Article

Data Driven Segmentation System for Product Optimisation in Retail

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Abstract – The rapidly evolving retail landscape necessitates the adoption of structured, data-driven strategies to maintain competitiveness and operational efficiency. Within this context, product bundling has proven to be an effective marketing and inventory optimisation strategy. However, many retailers continue to rely on manual bundling methods, which are labour-intensive and often fail to accommodate dynamic shifts in consumer purchasing behaviour. Traditional bundling approaches frequently overlook optimal product combinations, resulting in missed revenue opportunities and inefficient inventory utilisation. To address these limitations, this study introduces *SmartBundle*, an intelligent system designed to automate and enhance product bundling by integrating customer segmentation and data analytics techniques. The system was developed using the Systems Development Life Cycle (SDLC) methodology, providing a structured framework that guided the progression through key phases, including requirements analysis, system design, implementation, testing and maintenance. At its core, SmartBundle utilises a MySQL relational database structure for efficient data indexing and retrieval, which supports the scalable processing of customer and product data. By applying clustering algorithms, such as K-Means, the system is capable of categorising products based on purchasing patterns, identifying high-potential bundling opportunities and minimising the accumulation of surplus inventory. This data-driven method enables retailers to dynamically adjust their bundling strategies in response to market demands, thereby improving both operational performance and overall profitability.

Keywords: “Product”, “System”, “Bundling”, “Optimisation”, “Retail”

1. Introduction

In today's highly competitive retail landscape, product bundling has emerged as a highly effective approach not only for increasing sales volume but also for improving customer satisfaction. This approach involves combining several related products into a single package, offered to customers at a more attractive price than if they purchased each product separately. Retailers can attract customers through this strategy as it provides additional value while simplifying the purchasing process. For example, an electronics retailer may offer a bundle comprising a television, a sound system and related accessories at a reduced total price, thereby benefiting both the retailer and the customer. From a marketing perspective, such an approach also creates opportunities for producers to introduce new products to existing customers in a cost-effective manner.

Furthermore, bundling can contribute significantly to operational efficiency, particularly in the context of inventory and supply chain management. One of the long-standing challenges in retailing is the accumulation of unsold and outdated stock. Product bundling offers a viable solution to this issue by enabling retailers to pair fast-moving products with slow-moving inventory, thus reducing waste and optimising storage space. This strategy not only minimises potential losses but also increases the retailer's overall revenue.

This approach offers significant advantages, particularly in enhancing the perceived value of a product in the consumer’s mind and in encouraging the purchase of items that consumers might not have otherwise considered (Banciu, 2009). This has some strength in its ability to increase the value of the product in the consumer's mind, and in that it could stimulate consumers to buy those products they otherwise wouldn't even think of. By bundling products that are compatible with the main products, as a business, the retailer can come up with a more convincing offer that serves as a pull factor to attract a wider audience. From a product range consisting of hundreds of items, retailers typically offer bundled packages at a significant discount compared to purchasing each item separately. By implementing this bundling strategy, retailers can not only drive increased sales but also strengthen customer loyalty to a product. Bundling also improves consumer utility and surplus, as the overall value derived from the package exceeds the price paid (Liao et al., 2002).

They might package two similar products that have different sales rates to minimise waste and inventory space by selling them together. As such, retailers can reduce the risk of loss and increase their overall income. Establishing a strong relationship with customers constitutes a mutually beneficial strategy that yields advantages in both the short and long term.

Providing better offers that satisfy customer needs will foster mutual trust and a long-term relationship, thereby turning them into loyal customers. Lastly, product bundling has emerged as a strategic marketing and growth solution, not merely an effective marketing tool but also possessing the potential to drive growth and success in the fierce retail competition. Companies often face challenges in fully exploiting the benefits of product bundling due to the lack of a systematic mode that considers customer preferences, inventory constraints and sales performance. Traditional bundling methods often rely on manual selection or simple heuristics that do not maximise profits or meet the needs of different customer segments. Current product bundling approaches are often inefficient because they depend on static pricing models or general category groupings that fail to account for dynamically changing customer behaviour (Arora, 2011). Retailers frequently struggle to identify the most effective product combinations, resulting in missed sales opportunities and higher inventory holding costs. Without a data-driven bundling system, sales strategies remain inefficient and poorly targeted.

To address these issues, this study introduces SmartBundle, an intelligent system designed to optimise product bundling through the application of segmentation techniques. The distinctiveness of SmartBundle lies in its ability to integrate customer segmentation with bundling optimisation by leveraging data analytics and automation to support more informed and responsive decision-making by retailers. Unlike traditional methods, SmartBundle dynamically generates bundling compositions by analysing sales data and customer trends, enabling more targeted and efficient decision-making. This study contributes to the field of product bundling optimisation by introducing a more systematic approach to product bundling, thus reducing the reliance on manual selection, which is often inefficient. By using data analytics methods and segmentation algorithms, the SmartBundle system can identify demand patterns and form more strategic product packages.

SmartBundle enhances the literature by providing a systematic and data-driven method for product bundling. This decreases dependence on manual processes and allows for more accurate sales forecasting and inventory management. Retailers are thus empowered to find the best product combinations for different customer segments, reducing excess stock and increasing profitability. Furthermore, the system offers scalability and flexibility, enabling bundling strategies to be adjusted in real time based on market conditions. In doing so, SmartBundle helps maintain competitiveness in the fast-moving retail sector. Ultimately, its implementation not only refines bundling strategies but also offers a more personalised and satisfying shopping experience to customers.

2. Literature Review

In a volatile retail market, product bundling has emerged as a key method to increase sales and customer happiness. Retailers may encourage customer action and increase the perceived value of a purchase by offering discounts on bundled products. Several recent studies have explored the use of such data analytics and machine learning techniques to optimise this bundling strategy across multiple product categories. For example, Gavhane et al. (2019) developed a machine learning-driven system that uses historical purchase data to generate coherent product embeddings, which can then be used to design more effective bundled packages across multiple product categories. This approach demonstrates the potential of using data mapping systems to improve the impact of bundling strategies in the retail sector. Retailers not only have the opportunity to increase their sales, but also can increase the level of personalisation in the services they offer. (Dzulfikar et al., 2018). With this approach, retailers are able to provide more relevant and meaningful customer experiences. This includes understanding customer needs and wants in depth, which allows them to offer products and services that are more tailored to individual tastes. Retailers can not only attract customers, but also build stronger and more satisfying long-term relationships, which will ultimately lead to increased customer loyalty and higher sales revenue (Chinelato et al., 2021). Through a targeted approach, retailers can gain a better understanding of customers' wants and needs and thus provide the best products and services at the right time.

This action not only increases the customer's satisfaction, but also creates a more profound bond between the company and the customer, which in turn makes them loyal to the company and come back many times. By transforming data and analytics into patterns and trends in customer behaviour, retailers are able to come up with more efficient and innovative marketing strategies, which in turn make the shopping experience more fun and effective (Syaekhoni et al., 2018). The integration of customer segmentation into bundling strategies is the pivot that allows for the greatest customisation of products due to the user's needs and preferences. The study by Ye et al. (2017) proposes a framework that utilises product bundling data to get an accurate insight into the preferences of the customers, and as a result, the retailers can then develop bundling packages that are attractive to a particular segment of the market. This mode of action plays up the importance of comprehending the actions of the customer, as this is the key to the maximisation of bundling effectiveness.

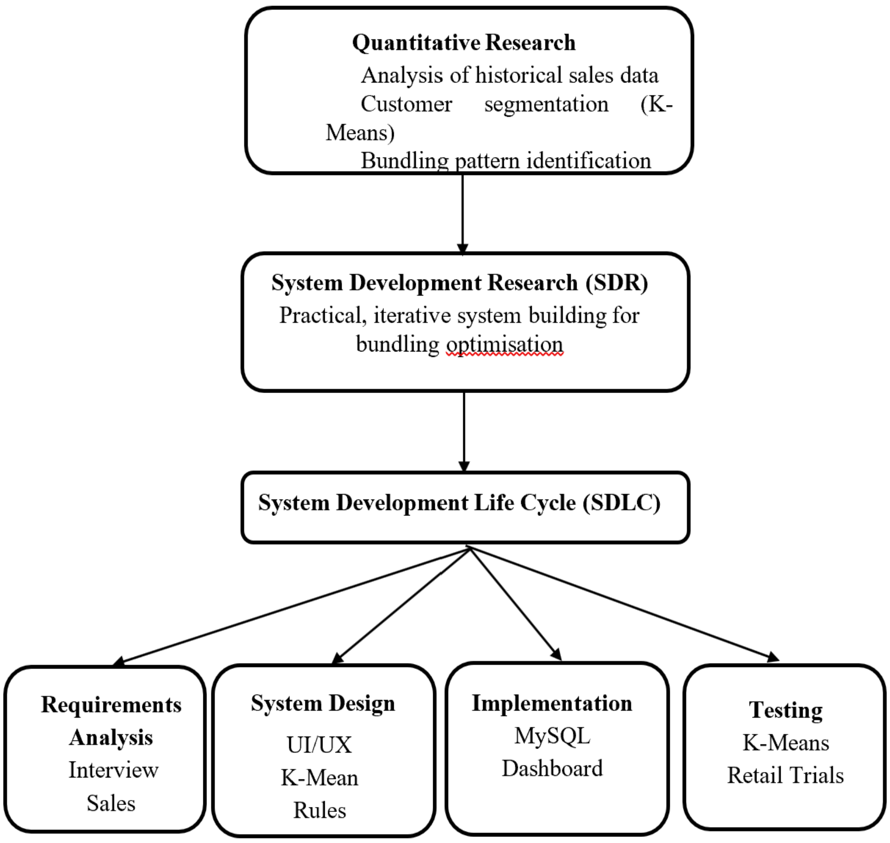
Furthermore, the dynamic effects of bundling as a product strategy have been studied by Li et al. (2018), who found that bundling can function as a dynamic user segmentation mechanism, thereby influencing long-term demand and increasing profitability. The dynamic user segmentation mechanism is a very important approach in understanding and meeting the diverse needs of customers. By using this technique, companies can identify and group users based on their changing behaviours, preferences and demographic characteristics. This process not only helps to respond to changes in market demand more efficiently but also serves to enhance the relevance of the products and services offered. The development of systems like SmartBundle requires a solid understanding of system development methodologies tailored for retail optimisation. A study by Son et al. (2021) demonstrates the application of System Design Optimisation (SDO) using GPU-based computing, which successfully significantly improved warehouse operational performance and workflow efficiency. The development of this technology highlights the important role of advanced system development methods in implementing more effective bundling solutions.

The rapid development of technology highlights the crucial role of advanced system development methods in implementing more effective bundling solutions. This statement is supported by Chevereva & Popova (2021) in this digital era, technological innovations not only enhance process efficiency but also enable the integration of various functions and applications into a single, unified platform. Advanced system development methods, such as the use of artificial intelligence and big data analytics, provide a competitive advantage to organisations by enabling them to identify user needs more accurately and offer customised solutions. With this approach, bundling solutions not only becomes more efficient but also more accessible and relevant to users, making them a more attractive option in an increasingly competitive market. This advancement also opens new opportunities for collaboration between various sectors, where companies can share resources and knowledge to create more innovative and effective solutions. Therefore, by integrating this methodology, the SmartBundle system is capable of dynamically adapting to market trends, optimising inventory management and ultimately increasing retail profits.

3. Methodology

This methodology combines elements from quantitative research and case study exploration to develop and validate automated product integration systems systematically. The system is designed to guarantee high performance by offering solutions driven by technological and design considerations, which significantly contribute to satisfying the growing market demand. The methodology combines quantitative analysis of sales data and customer segmentation with System Development Research (SDR), executed through a structured System Development Life Cycle (SDLC) consisting of five key phases: requirements analysis, design, implementation, testing and maintenance. The integration of machine learning, rule-based logic and UI/UX principles supports the development of a scalable, responsive and retailer-friendly SmartBundle system.

Figure 1: Integrated Methodology Framework for SmartBundle System Development



3.1 Quantitative Research

Quantitative research methods efficiently quantify data that is the non-subjective subject of study, offering an in-depth analysis of user interactions and preferences in the SmartBundle system. Indeed, the predominant strategy adopted is a data-driven approach, which is particularly well-suited for identifying trends and patterns that contribute to system enhancement and the attainment of sustained competitive advantage (Garg & Goyal, 2019). The strength of this research lies in its capacity to extract valuable insights from sales data, customer segmentation and bundling performance through the application of statistical techniques and machine learning, thereby supporting the development of optimal product bundling strategies. The results of this analysis will yield strategic insights, thus enabling decision-making and the design of successful marketing plans for targeted customer segments.

3.2 SmartBundle Development

The System Development Research (SDR) approach is the preferred one as it accommodates an orderly procedure for the testing, designing and improving of the SmartBundle system. The thing with System Development Research is that it shifts away from traditional theoretical approaches and moves towards a practical relationship with statistical data and the real-world outcomes. This technique is specifically applicable in the tech space as it allows innovation to be not only highly practical and scalable but also continuously relevant to the retail industry. Through the utilisation of SDR, the integration of machine learning, database management, and decision support systems can be rendered successful, thereby impacting the impact of bundling strategies (Rupnik et al.,2007). In this regard, SmartBundle has been implemented to establish a link between conventional bundling strategies and data-enabled retail optimisation, which gives a competitive advantage to retailers. Thanks to the fact that it allows for a comprehensive dynamic perspective of the reality of retail or other businesses, the system not only stirs up operational efficiencies but also helps retailers to harness customer data for precise market segmentation and personalised product offerings.

3.2.1 System Development Life Cycle

In the development of the SmartBundle system, each phase in the System Development Life Cycle (SDLC) plays an important role in ensuring that the resulting system is efficient, scalable and meets user needs. This process consists of five main phases, namely requirements analysis, design, implementation, testing and system maintenance. It aims to ensure that system development is carried out in an organised, efficient and meets end user needs.

i. Requirements Analysis

This phase aims to identify system requirements and understand the main challenges in implementing a product bundling strategy in the context of the retail industry. Through comprehensive business requirements analysis, several critical issues were identified. These include inefficiencies in the manual implementation of bundling strategies, which have led to missed sales opportunities, the need for more dynamic customer segmentation through data analytics techniques, the necessity to enhance inventory management effectiveness via automated bundling optimization and the requirement for system integration with a centralized database to ensure high-performance processing of bundling-related data (Barrios & Cruz,2017). The system requirements data was obtained through interviews with retail operators, analysis of previous sales records and case studies of successful product bundling implementations.

ii. System Design
The system design phase involves developing system architecture and planning algorithms to optimise product bundling. This process includes three main components, namely software architecture design, user interface and business logic. Software architecture design involves selecting appropriate technologies, including the use of MySQL for database management, the K-Means Clustering algorithm for product segmentation to produce bundling recommendations based on purchase patterns. From the user interface aspect, an interactive dashboard is developed to allow users to analyse bundling recommendations in a more intuitive and user-friendly way. Meanwhile, in the business logic design, the system utilizes a rule-based approach and machine learning integration (machine learning) to produce optimal product combinations that are suitable for retailer needs and customer behaviour.

iii. Implementation
The implementation phase involves the development of the SmartBundle system based on the technological specifications outlined during the design phase. The primary objective at this stage is to systematically integrate product segmentation and bundling processes into a cohesive, responsive system. A core component of this phase is the construction of a structured relational database using MySQL, designed to store and manage critical information such as product details, customer segmentation data and system-generated bundling recommendations. Furthermore, the K-Means clustering algorithm is implemented to automatically group products based on customer purchasing behaviour, allowing for real-time, data-driven segmentation analysis. To enhance usability and facilitate seamless access for end users, an interactive dashboard has been developed. This dashboard enables retailers to visualise, monitor and fine-tune bundling strategies dynamically, thereby ensuring the system's applicability in real-world retail settings.

iv. Testing
The system testing phase aims to evaluate the functionality, usability and effectiveness of the SmartBundle system in a real environment. Two key testing approaches are adopted: internal system testing and external end-user testing. Internal testing focuses on validating the system’s technical capabilities, particularly its ability to execute the K-Means clustering process and generate relevant bundling recommendations based on segmentation outputs. In parallel, end-user testing involves engaging selected retail operators to assess the system’s interface, clarity of data visualisation and its capacity to provide practical, commercially viable bundling suggestions. Feedback obtained from this phase serves to refine system

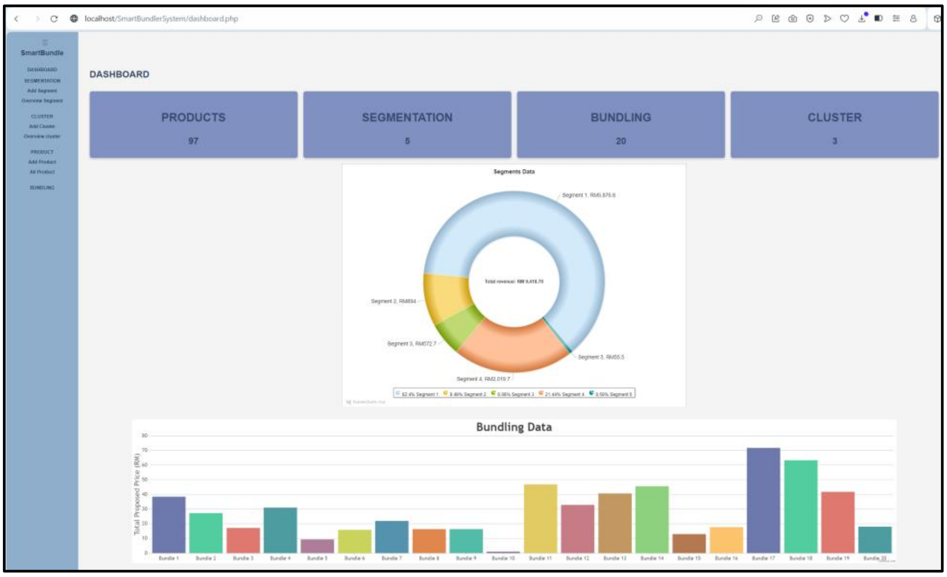
components, enhance user experience and ensure that the final product aligns with the operational needs of retail users.

v. Maintenance

The maintenance phase ensures that the SmartBundle system remains operational, efficient and adaptable to the changing demands of the retail sector. This phase is essential for maintaining the system's relevance and long-term functionality. Key activities include upgrading the database infrastructure, possibly through migration to a cloud-based system, to enhance data accessibility and scalability. Additionally, the bundling algorithm undergoes ongoing refinement to respond to shifts in consumer behaviour and sales trends. Regular system performance evaluations are carried out to identify technical issues and implement necessary upgrades. The adoption of the System Development Life Cycle (SDLC) approach guarantees that all system stages, from initial design to long-term maintenance, are carried out in a structured, iterative and quality-focused manner. This continuous development process not only improves system resilience and performance but also helps sustain customer satisfaction and boost sales outcomes (Souza, 2012). Consequently, SmartBundle is an efficient, environmentally conscious and data-driven solution capable of delivering significant value across the retail industry.

4. Findings and Discussion

Figure 2: Dashboard SmartBundle



The SmartBundle system comprises various modules as the main components. These modules are interconnected so that the overall management of the product is more effective. Illustrated in Figure 2 is the primary screen that is accessible for retailers as soon as they arrive at the web page. Retailers can use different buttons for the respective tasks of product, segment, bundling and cluster management, and at the same time, to get the necessary data analysis for the development of the bundling strategy for the purpose of increased profitability. SmartBundle is an alternative to this one with a simple user interface that provides users not only with the main dashboard, but also with the ability to receive visual data in clear and easy-to-understand charts. The visuals are mainly used to demonstrate product performance, customer segmentation, bundling outcomes and segment distributions, and therefore, they help to provide a perfect snapshot of the entire system's performance. The Add Segment option allows users to create new segments, such as hot and slow products based on product categories or sales levels, thereby making a marketing strategy much more precise. Again, people who use the Segment Overview section can analyse the differences between the parts and thus decide which is the best way to modify the bundling strategy. Additionally, by using the two features, Add Cluster and Cluster Overview, categorisation is achieved by the sales volume, the type, or the price of the items; in this way, inventory management is much easier and more efficient. This technique of clustering allows people to become more aware of what items are slow-selling and what products are really fast and popular among consumers; in this way, decision-making is facilitated. Moreover, with the functions Add Product and All Products, users are able to input and get the product details, e.g. pricing, product type and associated cluster classification. Through these actions, a more structured stock situation can be created and regularly updated. In more detail, the SmartBundle functionalities corresponding to the buttons are presented in Table 1.

Table 1: Button in SmartBundle System

Button	Function	Description
Dashboard	Take the user to the main dashboard of the SmartBundle system. This dashboard displays a summary of total products, segments, bundling and clusters.	Allows users to see an overview of system performance through visual summaries such as charts and reports. Help monitor sales and bundling strategies.
Add Segment	This allows users to add new segments based on criteria such as product category, sales level (fast-selling, slow-moving, moderate fast-selling).	It gives retailers the flexibility to divide products into specific segments to facilitate analysis and formulate more accurate marketing strategies.
Segment Overview	Provides an overview of all segments that have been created.	Allow users to review and compare segment performance and adjust strategies to improve bundling effectiveness.

Add Cluster	Allows users to add new clusters by grouping products by sales level, product type, or price.	Facilitates categorisation of products into clusters such as slow-moving, moderately fast-selling and top fast-selling for more efficient inventory management.
Cluster Overview	Provides a full list of clusters that have been added, along with product information in each cluster.	Allows users to identify products in a specific category, such as slow-moving or fast-selling, for further action.
Add Product	Allows users to add new products with information such as product name, price, type (slow-moving, moderately fast selling, etc.) and cluster.	Ensures that all products are recorded in the system to facilitate the segmentation and analysis process.
All Product	Provides a complete view of all products that have been added, including price, type and cluster information.	Help users monitor existing products and update product information for more systematic inventory management.
Bundling	Allows users to create product packages by combining products from various categories, such as slow-moving and fast-selling.	The bundling function helps increase sales of slow-moving products by combining them with best-selling products, reducing excess stock and creating additional value.

5. Discussions

Developing the SmartBundle system greatly impacts retailers and customers by improving product management and refining sales strategies in the retail industry. During the system testing phase, the SmartBundle system achieved a 22% rise in bundling-related sales and a 15% decrease in overstocked products in the pilot minimarkets. These results demonstrate the system's ability to tackle issues previously noted in the requirements analysis stage, especially the inefficiencies in manual bundling and the absence of dynamic segmentation. In contrast to previous research like Croft et al. (2021), which utilised static, rule-based bundling methods leading to minimal enhancements, SmartBundle utilises machine learning and K-Means clustering to generate real-time, data-informed bundling suggestions customised to customer buying habits. Similarly, Rao et al. (2018) highlighted the limitations of the shortcomings of manual analysis in creating strategic bundling offers, while SmartBundle incorporates an automated decision-support system, allowing for enhanced scalability, accuracy and market adaptability. This system enables retailers to categorise and segment products more efficiently according to sales performance through algorithmic analysis, resulting in more strategic inventory and promotional strategies. The addition of visual dashboards featuring intuitive graphical representations like bar charts and doughnut graphs helps retailers monitor segment performance and bundling results in real time, facilitating more precise and data-informed decisions. Moreover, employing SmartBundle helps decrease costs in bundling efforts by synchronising package deals with customer purchasing behaviours, thereby enhancing operational efficiency and boosting return on sales. From the customer's viewpoint, this data-focused bundling method guarantees access to the most pertinent and beneficial product combinations, improving their shopping experience and contentment. The organised product lineup and customised package suggestions enhance customer decision-making while also promoting greater brand loyalty. Essentially, SmartBundle enhances retailers' operational functions through smart product handling while also enhancing the consumer experience by providing tailored, data-driven buying choices.

6. Conclusions and Recommendations

SmartBundle is an advanced, data-driven system designed to support retailers in making more intelligent and strategic decisions regarding product bundling. By leveraging deep segmentation techniques and analysing customer purchasing patterns, the system provides a nuanced understanding of consumer behaviour and evolving market demands. Utilising analytical algorithms such as K-Means Clustering, SmartBundle effectively identifies sales trends, categorises products based on consumer behaviour and recommends optimised product bundles that enhance relevance and profitability. This data-centric approach allows retailers to move beyond intuition-based decision-making and instead adopt a rational, evidence-based strategy that improves customer satisfaction and maximises sales performance (Dogaru et al., 2020). In addition to enhancing bundling strategies, the implementation of SmartBundle contributes to more efficient inventory management, streamlined marketing efforts and an overall improvement in user experience by delivering personalised product offerings tailored to individual consumer preferences. Consequently, SmartBundle positions itself as a transformative innovation in retail technology—one that is fundamentally different from traditional bundling models and essential for businesses aiming to remain competitive in a rapidly evolving, data-driven marketplace. This system is expected to increase efficiency in product management, in line with technological trends that leverage data for better decision-making. Several strategies can be implemented to make sure that the system becomes more powerful. First, in addition to the SmartBundle application, it should be introduced in different sectors like food, garments and e-commerce to examine the viability of the system in other areas. Second, a cloud-based infrastructure should be used so the system can more easily access data and efficiently grow in overall size. Lastly, the introduction of advanced artificial intelligence, such as deep learning or reinforcement learning, can be studied to enable the system to respond to changing user behaviour in real-time.

7. Limitations of the Study

Although the development of the SmartBundle system shows great potential in optimising product bundling strategies, several limitations need to be acknowledged. First, the trial of this system was implemented in a specific retail environment with a small data size, which means data cannot represent all the behaviours of the shoppers in the different retail sectors accurately, and this particular activity has the potential to be further investigated for the general level of customers. The second limitation concerns the accessibility of these algorithms. Without any doubt, the usage of algorithms like K-Means Clustering for dividing the market and recommending the most suitable products is a good way out, but as we are using fixed parameters, it can still be a big trouble in terms of capturing new and more complex patterns or tendencies that can only be realised through advanced machine learning approaches. Moreover, this system still relies on the past sales data and has yet to integrate customers' feedback, while the contextual variables like season, promotion events or the geographical area were not used, thus influencing the effectiveness of the bundling (Fang et al., 2022).

8. Suggestions for Future Research

In this aspect, it is recommended that the next studies be conducted to verify the work of this system in various retail formats and the use of more data sets that are updated and diversified to ensure the system's scalability and steadfastness. The exploitation of data from the past can also go hand in hand with using recent data: actionable data and real-time analytics can be impactful, especially when adaptive methods such as reinforcement learning or neural networks are incorporated to make the system learn and adjust to new user behaviour. Furthermore, the additions of customer profiling, sentiment analysis and location-based recommendations will serve a more comprehensive and personally aimed bundling strategy.

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