS

In this study, an output-oriented DEA efficiency assessment was carried out for 92 coastal countries based on the evaluation of the output (LSCI) and the inputs (INFRA, COMP) specified in the methodology section. The results of the analysis are presented in Appendix 1. Among the five most efficient countries, four are located in East and South Asia. Accordingly, the five most efficient countries are China (DEA_CN = 1), Korea, Rep. (DEA_KR = 0.521), Malaysia (DEA_MY = 0.458), United States (DEA_US = 0.435), and Singapore (DEA_SG = 0.431). Furthermore, Estonia (DEA_EE = 0.033), Bulgaria (DEA_BG = 0.031), ICELAND (DEA_IS = 0.024), Liberia (DEA_LR = 0.023), and Albania (DEA_AL = 0.017) are the countries with the lowest efficiency scores.

The highest LSCI value in the dataset is 1.2k (China), while the lowest is 12.3 (Albania), and the mean LSCI value is 159.4. Singapore has the highest INFRA score of 4.6, whereas Libya ranks last with a score of 1.7. Singapore also has the highest COMP score of 4.4, while Somalia ranks last with 1.8. The mean INFRA score is 3.09, and the mean COMP score is 3.16. The findings indicate that China is the only country operating at full efficiency with a DEA score of 1. As discussed in detail in the Discussion section, East and South Asian countries are generally efficient, whereas the Baltic and Nordic regions display low efficiency levels.

4. DISCUSSION

4.1. The High-Quality, Small-Market Paradox: The Case of Northern Europe

The research findings indicate that the Nordic and Baltic countries have relatively low DEA efficiency scores compared to their comparatively high levels of INFRA and COMP values. It can be argued that this is related to their relatively small populations, limited domestic market size, and the fact that these countries do not assume the role of a mega hub on the scale of Rotterdam, Antwerp or Hamburg in the context of maritime transport, but rather function as regional gateways. The Baltic region access overseas markets through ports located in the geographic area between Hamburg and Le Havre (Notteboom, 2010). The Nordic mainland, on the other hand, has been integrated into Europe via the Øresund and Storebælt (Great Belt) bridges.

The Øresund crossing connects Denmark and Sweden by both road and rail (Ejermo et al., 2022), thus integrating Sweden into the European mainland. This system consists of a bridge and a tunnel and is 15.9 km long (Knowles, 2025). The 18-kilometre-long Storebælt (Great Belt), on the other hand, is a system comprising two bridges and one tunnel, connecting the Danish islands of Zealand and Funen to the Danish mainland. In this way, Øresund and Storebælt ensure Sweden–Denmark–Germany road and rail logistics integration. The Fehmarn tunnel, planned to be 18 kilometres in length, is currently under construction and, once completed, will connect Germany and Denmark via the islands of Fehmarn and Lolland (European Commission, 2024).

Although ports in the Kattegat region such as Gothenburg and Aarhus are of high importance at the regional scale, they are not located on the main trade route of liner services operating between Europe and the Far East. The need to sail an additional maritime leg to access this region leads these ports in the Kattegat area accommodating a limited number of large-sized liner vessels compared to hub ports on the main trade lanes (Notteboom, 2010). These geographical findings may help explain the relative DEA inefficiency of Baltic and Nordic countries in our model, and this result can be interpreted not as a failure of maritime logistics, but rather as a successful outcome of a high degree of integration and capacity sharing.

4.2. Emerging Maritime Transport Centres: The Relative Advantage of India, Malaysia and Sri Lanka

The research findings indicate that East and South Asian countries are prominently represented among the most DEA-efficient countries. Among these countries, Sri Lanka stands out as an interesting case. Although Sri Lanka's INFRA (2.4) and COMP

(2.7) scores are below the dataset average, container liner operators make regular calls at the Port of Colombo due to its hub position in the Indian Ocean, which positively affects the country's LSCI score (243.1). According to the DEA model, Sri Lanka appears to achieve a relatively high level of maritime connectivity despite having below-average levels of LPI inputs. As a major transshipment hub port, the Port of Colombo handled 6.9 million TEU of cargo in 2023 (Sri Lanka Ports Authority, 2025). The port competes with important Southeast Asian ports such as Singapore and Tanjung Pelepas for transshipment cargo (Kavirathna et al., 2018).

Due to its strategic position between East and West, another important maritime hub is Malaysia (Othman et al., 2016). Malaysia's role in international maritime transport can also be explained by the fact that it is one of the coastal states hosting the Strait of Malacca, which reduces the sailing distance between the Indian and Pacific Oceans (Qu & Meng, 2012). In addition, Malaysia is among the Asian coastal states with the longest coastline (Othman et al., 2016). Malaysia is able to transform its above-average input values (INFRA= 3.6, COMP= 3.7) into a relatively high level of maritime connectivity (LSCI = 494.6), and its DEA efficiency score places the country in 3rd position among the DMUs included in the model (DEA_MY = 0.458). One factor that very likely contributes to the relative efficiency of Malaysia is the business capacity of the Port of Tanjung Pelepas, which handled approximately 12.3 million TEU in 2024 (Port of Tanjung Pelepas, 2025).

India is an important maritime logistics hub that connects the South Asian hinterland to the Persian Gulf, East Africa and the Far East shipping corridors. In this context, Jawaharlal Nehru Port is among the most important ports in India in terms of throughput (Vinod & Prakash, 2024). The port is located in Navi Mumbai and handles a substantial share of the country's total TEU throughput (Jawaharlal Nehru Port Authority, 2025). According to the structure of the DEA model with LSCI as the output, India transforms its above-average level input values (INFRA= 3.2, COMP= 3.5) into a relatively high level of maritime connectivity output, which allows the country to rank as the seventh most efficient country among 92 countries in the dataset.

4.3. Relative Position of Türkiye in the Mediterranean Basin

The DEA findings indicate that Türkiye holds an advantageous position in terms of maritime connectivity compared with other countries in the Mediterranean region. The LPI values show that Türkiye has above-average input levels in terms of infrastructure (INFRA = 3.4) and logistics competence and quality (COMP= 3.5). The country is able to transform these inputs into a relatively high level of maritime connectivity (LSCI_TR = 279). Within the DEA model, Türkiye achieves an efficiency score of 0.274 and is ranked 16th among 92 coastal countries.

To put Türkiye's input/output values and DEA score into context, it is useful to compare them with countries in the Mediterranean basin. In Southern Europe, even though Italy, Greece and France have higher INFRA and COMP values than Türkiye, DEA efficiency of Türkiye is higher than DEA scores of these countries. In this region, the only country whose DEA efficiency score is higher than that of Türkiye is, understandably, Spain, which is a gateway between the Mediterranean and the Atlantic Ocean. For the Mediterranean basin as a whole, Spain ranks first, Egypt immediately ahead of Türkiye, while Italy and France rank below Türkiye.

Türkiye has the third-highest level of maritime connectivity (LSCI) among the Mediterranean countries, following Spain and Italy. The fact that Türkiye's relative DEA efficiency is below 1 (DEA_TR = 0.274) indicates that, given its current level of infrastructure and service quality, the country has the potential to achieve a greater LSCI value. Although Türkiye is not a country with insufficient connectivity, it would also not be accurate to say that it is fully exploiting its existing potential.

5. CONCLUSION

Research findings indicate that the relationship between INFRA, COMP and LSCI is neither straightforward nor one-dimensional, and that factors such as geographical location may also play a decisive role in maritime connectivity. The fact that Baltic countries have relatively low DEA efficiency despite their high levels of INFRA and COMP can be given as an example of this. This finding can be explained by these countries being strongly integrated into continental Europe, with feeder services (Notteboom, 2010), as well as extensive road and railway access to the main hub ports along the Hamburg–Le Havre range.

By contrast, Sri Lanka is able to generate a relatively high level of maritime connectivity with below-average INFRA and COMP values. In this particular case, it appears that the geographical advantage in attracting liner services outweighs the logistics infrastructure and service quality. Similarly, Türkiye stands out as the country with the third-highest DEA efficiency after Spain and Egypt among the Mediterranean basin countries; however, this efficiency level could be raised considerably further through logistics investments.

This study has several limitations. First, the proposed model is designed to assess countries' relative efficiency in transforming their logistics infrastructure and service quality into liner connectivity. It is possible to redesign the model using different criteria, which may in turn lead to different empirical findings. The annual TEU throughputs of countries were not considered as an output and could be incorporated into the model in future studies. The output-oriented research model evaluates the DEA efficiency within specific context of given inputs and output; therefore, efficiency/inefficiency scores reported here should not be interpreted as overall logistics performance of the countries. Finally, the dataset does not include Pakistan, Tunisia and Morocco, for which LPI data were unavailable. In addition, data for Vietnam were not incorporated into the model, which may introduce bias in the DEA results; therefore, it is recommended that Vietnam be included in the sample in future studies.

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Appendix 1: DEA Inputs, Output, and Efficiency Scores by Economy

Economy	LSCI[1]	LPI_INFRA[2]	LPI_COMP[2]	DEA_Eff.
China	1200.0	4	3.8	1.000
Korea. Rep.	625.2	4.1	3.8	0.521
Malaysia	494.6	3.6	3.7	0.458
United States	509.3	3.9	3.9	0.435
Singapore	594.8	4.6	4.4	0.431
Spain	409.8	3.8	3.9	0.359
India	330.9	3.2	3.5	0.345
Sri Lanka	243.1	2.4	2.7	0.338
United Kingdom	373.8	3.7	3.7	0.337
Hong Kong SAR. China	399.2	4	4	0.333
Japan	411.1	4.2	4.1	0.326
Netherlands	393.4	4.2	4.2	0.312
Taiwan. China	344.2	3.8	3.9	0.302
Belgium	353.6	4.1	4.2	0.288
Egypt, Arab Rep.	247.3	3	2.9	0.275
Turkiye	279.0	3.4	3.5	0.274
Indonesia	233.2	2.9	2.9	0.268
Saudi Arabia	273.7	3.6	3.3	0.263
Italy	287.4	3.8	3.8	0.252
Germany	316.9	4.3	4.2	0.246
United Arab Emirates	300.9	4.1	4	0.245
Thailand	264.3	3.7	3.5	0.239
France	260.8	3.8	3.8	0.229
Mexico	180.3	2.8	3	0.215
Panama	202.5	3.3	3	0.214
Colombia	183.2	2.9	3.1	0.211
Philippines	179.0	3.2	3.3	0.186
Greece	194.8	3.7	3.8	0.175
Jamaica	120.0	2.4	2.5	0.167

Peru	125.0	2.5	2.7	0.167
Portugal	176.3	3.6	3.6	0.163
Dominican Republic	127.2	2.7	2.6	0.157
Oman	140.9	3.2	3.2	0.147
Ghana	101.9	2.4	2.5	0.142
Brazil	132.8	3.2	3.3	0.138
Togo	94.0	2.3	2.4	0.136
Congo, Rep.	83.5	2.1	2.9	0.133
Israel	137.0	3.7	3.8	0.123
Australia	149.9	4.1	3.9	0.122
Canada	155.4	4.3	4.2	0.120
Chile	101.2	2.8	3.1	0.120
Bangladesh	82.4	2.3	2.7	0.119
Argentina	99.8	2.8	2.7	0.119
Costa Rica	96.2	2.7	2.9	0.119
Uruguay	96.1	2.7	3.1	0.119
Poland	123.5	3.5	3.6	0.118
Malta	124.8	3.7	3.4	0.116
Djibouti	80.2	2.3	2.8	0.116
Nigeria	82.3	2.4	2.3	0.114
Iraq	72.3	2.2	2.2	0.110
Libya	54.5	1.7	1.9	0.107
Algeria	65.7	2.1	2.2	0.104
South Africa	110.4	3.6	3.8	0.102
Qatar	111.4	3.8	3.9	0.098
Cameroon	60.1	2.1	2.1	0.095
New Zealand	105.1	3.8	3.7	0.092
Iran. Islamic Rep.	60.7	2.4	2.1	0.092
Angola	56.4	2.1	2.3	0.090
Sweden	112.5	4.2	4.2	0.089
Romania	68.8	2.9	3.3	0.079
Honduras	62.7	2.7	2.7	0.077
Slovenia	74.5	3.6	3.3	0.071
Denmark	87.2	4.1	4.1	0.071
Croatia	61.0	3	3.4	0.068
Cambodia	42.5	2.1	2.4	0.067
Lithuania	66.4	3.5	3.6	0.063
Cyprus	50.4	2.8	3.2	0.060
Somalia	33.5	1.9	1.8	0.059
Haiti	31.5	1.8	2	0.058
Gabon	35.7	2.2	2	0.057
Ireland	57.5	3.5	3.6	0.055
Finland	68.3	4.2	4.2	0.054
Norway	62.9	3.9	3.8	0.054

Namibia	43.4	2.8	2.9	0.052
Nicaragua	26.0	1.9	2.8	0.046
Madagascar	24.5	1.8	2.2	0.045
Kuwait	41.2	3.6	2.9	0.045
Venezuela. RB	31.3	2.4	2.5	0.043
Mauritania	24.8	2	2.5	0.041
Georgia	28.4	2.3	2.6	0.041
Latvia	39.8	3.3	3.7	0.040
Cuba	26.0	2.2	2.2	0.039
Guinea	27.6	2.4	2.7	0.038
Sudan	25.8	2.3	2.4	0.037
Bahrain	37.5	3.6	3.3	0.036
Congo. Dem. Rep.	23.5	2.3	2.4	0.034
El Salvador	22.2	2.2	2.7	0.034
Estonia	34.5	3.5	3.7	0.033
Bulgaria	28.4	3.1	3.3	0.031
Iceland	26.4	3.6	3.5	0.024
Liberia	16.7	2.4	2.4	0.023
Albania	12.3	2.7	2.3	0.017

Source: [1]UNCTAD (2025), [2]World Bank Group (2023)

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THE ROLE OF SEXUAL DESIRE ON ADVERTISING ATTRACTIVENESS AND ONLINE PURCHASE INTENTION: EVIDENCE FROM FRAGRANCE VIDEO COMMERCIALS

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ABSTRACT

Purpose- This study was conducted to examine the relationship between signs used in voluptuous video commercials, customer perceived attractiveness, and online purchase intention. Additionally, this study analyzed the role of individual sexual desire as a moderator in hypothesized relationships.

Methodology- The data were collected in two phases using convenience sampling technique and judgmental sampling technique. In total, 373 valid data, collected from respondents with previous online purchasing experiences, were analyzed using structural equation modeling (SEM).

Findings- The results revealed that signs positively influenced the customers' perception of advertisement attractiveness ($\beta = 0.412$, $p< 0.001$). Furthermore, the outcomes demonstrated the positive effect of perceived advertisement attractiveness on online intention to purchase ($\beta = 0.126$, $p< 0.05$). In addition, the indices indicated the positive moderating role of self-sexual desire on the relationships between signs-perceived advertisement attractiveness and perceived advertisement attractiveness-online purchase intention ($\beta = 0.751$, $p <0.001$; $\beta = 0.218$, $p<0.05$).

Conclusion- Despite the limitations in this study, the findings provide suggestions to practitioners and commercial designers in the perfume industry on how to create attractive advertisements to have the desired impact on customers, focusing on the customers' emotions and sexual desires. The outcomes of this study contribute to the literature on advertising and online customer purchase intention.

Keywords: Online purchase intention, semiotics, fragrances, sexual desire, Source Attractiveness Theory.
JEL Codes: M31, M37, D91

1. INTRODUCTION

Despite many obstacles, the rapid growth of online purchasing has been highlighted in many industries as a new approach to increase profitability (Jones et al., 2022). One of the main obstacles to online shopping is still the inability to physically inspect products on a computer screen (Lee & Park, 2014; Overmars & Poels, 2015). In the context of online purchasing, it was highlighted that the inability of a customer to physically access an advertised product causes the process of persuading the audience to purchase more challenging (Flavián et al., 2017). The actual functions and performance of the majority of products are possible to be observed through/in an advertisement; however, it is a challenging process for many products.

In the perfume industry, scent is undoubtedly the primary factor considered by customers when choosing a perfume. Unfortunately, due to technological limitations, the scent of a perfume cannot be smelled/felt via an advertisement, which makes the online purchase decision for customers more difficult (Mahdavi et al., 2020). A scientific report explained that the part of the human brain that process motivation, memory, and emotions (olfactory cortex) is also the part that detects smell (Herz, 2007; Mensing, 2023). For this reason, fragrance commercials make a great effort to create an attractive advertisement to manipulate and influence the audiences' feelings by featuring fantasies, sex, and desire using erotic signs in advertising (Reichert et al., 2011; Gramazio et al., 2021). A significant amount of studies have been conducted to determine the effects of different signs in advertisements on the customer perception of advertising attractiveness (e.g., Chen et al., 2005; Abdolreza Oboudi et al., 2022; Adomaitis et al., 2024), which consequently affects the customers' intention to purchase (Till & Busler, 2000; Liu et al., 2007; (Gramazio et al., 2021; Kim & Park, 2023). However, no previous studies have examined the relationships between voluptuous commercials' signs, perceived attractiveness of advertisements, and customer online purchase intention for online perfume shopping. Therefore, the primary aim of this study is to understand the degree of advertisement attractiveness from the customer's points of view given the advertisement signs and examine the effect of perceived attractiveness on customers' intentions to purchase perfume online.

Remarkably, it was noted that a specific type of advertising appeal influences the degree to which customers feel that they are connected to an advertisement (Bush et al., 1999). Marketing researchers, for instance, have found that buyers who have a generally favorable opinion of an advertisement's appeal are significantly more likely to buy the products advertised in that advertisement (Phelps & Thorson, 1991). According to Fabrigar and Petty (1999), advertisements that attempt to "match" the consumer in some manner, either through appearance, personality, or both, are also believed to have a greater chance of persuading them. It was investigated whether vivid information in the form of sexual appeal in advertising increases the degree of customer perception of attractiveness, which affects their purchase intention (Reichert et al., 2011; Gramazio et al., 2021; Kim & Park, 2023). To the best of our knowledge, no previous study has been conducted to explore the theory that semiotics in erotic advertisements may have a higher or lower influence on customers' perception level of advertisement attractiveness in different circumstances. In addition, a lack of research investigating the factors that may affect the perceived advertising attractiveness on customers' online purchase intention has been found in the relevant literature. As a secondary aim, to address these gaps, this study suggests that customers' perception of attractiveness in relation to signs in erotic video commercials may depend on the degree of individual sexual desire. Additionally, this study assumed that a customer's intention to purchase online depends on the level of the customer's sexual desire.

To examine the proposed relationships in this study, a total of 373 valid empirical data collected from audiences were analyzed. The respondents were asked to complete a self-administrative survey according to their perceptions towards the erotic Tom Ford video commercials launched in 2020 in which a new perfume was introduced.

The rest of the paper is comprised of a review of previous studies, hypotheses development, methodology, results, discussion and the limitations of the current study.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. Online purchase intention

The development of the internet has led to rapid changes in society and people's lifestyles. From a business perspective, for example, most people used traditional methods when they were shopping in the past. Recently, the internet has affected customers' preferences, encouraging them to attempt purchasing online (Arief et al., 2023). Online shopping can be done without any face-to face interaction between the seller/provider and buyer/user (Dahnil et al., 2014; Ha et al., 2015; Arief, 2021). Therefore, researches have indicated that online shopping has reshaped the buying process for a business by reducing the risk of carrying out the transaction process; however, it probably gives customers a feeling of uncertainty when making the decision regarding whether to order/shop online (Arief et al., 2023). The sources of such likely feelings might be customers' concerns about differences that may exist between the actual function, appearance or quality of what is virtualized online (Joseph Cronin & Morris, 1989; S. H. Chang et al., 2016) as well as concerns about the personal information confidentiality (Zhong, 2019). These reasons undoubtedly impact the customer's decision as to whether to make an online purchase and conversely, affect the company's shopping rate negatively. Therefore, creating trust has been suggested as a preventative action that can increase the confidence of customers in online shopping (Dai et al., 2013; Lim et al., 2016). However, it is believed that trust cannot be easily formed virtually in online platforms (Arief et al., 2023). Hence, there is an argument that, before making the decision to purchase, customers seek and evaluate the advertising's appeal (Munnukka et al., 2016; Kergoat et al., 2017), follow influencers who support or offer am advertised product (Audrezet et al., 2020; Asan, 2022) or review existing catalogs (Senecal & Nantel, 2004; Lee & Shin, 2014; Ha et al., 2015). All these actions are conducted by customers to increase their trust and assess the integrity of a product offered online (Mukherjee & Nath, 2007). The current study focuses on studying advertising and online purchase decisions.

2.2. Signs in advertising

Visual design is known as one of the most effective aspects or language used for communication purposes (Figl et al., 2010). Signs in visual design comprise vivid information that can help the customer understand/feel products better and change their attitude by putting them closer to a actual experience (Nowlis et al., 2004). It is recommended that signs are used in advertising as an effective communication tool (Pieters et al., 2010; Solík, 2014). The main purpose of adverting is to promote the product or service via textual or virtual to persuade the target audiences to purchase and relatively increase selling growth (Torresi, 2008). Therefore, signs in advertising are perceived as crucial tools in designing effective advertising to create a bridge between customers and communicators to increase the efficiency of communication and influence the customer persuasion (Şerban, 2014; Oputa et al., 2019).

According to existing literature, signs can be divided into verbal (linguistics) and non-verbal (non-linguistic) (Andhika Dhananjaya et al., 2019; Dewi et al., 2021; Simarmata et al., 2022). Signs are also explained in terms of verbal (linguistics) and visual signs (non-linguistic) (Eynullaeva & Woodward-Smith, 2012; Agustia & Karmini, 2020). Signs such as verbal and written language used in commercials are categorized as linguistics signs, while music, objects, and body language are in the category of non-linguistic signs. Both linguistic and non-linguistics signs have been determined to be influential elements for advertising attractiveness. For example, the results of neuromarketing studies indicated that the behavioral responses and attitudes of audiences about attractiveness are effected by the human voice (Casado-Aranda et al., 2017; Belin, 2021), color (Lynn & Shurgot, 1984; Oboudi et al., 2022), body shape (Del Zotto & Pegna, 2017; Del Zotto et al., 2020), and music (Peretz & Zatorre, 2012). More specifically, it was shown that erotic signs in advertising affected the attractiveness perception evaluated by audiences (Tanyildizi et al., 2020; Adomaitis et al., 2024).

A sign is possible to be viewed from different perspectives, and therefore, the interpretation of viewers can vary according to their cultural background, personalities or social norms (Şerban, 2014). Therefore, understanding the viewers' perception towards signs in advertising is crucial to attract the customers' attention and increase the perceived advertisement attractiveness (Chang et al., 2016; Kim & Park, 2023); therefore, this needs to be explored further. Hence, this study attempts to determine the relationship between signs and advertising attractiveness in sexually oriented advertising. Therefore, the following hypothesis is proposed:

H1: Signs have a positive impact on advertising attractiveness

2.3. Perceived Advertising Attractiveness

Attractiveness affects human behavior in individuals' everyday lives (Mulford et al., 1998; Langlois et al., 2000; Takahashi et al., 2006; Wilson & Eckel, 2006). In the context of marketing, the attractiveness of a product, service or commercial was shown to be influential in customers' behavioral intentions (Furaji et al., 2013). It was indicated that advertising attractiveness is correlated to the ability to communicate ((DeShields et al., 1996; Phau & Lum, 2000), behavior (Van de Sompel & Vermeir, 2016), and body shape (Bower, 2001). The degree to which an advertisement can astound or hold the interest of its audience is referred to as its attractiveness or power of impression (Sufa & Munas, 2012). Attractiveness to the target audience is necessary for advertising messages to be displayed in a way that can stir, evoke, and keep consumers' memories of the products on offer. The attractiveness of advertising is extremely important due to its role in improving and enhancing the success of communications with target audiences (Ikawati et al., 2021). Due to the fact that there are differences in human beings' perceptions, the concept of attractiveness varies among individuals based on their personal judgment (Horton, 2003), which is also a concern for markets to understand customers' perceptions towards and create attractive advertising.

The degree and intensity of perceived attractiveness can be explained by the theory of source attractiveness (Petty et al., 1997). The source attractiveness theory is founded on the basis of three aspects, namely similarity, familiarity and likability (Petty et al., 1997). Similarity is when audiences consider the commercial content/features like them; as a result, they find this commercial more attractive. Familiarity describes the level of audiences' knowledge about the advertised product, which means that more awareness about the product positively affects the audience's perceived attractiveness about the advertisement. Likability is the reflection of emotional affection towards physical appearance, behaviors, or other personal traits in an advertisement (Kiecker & Cowles, 2002; Sanders, 2005).

The desire of consumers to purchase fashion products is significantly influenced by aesthetic design and attractiveness (Eckman & Wagner, 1994; Seifert & Chattaraman, 2017). For example, using the fMRI image processing technique, neuron marketing studies have indicated that advertising attractiveness is a significant factor affecting customers' intention to purchase ((H. J. J. Chang et al., 2016). Additionally, research findings have revealed that the attractiveness of commercials from a customer perspective has a significant influence on their decision to buy (Guido et al., 2011; Gramazio et al., 2021). Due to the lack of research in an online purchasing context, this study aims to understand the effect of overall customers' perception of erotic advertising attractiveness on their decision to purchase online. Hence, it is hypothesized that:

H2: Perceived advertising attractiveness has a positive impact on online purchase intention.

2.4. Self-Sexual Desire as Moderator

Sexual desire is described as a drive, wish, or motivation to engage or participate in sexual activity or achieve sexual intimacy (Levine, 1987; Basson, 2000). The inclination of a person to act toward or away from sexual behavior depends on a number of forces (Levine, 2003; Mark et al., 2014). People's sexual desires are a reflection of their aesthetic preferences indicating how an individual feels and thinks about beauty in terms of age, race, and physical characteristics (Levine, 2002). The object of sexual desire can differ greatly depending on the individual (Mark et al., 2014). Sexual desire has been highlighted as a strong human behavior motivator, which consequently affects subsequent thoughts and behaviors (Sternberg, 1988). Sexual desire was suggested as the source of dispositional responses (include affective responses, informational responses, and fantasy responses) among individuals (White & Kelley, 1988). Erotophobia and erotophilia are the two main categories of sexual dispositions, which are dispositional reactions to sexual stimuli along a positive-negative dimension of affect and evaluation (White & Kelley, 1988). People who identify as erotophilic are more likely to discuss sex, educate themselves about sexual matters, take precautions against STDs (Sexually Transmitted Diseases), and comprehend material that is sexually explicit in the media. Conversely, erophobics exhibit a more conservative reaction to sexual stimuli and refuse to learn about sexually oriented contents. More precisely, erotophilic people are more likely than erotophobics to access and manipulate external sexual images internally (White & Kelley, 1988). Therefore, individuals with higher levels of positive sexual cognition are more likely to perceive sexually explicit content in product advertisements as a standard component of advertising, whereas individuals with higher levels of negative sexual cognition are more likely to have negative attitudes toward sexual stimuli and to react critically to sexually explicit advertising (Pan, 2014).

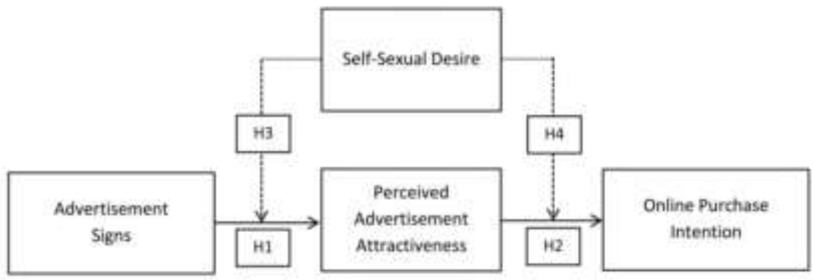
According to the concept of attractiveness similarity, consumers prefer products that match their personality (Aguirre-Rodriguez et al., 2012; Bekk et al., 2016). Findings indicate that similarity leads to liking and attraction, and conversely, dissimilarity causes ignorance (Byrne et al., 1986). For example, people like other people who have similar personality characteristics (Feingold, 1988; Shaw Taylor et al., 2011). We argue that customers perceive attraction towards erotic commercials based on their self-sexual desire and this also affects their intention to purchase online. This study therefore attempts to investigate whether individuals' sexual desire has a moderating role in customers' decision whether to purchase advertised perfume online. Therefore, this study suggests that the degree to which signs affect advertising attractiveness might be influenced by individual sexual desire. Additionally, it is suggested that individual sexual desire influences the impact of advertising attractiveness on customers' intention to purchase online. Hence, it is hypnotized that:

H3: Self-sexual desire moderates the relationship between semiotic signs and advertising attractiveness.

H4: Self-sexual desire moderates the relationship between advertising attractiveness and purchase intention.

On the basis of reviewed literature and hypothesis development, this study proposes the following research framework (Figure 1).

Figure 1: Conceptual Framework



3. DATA AND METHODOLOGY

3.1. Sign Extraction

According to the objective of this study, a voluptuous video commercial of a Tom Ford fragrance released in 2020 was chosen for analysis (https://www.youtube.com/watch?v=CoTU5GSKzyY). With the assistance of semiotics scholars, the signs were extracted, and they formed a multi-sign system consisting of both linguistic and non-linguistic signs. All linguistic and non-linguistic signs were considered important and were categorized into four groups as follows:

- Body shape (belly, breast, shoulder, waistline, eye, lips, biting, rubbing)
- Voice/noise (spoken person-music)
- Color (peachy, pink, black, red, yellow)
- Physical features (skin, peach, grapefruit, wood, peach core, water, sweats)

These categories were used to create the construction of signs in the survey questionnaires.

3.2. Data Collection

To collect the primary quantitative data, a self-administered questionnaire was distributed in February 2025. Using the convenience sampling technique, a form consisting of a filter question and a request for the recipient's email address was distributed to 500 respondents. Given the results of previous studies, students were shown to be interested in experiencing online shopping (e.g., Harahap & Amanah, 2018; Syahiman Ghazalle & Abdul Lasi, 2021). Hence, the sample of the study consisted of college/university students in Nicosia, Cyprus, due to the large number of available universities and students.

Given the results of the filter question, 93 respondents were eliminated from the rest of the data collection process due to not having experience in online purchasing. Therefore, a total of 407 respondents who had experienced online purchasing were listed with their email addresses. Using the judgmental sampling technique (non-probability) in the form of a Google survey, the questionnaire, including demographic and construct sections, was distributed to those on the email list. A voluptuous fragrance commercial of Tom Ford released in 2020 was attached to the online survey, and the respondents were asked to respond to each question according to their perception of the video commercial. A pilot study was conducted based on 30 participants to ensure the validity and reliability of the research instruments. According to the results, several corrections were made to the questions in terms of length, clarity, format, and the sequence of the items. After sharing the survey, a total of 373 responses were returned, indicating a satisfactory response rate of 91.67%. Therefore, 373 data were used for the data analysis process. All participants signed a term of free, informed consent, which was separated from the research protocol to ensure data anonymity. No incentives or rewards were provided to the participants.

3.3. Questionnaire Construct

The survey included two parts. The first was the demographics part, including questions on age, income, marital status, level of education, frequency of visiting the salon, and a filter question. The second part comprised the constructions and items of the survey questionnaire. The demographic data of the respondents is presented in Table 1.

Table 1: Respondents' Demographic Profile

Measure	Item	Frequency (N=373)	(%)
Gender	Male	104	27.88
	Female	269	72.17
Age	18-22	68	18.23
	23 - 27	114	30.56
	28- 32	73	19.57
	33- 37	45	12.06
	38- 43	48	12.87
	43- above	26	6.97
Education level	Bachelor student	254	68.18
	Master student	96	25.71
	Ph.D. student	23	6.17
Marital status	Single	311	83.35
	Married	52	13.94
	Divorced	10	2.68

The results showed that a majority of participants were female (72.17%), and in terms of age, most of them were between 23-27 years old (30.56%). According to the education level, most of the respondents were students at the bachelor level (68.18), while a smaller proportion were Ph.D. students (6.17). Furthermore, a majority of the participants were single (83.35%). The statistics indicated that most of the students had experienced online shopping before, were single bachelor students, in the 23-27 age range, and female.

3.4. Research instrument

Items for each of the proposed research constructs in the questionnaire were modified from earlier studies in the relevant literature to ensure content validity. Each of the constructions was given a minor adjustment to bring them into line with the purpose of the study. The dimensions of signs such as color (3items), voice/noise (7items), body shape (3items), and physical features (2items) were measured by items adopted from Kodžoman et al. (2022), F. Chen et al. (2022), Zoghaib (2017), Anglada-Tort et al. (2021) and van der Walt et al. (2007). In addition, items used to assess the perceived attractiveness were adopted from W. Kim & Cha (2021) (5items), while online purchase intention was evaluated using the items adopted from Al-Adwan et al. (2022) and Tilahun et al. (2023) (5items). For construct measurement, five-point Likert-type questions were employed (1 reflected "strongly disagree" and 5 reflected "strongly agree"). Table 2 shows the example item for each construct.

Table 2: Question Examples

Signs	Example
Color	The color of the XXX commercial was hot (black, red, and pink)
Voice/Noise	The music perfectly gives the feeling that the perfume is voluptuous.
Body shape	An advertisement with an attractive body shape grabs my attention.
Physical feature	The bitter peach perfectly gave me the feeling that the perfume is voluptuous.

Advertising Attractiveness	I think the XXX advertisement is attractive.
Online Purchase Intention	I am excited to purchase the product shown in the XXX advertisement.

Self-sexual desire was measured with the Self-Sexual Schema (SSS) survey questionnaire developed by Andersen & Cyranowski (1994). Self-Sexual Schema is a construct used in studies dealing with sexual reaction/behavior towards advertising (Reichert et al., 2011) in which participants are asked to accurately describe themselves using a seven-point scale ranging from zero (“not at all descriptive of me”) to six (“very much descriptive of me”). This survey has been designed in the form of two versions: one scale for males and one for females. In the female scale, 26 adjectives are measured and categorized based on the overall scores into three dimensions consisting of two positive (“passionate-romantic” and “open-direct”) and one negative dimension (“embarrassed-conservative”). According to previous research, the SSS female scores ranged from – 4 (negative) to 111 (positive; M = 60.37, Std. Dev. = 17.35). The reliability of the construct was tested using Cronbach's alpha and reported as 0.82 and 0.72 as a result of two different attempts (Andersen & Cyranowski, 1994; Wiederman & Hurst, 1997). On the other hand, the male version of SSS is evaluated based on 27 adjectives in categories of three dimensions, including “passionate-loving”, “powerful-aggressive”, and “open-minded-liberal”. In the male version, the scores range from 52 to 162 (M=106-304, Std. Dev. =19.21). The alpha values of the construct also were reported to be 0.86, 0.75, and 0.77 in three different researches (Andersen & Cyranowski, 1994; Schover et al., 2002; Sibley & Wilson, 2004). The SSS scale evaluates the same concept for both males and females; therefore, one scale can be used for data collection and the results can be evaluated based on the individual distance to the mean of the specific gender (Reichert et al., 2011).

3.5. Data Analysis

The data were analyzed using the valid statistical tools SPSS and AMOS (v.24). The values of Cronbach’s α, composite reliability (CR), average variance extracted (AVE), and confirmatory factor analysis were checked in order to assess the construct validity and reliability. The constructs’ relationships were examined using SEM multivariate analysis.

4. DATA ANALYSIS AND RESULTS

4.1. Reliability and Validity

As a prior step, common method bias (CMB) was checked to ensure the data were free of any CMB. The results of Harman’s single-factor test indicated that the first factor explained 40.17% of the total variance, which is less than the accepted limit, suggesting no common method bias in the data (Podsakoff et al., 2003). To assess the internal consistency, Cronbach's α and composite reliability (CR) indices were checked. The outcomes of the Cronbach's alpha and CR analyses revealed that all values were higher than the acceptable limit of 0.7 (Fornell & Larcker, 1981; Nunnally, 1975), and ranged from 0.72-0.85 and 0.83-0.95 for Cronbach's alpha and CR, respectively. Consequently, there was sufficient internal consistency across all constructs, indicating the satisfactory reliability of the research constructions. The indicators of Cronbach's α and composite reliability (CR) are shown in Table 5.

For construct validity, previous studies have indicated that to ensure convergent validity, the CR and AVE values should be higher than 0.7 and 0.5, respectively (Bagozzi & Yi, 1988). Additionally, the factor loading (FL) value for all items should be higher than 0.5 (Jalilvand et al., 2017). The sufficient condition for convergent validity was confirmed by the test results, which revealed that each of the FL, CR, and AVE indices in the measurement model was higher than the permissible threshold (Table 3).

Table 3: The Factor Loading, Reliability, And Validity Indicators

Construct	Items	Mean	FL	AVE	CR	Cronbach’s α
Signs (SI)				0.61	0.95	0.72
Color	SI1	4.65	0.91			
	SI2	4.96	0.82			
	SI3	4.30	0.90			
Noise/Voice	SI4	3.85	0.69			
	SI5	4.25	0.61			
	SI6	4.55	0.72			
	SI7	4.23	0.77			
	SI8	4.68	0.86			
	SI9	4.80	0.59			
	SI10	4.57	0.83			
Body shape	SI11	4.65	0.78			
	SI12	4.33	0.92			
	SI13	4.40	0.84			
Physical features	SI14	4.88	0.73			

	SI15	4.90	0.87			
Perceived Advertisement Attractiveness (PAA)	PAA1	4.56	0.88	0.87	0.94	0.78
	PAA2	4.35	0.92			
	PAA3	4.15	0.86			
	PAA4	4.86	0.93			
	PAA5	4.45	0.84			
Online Purchase Intention (OPI)	OPI1	4.41	0.61	0.51	0.83	0.85
	OPI2	3.80	0.76			
	OPI3	3.93	0.68			
	OPI4	3.24	0.65			
	OPI5	4.41	0.85			
Self-Sexual Desire	SSD 1-26	120.51	***	0.72	0.86	0.81

Note: *** shows that all loading factors for SSD were higher than 0.5.

Moreover, the pairwise construct comparison matrix of Fornell and Larcker (1981) was used to check the discriminant validity. The discriminant validity of a construct is confirmed when the square roots of its AVE are larger than the values of its correlation coefficient with other constructs. The Heterotrait–Monotrait ratio (HTMT) was also assessed to confirm the discriminant validity of the constructs (Cohen, 1988; Tian et al., 2022). Given that the HTMT values were lower than the acceptable threshold of 0.9, there was no discriminant validity (Henseler et al., 2015). Consequently, the discriminant and convergent validity were verified. The Fornell and Larcker test and HTMT test results are shown in Table 4.

Table 4: Discriminant Validity

Pairwise construct comparison				
Construct	**SI**	**PAA**	**OPI**	**SD**
SI	0.781			
PAA	0.433	0.932		
OPI	0.544	0.603	0.714	
SD	0.572	0.384	0.556	0.848
Heterotrait–Monotrait ratio (HTMT)				
Construct	**SI**	**PAA**	**OPI**	**SD**
SI	-			
PAA	0.725	-		
OPI	0.722	0.681	-	
SD	0.432	0.546	0.495	-

Notes: Bolded-italic indicators represent the square root of AVE. Values below the diagonal level are correlation coefficients; the level of significance is $p<0.05$.

4.2. Testing of Hypotheses

4.2.1. Direct Association

Structural equation modeling (SEM), a reliable multivariate technique, was used to test the proposed hypotheses. The goodness of model fit was accepted by the model-fit indices in the structural model ($\chi 2/df$= 2.26, GFI= 0.92, AGFI= 0.86, NFI=0.89, CFI=0.91, and RMSEA= 0.037). Table 5 presents the values of the constructs' relationships and model fit indices.

Table 5: Results of Relationships

Hypothesizes	**Path Estimate (β)**	**P-Value**	**Variance explained (R2)**	**Result**
H1: SI → ATT	0.412	***	0.58	Positive
H2: ATT → OPI	0.126	**	0.51	Positive
Model fit indices				
Fit indices	**Values**	**Acceptable value**	**Suggestions**	
GFI	0.92	⩾0.8	(Scott, 1995)	
AGFI	0.86	⩾0.8	(Scott, 1995)	
NFI	0.89	⩾0.8	(Hair et al., 2010)	
CFI	0.91	⩾0.9	(Bagozzi & Yi, 1988)	
RMSEA (	0.037	⩽0.08	(Bagozzi & Yi, 1988)	
χ2/df	2.26	⩽3	(Hayduk, 2023)	

Notes: *p<0.10; **p<0.05; ***p<0.001

The results revealed that all hypothesized relationships were significant at a p value greater than 0.05. The finding of a significant positive relationship between signs and perceived advertisement attractiveness supported H1 (β = 0.412, p< 0.001). Furthermore, the relationship between perceived advertisement attractiveness and online purchase intention supported H2: (β = 0.126, p< 0.05). The explained variances (R2) of perceived advertisement attractiveness and online purchase intention were 0.58 and 0.51 percent, respectively, indicating a medium effect size of R2 since the indices exceeded the cutoff value of 0.50 (Ozili, 2022).

4.2.2. Moderator Effect

To test the moderating effect of self-sexual desire on the relationship proposed in the model, a bootstrapping procedure was performed in AMOS. The results illustrated that self-sexual desire had a significant positive total effect on the relationship between signs and perceived advertisement attractiveness, and the relationship between perceived advertisement attractiveness and online purchase intention. This indicates an overall direct impact of the determinant variables on the predicted variables. The results are reported in Table 6.

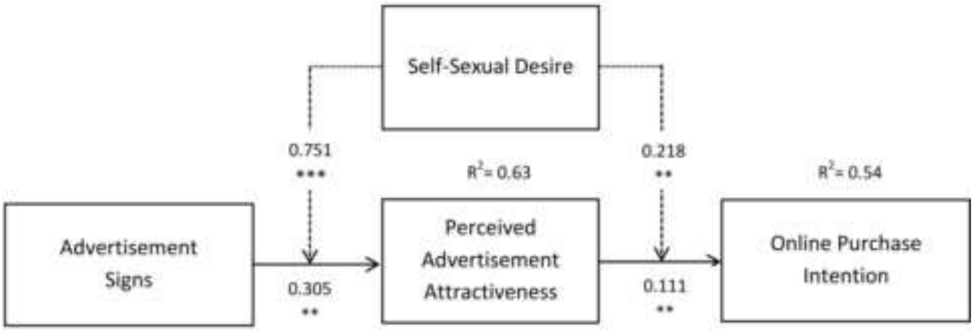
Table 6: Results of the Moderating Influence

Effects	**Path estimate (β)**	**p-value**	**BSE**	**BLCL**	**BUCL**
Direct effect					
SI - ATT	0.412	***	0.042	0.573	0.632
ATT - OPI	0.126	**	0.061	0.654	0.681
Total effect					
SI - ATT	0.305	**	0.033	0.585	0.647
ATT - OPI	0.111	**	0.054	0.690	0.711
Total Indirect effect					
SI * SD = ATT	0.751	***	0.025	0.651	0.725
ATT * SD = OPI	0.218	**	0.046	0.701	0.764
Hypotheses results					
		Indirect path estimates (β)	Probability value (p)	Result	Variance explained (R2)
H7: RI * SQ → AR		0.751	***	Positive	0.63
H8: RI * RB → AR		0.218	**	Positive	0.54

Note: BSE= boot standard error ; BLCL= boot lower confidence level; BUCL= boot upper confidence level; Notes: *p<0.10; **p<0.05; ***p<0.001

The results indicated that when self-sexual desire is included as a moderating variable, the influence of signs on perceived advertisement attractiveness and perceived advertisement attractiveness on online purchase intention significantly improves (β = 0.751, p <0.001; β = 0.218, p<0.05). This result thus highlights a total moderation of self-sexual desire on the relationship between signs and perceived advertisement attractiveness (BLCL= 0.651, BUCL = 725, p< 0.001) and perceived advertisement attractiveness and the online purchase intention (BLCL= 0.701, BUCL = 0.764, p<0.05). This statistical evidence also supports H3 and H4, suggesting that self-sexual desire is the essential ingredient for maximizing the impact of signs on advertising attractiveness, which increases the online purchasing intention towards the advertised product. Overall, the model suggests that 63% of the variation in perceived advertisement attractiveness is explained by signs, and 54% of online purchase intention by perceived advertisement attractiveness. According to the results, self-sexual desire had a stronger impact on the relationship between signs and perceived advertisement attractiveness. The results of hypothesis testing are shown in Figure 2 and Table 8.

Figure 2: Estimated Model



Note: * p <0.10; ** p<0.05; *** p<0.001.

Table 7: Hypotheses Results

H	Hypothesis Statement	Level	Result
H1	Signs have a positive impact on advertising attractiveness.	Significant	Supported
H2	Perceived advertising attractiveness has a positive impact on online purchase intention.	Significant	Supported
H3	Self-sexual desire moderates the relationship between semiotic signs and advertising attractiveness.	Significant	Supported
H4	Self-sexual desire moderates the relationship between advertising attractiveness and purchase intention.	Significant	Supported

5. FINDINGS AND DISCUSSIONS

5.1. Empirical Implications

The results of the analyses revealed that signs in the advertisement significantly influenced the customers' perception towards the advertisement's attractiveness ($\beta = 0.412$, $p < 0.001$). These findings are consistent with the results of previous studies (e.g., Tanyildizi et al., 2020; Adomaitis et al., 2024). Since testing the scent of perfume advertised online is impossible, this study highlighted erotic signs as a key driver influencing the perceptions of customers in a positive way, which can increase the attractiveness of video commercials for perfumes. However, it should be noted that it is obvious that using sexuality to promote products, whether directly or indirectly, can cause conflicting emotions. Relevant ideas, such as moral and ethical considerations, can aid in the explanation of reactions to sexual appeal (Reichert et al., 2011).

Furthermore, the outcomes of the current study demonstrated that customer perceived attractiveness positively influenced their intention to order the perfume online ($\beta = 0.126$, $p < 0.05$). This result supports the outcomes of previous studies in the literature (e.g., Guido et al., 2011; H. J. J. Chang et al., 2016; Gramazio et al., 2021). However, it should be mentioned that the significance level did not confirm a strong relationship between the variables (moderately), given the analysis's indices. These low-significant results might be affected by several factors, such as online purchasing limitation (Roper & S. Alkhalifah, 2020), shipping/delivering national restrictions (Surjandy et al., 2021), international bank transfer boundaries (such as nationality restriction) (Indiani & Fahik, 2020), lack of brand trust (Iqbal, 2021; Ling et al., 2010), and financial power (Law et al., 2016). Overall, the results of this study place emphasis on the importance of advertisement attractiveness perceived by customers, given the erotic signs in advertising, in online purchase decision-making in the perfume industry.

Lastly, this study's results demonstrated the influence of individual sexual desire on the relationship between sign-perceived attractiveness ($\beta = 0.751$, $p < 0.001$) and perceived attractiveness-online purchase intention ($\beta = 0.218$, $p < 0.05$). However, no study has been conducted to specifically test the moderating role of self-sexual desire in the advertising context; the outcomes confirmed the results of previous studies, highlighting the influential role of self-sexual desire in purchase decision-making (Reichert et al., 2011). In particular, the results illustrated that self-sexual desire had a greater positive influence on the relationship between signs and customer perceived attractiveness compared to the attractiveness-online purchase intention relationship. This result is assumed to be due to the high sexual desire of those participating in the study, considering that erotic signs that exist in advertising make advertising more attractive. This is supported by the theory of attractiveness similarity, suggesting that audiences prefer commercials that match their personality (Aguirre-Rodriguez et al., 2012; Bekk et al., 2016). Therefore, respondents liked the voluptuous video commercial due to its similarity to their interests; thus, it was perceived to be attractive for them (Byrne et al., 1986). It can be assumed that this result is due to the erotophilic personality of the respondents, who like/support material that is sexually explicit in the media.

5.2. Theoretical Implications

It was argued that trust is a key factor in customers' decisions to purchase online, which increases their confidence in ordering an advertised product (Dai et al., 2013; Lim et al., 2016). However, it has always been a challenge for marketers to create trust for customers virtually (Arief et al., 2023). Thus, customers constantly seek to persuade themselves to make the right decision to order an advertised product online. In this line, advertisement appeals were suggested as an influential factor affecting customer buying decision-making (Munnukka et al., 2016; Kergoat et al., 2017). The signs in the advertising increase the trust and confidence of customers towards the product, which consequently persuades them to decide to buy online (Mukherjee & Nath, 2007). Sings that are attractive in the eyes of customers significantly affect the customers' decisions to purchase online (Eckman & Wagner, 1994; Seifert & Chattaraman, 2017). As discussed earlier, both linguistic and non-linguistic signs were reported as influential elements for advertising attractiveness; signs in the form of human voice (Casado-Aranda et al., 2017; Belin, 2021), color (Lynn & Shurgot, 1984; Oboudi et al., 2022), body shape (Del Zotto & Pegna, 2017; Del Zotto et al., 2020), and music (Peretz & Zatorre, 2012). Furthermore, it was shown that erotic signs in advertising affected the attractiveness perception evaluated by audiences (Tanyildizi et al., 2020; Adomaitis et al., 2024), which consequently influenced their decision to purchase online (Guido et al., 2011; H. J. J. Chang et al., 2016; Gramazio et al., 2021). Therefore, the findings of this study support attractive signs from the customer perspective in advertising strongly affect potential customers to act towards online shopping.

According to the theory of source attractiveness, the degree of customer perceived attractiveness significantly depends on the advertisement similarity, familiarity, and likability from audiences' perspectives (Petty et al., 1997). Based on the source attractiveness theory, a commercial is more attractive to audiences if its contents are similar to their personality/character or when they have knowledge and emotional attachment to physical appearance, behaviors, or other personal traits in the advertised product (Kiecker & Cowles, 2002; Sanders, 2005). Therefore, the current study assumed that sexual desire is the strongest human behavior motivator, which relatively affects the subsequent thoughts and behaviors (Sternberg, 1988), and affects the attractiveness and online purchase decision-making for erotic video commercials. Given the outcomes of the study, the sexual desire of individuals was shown as a stimulator of customer perception of attractiveness and online purchasing decisions as well.

6. LIMITATIONS AND SUGGESTIONS

Several limitations were detected, and recommendations are provided to be addressed in future studies. Firstly, the target audience of this research was the students in the capital city of Cyprus, who might face difficulties in purchasing/ordering specific products online, thus affecting their decision to order online. Therefore, it is suggested that future studies consider larger regions as the target market to address and overcome these obstacles (e.g., socially, psychologically, geographically, and culturally). Secondly, this study's objective was not to specifically examine the effect of each element of signs in the proposed model. Therefore, it is suggested that future studies test the impact of each element independently on customer perception. Lastly, in future studies, researchers are suggested to focus on commercials for other products such as clothes, hair fashion, and cosmetics.

7. CONCLUSION

This study was conducted to examine the effect of signs in voluptuous video commercials on the customer perceptions of attractiveness and consequently on online purchase intention. Additionally, the influence of self-sexual desire on the proposed relationships was tested. To test the hypotheses in the model, a voluptuous video commercial of a Tom Ford perfume was chosen, and data were collected from students attending universities in Nicosia, Cyprus. Using SEM, 273 empirical data were tested, and the results revealed significant positive correlations among the constructs' relationships. Furthermore, the moderating effect of self-sexual desire was tested, and it was found to have a significant positive effect on signs-perceived advertisement attractiveness and perceived advertisement attractiveness-online purchase intention. However, the moderating effect was shown to be stronger between signs-perceived advertisement attractiveness relationships. The outcomes of this study contribute to the literature on behavioral intention, advertising, communication, and customer relationship marketing.

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