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Designing Customer Analytics Dashboard in Smart Device Retail Using Power BI

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Abstract

The adoption of data analytics has led to a paradigm shift in business decision-making, moving from intuition-based to data-driven strategies. Specifically in customer analytics, metrics such as Net Promoter Score (NPS), Customer Satisfaction Score (CSS), and Repeat Purchase Rate (RPR) are widely used to formulate customer retention strategies. Although dashboard applications like Microsoft Power BI support the visualization of these metrics, existing designs lack integrated filtering capabilities based on demographic characteristics such as gender and age group. This study aims to propose a Power BI dashboard application design that integrates NPS, CSS, and RPR with demographic filters to effectively convey customer loyalty, satisfaction, and advocacy. The research methodology includes four stages which are Power BI understanding, data acquisition, data pre-processing, and metric modeling. The dataset was collected by using an online questionnaire in January 2025 (N = 542). It must be validated and transformed before being modeled by using DAX. The proposed dashboard design offers an interactive interface, allowing users to explore insights through chart elements such as bars and pie slices. This design enhances user experience and supports intuitive analysis, making it a valuable tool for smart device retailers and manufacturers to make data-driven decisions. Additionally, the dashboard is adaptable to other business contexts with similar analytical needs. For real-world implementation, the inclusion of Key Performance Indicators (KPIs) for each metric is recommended to ensure that insights are actionable and aligned with business objectives.

Keywords: Business Analytics, Customer Analytics, Power BI, Dashboard, Data Analysis

1. INTRODUCTION

The adoption of data analytics in business has significantly transformed various sectors, especially the retail industry. Adewusi [1] highlighted a paradigm shift from intuition-based to data-driven approaches in business decision making process. This evident business leaders who mastered a solid understanding of data analytics principles and the ability to extract meaningful insights are more capable to manage the complexities of modern business competitions.

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Several studies have emphasized that the adoption of data analytics in retail businesses contributes to increased sales and reduced operational costs [2], [3]. Consistent with these findings, Anica-Popa et al. [4] observed the integration of structured data management and Artificial Intelligence (AI) enables the development of personalized advertising strategies. On the other hand, although data-driven insights have already begun to transform the retail sector, the potential remains unrealized partially because of challenges regarding data fragmentation, data security and lack of expertise in implementing advanced data analytics information systems for business [5].

In business analytics, customer purchase, customer satisfaction and customer visit are the top customer science techniques to process meaningful customer data and develop insights [6]. The techniques can be translated into metrics named Net Promoter Score (NPS), Customer Satisfaction Score (CSS), and Repeat Purchase Rate (RPR). NPS is a widely used metric for assessing customer loyalty, indicating the likelihood that customers will recommend a business, product, or brand to others [7]. Empirical evidence suggests that NPS can serve as a predictor of firm performance, particularly when incorporated into a comprehensive scorecard alongside other relevant metrics tailored to specific organizational needs [8]. Baquero [9] proposed an integrated approach by combining the NPS with the CSS to provide a more comprehensive evaluation of customer experience. While NPS reflects customers' likelihood of recommending a brand, CSS measures immediate satisfaction. It is essential to incorporate the RPR into the scorecard because of the strong correlation between repeat purchases and sustained customer loyalty [10].

Puspitasari, Rohaeni, and Harahap acknowledged Power BI not only as a data visualization tool, but a facility to accelerate reporting and strategic planning [11]. Developed by Microsoft, Power BI offers several advantages, including an interface that resembles Microsoft Excel in its data manipulation mode and the capability to connect instantly with a wide range of data sources. Moreover, Power BI adopts a freemium business model, enabling users to access desktop and web versions for free, while offering paid and scalable functionality for enterprise needs.

Mishra recommended Power BI for intensified real-time reporting that requires comprehensive and actionable insights [12]. Power BI has also emerged as a versatile tool supporting specific analytical approaches across diverse domains. Puspitasari successfully applied the accrued benefit method in financial data management [13]. Ningsih et al. developed a dashboard for Exploratory Data Analysis (EDA) for Sukamiskin Village, Indonesia, covering key demographic indicators such as population size, age distribution, education level, gender, marital status, and employment status [14].

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There remains a lack of dashboard application designs that effectively integrate metrics into a comprehensive business analytics tool among the various methods that have been scientifically proven to provide valuable business insights. In terms of customer analytics, the smart device industry exhibits unique attributes compared to the broader retail landscape. To enhance profitability, it is significantly more cost-effective to retain existing customers through repeat purchases from the same smart device brand than to acquire new ones [15]. Smart device manufacturers and retailers are increasingly required to implement customized marketing strategies that are capable to analyze the diverse characteristics of consumers, such as gender and age categories [16].

The objective of this study is to propose a Power BI dashboard application design that specifically facilitates customer analysis by integrating NPS, CSS, and RPR. The proposed solution is expected to contribute to customer behavior analysis specified by gender and age group for facilitating the formulation of market growth strategies. Additionally, the proposed solution not only delivers by using data visualization, but also conveys customer loyalty, satisfaction, and advocacy by using related metrics. This paper is organized as follows: Section 2 outlines the research methods, including Power BI, the dataset, data preprocessing, and data analysis. Section 3 presents the proposed Power BI dashboard design. Section 4 discusses the findings and suggests directions for future research. Section 5 lists the references that support this study.

2. METHODS

The research methods employed in this study encompasses several steps as illustrated in Figure 1. Power BI Understanding involves comprehending the process of inserting appropriate data visualization and developing metrics by using Data Analysis Expressions (DAX). The Data Acquisition step comprises collecting customer analytics data via an online questionnaire. The Data Pre-processing includes validating responses, correcting potential errors, and conducting basic calculations to prepare the dataset for the following process. The Data Analysis step involves applying RPR, CSS, and NPR.

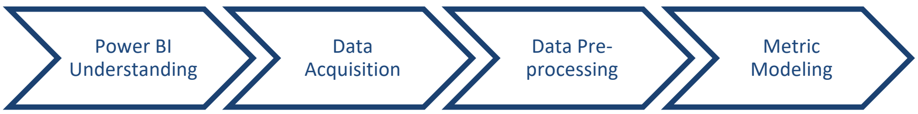

Figure 1. Research Methods

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2.1. Power BI Understanding

Microsoft Power BI is a business intelligence (BI) software designed to support data visualization and the integration of diverse data sources through interactive and dynamic interfaces. It enables users to create customized measures and perform complex data calculations using a formula language known as DAX [17], [18]. It is specifically designed for non-technical users, as its syntax closely resembles that of Microsoft Excel formulas. Power BI is available in a free version, which allows users to develop business intelligence proof-of-concept (PoC) solutions.

2.2. Data Acquisition

The dataset for this study was collected by using a questionnaire with careful attention to ethical considerations and privacy protection. First, all responses were collected anonymously. The only personally identifiable information (PII) obtained was the respondent's birthdate, which was used solely for age categorization. Additionally, participants were informed that their data would be used exclusively for academic research purposes.

The responds were acquired through an online survey administered via Google Forms, as summarized in Table 1. Each questionnaire item was answered by using a distinct data entry method, ensuring the quality and reliability of the collected value. Timestamp, which automatically generated by the system, records the date on which the questionnaire was completed and formatted as YYYY-MM-DD. Gender was collected by using radio button, limited to two options: "Male" and "Female". Birthdate was entered through a date-picker field. Location was inserted by using a free-text field restricted to text input. Smart Device Brand was captured using a combination of radio buttons for top brands such as Samsung or Apple and an open-text field to accommodate other brand names, ensuring the capture of diverse responses. Number of Products Owned was reported using a text field validated to accept only integer values. The responses will be categorized as "≥ 5" if the entered value exceeds five. Product Satisfaction and Brand Advocacy were measured using Likert-scale items corresponding to specific questionnaire statements. In order to maintain the quality of the Likert-scale input, both questions are answered strictly by choosing one of five available answers namely Strongly disagree, Disagree, Neutral, Agree, Strongly Agree. All answers are shown by using radio buttons, allowing respondents to choose only one answer for each question.

Table 1. Questionnaire Items, Descriptions and Questions

Item	Description	Question
Timestamp	The date on which the respondent completed the	-

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Item	Description	Question
	questionnaire generated by system	
Gender	The gender of the respondent, categorized as male and female	"Please choose your gender"
Birthdate	The respondent's date of birth	"Please enter your birthdate"
Location	The geographic area where the respondent lives	"Where do you live"
Smart Device Brand	The brand of smart device owned by the respondent	"Which smart device brand do you most purchased?"
Num. of Product	The total number of smart devices owned by the respondent from the specified brand	"How many smart devices do you own from the mentioned brand?"
Customer Satisfaction	A measurement of the respondents' satisfaction level with the product	"How satisfied are you with the performance and quality of the smart device produced by the mentioned brand?"
Brand Advocacy	A measurement of the respondent's willingness to recommend the brand to others	"How likely are you to recommend smart devices from the mentioned brand to others?"

Table 2 summarizes the characteristics of the respondents (N = 542). A total of 293 respondents (54%) identified as male, while 249 (46%) identified as female. The majority were young adults (n = 270; 50%), followed by teenagers (n = 179; 25%), adults (n = 89; 16%), and seniors (n = 4; 1%). Geographically, most respondents located in Jakarta (n = 300; 56%), with smaller proportions from Tangerang Selatan (n = 46; 9%), Kota Tangerang (n = 37; 7%), Bekasi (n = 23; 4%), Cirebon (n = 21; 4%), and 19 other cities (n = 96; 20%). In terms of brand ownership, Apple (n = 236; 44%) and Samsung (n = 181; 34%) were the most owned smart device brands. The majority of respondents reported owning four devices of the same brand (n = 287; 52%), followed by five or more (n = 125; 23%), three (n = 98; 18%), two (n = 22; 4%), and one (n = 10; 2%). Regarding satisfaction, most respondents agreed (n = 302; 56%) or strongly agreed (n = 146; 27%) that they were satisfied with their chosen brand. Similarly, a majority agreed (n = 273; 51%) or strongly agreed (n = 95; 18%) that they would recommend their chosen brand to others.

Table 2. The Acquired Dataset

Characteristics	n (%)
Gender	
Male	293 (54)
Female	249 (46)

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Characteristics	n (%)
Age Group	179 (25)
Teenagers (< 20 years old)	270 (50)
Young Adults (20-39 years old)	89 (16)
Adults (40-64 years old)	4 (1)
Seniors (>64 years old)	
Location	
Jakarta	300 (56)
Tangerang Selatan	46 (9)
Kota Tangerang	37 (7)
Bekasi	23 (4)
Cirebon	21 (4)
Other cities	96 (20)
Smart Device Brand	
Apple	236 (44)
Samsung	181 (34)
Xiaomi	51 (10)
Oppo	22 (4)
Other brands	67 (8)
Number of Product	
≥ 5	125 (23)
4	287 (52)
3	98 (18)
2	22 (4)
1	10 (2)
Customer Satisfaction	
Strongly Agree	146 (27)
Agree	302 (56)
Neutral	83 (15)
Disagree	8 (1)
Strongly Disagree	3 (1)
Brand Advocacy	
Strongly Agree	95 (18)
Agree	273 (51)
Neutral	149 (28)
Disagree	18 (3)
Strongly Disagree	7 (1)

2.3. Data Pre-processing

Google Sheets was utilized for data extraction, data correction, and basic calculations, while Power BI was employed for more complex computations, such as metric calculations. Data extraction was processed automatically by using *View Response* menu in Google Form. Each open-ended response collected by using text fields such as location and smart device brand (when text input is used) is subject to potential typographical errors and requires correction. For example, the entry

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"Jkt" may be standardized to "Jakarta" due to their equivalent meaning in terms of geographic location. Similarly, variations such as "Xiao Mi" or "xiaomi" can be standardized to "Xiaomi," as the values refer to the same smart device brand.

Table 3. Age Category and Age Range

Age Category	Age Range
Teenagers	< 20 Years Old
Young Adults	20 – 39 Years Old
Adults	40 – 64 Years Old
Seniors	> 64 Years Old

The subsequent data processing took place in Power BI. First, a new column titled Respond ID was generated as a unique integer-based identifier using the *Add Column* feature followed the *Index Column* submenu. Next, the age of each respondent was calculated by subtracting the Birthdate from the Response Date. A new column titled Age Category is created to contain age classification of column Age according to specification listed in Table 3. Additionally, Likert-scale responses were then transformed into numerical values. The response options were coded as follows: Strongly Disagree = 1, Disagree = 2, Neutral = 3, Agree = 4, and Strongly Agree = 5.

2.4. Metric Modeling

RPR measures the ratio of customers who engage in continuous purchasing of a specific smart device brand. The RPR value was obtained by dividing Number of Repeat Purchase Customers with the number of respondents, as presented in Equation 1.

$$RPR=\frac{Number\ of\ Repeat\ Purchase\ Customers}{n} \tag{1}$$

CSS measures the ratio of customer satisfaction regarding the owned smart device that is produced by the same brand. As presented in Equation 2, CSS value was calculated by dividing Number of Satisfied Customer with the number of respondents. The Number of Satisfied Customer was derived from the coded answers of questionnaire item Customer Satisfaction which valued “Agree” and “Strongly Agree”.

$$CSS=\frac{Number\ of\ Satisfied\ Customer}{n} \tag{2}$$

NPS measures customer loyalty metric that interprets how likely a customer is willing to recommend a product or service. NPS used the coded answers of

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questionnaire item Brand Advocacy. NPS is calculated as the difference between the percentage of promoters and the percentage of detractors. Detractors accumulate the number of customers who answered “Disagree”, “Strongly Disagree”, and “Neutral”, while promoters accumulate the number of customers who answered “Agree” and “Strongly Agree”. NPS value was calculated by running Equation 3.

$$NPS=100\times\left(\frac{NumPromoters\text{-}NumDetractors}{n}\right) \quad (3)$$

Where *NumDetractors* and *NumPromoters* can be calculated by applying Equations 4 and 5, respectively.

$$NumDetractors=\sum_{i=1}^{n} d(x_i),\ \ where\ d(x_i)=\begin{cases}1 & if\ x_i\leq 3\\ 0 & otherwise\end{cases} \quad (4)$$

$$NumPromoters=\sum_{i=1}^{n} p(x_i),\ \ where\ p(x_i)=\begin{cases}1 & if\ x_i=5\\ 0 & otherwise\end{cases} \quad (5)$$

NPS value ranges from –100 to 100, with higher values indicating stronger customer loyalty. An NPS value of 100 identifies all respondents are promoters and reflects the willingness to recommend the brand. On the other hand, a score of –100 indicates that all respondents are detractors. An NPS value between –100 and 0 suggests the domination of detractors and highlights potential risk regarding customer loyalty. In contrast, an NPS value between 0 and 100 indicates a greater proportion of promoters and implies a generally positive customer experience and a higher likelihood of brand advocacy.

3. RESULTS AND DISCUSSION

3.1. Customer Analytics Dashboard Design

As seen in Figure 2, the customer analytics dashboard design incorporates dynamic filtering features, enabling users to tailor data visualizations and metrics to specific demographic groups. By facilitating precise customer segmentation, the dynamic filters enhance the functional flexibility of the dashboard and support more targeted, data-driven insights.

For instance, Figure 2 describes among 542 Indonesian smart-device owners, most of them reside in Jakarta and report Apple as their chosen smart device brand. 76 % had made multiple purchases of devices from the same brand, 83 % expressed satisfaction with their overall experience, and 95 respondents indicated that they promote their chosen brand.

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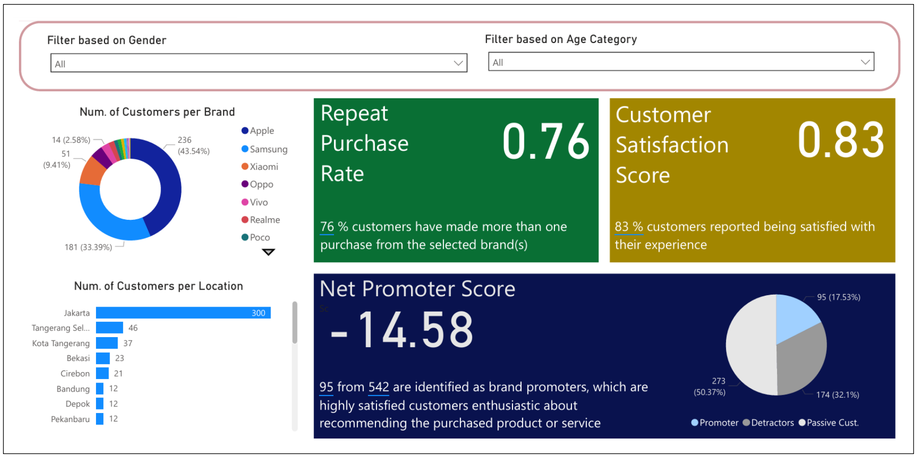

Figure 2. The User Interface of The Proposed Solution

3.2. Visual Elements in The Dashboard Design

Figure 3A displays a set of combo-boxes allowing users to specify customer gender and age group. Figure 3B illustrates the number of customers per brand and emphasizes the distribution of customer purchases across brands. Figure 3C shows the number of customers per location and focuses on describing purchase frequency based on geographic location. Figure 3D visualizes RPR with the interpretation of the metric. Figure 3E displays CSS value including its corresponding interpretation. Figure 3F depicts not only reports on the NPS value and the interpretation but also pie chart to clarify the proportion of promoters, passive customers, and detractors.

3.3. Dashboard Interactivity

The dashboard offers interactivity that enhances user experience in data exploration. The interactivity is enabled by selecting desirable values of gender or age group (Figure 3A) or selecting a visual element, such as a slice of a pie chart, a bar within a bar chart, or an item in a legend. The selected item remains highlighted while the non-selected items are visually faded. For example, Figure 4A displays overall distribution of customers per brand. Figure 4B illustrates how the visualization changes when a specific slice of the pie chart is selected. A similar effect is observed in the bar chart representing customer distribution by location; Figure 4C shows the overall distribution, and Figure 4D demonstrates the response when a particular bar is selected. Compared to the data visualization elements, the presentation of RPR, CSS, and NPS metrics only shows changes in the values without altering the visual representation.

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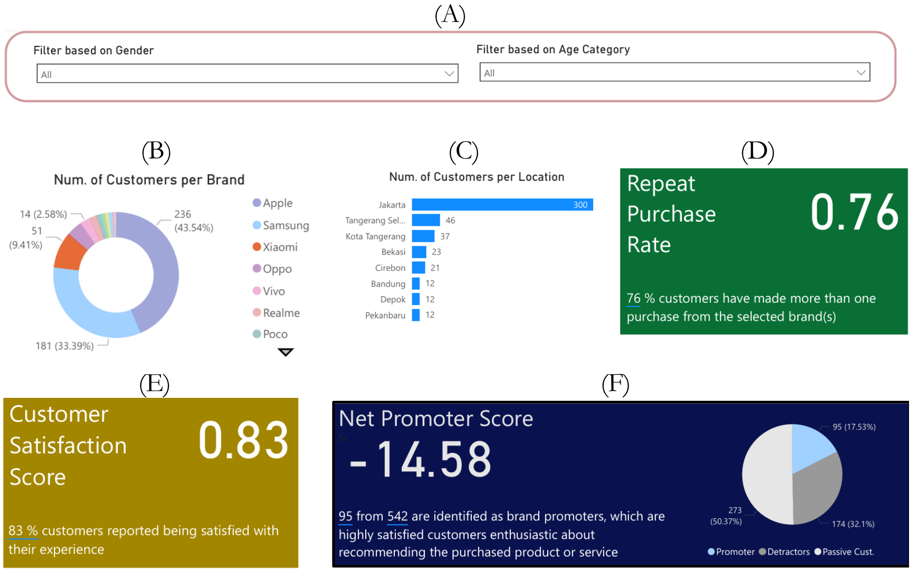

Figure 3. Visual Elements in the Proposed Solution

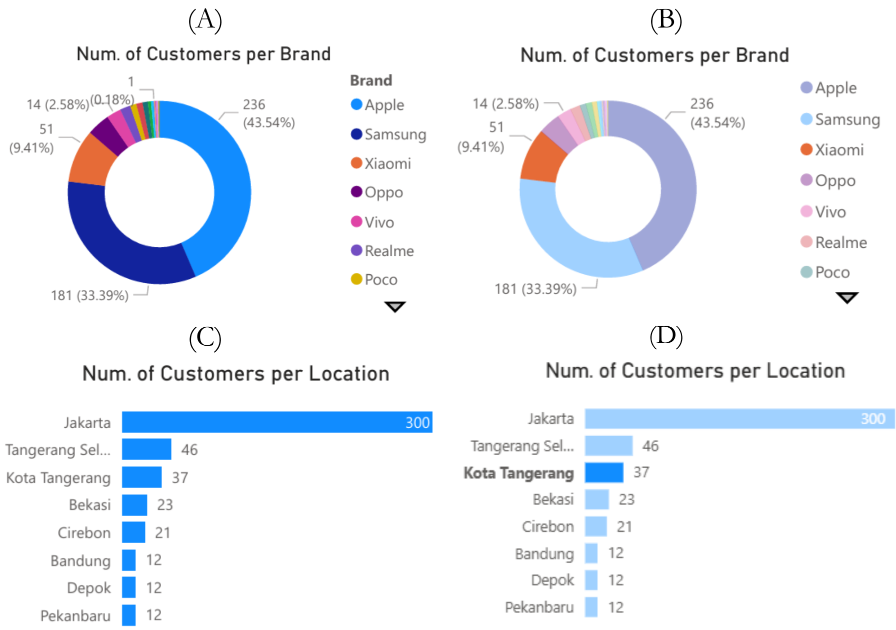

Figure 4. Visual Changes caused by the Dashboard Interactivity

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3.4. Discussions

The findings of this study highlight the significant potential of Microsoft Power BI as a highly effective platform for developing customer analytics dashboards in the smart device retail sector. Beyond simply transforming raw datasets into digestible metrics, the proposed dashboard excels in enabling detailed, user-driven exploration of customer behavior, particularly through demographic segmentation by gender and age group. This granularity is crucial for developing targeted, personalized customer retention strategies—making the dashboard not just a reporting tool but a strategic asset.

The design and features of the dashboard, as discussed in Section 3.1, allow for dynamic filtering capabilities that empower users to tailor visual insights based on specific customer groups. For instance, among the 542 Indonesian smart device owners analyzed, the dashboard reveals that most reside in Jakarta and predominantly favor Apple as their brand of choice. An impressive 76% reported repeat purchases from the same brand, while 83% expressed satisfaction with their customer experience, and 95 respondents indicated they would promote their selected brand. These metrics, contextualized within the dashboard interface, offer a powerful narrative on brand loyalty and customer engagement trends.

As illustrated in Figures 3A to 3F, visual elements such as combo-box filters for gender and age, brand distribution bar charts, geographic segmentation, and key metrics like RPR, CSS, and NPS are all embedded to enhance analytical depth and user interactivity. Moreover, the dynamic dashboard interactivity (Figures 4A to 4D) allows users to engage directly with the data by clicking specific visual components—such as pie chart slices or bar segments—to reveal focused insights. This interactivity is not just aesthetically pleasing but functionally impactful, promoting intuitive exploration and quicker decision-making.

However, to ensure successful real-world deployment, several considerations must be addressed. First, end-users must possess a sound understanding of the visualizations and the business implications of the metrics presented. For instance, while RPR, CSS, and NPS are explained within the dashboard, their strategic interpretation requires foundational knowledge of customer analytics. Second, a basic proficiency in using Power BI is necessary to navigate, interact with, and derive value from the dashboard's features effectively.

Although the study successfully demonstrates Power BI's capabilities in transforming customer data into actionable insights, several limitations must be acknowledged and addressed in future research. Firstly, the current version of the dashboard does not incorporate Key Performance Indicators (KPIs) to define performance targets for each metric [19]. The absence of KPIs restricts users from

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benchmarking and tracking progress over time. Secondly, the analytical scope could be expanded by integrating additional metrics such as Customer Lifetime Value (CLV) [20], [21] and Churn Rate (CR) [22], which are critical for understanding long-term customer value and potential attrition risks.

Furthermore, the survey instrument could be improved by adding follow-up questions that probe into the reasons behind customers' satisfaction levels and their advocacy attitudes [23]. Capturing this qualitative data could open avenues for text mining approaches, providing deeper insight into what drives customer loyalty or dissatisfaction. Understanding these motivations would complement the quantitative metrics and offer a richer, more actionable understanding of customer behavior.

Finally, a promising direction for future work lies in integrating Large Language Models (LLMs) into the dashboard to support automated interpretation of dashboard outputs. Prior studies in the health technology domain have shown that LLMs can effectively translate complex datasets into natural language narratives [6], [24], [25]. Embedding such models into the dashboard could dramatically enhance accessibility, especially for non-technical users, by generating easy-to-understand summaries of key insights, thereby facilitating quicker, more informed decision-making. In conclusion, while the proposed Power BI dashboard already delivers significant value in customer analytics, strategic enhancements—including KPI integration, advanced metrics, improved survey design, and LLM-driven automation—can further elevate its role as a vital decision-support tool in the smart device retail industry.

4. CONCLUSION

This study proposes the design of a customer analytics dashboard using Microsoft Power BI to support data-driven decision-making in the smart device retail business. The proposed solution enables the delivery of filtered, meaningful insight that can assist smart device manufacturers and retailers in formulating optimized, tailored, and strategic decisions aimed at customer retention. Key features of the dashboard include demographic filters based on gender and age categories using combo boxes, smart device brand distribution visualized by using pie charts, and location distribution presented with bar charts. The integration of interactive elements, such as selectable bar and slice of the charts, enhances the user experience by enabling intuitive data exploration. The dashboard design is adaptable and can accommodate other types of business data requiring similar analytical frameworks. For real-world implementations, it is essential to integrate KPI for each metric to ensure the insights are actionable. Additionally, to support users with limited experience and knowledge in customer analytics, the incorporation of LLMs is recommended to enhance data interpretation.

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DATA AVAILABILITY

The dataset used in this study is publicly accessible at https://zenodo.org/records/15585147

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