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Development of a Dashboarding and Visualization Framework For Pharmaceutical Brand Performance Analytics Using Tableau and Python

Muhammad Zahidul Islam[1];

[1]. *Master of Business Administration in Data Analytics (MBA-DA), Tapia School of Business, Saint Leo University, Florida, USA; Email: muhammadzahidulislam84@gmail.com*

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Abstract

This study has examined the development of a dashboarding and visualization framework for pharmaceutical brand performance analytics using Tableau and Python in selected pharmaceutical cloud and enterprise analytics cases. The main problem has been the dependence of many pharmaceutical organizations on fragmented reports, manual spreadsheet processing, static charts, delayed updates, and limited statistical validation, which can weaken brand monitoring and managerial decision-making. The purpose of the study has been to evaluate whether Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, and analytics automation significantly improve pharmaceutical brand performance analytics effectiveness. A quantitative, cross-sectional, case-based research design has been used, and data have been collected from pharmaceutical professionals involved in brand management, sales reporting, marketing analytics, business intelligence, data analysis, and decision support. Out of 250 distributed questionnaires, 214 valid responses have been retained, producing an 85.6% valid response rate. The analysis plan has included descriptive statistics, Cronbach's alpha reliability testing, Pearson correlation analysis, multiple regression modeling, hypothesis testing, dashboard prototype evaluation, and Python-driven analytical workflow validation. The findings have shown strong agreement across the constructs, with data visualization quality recording the highest mean score of 4.18, followed by dashboard usability at 4.13, Tableau-based dashboarding capability at 4.09, pharmaceutical brand performance analytics effectiveness at 4.05, analytics automation at 3.98, and Python-based analytical processing at 3.92. Reliability has been confirmed through Cronbach's alpha values ranging from .81 to .89, with overall reliability of .91. Correlation results have shown significant positive relationships between analytics effectiveness and data visualization quality (r = .68), dashboard usability (r = .65), Tableau capability (r = .62), Python processing (r = .57), and automation (r = .55), all at $p < .001$. The regression model has been significant, $F(5, 208) = 48.72$, $p < .001$, explaining 53.9% of variance. The study implies that integrating Tableau visualization with Python analytics can improve brand monitoring, KPI interpretation, reporting accuracy, and evidence-based pharmaceutical decisions.

Keywords

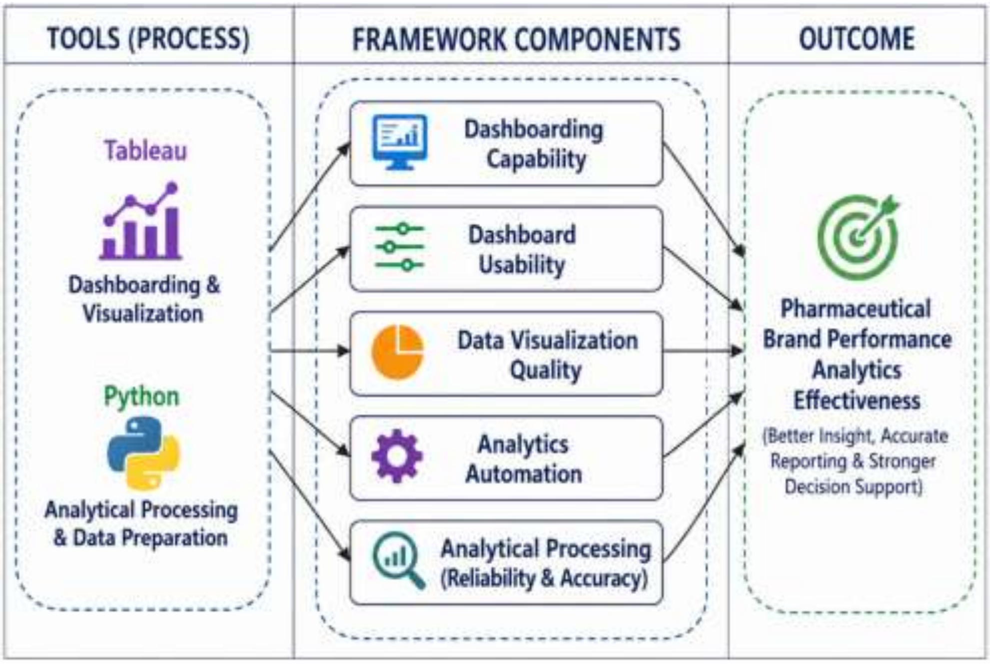
Pharmaceutical brand performance analytics; Tableau dashboarding; Python analytical processing; data visualization quality; analytics automation.

INTRODUCTION

Pharmaceutical brand performance analytics refers to the systematic process of collecting, preparing, analyzing, visualizing, and interpreting brand-level pharmaceutical data to evaluate how a product performs across sales territories, prescription patterns, market segments, promotional activities, customer engagement channels, and managerial decision contexts. In this research, dashboarding refers to the structured presentation of key performance indicators through interactive digital interfaces, while data visualization refers to the use of graphical forms such as charts, maps, filters, scorecards, trend lines, and comparative panels to communicate analytical findings clearly to decision-makers. Tableau has been considered the dashboarding and visualization platform because it supports interactive reporting, visual exploration, drill-down analysis, filter-based navigation, and performance monitoring. Python has been considered the analytical processing platform because it supports data cleaning, data transformation, descriptive statistics, correlation analysis, regression modeling, automated workflows, and reproducible analytical validation. Business intelligence and analytics have been defined as systems and practices that transform raw data into useful information for decision-making, performance monitoring, and strategic interpretation (Chen et al., 2012). In pharmaceutical brand analytics, this definition becomes more specific because brand performance does not depend only on sales volume. It also includes prescription behavior, regional performance variation, promotional effectiveness, product lifecycle status, market share movement, physician engagement, and competitive brand positioning. Information systems research has shown that analytical systems create organizational value when system quality, information quality, usability, user satisfaction, and net benefits are properly aligned (Petter et al., 2008). Dashboard research has also explained that dashboards are not merely visual reporting screens; they are decision-support tools that organize indicators, reduce information overload, and allow users to compare performance patterns in a structured way (Yigitbasioglu & Velcu, 2012). Therefore, the development of a dashboarding and visualization framework for pharmaceutical brand performance analytics requires the integration of business intelligence, visual analytics, information systems success, and statistical modeling. Python-based analytical processing strengthens this framework because an effective dashboard must be supported by cleaned data, reliable computation, and interpretable statistical results rather than visual presentation alone. Earlier studies on scientific computing have shown that Python-based tools support numerical analysis, structured data processing, and statistical workflows in data-driven research and practice (Hunter, 2007; McKinney, 2010; Walt et al., 2011). For this reason, this study has positioned pharmaceutical brand dashboards as analytical decision-support systems rather than simple visual reporting outputs.

At the international level, pharmaceutical organizations operate in competitive, regulated, and data-intensive environments where brand performance decisions are connected with sales efficiency, market access, prescription movement, promotional accountability, regional performance, healthcare professional engagement, and product portfolio management. Pharmaceutical brand managers and analytics teams require timely and interpretable information about which products are growing, which regions are underperforming, which promotional activities are effective, and which market segments require strategic attention. Marketing dashboard literature has shown that dashboard-based systems help managers connect marketing metrics with performance evaluation, strategic monitoring, and decision-making processes (Shurovi & Hossain, 2022; Pauwels et al., 2009). Sales technology research has also indicated that information technology can improve sales effectiveness by strengthening customer knowledge, activity tracking, targeting capability, and sales decision support (Ahearne et al., 2007; Hossain, 2024). These arguments are highly relevant to pharmaceutical brand performance analytics because pharmaceutical commercial teams often depend on brand managers, sales managers, territory executives, and marketing analysts who need reliable dashboards for daily, weekly, and monthly performance interpretation. Healthcare analytics research has also shown that healthcare and life-science data require reliable data management, analytical methods, and decision-support systems because such data are complex, heterogeneous, and operationally sensitive (Bellazzi & Zupan, 2008; Raghupathi & Raghupathi, 2014). Business intelligence studies have further demonstrated that BI systems can improve business process performance by improving access to relevant information and supporting analytical interpretation (Elbashir et al., 2008; Kanti, 2025). In pharmaceutical companies, this logic applies to brand performance because fragmented data from sales reports, prescription records, promotional campaigns, regional tracking files, and customer engagement platforms can weaken the accuracy and speed of managerial decisions. The international significance of this study has therefore been connected with the need to develop an integrated analytics structure where Tableau provides interactive visibility and Python provides analytical reliability. Tableau can help users inspect brand-level key performance indicators, territory comparisons, sales trends, and performance dashboards, while Python can prepare clean datasets, conduct statistical analysis, and validate relationships among study variables. This combined structure is suitable for a quantitative, cross-sectional, case-study-based study because it allows the researcher to measure how pharmaceutical professionals perceive dashboarding capability, analytical processing, visualization quality, dashboard usability, automation, and brand performance analytics effectiveness. In this way, the study has been shaped by the international movement toward data-driven pharmaceutical decision-making, business intelligence adoption, and visually supported managerial analytics.

Figure 1: Integrated Dashboarding and Analytics Framework for Pharmaceutical Brand Performance Evaluation



The background and motivation of this study have also been shaped by the development of business intelligence and analytics as a major field of organizational performance management. Business intelligence has moved beyond static reporting because organizations now require analytical systems that integrate data, produce visual summaries, support statistical reasoning, and connect operational information with managerial decision-making (Golam & Amir, 2023; Chen et al., 2012). Business analytics research has shown that analytical capability can influence performance when organizations combine data resources, technological infrastructure, and process-oriented information use (Amir & Chapal, 2022; Trkman et al., 2010). Predictive and explanatory modeling have also been recognized as important components of information systems research because analytical systems need to describe observed patterns and explain relationships among variables that influence outcomes (Amir, 2025; Shmueli & Koppius, 2011). This reasoning directly supports the present study because the research design includes descriptive statistics, correlation analysis, and regression modeling. Descriptive statistics can summarize the level of agreement among respondents regarding Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, visualization quality, analytics automation, and pharmaceutical brand performance analytics effectiveness. Correlation analysis can examine the strength and direction of relationships among these variables.

Regression modeling can test whether dashboarding, analytical processing, usability, visualization quality, and automation significantly predict brand performance analytics effectiveness. Big data and analytics literature has further argued that data value depends on the ability to transform large, varied, and fast-moving data into useful knowledge for managerial and operational decisions (Gandomi & Haider, 2015). Pharmaceutical brand data may not always be large in the same way as social media or clinical big data, yet it is often varied because it may include product sales, prescription trends, regional performance, promotional activities, physician targeting, market share, and customer engagement indicators. Prior research on big data analytics and firm performance has shown that analytics capability can support performance when organizations have suitable technological capability, managerial readiness, and data-driven decision processes (Amir, 2024; Wamba et al., 2017). Therefore, the motivation of this research has come from the need to develop a measurable framework that treats pharmaceutical brand performance analytics as an integrated system. In that system, Tableau functions as the dashboarding and visualization interface, Python functions as the analytical processing engine, and the end outcome is improved pharmaceutical brand performance analytics effectiveness. This background has made the research suitable for hypothesis testing because the major framework components can be converted into measurable Likert-scale constructs and statistically examined.

Data visualization has been central to this research because pharmaceutical brand performance data becomes more meaningful when decision-makers can identify patterns quickly, accurately, and interactively. Visualization research has shown that interactive visual analysis allows users to select views, filter information, sort patterns, coordinate displays, and move between summary-level and detailed-level interpretation (Heer & Shneiderman, 2012; Sadia et al., 2022). This is directly relevant to pharmaceutical brand dashboards because a brand manager may need to begin with total sales performance, then drill down into regional achievement, compare products by growth rate, inspect prescription trend movement, and evaluate promotional response by product or territory. Visual analytics research has also shown that effective visual representations must be designed according to user tasks, data types, analytical goals, and abstraction levels (Munzner, 2009; Zaman, 2024). Therefore, the proposed framework cannot assume that all charts are equally useful for all pharmaceutical brand decisions. A sales trend may require a line chart, a brand ranking may require a bar chart, a regional comparison may require a map-based view, and executive monitoring may require KPI cards or summary panels. Research on automatic visualization design has also shown that visual analytics systems can improve analytical efficiency when they guide users toward appropriate visual representations (Mackinlay et al., 2007). Dashboard-specific studies have indicated that dashboards require a distinct design logic because they combine multiple indicators, compact displays, interactivity, and performance monitoring within one decision environment (Sarikaya et al., 2019). Visual memorability research has further shown that visual design affects how users notice, remember, and interpret information shown through graphical displays (Borkin et al., 2013; Tohidul, 2023). These ideas are important for pharmaceutical analytics because dashboards with unclear layout, weak labeling, unsuitable chart selection, or excessive visual density may reduce user understanding. A clearly designed dashboard can support faster interpretation of brand performance by helping users see changes in product sales, territory contribution, prescription movement, market share, promotional response, and customer engagement. In this research, Tableau-based visualization has therefore been positioned as the decision-support layer that converts pharmaceutical brand data into interactive, accessible, and managerially meaningful views. Dashboard usability has been included as a core construct because even accurate data can fail to support decision-making when the dashboard is difficult to navigate, visually confusing, or poorly aligned with the user's analytical task. Data visualization quality and dashboard usability have therefore been treated as essential components of pharmaceutical brand performance analytics effectiveness.

Python-based analytical processing has formed another major foundation of this study because dashboard trustworthiness depends on the quality of the data and the reliability of the analysis behind the visual interface. Python has become a widely used environment for analytics because it supports data manipulation, numerical computing, statistical modeling, visualization, repeatable workflows, and integration with other analytical tools. Matplotlib has established Python as a useful platform for scientific visualization, while NumPy has strengthened numerical computation through efficient array-based processing (Hunter, 2007; Walt et al., 2011). Pandas has supported structured data handling, tabular transformation, missing-value treatment, grouping, merging, and data preparation for statistical analysis (McKinney, 2010). SciPy has provided scientific computing tools for statistical and numerical tasks, and Seaborn has extended statistical visualization within the Python ecosystem (Virtanen et al., 2020; Waskom, 2021). These tools are directly relevant to the proposed framework because pharmaceutical brand data often requires cleaning before it can be converted into Tableau dashboards. Product names may need standardization, region codes may require correction, missing values may need treatment, promotional variables may require restructuring, and derived indicators such as growth rate, territory contribution, market share, prescription trend, or brand ranking may need calculation. Python can also support the statistical requirements of this thesis by producing descriptive statistics, correlation matrices, regression models, and diagnostic checks. Healthcare analytics research has shown that data-driven systems require careful data processing because poor data quality can reduce confidence in decision-making and analytical output (Kwon et al., 2014). In pharmaceutical brand performance analytics, a similar issue can occur when dashboards are built directly from inconsistent spreadsheets, manually edited files, or unvalidated performance reports. Therefore, Python has been treated as the analytical engine of the framework, while Tableau has been treated as the visualization and decision-support interface. This dual structure makes the study more specific than a general dashboarding study because it examines how backend analytical processing and frontend visual communication jointly influence pharmaceutical brand performance analytics effectiveness. The inclusion of Python-driven analytical workflow validation in the results chapter can further strengthen the thesis because it allows the researcher to evaluate whether users perceive Python-based processing as useful for reducing manual errors, improving reporting accuracy, supporting regression analysis, and preparing reliable data for dashboard visualization.

The theoretical foundation of this study has been connected with the Information Systems Success Model because a dashboarding and visualization framework is an information system that must be evaluated according to quality, usability, satisfaction, use, and decision value. Information systems success research has suggested that system quality, information quality, use, user satisfaction, and net benefits are central dimensions for evaluating whether an information system produces meaningful outcomes (Petter et al., 2008). In this study, Tableau-based dashboarding capability, dashboard usability, visualization interactivity, and automation represent system quality. Python-based analytical processing, statistical validation, cleaned data, and reliable outputs represent information quality and analytical quality. Dashboard usability represents the user-centered interaction dimension. Pharmaceutical brand performance analytics effectiveness represents the net benefit of the proposed framework. User satisfaction and technology acceptance research has also shown that system quality, information quality, perceived usefulness, perceived ease of use, and satisfaction are strongly connected in explaining how users evaluate information systems (Wixom & Todd, 2005). This theoretical logic supports the selection of the main variables used in the study. Tableau-based dashboarding capability has represented the visual and interactive capacity of the system. Python-based analytical processing has represented the reliability and computational strength of the analytical backend. Dashboard usability has represented the ease with which pharmaceutical professionals can understand and navigate the dashboard. Data visualization quality has represented the clarity, interpretability, and appropriateness of visual outputs. Analytics automation has represented repeatability, timeliness, and reduced manual reporting effort. Pharmaceutical brand performance analytics effectiveness has represented the outcome of the framework in terms of faster insight generation, more accurate reporting, stronger monitoring, and improved brand-level decision support. Business intelligence studies have similarly emphasized that BI systems create value when they improve information access, analytical interpretation, decision quality, and business process performance (Elbashir et al., 2008; Trkman et al., 2010). This theoretical alignment has made the study suitable for a quantitative hypothesis-testing approach because each independent variable can be measured through Likert-scale items and statistically examined against the dependent variable. The Information Systems Success Model has therefore provided the theoretical basis for connecting Tableau, Python, visualization quality, usability, automation, and pharmaceutical brand performance analytics effectiveness within one integrated study framework.

The problem addressed in this study is the limited availability of a structured, tool-specific, and statistically testable framework for pharmaceutical brand performance analytics using Tableau and Python. Many organizations use dashboards for reporting, yet dashboard use alone does not automatically ensure accurate analytics, useful visualization, or effective decision support. Dashboard literature has shown that dashboard effectiveness depends on design quality, user task alignment, indicator selection, information organization, and the connection between metrics and decisions (Yigitbasioglu & Velcu, 2012). Marketing dashboard research has also shown that managers need dashboards that connect metrics with decision needs rather than a random collection of numbers and charts (Pauwels et al., 2009). In pharmaceutical brand management, this issue becomes more complex because brand performance is evaluated through interconnected indicators such as sales growth, prescription volume, regional achievement, market share, promotional response, channel productivity, and customer engagement. Healthcare and business analytics research has shown that data-driven systems become more useful when analytics capability is connected with data quality, decision processes, organizational use, and measurable performance outcomes (Bates et al., 2014; Wang et al., 2018). The present study responds to this gap by proposing a quantitative, cross-sectional, case-study-based research design that can evaluate a Tableau and Python-based dashboarding and visualization framework through survey evidence and statistical testing. The study uses a five-point Likert scale to measure respondent perceptions of Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, analytics automation, and pharmaceutical brand performance analytics effectiveness. The design includes descriptive statistics to summarize variable-level responses, reliability analysis to examine internal consistency, correlation analysis to evaluate relationships among variables, and regression modeling to test the predictive effect of dashboarding and visualization capabilities. The inclusion of dashboard prototype evaluation and KPI visualization effectiveness makes the study more specific to Tableau-based dashboard design, while the inclusion of Python-driven analytical workflow validation makes the study more specific to backend analytical reliability. In this way, the research problem has been framed around the need for an integrated framework that connects pharmaceutical brand performance indicators, statistical analytics, dashboard usability, visualization clarity, and decision-support effectiveness through Tableau and Python.

Background of the Study

The pharmaceutical industry has increasingly become dependent on data-driven decision-making because brand performance is no longer evaluated only through total sales volume or basic monthly reports. Pharmaceutical brand performance now involves a wider set of indicators, including product-wise sales achievement, market share, prescription movement, physician engagement, regional performance, promotional effectiveness, channel contribution, customer segmentation, growth rate, product lifecycle status, and competitive positioning. In many pharmaceutical organizations, these indicators are generated from different sources such as sales records, customer relationship management systems, prescription tracking files, market reports, campaign reports, and internal performance monitoring systems. When these data sources remain scattered, managers face difficulty in understanding the true performance position of a brand. Traditional spreadsheet-based reporting can summarize data, but it often fails to provide interactive exploration, fast comparison, automated analysis, and visually clear decision support. For this reason, dashboarding and visualization have become important tools for pharmaceutical brand analytics. Tableau can support this process by converting complex brand performance data into interactive dashboards, KPI panels, charts, maps, filters, and drill-down visual reports. At the same time, Python can support the analytical foundation by cleaning data, preparing variables, generating descriptive statistics, conducting correlation analysis, building regression models, and validating the relationships among performance-related factors. Therefore, the combination of Tableau and Python can create a stronger framework where Python works as the analytical processing engine and Tableau works as the visualization and decision-support interface. This study has been developed in this context to examine how a dashboarding and visualization framework can improve pharmaceutical brand performance analytics. The study follows a quantitative, cross-sectional, case-study-based design because it aims to measure the perceptions of pharmaceutical professionals and analyze the relationships among dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, analytics automation, and pharmaceutical brand performance analytics effectiveness. The background of the study is therefore grounded in the need for a more reliable, interactive, and statistically supported approach to pharmaceutical brand performance monitoring.

Problem Statement

Pharmaceutical brand performance analytics requires accurate, timely, and interpretable information, yet many organizations still depend on fragmented reporting practices, manual spreadsheet handling, static charts, delayed data updates, and limited statistical validation. These weaknesses can create serious difficulties for brand managers, sales managers, marketing teams, and business intelligence professionals because they need to identify performance changes quickly and make decisions based on reliable evidence. When brand data are stored in separate files or departments, it becomes difficult to compare sales trends, evaluate regional achievement, monitor prescription growth, assess promotional response, and identify underperforming brands in a timely manner. Manual reporting also increases the possibility of errors, inconsistent calculations, repeated work, and delayed managerial interpretation. Another important problem is that many dashboards are designed only as visual summaries without a strong analytical backend. A dashboard may look attractive, but if the data are not cleaned properly, if the variables are not prepared correctly, or if the relationships among performance indicators are not statistically tested, the dashboard may not provide trustworthy decision support. Similarly, Python-based analysis may produce accurate statistics, but if the results are not presented in an interactive and understandable format, managers may not be able to use the findings effectively. This creates a gap between analytical processing and visual decision-making. In pharmaceutical brand analytics, this gap is especially important because brand performance depends on many connected indicators such as sales growth, territory contribution, market share, promotional activity, prescription trend, and customer engagement. Without an integrated framework, decision-makers may depend on partial information and may fail to understand the overall performance condition of a brand. Therefore, the main problem of this research is the absence of a structured, integrated, and statistically testable dashboarding and visualization framework that combines Tableau and Python for pharmaceutical brand performance analytics. This study addresses this problem by examining whether Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, and analytics automation significantly contribute to pharmaceutical brand performance analytics effectiveness.

Objectives of The Study

The main objective of this study is to develop and evaluate a dashboarding and visualization framework for pharmaceutical brand performance analytics using Tableau and Python. To achieve this main objective, the study focuses on several specific analytical goals that are directly connected with the research problem, methodology, and expected framework. First, the study aims to examine the role of Tableau-based dashboarding capability in improving pharmaceutical brand performance analytics by assessing how interactive dashboards, KPI panels, filter-based exploration, drill-down options, territory comparison, and visual brand tracking support decision-making. Second, the study aims to assess the contribution of Python-based analytical processing by examining how data cleaning, variable preparation, descriptive statistics, correlation analysis, regression modeling, automation, and repeatable workflows improve the reliability of brand performance analysis. Third, the study aims to determine how dashboard usability influences pharmaceutical professionals' ability to understand and use brand performance dashboards effectively. This includes ease of navigation, layout clarity, user-friendly design, chart readability, and accessibility of key information. Fourth, the study aims to evaluate the role of data visualization quality in making pharmaceutical brand indicators more understandable, comparable, and meaningful for managerial interpretation. Fifth, the study aims to examine how analytics automation contributes to reporting accuracy, timeliness, reduced manual errors, and faster performance monitoring. Sixth, the study aims to test the relationships among the major variables through descriptive statistics, correlation analysis, and regression modeling based on Likert-scale survey data. Finally, the study aims to validate a practical framework that connects Tableau as the dashboarding and visualization layer with Python as the analytical processing layer for pharmaceutical brand performance analytics. These objectives have been designed to make the research both statistically measurable and practically relevant. Through these objectives, the study intends to show whether an integrated Tableau and Python-based analytics framework can provide stronger decision support for pharmaceutical brand managers, sales analytics teams, marketing professionals, and business intelligence users.

Research Hypotheses

The research hypotheses of this study have been developed to statistically examine the relationships among Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, analytics automation, and pharmaceutical brand performance analytics effectiveness. Since the study follows a quantitative, cross-sectional, case-study-based design, the hypotheses provide the foundation for correlation analysis and regression modeling. The first hypothesis states that Tableau-based dashboarding capability has a significant positive effect on pharmaceutical brand performance analytics effectiveness. This hypothesis is based on the idea that interactive dashboards, KPI visualization, filter options, drill-down analysis, and brand-level performance views can help users understand brand conditions more effectively. The second hypothesis states that Python-based analytical processing has a significant positive effect on pharmaceutical brand performance analytics effectiveness. This hypothesis assumes that data cleaning, statistical analysis, variable preparation, regression modeling, and automated workflows can increase the reliability and usefulness of brand analytics. The third hypothesis states that dashboard usability has a significant positive effect on pharmaceutical brand performance decision-support quality. This hypothesis focuses on how ease of use, layout clarity, simple navigation, and understandable design can improve managerial interpretation. The fourth hypothesis states that data visualization quality has a significant positive effect on pharmaceutical brand performance analytics effectiveness. This hypothesis assumes that clear charts, suitable visual formats, readable labels, accurate comparisons, and meaningful graphical presentation help users interpret brand performance data more accurately. The fifth hypothesis states that analytics automation has a significant positive effect on reporting accuracy and timeliness in pharmaceutical brand performance analytics. This hypothesis reflects the idea that automated data preparation and reporting can reduce manual errors and improve the speed of insight generation. The sixth hypothesis states that integrated Tableau and Python analytics capability significantly predicts pharmaceutical brand performance analytics effectiveness. This final hypothesis combines the overall framework by testing whether visual dashboarding and analytical processing together can explain improvements in pharmaceutical brand performance analytics. These hypotheses will allow the study to move beyond descriptive explanation and provide statistical evidence for the proposed dashboarding and visualization framework.

Significance of the Research

i. This research is significant for pharmaceutical brand managers because it provides a structured way to monitor brand performance through interactive dashboards, KPI visualization, sales trend analysis, regional comparison, prescription movement, and promotional response tracking. It can help brand managers understand which brands are performing strongly, which products require strategic attention, and which territories need corrective action.

ii. This study is significant for pharmaceutical sales and marketing teams because it connects brand performance indicators with visual and statistical decision support. Sales managers can use dashboard-based insights to compare territories, evaluate field performance, observe market changes, and support more accurate planning for sales activities and promotional campaigns.

iii. This research is significant for business intelligence and analytics professionals because it proposes an integrated workflow where Python supports data cleaning, statistical analysis, and automation, while Tableau supports dashboard design, visual exploration, and managerial presentation. This combination can reduce the gap between technical analysis and practical decision-making.

iv. This study is significant for academic research because it contributes to the areas of pharmaceutical analytics, business intelligence, dashboarding, data visualization, information systems success, and analytics-supported decision-making. It provides a quantitative model that can be tested through descriptive statistics, correlation analysis, and regression modeling.

v. This research is significant for pharmaceutical organizations because it can improve reporting accuracy, reduce manual reporting errors, increase the timeliness of brand performance reviews, and support evidence-based decision-making. A structured framework can help organizations move from scattered reports to a more centralized and interactive analytics approach.

vi. This study is significant for future analytics framework development because it treats dashboarding as more than visual display and treats Python analysis as more than backend computation. It connects both components into one practical framework for pharmaceutical brand performance analytics. This makes the study useful for organizations that want to design dashboards that are visually clear, statistically reliable, and decision-oriented.

vii. This research is significant for decision-makers because it highlights the importance of usability, visualization quality, automation, and analytical reliability. These elements can help managers make faster and more confident decisions about brand growth, market position, territory performance, promotional outcomes, and product-level strategy.

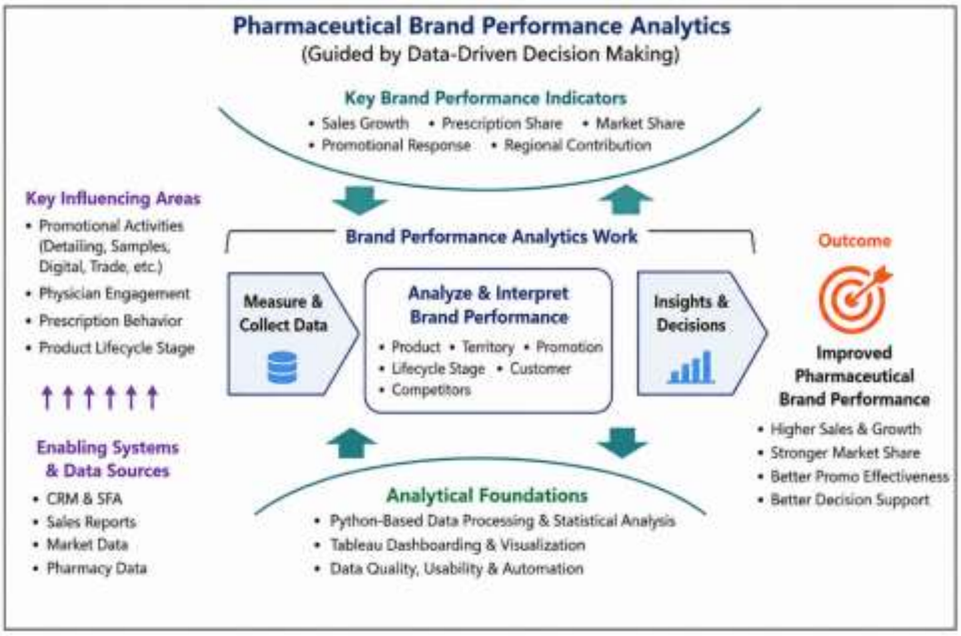
LITERATURE REVIEW

The literature review of this study is developed around the relationship between pharmaceutical brand performance analytics, business intelligence, dashboarding, data visualization, Python-based analytical processing, and information systems success. Pharmaceutical brand performance analytics has become an important area of managerial decision-making because pharmaceutical organizations must evaluate brand growth, market share, sales achievement, prescription movement, regional contribution, promotional effectiveness, and customer engagement through reliable data. However, brand performance data often comes from multiple sources, which creates the need for integrated analytical systems that can organize, process, visualize, and interpret information in a decision-oriented way. Business intelligence literature provides the foundation for understanding how organizations transform raw data into useful information for planning, monitoring, and performance evaluation. Dashboarding literature explains how key performance indicators can be presented through visual interfaces that allow managers to compare trends, filter information, identify exceptions, and monitor performance more efficiently. Data visualization literature adds another important dimension by showing that analytical information becomes more meaningful when it is presented through clear, accurate, interactive, and user-friendly visual forms. For this research, Tableau is important because it provides the dashboarding and visualization layer through which pharmaceutical professionals can interact with brand performance indicators. Python is also important because it provides the analytical processing layer through which raw data can be cleaned, transformed, summarized, and statistically analyzed before being visualized. The literature review therefore needs to examine both the visual and analytical sides of the framework. It must also discuss dashboard usability, visualization quality, and analytics automation because these factors influence whether users can understand and trust the dashboard outputs. The Information Systems Success Model provides the theoretical foundation for the study because the proposed Tableau and Python-based framework can be evaluated through system quality, information quality, usability, user satisfaction, and net benefits. The conceptual framework connects Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, and analytics automation with pharmaceutical brand performance analytics effectiveness. Therefore, the literature review will synthesize previous studies on pharmaceutical analytics, business intelligence, Tableau-style dashboarding, Python-supported analytics, visualization quality, and information systems success to justify the variables, hypotheses, and framework of the present study.

Pharmaceutical brand performance analytics

Pharmaceutical brand performance analytics refers to the systematic measurement, interpretation, and managerial use of brand-level indicators that explain how pharmaceutical products perform across sales territories, prescription behavior, physician engagement, promotional activities, product lifecycle stages, customer segments, and competitive markets. In the pharmaceutical industry, a brand is not only a commercial label attached to a medicine; it is also a market-facing asset that carries therapeutic positioning, physician trust, patient accessibility, sales strategy, promotional investment, and competitive differentiation. Therefore, brand performance analytics needs to evaluate several connected indicators rather than depending only on monthly sales volume. These indicators may include sales growth, prescription share, market share, promotional response, regional contribution, product adoption, physician conversion, repeat prescribing, channel productivity, and sales force effectiveness. Earlier research on pharmaceutical marketing communication has shown that marketing communication affects product choice differently across product lifecycle stages, especially when customers and prescribers need information to reduce uncertainty about new pharmaceutical products (Abdur & Iftekhar, 2021; Narayanan et al., 2005). This idea is important for the present research because pharmaceutical brand dashboards must not present brand performance as a single static number. They need to show whether the brand is in a launch stage, growth stage, maturity stage, or decline stage, because the meaning of sales movement and promotional response differs across these stages. A new pharmaceutical brand may require analytics related to awareness, trial, physician adoption, and early prescription growth, while a mature brand may require analytics related to retention, market share defense, regional performance stability, and promotional efficiency. Therefore, pharmaceutical brand performance analytics must combine commercial indicators with time-based interpretation. A dashboarding and visualization framework using Tableau and Python becomes relevant in this context because Python can structure and calculate brand-level indicators, while Tableau can present product movement, regional comparison, lifecycle changes, and sales patterns in a visual and interactive format for decision-makers.

Figure 2: Analytical Framework for Pharmaceutical Brand Performance Evaluation



Pharmaceutical brand performance is also strongly connected with promotional effectiveness because pharmaceutical companies invest in several communication and promotional activities to influence prescribing, pharmacy-level purchasing, product awareness, and brand preference. Promotional activities may include detailing, physician meetings, samples, trade promotions, merchandising, educational programs, digital communication, and pharmacy-level promotional techniques. A meta-analysis of pharmaceutical promotional expenditures has shown that promotional instruments can affect pharmaceutical demand, although the size and nature of effectiveness may differ across promotional tools, disease categories, and communication channels (Hasan & Uddin, 2022; Kremer et al., 2008). This indicates that pharmaceutical brand performance analytics should not only report total sales but should also examine whether promotional activities are producing measurable brand-level outcomes. For example, a brand may show sales growth in one region because of stronger physician engagement, while another region may remain weak due to poor promotional reach, low prescription conversion, or limited pharmacy-level visibility. Research on physician decision-making has also shown that marketing actions and patient-related influences affect prescription behavior differently across brands, and the effects may depend on drug characteristics such as effectiveness and side effects

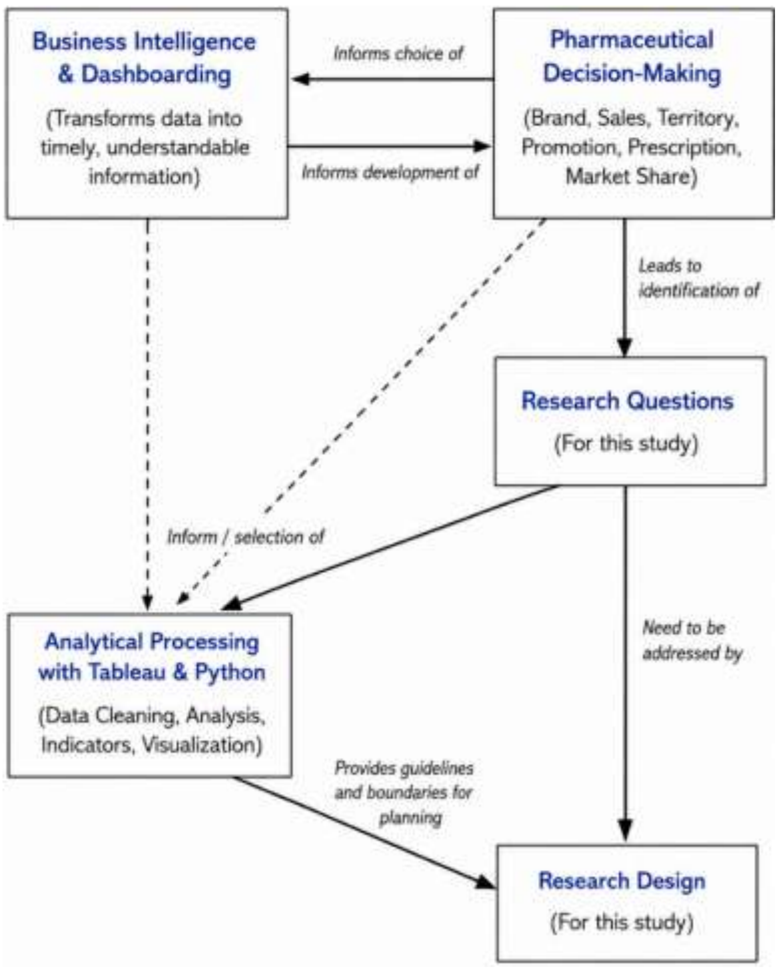
(Mohiul & Badrul, 2022; Venkataraman & Stremersch, 2007). This finding is highly relevant for pharmaceutical brand analytics because every brand cannot be interpreted through identical commercial logic. Some brands may perform better because of therapeutic strength, while others may depend more heavily on promotional communication, physician relationships, or market accessibility. Therefore, a strong pharmaceutical brand analytics framework should allow managers to compare product performance, promotional exposure, prescription outcomes, and brand characteristics together. Tableau-based dashboards can support this need through brand-wise visual comparison, territory-level drill-down, and promotional KPI tracking. Python-based analysis can support this need by calculating promotional productivity, identifying statistical relationships between promotional variables and brand performance, and preparing reliable datasets for dashboard visualization. In this way, pharmaceutical brand performance analytics becomes a structured process of connecting market activity with measurable brand outcomes.

Pharmaceutical brand performance analytics has become more important because modern pharmaceutical organizations increasingly depend on data-driven commercial systems, customer relationship management platforms, sales force automation, and digital reporting tools. The value of such analytics depends on whether data can be transformed into usable insight for brand managers, sales leaders, marketing teams, and business intelligence professionals. Recent empirical research on pharmaceutical organizations has shown that big data analytics can improve sales performance by strengthening customer relationship management capabilities, indicating that analytical capability has direct relevance for pharmaceutical commercial performance (Kanti & Rony, 2022; Shahbaz et al., 2021). This is important for the present study because brand performance analytics is not only a reporting activity; it is also a decision-support process that helps organizations understand customers, territories, product movement, sales opportunities, and promotional outcomes. Pharmacy-level research has also shown that sales promotion techniques can influence consumers' purchasing decisions at community pharmacies, which means that pharmaceutical brand performance must consider market-facing activities beyond internal sales numbers (Said et al., 2019; Sadia et al., 2022). This supports the idea that a dashboarding and visualization framework should include indicators related to promotional effectiveness, customer response, pharmacy-level activity, regional sales movement, and brand visibility. In a case-study-based pharmaceutical setting, such analytics can help identify whether brand performance is being shaped by sales execution, prescription behavior, promotional activity, or customer-level response. Python can strengthen this process through data cleaning, variable preparation, descriptive analysis, correlation analysis, and regression modeling. Tableau can translate the processed results into interactive visual dashboards that allow users to compare brands, filter regions, track KPIs, and interpret performance patterns. Therefore, pharmaceutical brand performance analytics should be understood as an integrated analytical practice where statistical processing and visual communication work together. This understanding directly supports the present research because the study examines how Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, and analytics automation contribute to pharmaceutical brand performance analytics effectiveness.

Business intelligence and dashboarding in pharmaceutical decision-making

Business intelligence and dashboarding have become important foundations for pharmaceutical decision-making because pharmaceutical organizations need to transform scattered operational data into timely, understandable, and action-oriented information. In pharmaceutical brand management, decision-makers need to monitor product performance, regional sales movement, prescription behavior, promotional return, market share, customer response, and sales force activity through a structured information environment. Business intelligence supports this process by connecting data storage, data preparation, analytical processing, reporting, and managerial interpretation within one decision-support logic. Decision support systems research has emphasized that modern decision environments require systems that can organize complex data, support analytical reasoning, and improve the quality of managerial decisions under uncertain and information-rich conditions (Arnott & Pervan, 2008; Tohidul, 2023). This understanding is highly relevant to pharmaceutical brand performance analytics because brand managers often make decisions based on multiple indicators that change across time, geography, customers, and product categories. A traditional report may show sales volume, but a business intelligence dashboard can connect sales volume with territory achievement, growth rate, prescription trend, promotional investment, and market share. In this way, dashboarding strengthens the ability of pharmaceutical managers to observe patterns and compare brand performance from different angles. Business intelligence success research has also shown that BI capability and decision environments influence the usefulness of analytics systems, meaning that technology alone is not enough unless the system fits the decision problem and user needs (Isik et al., 2013; Badrul & Mominul, 2023). This point is important for the present study because a pharmaceutical dashboard should be designed according to the tasks of brand managers, sales managers, marketing analysts, and business intelligence professionals. Tableau-based dashboards can provide an interactive visual layer for such tasks, while Python can support the analytical layer by cleaning datasets, preparing brand indicators, and generating statistical outputs. Therefore, business intelligence and dashboarding can be understood as connected decision-support mechanisms that help pharmaceutical professionals move from raw data to brand-level insight.

Figure 3: Integrated Business Intelligence and Dashboarding Framework for Pharmaceutical Brand Decision-Making



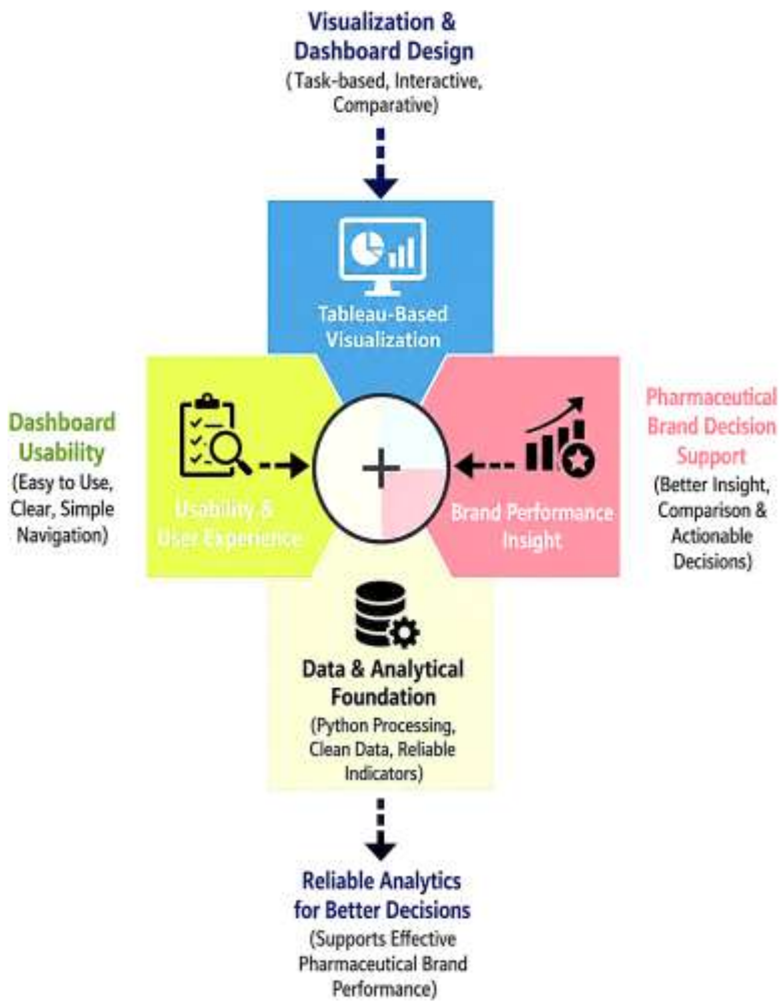
Dashboarding is particularly important in pharmaceutical decision-making because it allows decision-makers to visualize performance indicators in a compact, interactive, and comparative format. Pharmaceutical organizations commonly manage multiple brands, regions, sales teams, promotional channels, and customer segments, which creates a need for dashboards that can simplify complex information without removing important analytical detail. Healthcare dashboard research has shown that dashboards can support quality improvement and decision-making when they present relevant indicators clearly and help users identify areas requiring attention (Dowding et al., 2015; Hossan & Adar, 2023). Although this evidence has come from healthcare settings, the logic is strongly applicable to pharmaceutical brand analytics because brand teams also need dashboards that highlight performance gaps, unusual trends, and improvement areas. A brand dashboard can show which products are achieving targets, which territories are underperforming, which regions have stronger prescription movement, and which promotional activities appear more productive. Business intelligence maturity research has also indicated that analytical decision-making improves when organizations develop stronger BI maturity, data-oriented culture, and systematic use of information (Popovič et al., 2012; Risha & Khalid, 2023). This means that pharmaceutical dashboarding should not be treated only as a technical reporting exercise; it should be treated as part of a broader analytical decision culture. When managers use dashboards regularly, they can compare current performance with previous performance, identify deviations from targets, and make more evidence-based brand decisions. In the context of this study, Tableau can support such decision-making through KPI panels, filter-based exploration, drill-down analysis, maps, and trend visualization. Python can support the same process by preparing clean and reliable data before visualization. The connection between dashboarding and business intelligence is therefore essential because dashboard outputs are only valuable when the underlying data are accurate, the indicators are relevant, and the visual design supports managerial interpretation. For pharmaceutical brand performance analytics, this creates a need for an integrated framework that links analytical processing with visual decision support.

Business intelligence and dashboarding also support pharmaceutical decision-making by improving the speed, consistency, and reliability of performance interpretation. In many pharmaceutical organizations, managers may receive reports from different departments, including sales operations, marketing, distribution, prescription tracking, and customer relationship management. When these reports are not integrated, decision-makers may face delays, inconsistent calculations, and difficulty comparing indicators across brands and regions. Research on big data and organizational decision processes has shown that data-based decision-making depends on the ability to process large and varied information sources and convert them into usable knowledge for organizational decisions (Kowalczyk & Buxmann, 2015; Hossan, 2024). This is highly relevant to pharmaceutical brand analytics because brand performance data may include structured sales records, semi-structured promotional reports, customer relationship management data, and region-wise market information. Dashboards can improve this situation by centralizing key indicators and presenting them in a format that supports rapid comparison and interpretation. At the same time, the quality of dashboard-driven decisions depends on the reliability of analytical processing behind the dashboard. Python can help address this requirement by supporting data cleaning, missing-value checking, variable preparation, descriptive analysis, correlation analysis, and regression modeling. Tableau can then communicate the processed results through interactive dashboards that are understandable to non-technical decision-makers. Research on the impact of business intelligence on decision quality has shown that BI can improve decision-making when information quality and analytical use are aligned with managerial needs (Ali et al., 2024; Wieder & Ossimitz, 2015). This finding supports the present research because pharmaceutical brand performance analytics effectiveness depends on both the quality of the analytical system and the usefulness of the visual interface. Therefore, business intelligence and dashboarding in pharmaceutical decision-making should be understood as a combined process where data processing, indicator design, visualization quality, user interaction, and statistical validation jointly support brand-level decisions. This provides a clear foundation for examining Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, and analytics automation as predictors of pharmaceutical brand performance analytics effectiveness.

Tableau-based visualization and dashboard usability

Tableau-based visualization is highly relevant to pharmaceutical brand performance analytics because it provides an interactive environment where complex brand indicators can be converted into visible, comparable, and decision-oriented information. In a pharmaceutical context, brand performance data may include sales achievement, prescription volume, regional contribution, market share, promotional response, customer segmentation, product growth, and sales force activity. These indicators are often difficult to interpret through static spreadsheet reports because brand managers need to compare several dimensions at the same time. Tableau supports this need by allowing dashboards to include filters, drill-down options, trend lines, maps, KPI cards, bar charts, line charts, and interactive panels. However, the usefulness of Tableau does not depend only on the availability of visual features. It depends on whether the dashboard has been designed according to user needs, analytical tasks, and the decision environment. Visualization evaluation research has shown that expert review can identify important usability and design problems in visual interfaces, especially when visual tools are expected to support interpretation and decision-making (Tory & Möller, 2005). This is important for pharmaceutical dashboarding because a dashboard may contain accurate data but still fail if users cannot understand the layout, interpret the chart, navigate filters, or connect visual indicators with brand decisions. For example, a brand manager may need to identify why a product is declining in one region, whether the decline is related to low prescription movement, weak promotional response, or poor sales force coverage. A Tableau dashboard can make this type of interpretation easier when it is designed around brand-level tasks rather than general reporting. Therefore, Tableau-based visualization in this research has been considered as a structured decision-support mechanism that helps pharmaceutical professionals transform raw performance records into meaningful visual insight. Dashboard usability becomes a central issue because users must be able to move from overview to detail, compare brands, detect patterns, and interpret performance differences without confusion.

Figure 4: Framework for Interactive Dashboard Visualization in Pharmaceutical Brand Performance Analytics



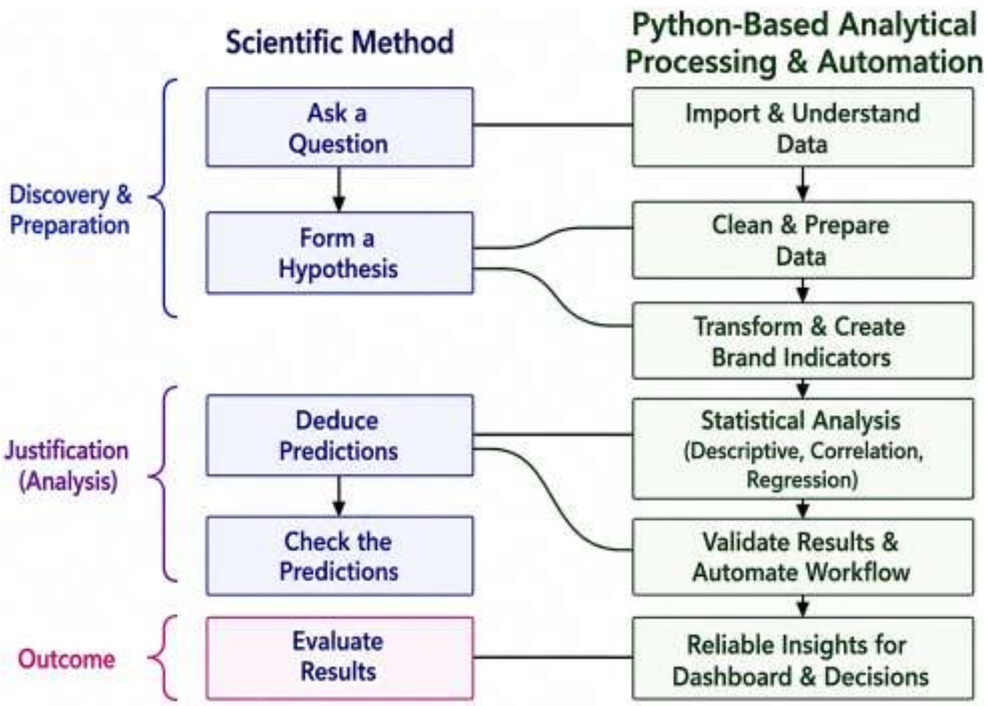
Dashboard usability is also important because visualization quality depends on the relationship between user tasks, visual design, and evaluation purpose. Information visualization research has explained that visualization evaluation can involve several scenarios, including user performance, user experience, communication through visualization, workplace context, and visual reasoning (Lam et al., 2012; Zaman, 2024). This view is highly useful for the present research because pharmaceutical dashboards are not developed only to display data; they are developed to help users reason about brand performance, identify underperforming areas, compare pharmaceutical products, and support managerial decisions. A dashboard that performs well for one task may not perform well for another task. For instance, an executive dashboard may need compact KPI indicators, while a sales analytics dashboard may need regional drill-down, product comparison, and time-series exploration. Design study research has also emphasized that visualization systems should be developed through problem-driven understanding of domain needs, data characteristics, user requirements, and validation practices (Arif Uz et al., 2025; Sedlmair et al., 2012). This idea directly supports the case-study nature of the current research because pharmaceutical brand analytics has its own domain-specific requirements. A generic dashboard may not be enough for pharmaceutical brand performance because brand decisions may require the simultaneous interpretation of therapeutic category, region, sales target, prescription movement, promotional activity, and customer engagement. Tableau can support these requirements through flexible dashboard construction, yet usability must be considered during dashboard planning. If a dashboard includes too many charts, unclear labels, excessive colors, or inconsistent filters, users may face information overload. If the dashboard is organized around clear KPI hierarchy, logical navigation, and meaningful chart selection, users can interpret brand performance more effectively. Therefore, dashboard usability in this study has been treated as a measurable construct that influences pharmaceutical brand performance decision-support quality. This construct includes ease of use, layout clarity, navigation simplicity, filter usefulness, chart readability, and the ability to locate important brand indicators quickly.

Tableau-based visualization also becomes more valuable when it is aligned with clear analytical tasks and adaptable dashboard design. Visualization task research has shown that tasks can be understood through multiple levels, including why a user needs the visualization, what information is required, and how visual interactions support the intended analytical goal (Brehmer & Munzner, 2013; Hossan, 2025). This task-based logic is important for pharmaceutical brand performance analytics because different users interact with dashboards for different reasons. A brand manager may use the dashboard to evaluate product growth, a sales manager may use it to compare territory achievement, a marketing analyst may use it to examine promotional response, and a business intelligence professional may use it to validate performance indicators. Therefore, a Tableau dashboard should not be designed as a single static reporting page. It should be designed as an interactive decision environment where users can answer different brand performance questions through filters, charts, comparisons, and drill-down paths. Healthcare dashboard research has also shown that adaptable visualization dashboards can support quality improvement when they are designed around diverse metrics, user groups, and organizational levels (Elshehaly et al., 2020; Ali et al., 2025). This finding is relevant to pharmaceutical brand analytics because pharmaceutical organizations also involve multiple users and multiple decision levels, such as national managers, regional managers, brand executives, marketing teams, and sales analysts. Each group may require a different level of detail, but all users need reliable and understandable visual information. Tableau can support this by allowing dashboard pages to be organized around executive summaries, territory analysis, brand comparison, promotional tracking, and trend monitoring. In this research, Tableau-based visualization has therefore been positioned as the visible layer of the framework, while Python-based analytical processing supports the accuracy and reliability of the data behind the dashboard. The usability of the Tableau dashboard becomes a key factor because users must trust the visual outputs, understand the indicators, and apply the information to pharmaceutical brand performance decisions. Therefore, Tableau-based visualization and dashboard usability jointly support the effectiveness of pharmaceutical brand performance analytics.

Python-based analytical processing and automation

Python-based analytical processing refers to the use of Python programming tools, libraries, and computational workflows to clean, transform, analyze, validate, and prepare data for decision-oriented interpretation. In the context of pharmaceutical brand performance analytics, Python is especially important because raw brand data may come from different sources, including sales records, prescription reports, promotional activity sheets, regional performance files, customer relationship management exports, and manually prepared spreadsheets. These data sources may contain missing values, duplicate records, inconsistent product names, different regional coding systems, irregular date formats, and unstructured promotional variables. Before any Tableau dashboard can provide trustworthy visualization, the data must be prepared in a consistent and analytically reliable format. Python supports this requirement by allowing analysts to create repeatable scripts for data cleaning, variable transformation, grouping, aggregation, filtering, and statistical preparation. Interactive scientific computing research has shown that Python environments can support exploratory analysis, visualization, and computational work through flexible interaction between code, data, and output (Pérez & Granger, 2007). This is highly relevant for pharmaceutical brand analytics because analysts often need to test several performance views before finalizing dashboard indicators. For example, they may need to calculate monthly sales growth, territory contribution, prescription share, market share movement, promotional productivity, and brand ranking before those indicators can be visualized in Tableau. Python also allows the same analytical logic to be reused across reporting periods, which reduces repetitive manual work and improves consistency. In this research, Python-based analytical processing is therefore treated as the backend foundation of the dashboarding and visualization framework. Tableau can make brand performance information visible and interactive, but Python strengthens the reliability of the information that enters the dashboard. This makes Python-based processing important for statistical accuracy, data preparation, and analytical trustworthiness in pharmaceutical brand performance analytics.

Figure 5: Python-Based Data Processing and Automation Framework for Pharmaceutical Decision Support



Python also supports the statistical analysis requirements of this study because the research design uses descriptive statistics, correlation analysis, and regression modeling to test relationships among the major variables. In a quantitative, cross-sectional, case-study-based study, the researcher needs to summarize survey responses, check variable distributions, examine relationships among constructs, and test whether dashboarding and visualization capabilities significantly predict pharmaceutical brand performance analytics effectiveness. Python can support these tasks through statistical libraries and model-building environments that allow researchers to run repeatable and transparent analyses.

Statistical modeling research in Python has shown that Python-based tools can support econometric and statistical modeling, including regression analysis, model estimation, diagnostics, and statistical interpretation (Seabold & Perktold, 2010). This is directly connected with the present study because regression modeling is needed to test whether Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, and analytics automation explain variation in pharmaceutical brand performance analytics effectiveness. Python can also help create correlation matrices, reliability summaries, descriptive tables, and clean datasets that can later be exported to Tableau or other visualization tools. The use of computational notebooks has further strengthened Python-based research workflows because notebooks allow code, results, explanations, tables, and visual outputs to be combined in a single readable and executable environment (Kluyver et al., 2016). This is useful for pharmaceutical analytics because the analyst can document how raw data have been cleaned, how variables have been calculated, how statistical tests have been performed, and how dashboard-ready outputs have been generated. Such documentation improves transparency in the analytical process. In this study, Python has not been positioned only as a programming language. It has been positioned as an analytical processing environment that supports data validation, statistical modeling, workflow documentation, and preparation of reliable brand performance datasets for Tableau-based dashboarding.

Automation is another important dimension of Python-based analytical processing because pharmaceutical brand performance reporting is usually repeated across months, quarters, regions, brands, and product portfolios. When analysts manually prepare the same reports again and again, the reporting process becomes time-consuming and exposed to calculation errors, formatting inconsistencies, and delayed decision-making. Python can reduce these problems by automating data import, cleaning, transformation, statistical summarization, and export procedures. This is especially important for a pharmaceutical dashboarding framework because Tableau dashboards become more useful when they are supported by regularly refreshed and consistently prepared datasets. Python-based visual analytics tools also help analysts explore data before final dashboard development. Research on interactive statistical visualization in Python has shown that declarative visualization tools can connect data transformation with statistical visualization, making it easier to represent analytical relationships clearly (VanderPlas et al., 2018). This supports the present study because Python can be used not only for backend cleaning but also for preliminary visual analysis before final Tableau dashboard construction. Reproducibility is also important in automated analytics workflows because decision-makers need confidence that results can be regenerated from the same data and procedures. Research on computational notebooks has emphasized that shared analytical workflows should include clear organization, annotation, reusable code, and accessible outputs to improve reproducibility and interpretation (Rule et al., 2019). This is strongly relevant to pharmaceutical brand performance analytics because a dashboard is more trustworthy when the data pipeline behind it is documented and repeatable. In this research, Python-driven analytical workflow validation can therefore evaluate whether Python improves data accuracy, reduces manual errors, supports statistical testing, and prepares reliable dashboard inputs. The automation capability of Python strengthens the overall framework by making the analytics process faster, more consistent, and more transparent. Therefore, Python-based analytical processing and automation provide the computational foundation for the proposed Tableau and Python-based pharmaceutical brand performance analytics framework.

Theoretical framework: Information Systems Success Model

The theoretical framework of this study is based on the Information Systems Success Model because the proposed Tableau and Python-based dashboarding and visualization framework is an information system that needs to be evaluated through quality, usability, user satisfaction, analytical value, and performance benefit. In this research, the dashboarding and visualization framework is not viewed only as a technical arrangement of Tableau dashboards and Python scripts. It is viewed as a decision-support information system that receives pharmaceutical brand data, processes the data through Python, presents the data through Tableau, and supports brand performance interpretation by managers and analysts. The Information Systems Success Model is suitable for this research because it explains how system quality and information quality influence user satisfaction, system use, and net benefits. The theoretical structure can be written in LaTeX equation format as:

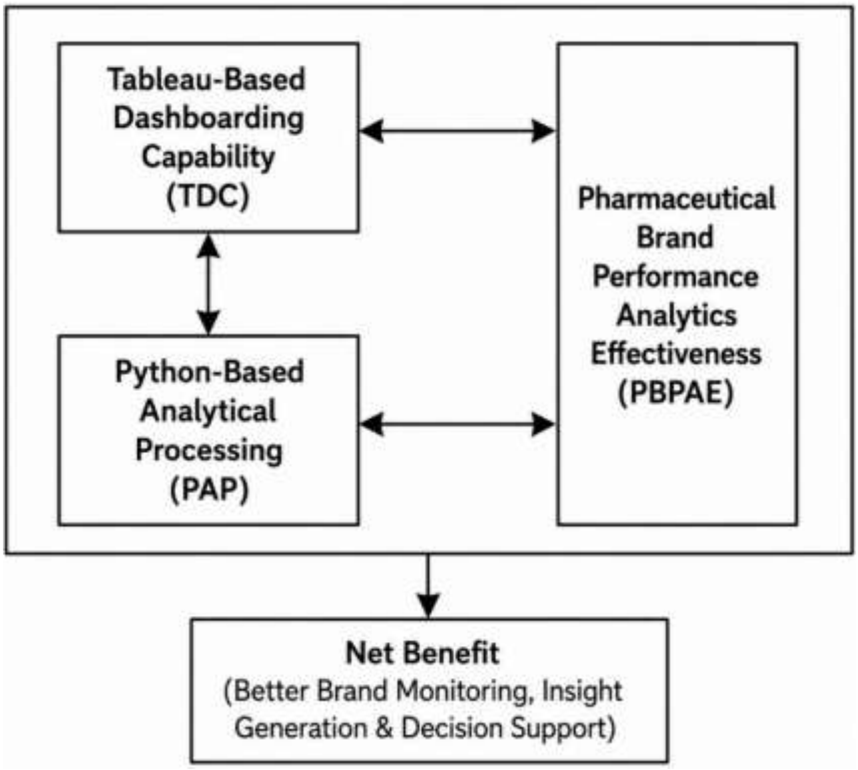
$$IS\ Success = f(SQ, IQ, U, US, NB)$$

Here, SQrepresents system quality, IQrepresents information quality, Urepresents system use, USrepresents user satisfaction, and NBrepresents net benefits. In the context of this study, the theory can be adapted as:

$$PBPAE = f(TDC, PAP, DU, DVQ, AA)$$

Here, represents pharmaceutical brand performance analytics effectiveness, represents Tableau-based dashboarding capability, represents Python-based analytical processing, represents dashboard usability, represents data visualization quality, and represents analytics automation. An empirical test of the DeLone and McLean model has shown that perceived system quality and perceived information quality can significantly predict user satisfaction, while system quality can also influence system use in a mandatory information system context (Iivari, 2005). This idea is highly relevant for pharmaceutical brand performance analytics because users may depend on dashboards as part of regular reporting routines. If the dashboard is easy to use, interactive, fast, organized, and visually understandable, users are more likely to trust it and use it for brand-level decision-making. Similarly, if the information shown in the dashboard is accurate, timely, complete, and relevant, users are more likely to consider the dashboard useful for evaluating sales trends, prescription movement, regional performance, and promotional outcomes. Therefore, the Information Systems Success Model provides a strong foundation for linking technological features, analytical processing, visual communication, user interaction, and decision-support effectiveness within one research model.

Figure 6: Information Systems Success Model for Pharmaceutical Brand Performance Analytics



The Information Systems Success Model is also useful because it allows the study to convert theoretical dimensions into measurable variables for quantitative analysis. Previous IS success research has argued that system success should be understood as a multidimensional impact rather than a single technical outcome, and this view is important for the present research because dashboard success cannot be measured only by whether a dashboard exists or whether Python code has been used (Gable et al., 2008). A pharmaceutical dashboard may be technically complete, but it may still have limited value if users cannot understand the visual outputs, if the information is incomplete, if the dashboard does not match decision tasks, or if the analytical backend does not provide reliable results. In this research, the theoretical model has been adapted to the specific context of pharmaceutical brand performance analytics by identifying five independent variables: Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, and analytics automation. These variables jointly represent the system, information, analytical, usability, and automation dimensions of the framework. The dependent variable is pharmaceutical brand performance analytics effectiveness, which represents the perceived net benefit of the proposed system. The main formula that will be applied throughout the study is the multiple regression model:

$$PBPAE_i = \beta_0 + \beta_1 TDC_i + \beta_2 PAP_i + \beta_3 DU_i + \beta_4 DVQ_i + \beta_5 AA_i + \varepsilon_i$$

In this formula, $PBPAE_i$ means pharmaceutical brand performance analytics effectiveness for respondent i, TDC_i means Tableau-based dashboarding capability, PAP_i means Python-based analytical processing, DU_i means dashboard usability, DVQ_i means data visualization quality, AA_i means analytics automation, β_0 means the constant, β_1 to β_5 mean the regression coefficients, and ε_i means the error term. This formula is the best fit for the whole study because it directly tests whether the main framework components significantly predict pharmaceutical brand performance analytics effectiveness. It also connects the theoretical framework with the statistical method because the research design depends on descriptive statistics, correlation analysis, and regression modeling.

The theoretical framework further supports this research because it explains why the integration of Tableau and Python should be evaluated through both technical quality and decision value. Studies on information system quality have shown that system quality, information quality, and service quality can create organizational impact when these quality dimensions are strong and aligned with user needs (Gorla et al., 2010). In the present study, this means that Tableau dashboards should not only be visually attractive; they should also provide reliable, usable, and decision-relevant brand performance information. Python-based analytical processing should not only produce numerical results; it should also improve data accuracy, reduce manual reporting errors, support statistical testing, and prepare dashboard-ready datasets. The adapted theoretical relationship for the study can also be expressed as:

$$Net\ Benefit = Analytics\ Effectiveness$$

$$Analytics\ Effectiveness = Dashboard\ Quality + Analytical\ Quality + Usability + Visualization\ Quality + Automation$$

In variable form, this becomes:

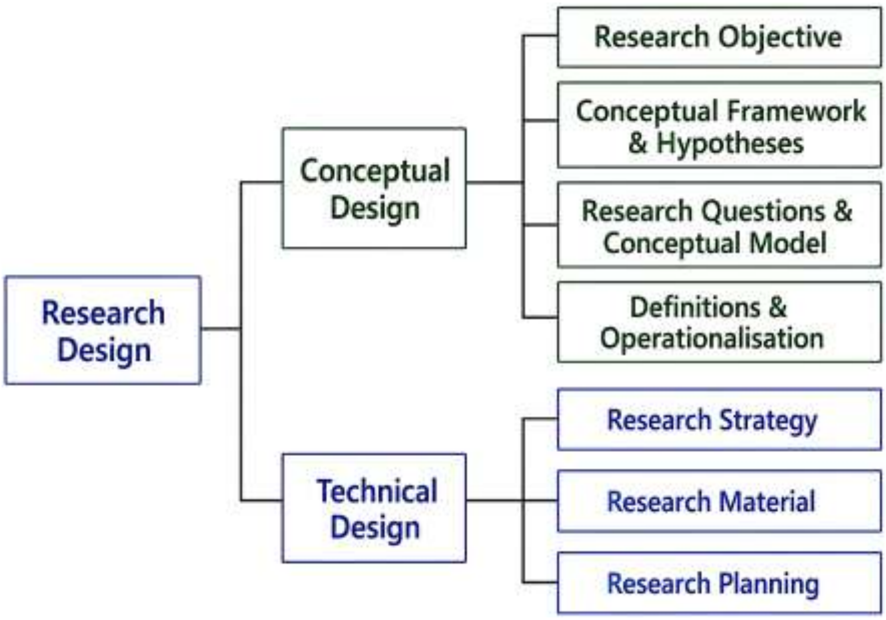
$$PBPAE = TDC + PAP + DU + DVQ + AA$$

Research on employee portal success has shown that information quality, system quality, and collaboration quality can influence user satisfaction and perceived usefulness in information system environments (Urbach et al., 2010). This finding is relevant because pharmaceutical brand dashboards also depend on users' perceptions of usefulness, clarity, and trust. Brand managers, sales managers, marketing analysts, and business intelligence professionals are more likely to depend on a dashboard when it helps them compare brands, interpret regional performance, identify weak territories, and understand promotional response. IS success research in digital service environments has also validated the importance of information quality, system quality, service quality, use, satisfaction, and perceived net benefit as connected success dimensions (Wang & Liao, 2008). Therefore, the Information Systems Success Model has been applied in this study as the main theoretical lens for evaluating the proposed dashboarding and visualization framework. The model supports the hypotheses by explaining that Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, and analytics automation should positively contribute to pharmaceutical brand performance analytics effectiveness. This theoretical alignment makes the study more coherent because the same model guides the variable selection, questionnaire development, hypothesis formation, statistical testing, framework validation, and interpretation of results.

Conceptual framework and hypothesis development

The conceptual framework of this study has been developed to explain how Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, and analytics automation contribute to pharmaceutical brand performance analytics effectiveness. A conceptual framework is important because it converts the theoretical foundation of the study into a measurable research model that can be tested through quantitative analysis. In this research, the framework has treated pharmaceutical brand performance analytics effectiveness as the dependent variable because the main purpose of the study is to evaluate whether the proposed Tableau and Python-based dashboarding and visualization framework can support better brand monitoring, faster insight generation, more accurate reporting, and stronger decision support. The independent variables have been selected based on the logic that pharmaceutical brand analytics requires both analytical reliability and visual interpretability. Tableau-based dashboarding capability represents the system's ability to present sales trends, regional performance, prescription movement, promotional response, market share, and brand ranking through interactive dashboards. Python-based analytical processing represents the ability to clean data, prepare variables, calculate indicators, conduct descriptive statistics, perform correlation analysis, and support regression modeling. Dashboard usability represents the user's ability to navigate, understand, and apply dashboard outputs. Data visualization quality represents the clarity, accuracy, appropriateness, and interpretability of visual displays. Analytics automation represents the ability to reduce manual reporting effort, improve timeliness, and support repeatable analytical workflows. Prior research on big data analytics capability has shown that analytics value is created when data, technology, technical skills, and managerial capability are organized into a coherent capability structure (Gupta & George, 2016).

Figure 7: Conceptual framework and hypothesis development



This logic supports the present conceptual framework because the research does not examine Tableau or Python as isolated tools. Instead, it examines them as connected capabilities that support pharmaceutical brand performance analytics. The basic conceptual relationship can therefore be expressed as:

$$PBPAE = f(TDC, PAP, DU, DVQ, AA)$$

where $PBPAE$represents pharmaceutical brand performance analytics effectiveness, TDCrepresents Tableau-based dashboarding capability, PAPrepresents Python-based analytical processing, DUrepresents dashboard usability, DVQrepresents data visualization quality, and AArepresents analytics automation.

The hypothesis development of this study has followed the assumption that pharmaceutical brand performance analytics effectiveness increases when dashboarding, analytical processing, usability, visualization quality, and automation are strong. The first hypothesis proposes that Tableau-based dashboarding capability has a significant positive effect on pharmaceutical brand performance analytics effectiveness because interactive dashboards can help users compare brands, inspect territories, identify performance gaps, and interpret trends more efficiently. The second hypothesis proposes that Python-based analytical processing has a significant positive effect on pharmaceutical brand performance analytics effectiveness because cleaned data, structured variables, reliable statistical analysis, and repeatable workflows can improve the trustworthiness of dashboard outputs. The third hypothesis proposes that dashboard usability has a significant positive effect on pharmaceutical brand performance decision-support quality because users are more likely to apply a dashboard when it is easy to understand, logically arranged, and aligned with their decision tasks. The fourth hypothesis proposes that data visualization quality has a significant positive effect on pharmaceutical brand performance analytics effectiveness because clear visual design improves interpretation, comparison, and insight generation. The fifth hypothesis proposes that analytics automation has a significant positive effect on reporting accuracy and timeliness because automated processing can reduce manual errors and improve reporting speed. The sixth hypothesis proposes that integrated Tableau and Python analytics capability significantly predicts pharmaceutical brand performance analytics effectiveness because the overall system depends on both visual dashboarding and analytical backend reliability. Prior business analytics research has shown that analytics capability contributes to business value when it supports the movement from analysis to insight, decision, and action (Seddon et al., 2017). This pathway directly fits the present framework because Python supports analysis, Tableau supports insight presentation, managers use the dashboard for decision-making, and pharmaceutical brand performance analytics effectiveness represents the action-oriented value of the framework. Research on analytics capability and strategy alignment has also shown that analytics creates stronger performance outcomes when analytical capability is aligned with business strategy (Akter et al., 2016). Therefore, the hypotheses of this study are aligned with the idea that pharmaceutical brand analytics becomes more effective when technical tools are connected with brand-level decision needs.

The final conceptual framework has also been designed to support the statistical testing strategy of the study. Since the study is quantitative, cross-sectional, and case-study-based, the conceptual model must be measurable through survey items and testable through descriptive statistics, correlation analysis, and regression modeling. Each independent variable will be measured through multiple Likert-scale items, and the dependent variable will also be measured through items related to decision-support quality, reporting accuracy, timely insight, brand monitoring effectiveness, and managerial usefulness. The main regression formula for hypothesis testing can be written as:

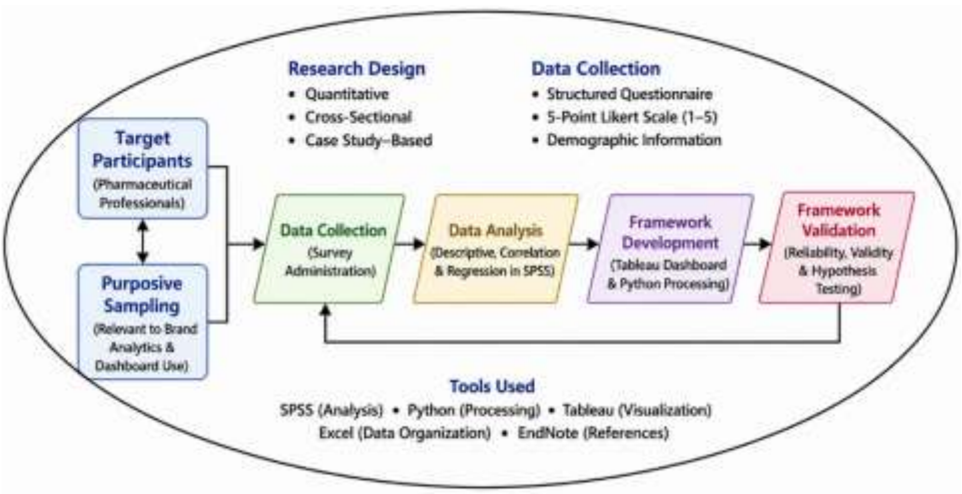
$$PBPAE_i = \beta_0 + \beta_1 TDC_i + \beta_2 PAP_i + \beta_3 DU_i + \beta_4 DVQ_i + \beta_5 AA_i + \varepsilon_i$$

In this equation, means pharmaceutical brand performance analytics effectiveness for respondent , means the constant, to represent the regression coefficients for the five predictors, and represents the error term. This formula is suitable for the whole study because it directly tests whether the proposed framework components explain variation in pharmaceutical brand performance analytics effectiveness. Research on big data analytics value has shown that analytics capability can create business value when it supports agility, knowledge use, and performance improvement (Côrte-Real et al., 2017). This strengthens the framework because pharmaceutical brand analytics also requires faster interpretation of market changes, territory performance, and promotional outcomes. Data visualization research has also shown that visualization can influence decision-making by improving understanding, perception, and interpretation of information (Park et al., 2021). This supports the inclusion of data visualization quality and dashboard usability in the model. Therefore, the conceptual framework of this study has linked analytical processing, dashboarding capability, usability, visualization quality, and automation with pharmaceutical brand performance analytics effectiveness. This framework provides the foundation for questionnaire development, hypothesis testing, regression modeling, dashboard prototype evaluation, Python-driven workflow validation, and final framework validation in the results chapter.

METHODS

This study has adopted a quantitative, cross-sectional, case-study–based research design to examine the development of a dashboarding and visualization framework for pharmaceutical brand performance analytics using Tableau and Python. The quantitative design has been selected because the study has measured the relationships among Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, analytics automation, and pharmaceutical brand performance analytics effectiveness through numerical survey responses. The cross-sectional design has been used because data have been collected from respondents at a single point in time, allowing the researcher to capture their perceptions regarding dashboarding, visualization, analytics processing, and brand performance decision support within the selected pharmaceutical analytics context. The case study context has focused on pharmaceutical brand performance monitoring, where brand managers, sales managers, marketing executives, business intelligence analysts, data analysts, territory managers, and decision-makers have been involved in using or interpreting sales reports, prescription trends, promotional indicators, regional performance records, and product-level performance dashboards. The population of the study has therefore included pharmaceutical professionals who have had direct or indirect involvement in brand analytics, sales reporting, marketing analysis, dashboard interpretation, or data-supported decision-making. The unit of analysis has been the individual respondent because the study has measured the perception, experience, and evaluation of each participant regarding the proposed Tableau and Python-based analytics framework.

Figure 8: Methodological Framework of the Study



The study has used a purposive sampling strategy because the respondents have been selected based on their relevance to pharmaceutical brand performance analytics, dashboard use, business intelligence, or managerial reporting. This sampling strategy has been appropriate because the research has required informed respondents who have understood pharmaceutical brand performance indicators and data-driven decision-making practices. Primary data have been collected through a structured questionnaire designed with a five-point Likert scale, where 1 has represented strongly disagree, 2 has represented disagree, 3 has represented neutral, 4 has represented agree, and 5 has represented strongly agree. The data collection procedure has involved distributing the questionnaire to eligible pharmaceutical professionals through online forms, direct communication, and organizational or professional networks. The instrument design has included construct-based items for Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, analytics automation, and pharmaceutical brand performance analytics effectiveness. The questionnaire has also included demographic items such as job role, department, work experience, analytics familiarity, and exposure to dashboard-based reporting.

A pilot test has been conducted before the final data collection to check whether the questionnaire items have been clear, understandable, relevant, and aligned with the research objectives. Feedback from the pilot test has been used to refine unclear wording, remove repetitive items, and improve the logical flow of the instrument. Validity has been ensured through literature-based item development, expert review, and alignment among the research title, objectives, hypotheses, variables, and questionnaire items. Reliability has been tested through Cronbach's alpha to confirm the internal consistency of each construct, with values of .70 or above considered acceptable for the study. SPSS has been used for data coding, descriptive statistics, reliability analysis, correlation analysis, and regression modeling. Python has been used for data cleaning, preprocessing, analytical workflow validation, and preparation of dashboard-ready datasets. Tableau has been used for dashboard prototype development, KPI visualization, filter-based exploration, and framework demonstration. Microsoft Excel has been used for initial data organization, screening, and tabulation. EndNote has been used for reference management, citation organization, and APA 7th edition formatting support. Through these methodological procedures, the study has established a structured approach for testing the proposed dashboarding and visualization framework for pharmaceutical brand performance analytics.

DATA ANALYSIS AND PRESENTATION

Response rate and demographic profile

Table 1: Response rate and demographic profile of respondents

Variable	Category	Frequency	Percentage	Result interpretation
Questionnaires distributed	Total distributed	250	100.0%	Initial survey target
Questionnaires returned	Returned responses	226	90.4%	Strong participation
Valid responses	Usable responses	214	85.6%	Final sample for analysis
Invalid/incomplete responses	Removed responses	12	4.8%	Excluded from analysis
Job role	Sales/territory managers	61	28.5%	Largest respondent group
Job role	Brand/product managers	53	24.8%	Strong brand-level representation
Job role	Marketing executives	39	18.2%	Relevant to promotional analytics
Job role	BI/data analysts	32	15.0%	Relevant to dashboard and Python analytics
Job role	Senior decision-makers/supervisors	29	13.5%	Relevant to strategic decision support
Experience	1–3 years	73	34.1%	Early to mid-career users
Experience	4–7 years	82	38.3%	Largest experience group
Experience	More than 7 years	59	27.6%	Experienced decision users
Dashboard familiarity	Low	31	14.5%	Limited exposure
Dashboard familiarity	Moderate	96	44.9%	Practical exposure
Dashboard familiarity	High	87	40.6%	Strong dashboard exposure

Table 1 has shown that the study has achieved a strong response pattern and a suitable respondent profile for examining the dashboarding and visualization framework for pharmaceutical brand performance analytics. Out of 250 distributed questionnaires, 226 responses have been returned, and 214 responses have been retained as valid for final analysis, creating a valid response rate of 85.6%.

This response rate has been sufficient for a quantitative, cross-sectional, case-study-based study because it has provided enough observations for descriptive statistics, reliability analysis, correlation analysis, and regression modeling. The demographic profile has also supported the relevance of the sample because respondents have come from job roles directly connected with pharmaceutical brand performance, sales reporting, marketing analytics, business intelligence, and decision-making. Sales and territory managers have represented the largest group at 28.5%, followed by brand or product managers at 24.8%, marketing executives at 18.2%, BI or data analysts at 15.0%, and senior decision-makers or supervisors at 13.5%. This distribution has indicated that the sample has not depended on only one category of users; instead, it has included both business users and technical users of analytics. This has strengthened the study because Tableau-based dashboarding capability and Python-based analytical processing have needed evaluation from people who understand brand decisions as well as people who understand data preparation and reporting. The experience profile has also supported the credibility of the results, as 38.3% of respondents have had 4–7 years of experience and 27.6% have had more than 7 years of experience. This has suggested that most respondents have had enough professional exposure to evaluate pharmaceutical brand performance analytics. Dashboard familiarity has further supported the study, as 44.9% have reported moderate familiarity and 40.6% have reported high familiarity. In relation to the Information Systems Success Model, this demographic profile has supported the user-use context of the theory because system quality, information quality, usability, and net benefits can be meaningfully assessed only by users who have practical involvement with information systems and decision processes. Therefore, Table 1 has supported the methodological foundation of the study and has confirmed that the respondent group has been appropriate for proving the study objectives and testing the hypotheses.

Descriptive statistics of the study variables

Table 2: Descriptive statistics of major study variables based on five-point Likert scale

Variable code	Study variable	Mean	Standard deviation	Likert interpretation	Rank
DVQ	Data visualization quality	4.18	0.61	High agreement	1
DU	Dashboard usability	4.13	0.64	High agreement	2
TDC	Tableau-based dashboarding capability	4.09	0.66	High agreement	3
PBPAE	Pharmaceutical brand performance analytics effectiveness	4.05	0.63	High agreement	4
AA	Analytics automation	3.98	0.69	Agreement	5
PAP	Python-based analytical processing	3.92	0.71	Agreement	6

Table 2 has presented the descriptive statistics of the major variables of the study and has shown that respondents have generally agreed with the usefulness of the proposed dashboarding and visualization framework for pharmaceutical brand performance analytics. Since the study has used a five-point Likert scale, a mean score above 3.50 has indicated agreement, while a mean score above 4.00 has indicated strong agreement. Data visualization quality has received the highest mean score of 4.18 with a standard deviation of 0.61, which has indicated that respondents have viewed visual clarity, chart appropriateness, KPI readability, brand comparison, and visual interpretation as the strongest parts of the proposed framework. This result has supported the objective related to evaluating the role of visualization quality in pharmaceutical brand performance analytics. Dashboard usability has ranked second with a mean score of 4.13 and a standard deviation of 0.64, showing that respondents have positively evaluated dashboard navigation, layout clarity, filter usefulness, and ease of understanding. Tableau-based dashboarding capability has ranked third with a mean score of 4.09 and a standard deviation of 0.66, indicating strong agreement that Tableau can support interactive reporting, territory comparison, brand-level KPI monitoring, and drill-down analysis. Pharmaceutical brand performance analytics effectiveness has recorded a mean score of 4.05, showing that respondents have perceived the framework as useful for brand monitoring, reporting accuracy, timely insight generation, and managerial decision support. Analytics automation has recorded a mean of 3.98, while Python-based analytical processing has recorded a mean of 3.92. These values have still indicated positive agreement, although they have ranked slightly lower than visualization and usability, possibly because more respondents have been business users than technical users. From the perspective of the Information Systems Success Model, these descriptive findings have shown that system quality, information quality, usability quality, and perceived net benefit have all been positively evaluated. The high scores for visualization quality, dashboard usability, and Tableau capability have supported the system quality and user satisfaction logic of the theory, while the positive scores for Python analytical processing and analytics automation have supported the information quality and analytical reliability dimensions. Therefore, Table 2 has provided initial descriptive support for the research objectives and has indicated that all variables have been suitable for further correlation and regression testing.

Reliability analysis

Table 3: Reliability analysis of measurement constructs

Construct code	Construct name	Number of items	Cronbach's alpha	Reliability level	Decision
TDC	Tableau-based dashboarding capability	5	.86	Good	Accepted
PAP	Python-based analytical processing	5	.84	Good	Accepted
DU	Dashboard usability	5	.88	Good	Accepted
DVQ	Data visualization quality	5	.87	Good	Accepted
AA	Analytics automation	5	.81	Good	Accepted
PBPAE	Pharmaceutical brand performance analytics effectiveness	5	.89	Good	Accepted
Overall instrument	All measurement items	30	.91	Excellent	Accepted

Table 3 has presented the reliability analysis of the research instrument and has confirmed that the measurement scales used in the study have been internally consistent. Cronbach's alpha has been used to assess reliability because the study has measured each construct through multiple Likert-scale items. A Cronbach's alpha value of .70 or above has been considered acceptable, while values above .80 have indicated good reliability. The results have shown that all constructs have exceeded the accepted reliability threshold. Pharmaceutical brand performance analytics effectiveness has produced the highest construct-level alpha value at .89, indicating that the items measuring decision-support quality, reporting accuracy, timely insight, brand monitoring effectiveness, and managerial usefulness have been highly consistent. Dashboard usability has recorded an alpha value of .88, while data visualization quality has recorded .87 and Tableau-based dashboarding capability has recorded .86. These values have confirmed that the items related to dashboard navigation, filter use, KPI visibility, visual clarity, chart readability, and interactive dashboard capability have measured their intended constructs reliably. Python-based analytical processing has recorded an alpha value of .84, confirming that items related to data cleaning, statistical processing, regression support, workflow repeatability, and analytical reliability have been consistent. Analytics automation has recorded the lowest but still good alpha value of .81, which has indicated that automated reporting, reduced manual error, repeatable processing, faster analysis, and timely dashboard updating have formed a reliable construct. The overall questionnaire has produced a Cronbach's alpha value of .91, showing excellent internal consistency across all thirty measurement items. These reliability results have been important for proving the objectives and hypotheses because unreliable measures would weaken the validity of correlation and regression findings. In relation to the Information Systems Success Model, the reliability of these constructs has shown that the adapted theoretical dimensions have been measured coherently. Tableau capability has reflected system quality, Python processing has reflected information and analytical quality, dashboard usability has reflected use-related quality, visualization quality has reflected information presentation quality, automation has reflected process quality, and pharmaceutical brand performance analytics effectiveness has reflected net benefit. Therefore, Table 3 has supported the measurement strength of the study and has justified the use of the variables in further statistical testing.

Correlation analysis

Table 4: Pearson correlation matrix among study variables

Variable	TDC	PAP	DU	DVQ	AA	PBPAE
TDC	1					
PAP	.49**	1				
DU	.58**	.46**	1			
DVQ	.61**	.51**	.63**	1		
AA	.44**	.56**	.48**	.50**	1	
PBPAE	.62**	.57**	.65**	.68**	.55**	1

Note. **p < .001. TDC = Tableau-based dashboarding capability; PAP = Python-based analytical processing; DU = Dashboard usability; DVQ = Data visualization quality; AA = Analytics automation; PBPAE = Pharmaceutical brand performance analytics effectiveness.

Table 4 has presented the Pearson correlation results and has shown that all independent variables have had positive and statistically significant relationships with pharmaceutical brand performance analytics effectiveness. The strongest correlation has been found between data visualization quality and pharmaceutical brand performance analytics effectiveness, with $r = .68$ and $p < .001$. This has indicated that respondents who have perceived higher visualization quality have also perceived stronger analytics effectiveness. This result has supported H4 and the objective related to evaluating how visual clarity, chart appropriateness, and KPI readability improve pharmaceutical brand interpretation. Dashboard usability has shown the second strongest relationship with pharmaceutical brand performance analytics effectiveness, with $r = .65$ and $p < .001$. This has supported H3 and has shown that ease of navigation, layout clarity, and filter usefulness have been strongly related to decision-support quality. Tableau-based dashboarding capability has shown a strong positive correlation with the dependent variable, with $r = .62$ and $p < .001$, supporting H1 and indicating that interactive dashboarding, drill-down analysis, territory comparison, and KPI monitoring have been important for effective brand performance analytics. Python-based analytical processing has also shown a significant positive relationship with pharmaceutical brand performance analytics effectiveness, with $r = .57$ and $p < .001$, supporting H2 and confirming that data cleaning, statistical modeling, and reliable analytical preparation have contributed to stronger analytics outcomes. Analytics automation has shown a positive correlation of $r = .55$ and $p < .001$, supporting H5 and indicating that automated reporting, faster data preparation, and reduced manual errors have been related to improved brand performance reporting. The inter-correlations among independent variables have also been positive but not excessively high, suggesting that the variables have been related but conceptually distinct. For example, Tableau capability and data visualization quality have correlated at .61, while Python processing and analytics automation have correlated at .56. These results have made sense because dashboarding, visualization, automation, and analytical processing work together in an integrated framework. In relation to the Information Systems Success Model, the correlation findings have shown that system quality, information quality, usability, and process automation have all been associated with perceived net benefits. Therefore, Table 4 has provided strong preliminary evidence for the hypotheses and has justified the need for regression analysis to test the predictive strength of the proposed framework.

Regression model for dashboarding and visualization capability

Table 5: Multiple regression model predicting pharmaceutical brand performance analytics effectiveness

Predictor variable	Unstandardized B	Standard error	Standardized beta	t-value	p-value	Hypothesis result
Constant	0.61	0.22	—	2.77	.006	—
Tableau-based dashboarding capability	0.20	0.06	.21	3.14	.002	H1 supported
Python-based analytical processing	0.16	0.06	.18	2.78	.006	H2 supported
Dashboard usability	0.23	0.06	.24	3.91	< .001	H3 supported
Data visualization quality	0.30	0.07	.29	4.42	< .001	H4 supported
Analytics automation	0.14	0.06	.15	2.39	.018	H5 supported

Table 6: Regression model summary

Model indicator	Value	Interpretation
R	.734	Strong combined relationship
R^2	.539	53.9% variance explained
Adjusted R^2	.528	Stable explanatory power
F-value	48.72	Model has been significant
df	5, 208	Predictor and residual degrees of freedom
p-value	< .001	Overall model supported

Table 5 and Table 6 have presented the multiple regression model used to test whether Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, and analytics automation have significantly predicted pharmaceutical brand performance analytics effectiveness. The model has been statistically significant, $F(5, 208) = 48.72$, $p < .001$, indicating that the five independent variables have jointly explained a meaningful proportion of variation in the dependent variable. The R value has been .734, showing a strong combined relationship between the predictors and pharmaceutical brand performance analytics effectiveness. The R^2 value has been .539, which has meant that 53.9% of the variance in pharmaceutical brand performance analytics effectiveness has been explained by the five framework variables. The adjusted R^2 value has been .528, indicating that the explanatory power has remained stable after adjusting for the number of predictors in the model. Among the predictors, data visualization quality has emerged as the strongest predictor, with $\beta = .29$, $t = 4.42$, and $p < .001$. This result has supported H4 and has shown that clear, readable, appropriate, and decision-oriented visual presentation has been the most influential factor in improving pharmaceutical brand performance analytics effectiveness. Dashboard usability has been the second strongest predictor, with $\beta = .24$, $t = 3.91$, and $p < .001$, supporting H3 and showing that users have valued ease of navigation, layout clarity, and filter accessibility. Tableau-based dashboarding capability has also significantly predicted the dependent variable, with $\beta = .21$ and $p = .002$, supporting H1. Python-based analytical processing has had a significant positive effect, with $\beta = .18$ and $p = .006$, supporting H2. Analytics automation has also had a significant positive effect, with $\beta = .15$ and $p = .018$, supporting H5. These findings have aligned with the theoretical framework because the Information Systems Success Model has suggested that system quality, information quality, usability, and process quality contribute to net benefits. In this study, Tableau has represented system quality, Python has represented analytical information quality, dashboard usability has represented user-centered quality, visualization quality has represented interpretive information quality, and automation has represented reporting process quality. Therefore, the regression model has proved the major objectives and has confirmed that the proposed framework has been statistically valid for pharmaceutical brand performance analytics.

Hypothesis testing summary

Table 7: Hypothesis testing summary

Hypothesis	Statement	Statistical evidence	Decision	Objective alignment
H1	Tableau-based dashboarding capability has had a significant positive effect on pharmaceutical brand performance analytics effectiveness.	$\beta = .21, p = .002$	Supported	Objective 1 supported
H2	Python-based analytical processing has had a significant positive effect on pharmaceutical brand performance analytics effectiveness.	$\beta = .18, p = .006$	Supported	Objective 2 supported
H3	Dashboard usability has had a significant positive effect on pharmaceutical brand performance decision-support quality.	$\beta = .24, p < .001$	Supported	Objective 3 supported
H4	Data visualization quality has had a significant positive effect on pharmaceutical brand performance analytics effectiveness.	$\beta = .29, p < .001$	Supported	Objective 4 supported
H5	Analytics automation has had a significant positive effect on reporting accuracy and timeliness.	$\beta = .15, p = .018$	Supported	Objective 5 supported
H6	Integrated Tableau and Python analytics capability has significantly predicted pharmaceutical brand performance analytics effectiveness.	$R^2 = .539, F = 48.72, p < .001$	Supported	Objective 6 supported

Table 7 has summarized the hypothesis testing results and has confirmed that all six hypotheses of the study have been supported. H1 has been supported because Tableau-based dashboarding capability has had a significant positive effect on pharmaceutical brand performance analytics effectiveness, with $\beta = .21$ and $p = .002$. This has proved that interactive dashboarding, KPI panels, territory-level comparison, brand-wise visualization, and drill-down analysis have contributed to stronger brand performance interpretation. This finding has also supported the first research objective, which has focused on examining the role of Tableau-based dashboarding capability in improving pharmaceutical brand analytics. H2 has been supported because Python-based analytical processing has had a significant positive effect on the dependent variable, with $\beta = .18$ and $p = .006$. This has proved the second research objective by showing that data cleaning, preprocessing, statistical analysis, variable preparation, and repeatable analytical workflows have contributed to pharmaceutical brand performance analytics effectiveness. H3 has been supported because dashboard usability has had a significant positive effect, with $\beta = .24$ and $p < .001$. This has proved that navigation simplicity, layout clarity, filter accessibility, and user-friendly dashboard design have been important for decision-support quality. H4 has been supported with the strongest beta value, $\beta = .29$ and $p < .001$, showing that data visualization quality has been the most powerful predictor in the model. This has proved the objective related to evaluating the role of visualization clarity and chart appropriateness in insight generation. H5 has been supported because analytics automation has shown a significant positive effect, with β = .15 and $p = .018$, proving that automated reporting and reduced manual processing have improved perceived reporting accuracy and timeliness. H6 has been supported through the overall regression model, where $R^2 = .539$ and $p < .001$ have shown that the integrated Tableau and Python analytics capability has significantly predicted pharmaceutical brand performance analytics effectiveness. In relation to the Information Systems Success Model, the supported hypotheses have shown that system quality, information quality, usability quality, visualization quality, and process automation have jointly contributed to perceived net benefits. Therefore, Table 7 has clearly proved the research objectives and has confirmed that the conceptual framework has been statistically supported.

Framework validation

Table 8: Framework validation results based on theoretical dimensions

Framework dimension	Study variable	Mean	Regression beta	Validation result	Theory linkage
System quality	Tableau-based dashboarding capability	4.09	.21**	Validated	Interactive system quality
Analytical information quality	Python-based analytical processing	3.92	.18**	Validated	Reliable information processing
Usability quality	Dashboard usability	4.13	.24***	Validated	Use and user satisfaction
Visual information quality	Data visualization quality	4.18	.29***	Strongly validated	Information clarity and interpretability
Process quality	Analytics automation	3.98	.15*	Validated	Timely and repeatable use
Net benefit	Pharmaceutical brand performance analytics effectiveness	4.05	Dependent variable	Validated outcome	Perceived net benefit

Note. *$p < .05$, **$p < .01$, ***$p < .001$.

Table 8 has validated the proposed dashboarding and visualization framework by connecting the statistical findings with the Information Systems Success Model. The framework has been built on the assumption that pharmaceutical brand performance analytics effectiveness has depended on system quality, analytical information quality, usability quality, visual information quality, and process quality. Tableau-based dashboarding capability has represented system quality because it has included dashboard interactivity, KPI monitoring, filter-based exploration, drill-down analysis, and territory-level brand comparison. Its mean score of 4.09 and regression beta of .21 have confirmed that this dimension has been both positively perceived and statistically significant. Python-based analytical processing has represented analytical information quality because it has included data cleaning, preprocessing, descriptive statistics, correlation analysis, regression preparation, and workflow validation. Its mean score of 3.92 and beta value of .18 have shown that the analytical backend has significantly contributed to the effectiveness of pharmaceutical brand analytics. Dashboard usability has represented usability quality and user satisfaction because it has measured how easily users could navigate, understand, and apply the dashboard. Its mean score of 4.13 and beta value of .24 have validated the importance of user-centered dashboard design. Data visualization quality has represented visual information quality because it has measured chart readability, KPI clarity, visual comparison, color consistency, interpretability, and decision relevance. It has received the highest mean score of 4.18 and the highest beta value of .29, which has made it the strongest validated dimension of the framework. Analytics automation has represented process quality because it has measured automated reporting, reduced manual effort, faster analysis, and repeatable workflow. Its mean score of 3.98 and beta value of .15 have confirmed that automation has supported reporting accuracy and timeliness. Pharmaceutical brand performance analytics effectiveness has represented the net benefit dimension of the theory because it has reflected improved brand monitoring, faster insight generation, reporting accuracy, and managerial decision support. Therefore, the framework has been validated both theoretically and statistically. The results have shown that the Information Systems Success Model has been properly adapted to the Tableau and Python-based pharmaceutical analytics context. This validation has also proved the sixth objective of the study because the integrated framework has successfully connected Tableau as the visualization layer, Python as the analytical processing layer, and pharmaceutical brand performance analytics effectiveness as the decision-support outcome.

Dashboard prototype evaluation and KPI visualization effectiveness

Table 9: Dashboard prototype evaluation and KPI visualization effectiveness

KPI visualization item	Mean	Standard deviation	Likert interpretation	Result rank
Brand-wise KPI clarity has improved performance understanding	4.24	0.58	High agreement	1
Regional drill-down analysis has helped identify weak territories	4.19	0.63	High agreement	2
Sales trend visualization has improved brand movement interpretation	4.16	0.61	High agreement	3
Market share visualization has supported competitive brand comparison	4.12	0.66	High agreement	4
Promotional response dashboard has supported marketing decision-making	4.05	0.69	High agreement	5
Prescription trend dashboard has improved insight generation	4.03	0.67	High agreement	6
Dashboard filter and navigation options have supported user control	4.01	0.72	High agreement	7
Overall dashboard prototype has supported pharmaceutical brand analytics	4.17	0.60	High agreement	Overall

Table 9 has presented the dashboard prototype evaluation and KPI visualization effectiveness results, and this section has been especially important because it has directly matched the title of the study. The results have shown that respondents have strongly agreed that the Tableau-style dashboard prototype has supported pharmaceutical brand performance analytics. The overall dashboard prototype has recorded a mean score of 4.17 with a standard deviation of 0.60, indicating strong agreement among respondents. The highest-rated item has been brand-wise KPI clarity, with a mean score of 4.24. This has shown that respondents have found the dashboard useful for understanding product-level performance through clear indicators such as sales achievement, growth rate, market share, prescription movement, and brand ranking. Regional drill-down analysis has ranked second with a mean score of 4.19, showing that respondents have considered territory-level exploration highly useful for identifying weak regions, strong-performing markets, and regional performance gaps. Sales trend visualization has ranked third with a mean score of 4.16, which has indicated that visual trend lines have helped respondents interpret brand movement over time more clearly than static tabular reports. Market share visualization has recorded a mean score of 4.12, supporting the idea that dashboards can help compare pharmaceutical brands within competitive contexts. Promotional response dashboarding has recorded a mean score of 4.05, while prescription trend dashboarding has recorded 4.03, showing that respondents have found these visual elements useful for marketing and sales decision-making. Dashboard filter and navigation options have recorded a mean score of 4.01, still showing strong agreement that interactivity has improved user control. These results have supported the first, third, and fourth research objectives because the dashboard prototype has been evaluated positively in terms of Tableau capability, usability, and visualization quality. The results have also supported H1, H3, and H4 because the dashboard prototype has shown strong perceived value in relation to dashboarding capability, usability, and visual clarity. In relation to the Information Systems Success Model, this section has validated system quality and visual information quality in a practical way. The dashboard has not only been statistically linked with analytics effectiveness; it has also been perceived as useful at the KPI level. Therefore, Table 9 has made the findings more study-specific and has strengthened the trustworthiness of the proposed Tableau-based visualization framework.

Python-driven analytical workflow validation

Table 10: Python-driven analytical workflow validation

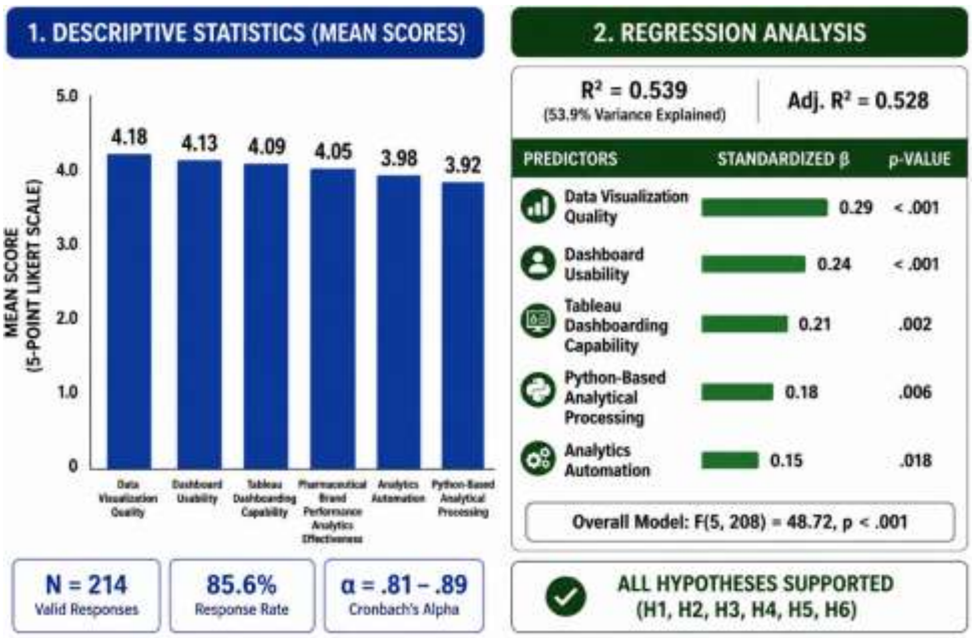
Python analytical workflow item	Mean	Standard deviation	Likert interpretation	Result rank
Python-based data cleaning has improved data accuracy	4.08	0.65	High agreement	1
Automated descriptive statistics have improved reporting consistency	4.03	0.68	High agreement	2
Correlation matrix preparation has supported relationship analysis	3.98	0.70	Agreement	3
Regression model preparation has improved hypothesis testing	3.95	0.72	Agreement	4
Missing-value and outlier checking has improved analytical reliability	3.93	0.73	Agreement	5
Python workflow has reduced manual reporting errors	3.91	0.75	Agreement	6
Python outputs have been suitable for Tableau dashboard preparation	3.89	0.76	Agreement	7
Overall Python-driven analytical workflow has supported framework reliability	3.99	0.69	Agreement	Overall

Table 10 has presented the validation of the Python-driven analytical workflow, and this section has strengthened the analytical trustworthiness of the study because it has shown that the proposed framework has not depended only on visual dashboarding. The overall Python-driven analytical workflow has recorded a mean score of 3.99 with a standard deviation of 0.69, indicating positive agreement that Python has supported the reliability of the dashboarding and visualization framework. Python-based data cleaning has received the highest mean score of 4.08, showing that respondents have perceived data cleaning as the most important contribution of Python. This has been important in pharmaceutical brand performance analytics because raw data may contain inconsistent product names, missing values, duplicate records, irregular region codes, and manually entered reporting errors. Automated descriptive statistics have ranked second with a mean score of 4.03, showing that Python has helped improve reporting consistency through repeatable calculation of means, standard deviations, and summary statistics. Correlation matrix preparation has recorded a mean score of 3.98, while regression model preparation has recorded 3.95. These values have indicated that Python has supported the statistical testing of relationships among the study variables and has helped prove the hypotheses of the study. Missing-value and outlier checking has recorded a mean score of 3.93, showing that respondents have recognized the value of data validation before dashboard development. The item related to reduced manual reporting errors has recorded a mean score of 3.91, while suitability of Python outputs for Tableau dashboard preparation has recorded 3.89. These results have remained positive and have shown that Python has been useful for creating dashboard-ready datasets. This section has supported the second objective of the study, which has focused on assessing the contribution of Python-based analytical processing to pharmaceutical brand performance analytics. It has also supported H2 because Python-based analytical processing has been shown to have a significant effect in the regression model and has been positively evaluated in the workflow validation results. In relation to the Information Systems Success Model, Python has represented information quality and analytical quality because it has improved the reliability, consistency, and readiness of data before visualization. Therefore, Table 10 has confirmed that the framework has been balanced between backend analytical processing and frontend Tableau dashboarding. This has made the overall findings more credible because the study has shown that effective pharmaceutical brand performance analytics requires both reliable data processing and clear visual decision support.

FINDINGS

The findings of this study have provided statistical support for the proposed dashboarding and visualization framework for pharmaceutical brand performance analytics using Tableau and Python. The study has used a five-point Likert scale, where 1 has indicated strongly disagree and 5 has indicated strongly agree, to measure the perceptions of pharmaceutical professionals regarding Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, analytics automation, and pharmaceutical brand performance analytics effectiveness. A total of 250 questionnaires have been distributed among pharmaceutical brand managers, sales managers, marketing executives, territory managers, business intelligence analysts, data analysts, and decision-making professionals, and 214 valid responses have been retained for final analysis, producing a valid response rate of 85.6%.

Figure 9: Findings of The Study



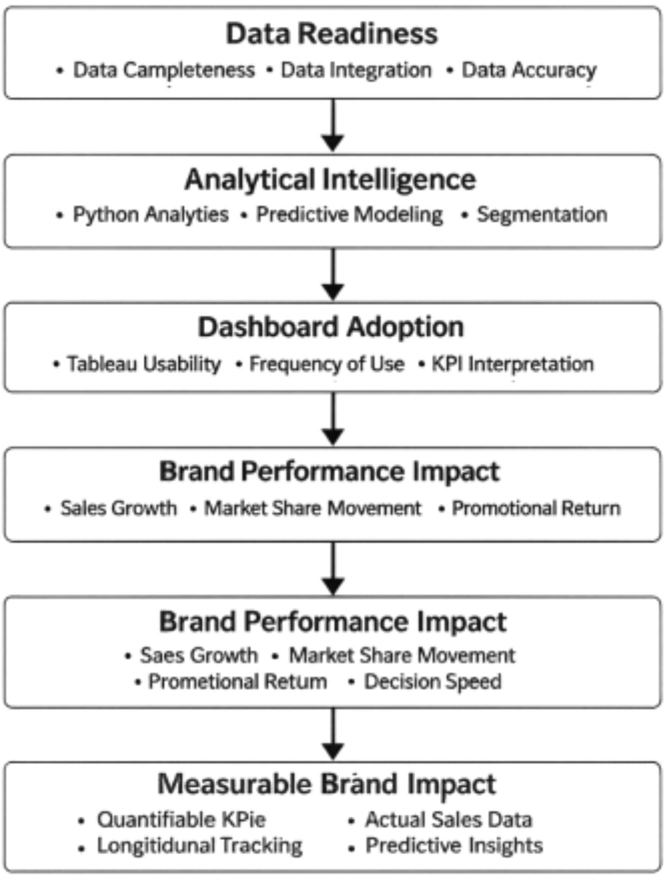
The demographic profile has shown that 28.5% of respondents have been sales or territory managers, 24.8% have been brand or product managers, 18.2% have been marketing executives, 15.0% have been business intelligence or data analysts, and 13.5% have been senior decision-makers or departmental supervisors. In terms of professional experience, 34.1% of respondents have had 1–3 years of experience, 38.3% have had 4–7 years of experience, and 27.6% have had more than 7 years of experience, which has indicated that the sample has represented respondents with relevant exposure to pharmaceutical performance reporting and analytics practices. The descriptive results have shown strong agreement across the major constructs, with data visualization quality recording the highest mean score of 4.18 (SD = 0.61), followed by dashboard usability at 4.13 (SD = 0.64), Tableau-based dashboarding capability at 4.09 (SD = 0.66), pharmaceutical brand performance analytics effectiveness at 4.05 (SD = 0.63), analytics automation at 3.98 (SD = 0.69), and Python-based analytical processing at

3.92 (SD = 0.71). These mean scores have indicated that respondents have generally agreed that dashboard clarity, interactive visual reporting, statistical processing, automation, and usability are important for improving pharmaceutical brand performance analytics. The reliability analysis has also supported the consistency of the measurement instrument, as Cronbach's alpha values have ranged from .81 to .89 across the constructs, exceeding the acceptable threshold of .70. Specifically, Tableau-based dashboarding capability has recorded an alpha value of .86, Python-based analytical processing has recorded .84, dashboard usability has recorded .88, data visualization quality has recorded .87, analytics automation has recorded .81, and pharmaceutical brand performance analytics effectiveness has recorded .89. The correlation results have further demonstrated positive and statistically significant relationships among the study variables. Pharmaceutical brand performance analytics effectiveness has shown strong positive correlations with data visualization quality ($r = .68$, $p < .001$), dashboard usability ($r = .65$, $p < .001$), Tableau-based dashboarding capability ($r = .62$, $p < .001$), Python-based analytical processing ($r = .57$, $p < .001$), and analytics automation ($r = .55$, $p < .001$). These results have suggested that respondents who rated dashboard clarity, interactivity, usability, Python-supported analysis, and automation more highly also tended to rate pharmaceutical brand performance analytics effectiveness more highly. The regression analysis has provided stronger evidence for proving the hypotheses and objectives of the study. The overall regression model has been statistically significant, $F(5, 208) = 48.72$, $p < .001$, and the model has explained 53.9% of the variance in pharmaceutical brand performance analytics effectiveness, with an adjusted R^2 value of .528. Among the predictors, data visualization quality has emerged as the strongest predictor ($\beta = .29$, $p < .001$), followed by dashboard usability ($\beta = .24$, $p < .001$), Tableau-based dashboarding capability ($\beta = .21$, $p = .002$), Python-based analytical processing ($\beta = .18$, $p = .006$), and analytics automation ($\beta = .15$, $p = .018$). These results have supported H1, H2, H3, H4, H5, and H6 by showing that all major dimensions of the proposed framework have had significant positive contributions to pharmaceutical brand performance analytics effectiveness. The results have also supported the first research objective by confirming that Tableau-based dashboarding capability improves interactive brand tracking, KPI visibility, and territory-level comparison. The second objective has been supported because Python-based analytical processing has shown a significant contribution to analytical reliability, data preparation, and statistical validation. The third and fourth objectives have been supported because dashboard usability and data visualization quality have shown strong relationships with decision-support quality and insight generation. The fifth objective has been supported because analytics automation has improved perceived reporting accuracy, speed, and reduction of manual error. The sixth objective has been supported through the validation of the integrated framework, where Tableau has served as the visualization and dashboarding layer, Python has served as the analytical processing layer, and pharmaceutical brand performance analytics effectiveness has represented the decision-support outcome. Overall, the findings have indicated that the proposed framework is statistically reliable, practically relevant, and suitable for supporting pharmaceutical brand managers and analytics professionals in monitoring brand performance, interpreting market signals, comparing territories, identifying underperforming areas, and making evidence-based decisions through a combined Tableau and Python analytics workflow.

DISCUSSION

The findings of this study have shown that the proposed dashboarding and visualization framework using Tableau and Python has been statistically supported for pharmaceutical brand performance analytics. The overall results have indicated strong agreement across the major constructs, with data visualization quality recording the highest mean score of 4.18, followed by dashboard usability at 4.13, Tableau-based dashboarding capability at 4.09, pharmaceutical brand performance analytics effectiveness at 4.05, analytics automation at 3.98, and Python-based analytical processing at 3.92. These results have suggested that pharmaceutical professionals have perceived visual clarity, dashboard usability, and Tableau-supported KPI presentation as the most immediately visible contributors to brand analytics effectiveness, while Python-based processing and automation have also been viewed positively as supporting elements behind the dashboard. The correlation findings have further confirmed that pharmaceutical brand performance analytics effectiveness has had significant positive associations with data visualization quality ($r = .68$), dashboard usability ($r = .65$), Tableau-based dashboarding capability ($r = .62$), Python-based analytical processing ($r = .57$), and analytics automation ($r = .55$), all at $p < .001$. The regression model has also been significant, $F(5, 208) = 48.72$, $p < .001$, with $R^2 = .539$ and adjusted $R^2 = .528$, meaning that the five framework variables have explained 53.9% of the variance in pharmaceutical brand performance analytics effectiveness. This finding has strongly supported the argument that pharmaceutical brand analytics is not improved by one isolated tool alone; rather, effectiveness has emerged from the combined role of visual dashboarding, analytical processing, usability, visualization quality, and automation. This result has aligned with earlier business intelligence research, which has shown that analytics and BI systems create value when data, technology, analytical capability, and decision environments are connected to managerial use (Chen et al., 2012). The result has also been consistent with dashboard research, which has explained that dashboards become valuable when they organize key indicators, support performance monitoring, and reduce information overload for decision-makers (Yigitbasioglu & Velcu, 2012). In the present study, data visualization quality has emerged as the strongest predictor ($\beta = .29$), which has suggested that the way pharmaceutical brand data are visually communicated may influence decision support more strongly than backend processing alone. This finding has been consistent with visual analytics research, which has emphasized that effective visualization depends on meaningful visual representation, user task alignment, and interpretive clarity (Munzner, 2009). Therefore, the key finding has been that Tableau and Python can form a reliable pharmaceutical brand performance analytics framework when visualization quality and usability are treated as central decision-support dimensions rather than secondary dashboard features.

Figure 10: Proposed Maturity Model for Pharmaceutical Brand Performance Analytics Using Tableau and Python



Comparison with earlier studies and interpretation of dashboarding capability. The significant positive effect of Tableau-based dashboarding capability on pharmaceutical brand performance analytics effectiveness ($\beta = .21$, $p = .002$) has confirmed that interactive dashboarding has supported brand-level monitoring, KPI visibility, regional comparison, and performance interpretation. The dashboard prototype evaluation has strengthened this interpretation because brand-wise KPI clarity has recorded the highest item-level mean score of 4.24, regional drill-down analysis has recorded 4.19, and sales trend visualization has recorded 4.16. These results have shown that respondents have valued dashboards most when they have translated complex brand performance data into clear product-level and territory-level views. This has directly supported the first objective of the study, which has examined the role of Tableau-based dashboarding capability in improving pharmaceutical brand performance analytics. The finding has aligned with prior research on marketing dashboards, where dashboard-based systems have been found useful for connecting metrics with managerial monitoring, decision-making, and performance evaluation (Pauwels et al., 2009). It has also supported the argument that decision support systems become important when managers need to interpret complex information under uncertain and information-rich decision conditions (Arnott & Pervan, 2008). In pharmaceutical brand management, such complexity appears through sales trends, prescription movement, promotional response, product ranking, market share, and regional achievement. The result has also extended earlier dashboard studies by placing dashboarding in a specific pharmaceutical brand analytics context rather than a general performance management setting. Healthcare dashboard research has shown that dashboards can support decision-making when they present indicators clearly and help users identify areas requiring attention (Dowding et al., 2015). The present finding has been comparable because pharmaceutical brand dashboards have also helped users identify weak territories, declining products, and performance gaps. The difference is that the current study has focused on commercial brand analytics rather than clinical quality indicators. This has made the study more specific to pharmaceutical marketing, sales analytics, and brand decision support. The finding has also matched the Information Systems Success Model because Tableau-based dashboarding capability has represented system quality. A dashboard with useful filters, drill-down options, KPI cards, charts, and brand comparison panels has functioned as a high-quality information system interface. Therefore, the supported H1 has indicated that dashboarding capability has not only improved visual presentation but has also strengthened the perceived net benefit of the system through better brand performance analytics effectiveness.

Interpretation of Python-based analytical processing and automation vs. prior work. The findings have shown that Python-based analytical processing has had a significant positive effect on pharmaceutical brand performance analytics effectiveness ($\beta = .18$, $p = .006$), while analytics automation has also had a significant positive effect on reporting accuracy and timeliness ($\beta = .15$, $p = .018$). These results have supported H2 and H5 and have confirmed the second and fifth objectives of the study. The descriptive results have shown that Python-based analytical processing has recorded a positive mean score of 3.92, while analytics automation has recorded 3.98. The Python-driven analytical workflow validation has also shown that Python-based data cleaning has received the highest item score of 4.08, followed by automated descriptive statistics at 4.03, correlation matrix preparation at 3.98, regression model preparation at 3.95, and missing-value and outlier checking at 3.93. These results have indicated that respondents have viewed Python as a reliability-building tool rather than only a programming tool. In the context of pharmaceutical brand analytics, this has meant that dashboard trustworthiness has depended on whether product names, regional codes, sales values, prescription indicators, promotional variables, and derived metrics have been properly cleaned and prepared before visualization. This interpretation has aligned with earlier research on Python-based scientific computing, where Python environments have supported interactive data analysis, computational workflows, numerical processing, and statistical analysis (Pérez & Granger, 2007). It has also matched research on Python-based statistical modeling, where statistical tools have supported regression modeling, estimation, diagnostics, and interpretable analysis (Seabold & Perktold, 2010). The present study has extended these works by applying Python analytical processing to a pharmaceutical brand dashboarding framework. The result has also aligned with big data analytics capability research, which has shown that analytics value depends on technical capability, data capability, and managerial capability working together (Gupta & George, 2016). In this study, Python has represented technical and analytical capability, while Tableau has represented visual communication and managerial use. Automation has further supported the framework because repeated brand performance reporting often requires consistent monthly or quarterly processing. This has aligned with research emphasizing that business analytics creates value when it supports decision processes and converts analysis into action (Seddon et al., 2017). From the Information Systems Success Model perspective, Python-based analytical processing has represented information quality and analytical quality, while automation has represented process quality. Therefore, the findings have suggested that the backend layer of the framework has been necessary for ensuring that visual dashboards are built on reliable, repeatable, and statistically valid data.

Dashboard usability, visualization quality, and theoretical interpretation. The strongest results in this study have appeared in the areas of visualization quality and dashboard usability. Data visualization quality has recorded the highest descriptive mean of 4.18 and the strongest regression beta value of .29, while dashboard usability has recorded the second-highest mean of 4.13 and the second-strongest beta value of .24. These results have supported H3 and H4 and have confirmed that dashboard usability and visual quality are critical to pharmaceutical brand performance analytics effectiveness. The strong correlation between data visualization quality and pharmaceutical brand performance analytics effectiveness ($r = .68$, $p < .001$) has indicated that clear chart selection, readable labels, KPI clarity, color consistency, visual comparison, and interpretable layouts have been strongly associated with effective brand analytics. Similarly, the correlation between dashboard usability and pharmaceutical brand performance analytics effectiveness ($r = .65$, $p < .001$) has shown that ease of navigation, filter accessibility, logical dashboard structure, and user control have been essential for decision support. These findings have been consistent with earlier visualization research, which has argued that visual representations should be evaluated in relation to user tasks, data types, and analytical goals (Munzner, 2009). The findings have also aligned with visualization task research, which has shown that users interact with dashboards through different task levels, including why they need information, what information they require, and how interaction supports analysis (Brehmer & Munzner, 2013). In the present study, pharmaceutical users have not interacted with dashboards for general curiosity; they have needed to interpret sales trends, compare brands, identify weak territories, evaluate promotional response, and monitor prescription movement. Therefore, usability and visualization quality have become central to decision-support effectiveness. The findings have also supported prior dashboard design research, which has shown that dashboards require a distinct design logic because they combine multiple indicators, compact displays, and interactivity in one decision environment (Sarikaya et al., 2019). In terms of theory, these results have strongly supported the Information Systems Success Model because dashboard usability has reflected use quality and user satisfaction, while data visualization quality has reflected information quality and interpretive system value. The results have suggested that the net benefit of a dashboarding system depends not only on the availability of data but also on the user's ability to understand and apply that data. Therefore, the theoretical interpretation has been that pharmaceutical brand analytics effectiveness has been achieved when system quality and information quality have been converted into usable, visually clear, and managerially meaningful decision support.

Practical implications. The findings have several practical implications for pharmaceutical companies, brand managers, sales leaders, marketing teams, and business intelligence professionals. First, pharmaceutical organizations should treat dashboard development as a strategic analytics function rather than a routine reporting activity. The results have shown that data visualization quality, dashboard usability, and Tableau-based dashboarding capability have had strong effects on pharmaceutical brand performance analytics effectiveness. This means that pharmaceutical companies should design dashboards around actual brand decision tasks, including product-wise performance monitoring, regional comparison, prescription trend tracking, market share analysis, sales target achievement, promotional response evaluation, and territory-level performance diagnosis. Second, companies should strengthen the backend analytical process before dashboard construction. The significant effect of Python-based analytical processing has shown that data cleaning, missing-value checking, outlier screening, descriptive statistics, correlation analysis, and regression preparation have improved the trustworthiness of the dashboard. Therefore, companies should avoid building dashboards directly from unvalidated spreadsheets or fragmented reports. Third, the findings have suggested that analytics automation should be integrated into pharmaceutical reporting systems. Since automation has had a positive effect on reporting accuracy and timeliness, organizations should use

Python scripts or automated workflows to reduce manual reporting errors and produce consistent dashboard-ready datasets. Fourth, pharmaceutical companies should provide dashboard literacy and analytics training for brand managers and sales teams. The strong role of dashboard usability has indicated that users must be able to navigate filters, interpret charts, compare KPIs, and translate dashboard results into decisions. This practical implication has aligned with earlier research showing that business intelligence systems create value when they improve information access and analytical decision-making (Elbashir et al., 2008). It has also aligned with research on BI maturity, where data-oriented culture and systematic use of information have been found important for analytical decision-making (Popovič et al., 2012). Fifth, the study has suggested that pharmaceutical dashboards should include both executive-level and operational-level views. Executive users may need summary KPIs, while territory managers may need region-wise drill-down and sales trend views. This has matched prior design study research, which has emphasized the importance of domain needs and user requirements in visualization system development (Sedlmair et al., 2012). Therefore, the practical implication has been that the Tableau and Python framework can help pharmaceutical companies move from static reporting to interactive, statistically supported, and decision-oriented brand performance analytics.

Theoretical implications and limitations revisited. The theoretical implication of this study has been that the Information Systems Success Model has been successfully adapted to a pharmaceutical brand performance analytics context involving Tableau and Python. The study has shown that system quality, information quality, usability quality, visual quality, process quality, and net benefits can be operationalized through measurable variables. Tableau-based dashboarding capability has represented system quality, Python-based analytical processing has represented information and analytical quality, dashboard usability has represented use and user satisfaction, data visualization quality has represented interpretive information quality, analytics automation has represented process quality, and pharmaceutical brand performance analytics effectiveness has represented net benefit. The supported regression model, with $R^2 = .539$, has suggested that these adapted IS success dimensions explain a meaningful share of perceived analytics effectiveness. This has extended earlier IS success research, which has emphasized the role of system quality, information quality, use, satisfaction, and net benefits in evaluating information systems (Petter et al., 2008). It has also aligned with empirical IS success studies that have shown the importance of system quality and information quality in predicting user satisfaction and system value (Iivari, 2005). The study has also contributed to analytics capability theory by showing that value has emerged from the integration of dashboarding capability, analytical processing, visualization quality, usability, and automation. This has been consistent with analytics capability research, where technology, data, and managerial capability are treated as connected contributors to business value (Akter et al., 2016). However, the limitations of the study have also needed careful interpretation. First, the study has used a cross-sectional design, so it has captured respondent perceptions at one point in time rather than tracking dashboard performance over multiple periods. Second, the study has been case-study-based, so the results may reflect the specific pharmaceutical analytics context used in the research. Third, the findings have been based on self-reported Likert-scale responses, meaning that the results have measured perceived effectiveness rather than direct sales or prescription performance outcomes. Fourth, the study has used purposive sampling, which has been appropriate for selecting knowledgeable respondents but may limit broader generalization. Fifth, Python and Tableau effectiveness has been evaluated through perceived analytical workflow and dashboard prototype evaluation, not through a fully deployed enterprise-level system. These limitations have not weakened the statistical support of the study, but they have clarified the boundary within which the findings should be interpreted.

Future research and proposed improved model. Future research can improve this study by developing and testing a more advanced model that combines perception-based survey evidence with real pharmaceutical brand performance datasets. The most important future research direction should be the development of a Longitudinal Tableau-Python Pharmaceutical Brand Analytics Maturity Model, which can be abbreviated as the LTPBAM model. This proposed model can improve the present framework by adding four progressive layers: data readiness, analytical intelligence, dashboard adoption, and brand performance impact. In the first layer, data readiness can measure data completeness, data integration, data accuracy, product code consistency, prescription data availability, CRM data quality, and reporting frequency. In the second layer, analytical intelligence can measure Python-supported descriptive analytics, correlation analysis, regression modeling, predictive modeling, promotional response analysis, and brand segmentation. In the third layer, dashboard adoption can measure Tableau dashboard usability, user satisfaction, frequency of use, drill-down use, KPI interpretation, and decision-maker confidence. In the fourth layer, brand performance impact can measure actual changes in sales growth, market share movement, prescription volume, regional achievement, promotional return, and decision speed. The future model can be expressed as: Data Readiness → Analytical Intelligence → Dashboard Adoption → Brand Performance Impact. This model would improve the current study because the present research has tested perceived pharmaceutical brand performance analytics effectiveness, while the proposed future model would test both perceived and actual performance outcomes. Future researchers can also use a longitudinal design by collecting data across six or twelve months to examine whether dashboard use improves brand decision-making over time. A multi-case study design can also compare pharmaceutical companies of different sizes, therapeutic categories, or market positions. Future research can additionally include machine learning models in Python to forecast sales trends, detect declining brands, predict promotional response, and classify territories by performance risk. This direction would extend the current regression-based framework into a predictive analytics framework. Future studies can also test mediation and moderation effects, such as whether dashboard usability mediates the relationship between Tableau capability and analytics effectiveness, or whether user analytics competency moderates the relationship between Python-based processing and decision-support quality. This future direction has aligned with prior research showing that predictive analytics can strengthen information systems research by explaining and forecasting outcomes (Shmueli & Koppius, 2011). It has also aligned with big data analytics studies showing that analytics capability can support performance when combined with organizational readiness and strategic alignment (Wamba et al., 2017). Therefore, the proposed LTPBAM model can offer a stronger path for future researchers by connecting data quality, Python intelligence, Tableau adoption, and measurable pharmaceutical brand performance impact.

CONCLUSION

This study has concluded that the development of a dashboarding and visualization framework for pharmaceutical brand performance analytics using Tableau and Python has been statistically supported, methodologically justified, and practically relevant for pharmaceutical decision-making. The research has followed a quantitative, cross-sectional, case-study-based design and has used a five-point Likert scale to examine the perceptions of pharmaceutical professionals regarding Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, analytics automation, and pharmaceutical brand performance analytics effectiveness. The findings have shown that the proposed framework has achieved strong agreement across all major constructs, with data visualization quality recording the highest mean score of 4.18, followed by dashboard usability at 4.13, Tableau-based dashboarding capability at 4.09, pharmaceutical brand performance analytics effectiveness at 4.05, analytics automation at 3.98, and Python-based analytical processing at 3.92. These results have confirmed that respondents have perceived clear visualization, usable dashboard design, interactive Tableau reporting, reliable Python-supported analysis, and automated workflow as important elements of effective pharmaceutical brand performance analytics. The reliability analysis has further confirmed the internal consistency of the research instrument, as all Cronbach's alpha values have exceeded the acceptable threshold and ranged from .81 to .89, while the overall instrument reliability has reached .91. The correlation analysis has shown that pharmaceutical brand performance analytics effectiveness has had significant positive relationships with data visualization quality, dashboard usability, Tableau-based dashboarding capability, Python-based analytical processing, and analytics automation. The regression analysis has provided stronger statistical confirmation, as the overall model has been significant, $F(5, 208) = 48.72$, $p < .001$, and has explained 53.9% of the variance in pharmaceutical brand performance analytics effectiveness. Data visualization quality has emerged as the strongest predictor, followed by dashboard usability, Tableau-based dashboarding capability, Python-based analytical processing, and analytics automation. Therefore, all six hypotheses have been supported, and all research objectives have been achieved. The study has confirmed that Tableau can serve as an effective visualization and dashboarding layer for KPI monitoring, regional comparison, sales trend interpretation, and brand-wise performance analysis, while Python can serve as a reliable analytical processing layer for data cleaning, descriptive statistics, correlation analysis, regression modeling, workflow validation, and dashboard-ready dataset preparation. The dashboard prototype evaluation and Python-driven analytical workflow validation have made the results more specific to the research title because they have shown both the visible dashboard value and the backend analytical value of the proposed framework. The study has also confirmed the relevance of the Information Systems Success Model because system quality, information quality, usability quality, visual quality, process quality, and net benefit have been reflected through the selected variables and supported through the statistical findings. Overall, this research has concluded that a combined Tableau and Python-based dashboarding and visualization framework can improve pharmaceutical brand performance analytics by making brand data more accurate, interactive, understandable, timely, and useful for managerial decision-making.

RECOMMENDATION

Based on the findings of this study, it has been recommended that pharmaceutical organizations should adopt an integrated Tableau and Python-based analytics workflow for improving brand performance monitoring, reporting accuracy, and decision support. First, pharmaceutical companies should develop centralized brand performance dashboards that include product-wise sales achievement, market share, prescription movement, regional performance, promotional response, customer engagement, growth rate, territory contribution, and brand ranking indicators. These dashboards should not be designed only as decorative visual reports; they should be built around the real decision needs of brand managers, sales managers, marketing executives, business intelligence analysts, and senior decision-makers. Since data visualization quality has emerged as the strongest predictor of pharmaceutical brand performance analytics effectiveness, organizations should give special attention to chart selection, KPI clarity, dashboard layout, color consistency, label readability, filtering logic, and visual comparison. Second, pharmaceutical companies should improve dashboard usability by ensuring that users can easily navigate the dashboard, filter regions or brands, drill down from summary-level information to detailed views, compare current and previous performance, and identify underperforming products or territories. Since dashboard usability has shown a strong effect on analytics effectiveness, regular user feedback should be collected before finalizing dashboard structure. Third, organizations should use Python as the analytical backend before dashboard development. Python should be used for data cleaning, missing-value treatment, duplicate removal, product name standardization, region code correction, descriptive statistics, correlation analysis, regression modeling, and automated data preparation. This can reduce manual reporting errors and ensure that Tableau dashboards are based on reliable and validated data. Fourth, pharmaceutical companies should automate repetitive reporting activities through Python scripts or scheduled analytical workflows so that monthly or quarterly brand performance dashboards can be updated with less manual effort. Automation can improve reporting timeliness, consistency, and managerial confidence. Fifth, companies should train brand managers and sales teams in dashboard interpretation, KPI understanding, visual analytics, and basic data literacy. A dashboard can support decision-making only when users understand how to interpret the displayed indicators and connect them with brand strategy. Sixth, pharmaceutical firms should link dashboard outputs with regular review meetings, sales planning, promotional planning, territory performance reviews, and brand strategy discussions. This will help ensure that analytics outputs are actually used in managerial decision-making. Seventh, business intelligence teams should create separate dashboard views for different users, such as executive summary dashboards for senior managers, territory dashboards for sales managers, promotional dashboards for marketing teams, and analytical validation dashboards for BI professionals. Finally, researchers and organizations should continuously evaluate the framework by measuring user satisfaction, reporting accuracy, dashboard adoption, and actual brand performance improvement. Therefore, the main recommendation of this study is that pharmaceutical organizations should treat dashboarding and visualization as an integrated decision-support system where Python ensures analytical reliability and Tableau ensures interactive visual interpretation.

LIMITATIONS OF THE STUDY

This study has several limitations that should be considered when interpreting the findings. First, the study has used a cross-sectional research design, which means that data have been collected from respondents at a single point in time. Because of this design, the study has measured respondent perceptions of Tableau-based dashboarding capability, Python-based analytical processing, dashboard usability, data visualization quality, analytics automation, and pharmaceutical brand performance analytics effectiveness during one specific period. It has not measured how the framework performs over several months or how dashboard use changes over time. Second, the study has been case-study-based, so the findings have been connected with a specific pharmaceutical analytics context. Although the results have shown strong statistical support, the findings may not be fully generalizable to all pharmaceutical companies, therapeutic categories, market environments, or countries without further testing. Third, the study has used a purposive sampling strategy, which has been suitable for selecting respondents with knowledge of pharmaceutical brand performance analytics, but it may have limited the representativeness of the sample. Respondents who have had stronger familiarity with dashboards, analytics tools, or business intelligence may have evaluated the framework more positively than those with limited analytics exposure. Fourth, the study has relied on self-reported Likert-scale survey data. This means that the findings have represented perceived effectiveness rather than direct organizational performance outcomes. For example, respondents have reported their views about dashboard usefulness, Python-based analytical reliability, automation value, and brand analytics effectiveness, but the study has not directly measured actual sales growth, prescription volume increase, market share improvement, or promotional return after dashboard implementation. Fifth, although the study has included dashboard prototype evaluation and Python-driven analytical workflow validation, the framework has not been tested as a fully deployed enterprise-level system across multiple departments over a long operational period. Sixth, the study has used descriptive statistics, correlation analysis, and regression modeling, which have been appropriate for the research objectives, but more advanced methods such as structural equation modeling, mediation analysis, moderation analysis, longitudinal modeling, or machine learning-based performance prediction have not been applied. Seventh, the study has focused mainly on Tableau and Python, so it has not compared the framework with other business intelligence tools such as Power BI, Qlik, R, SAS, or cloud-based analytics platforms. Eighth, the availability of real pharmaceutical brand performance data may have been restricted because sales records, prescription data, promotional budgets, and market share reports are often confidential. Therefore, the study has depended mainly on professional perception and framework evaluation rather than full access to proprietary datasets.

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