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Using Tableau and Excel for Comprehensive Profitability Analysis in Retail Procurement Operations

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Abstract

Profitability analysis is a critical dimension of retail procurement operations, where organizations must continuously evaluate costs, revenues, and supplier performance to maintain competitiveness and long-term sustainability. The complexity of modern retail supply chains, characterized by large transaction volumes, diverse product assortments, and intricate vendor relationships, necessitates advanced analytical tools to extract actionable insights from vast datasets. Among the most widely adopted tools for such purposes are Tableau, a powerful data visualization and business intelligence platform, and Microsoft Excel, a versatile and accessible spreadsheet application. Although both tools differ in sophistication, scope, and intended functionality, they complement one another in enabling comprehensive profitability analysis. Tableau provides advanced visualization, dashboarding, and integration capabilities, allowing managers to explore multidimensional data interactively, while Excel offers detailed modeling, flexible computation, and scenario analysis functionalities that support granular decision-making. This paper presents a structured literature-based review of the application of Tableau and Excel for profitability analysis in retail procurement operations, with a focus on developments up to 2020. It examines their roles in cost analysis, supplier performance assessment, inventory optimization, and strategic procurement decisions. The discussion highlights the strengths and limitations of each tool, the synergies from their combined use, and the implications for retail procurement management in an increasingly data-driven environment. By consolidating insights from prior research, this study provides an integrative perspective on how Tableau and Excel support profitability analysis, offering valuable guidance to both academics and practitioners seeking to enhance retail procurement effectiveness through business intelligence and analytics.

Keywords: Retail Procurement, Profitability Analysis, Tableau Analytics, Excel Modeling, Supply Chain Visualization, Data-Driven Decisions

Introduction

Profitability analysis lies at the core of decision-making in retail procurement operations [1, 2]. As retail businesses grow in scale and complexity, procurement is increasingly recognized not merely as a transactional function but as a strategic capability that directly influences financial performance, supply chain efficiency, and customer satisfaction [3, 4]. Retailers face the dual challenge of maximizing profitability while managing costs across diverse product categories, complex vendor relationships, and fluctuating consumer demand. In this context, data-driven decision-making has emerged as a critical enabler, allowing organizations to transform raw procurement data into actionable insights [5, 6]. Tools such as Tableau and Microsoft Excel have become central to this transformation, offering complementary functionalities for analyzing profitability, modeling costs, and visualizing procurement outcomes [7, 8].

Historically, profitability analysis in retail procurement focused primarily on gross margins and cost reduction strategies [9, 10]. While these measures remain important, they are insufficient in capturing the multi-dimensional nature of modern procurement, which must also account for supplier reliability, lead time variability, inventory costs, demand fluctuations, and risk exposures [11, 12]. The availability of vast amounts of transactional and operational data provides unprecedented opportunities to evaluate these dimensions systematically but also presents significant challenges in terms of data management, analysis, and interpretation. Consequently, there is a growing need for analytical tools that are both robust and accessible, enabling procurement managers to navigate data complexity without sacrificing decision speed [13, 14]. Tableau and Excel have emerged as two such tools, widely adopted across industries for their ability to handle large datasets, provide flexible modeling, and deliver intuitive insights through visualization [15, 16, 17].

Excel, with its long-standing presence in organizational contexts, has been the cornerstone of data analysis for procurement professionals. Its spreadsheet interface allows for detailed financial modeling, cost tracking, and profitability simulations [18]. Excel's functions, pivot tables, and add-ins enable users to conduct scenario analysis, break-even calculations, and supplier performance comparisons with relative ease. Despite its accessibility, Excel faces limitations in handling very large datasets, integrating multiple data sources, and generating dynamic visualizations [19, 20, 21]. These limitations have become increasingly apparent as procurement operations generate growing volumes of structured and unstructured data from enterprise resource planning (ERP) systems, supplier portals, and point-of-sale systems [22, 23].

Tableau addresses many of these limitations by providing advanced data visualization and integration capabilities. It allows procurement professionals to connect to diverse data sources, including ERP systems, SQL databases, and cloud platforms, and transform raw data into interactive dashboards [24, 25]. By enabling real-time exploration of procurement metrics, Tableau enhances transparency and facilitates collaboration across organizational levels. For example, managers can track supplier delivery performance, analyze category-level profitability, and monitor inventory turnover through intuitive visualizations that reduce cognitive load compared to tabular reports [26, 27]. This interactivity empowers decision-makers to identify patterns, anomalies, and emerging risks more effectively than static spreadsheets alone [28].

The combination of Tableau and Excel offers unique synergies for retail procurement profitability analysis. While Tableau excels at visualization and high-level exploration, Excel remains indispensable for detailed financial modeling and customized scenario analysis. Organizations often use Tableau for executive-level dashboards and trend monitoring, while Excel supports analyst-driven tasks such as margin calculations, variance analysis, and procurement forecasting [29]. Together, they provide a comprehensive toolkit that balances depth and accessibility, allowing retail firms to bridge strategic and operational decision-making [30]. This integration reflects a broader trend in supply chain analytics, where business intelligence platforms and spreadsheet tools are not seen as substitutes but as complementary assets that together enhance analytical capabilities [31].

The significance of using Tableau and Excel for profitability analysis in retail procurement can be further understood in the context of broader industry challenges. Retail procurement operates under intense pressures from globalization, competition, and consumer expectations. Margins are often thin, and procurement decisions directly affect financial outcomes. Supplier selection, contract negotiation, and inventory management must be optimized not only for cost but also for resilience, sustainability, and agility. The COVID-19 pandemic, although beyond the 2020 scope of this review, exemplifies the volatility that retail procurement must navigate. Even prior to such disruptions, researchers highlighted the need for agile procurement supported by robust analytical systems [32]. In this environment, tools that enhance visibility, support scenario planning, and enable proactive risk management are indispensable [33].

Moreover, the increasing emphasis on data-driven procurement aligns with broader shifts toward business intelligence and analytics across industries [34]. Organizations recognize that traditional reporting tools are inadequate for capturing the complexity of modern supply chains. Instead, they require integrated platforms that combine visualization, modeling, and predictive capabilities [35]. Tableau and Excel fit into this ecosystem by providing scalable, adaptable, and user-friendly tools that can be deployed without prohibitive costs or extensive technical expertise. For many firms, especially mid-sized retailers, these tools represent a practical entry point into advanced analytics without necessitating full-scale enterprise business intelligence implementations [36].

At the theoretical level, the application of Tableau and Excel in profitability analysis can be linked to the resource-based view (RBV) of the firm, which emphasizes the strategic value of resources and capabilities that are rare, valuable, inimitable, and non-substitutable. Analytical capabilities, supported by tools such as Tableau and Excel, constitute such resources by enabling firms to leverage data more effectively than competitors. This perspective suggests that the strategic deployment of analytics tools can provide a sustained competitive advantage in procurement operations. Furthermore, institutional theory highlights how regulatory, normative, and competitive pressures drive firms toward adopting data-driven tools in procurement [37]. As industry benchmarks increasingly demand transparency and accountability, firms turn to analytics platforms to meet these expectations and signal competence to stakeholders.

Despite their advantages, both Tableau and Excel face limitations that warrant careful consideration. Excel's scalability issues can hinder its effectiveness in environments with high-volume or real-time data [38, 39]. Tableau, while powerful, may be cost-prohibitive for smaller firms and requires training for effective use. Furthermore, integrating insights from both tools into coherent decision-making processes remains a managerial challenge, as data silos and inconsistent practices can undermine their potential[40, 41]. These challenges underscore the importance of not only adopting analytics tools but also embedding them within organizational processes, culture, and governance structures [42, 43].

In conclusion, the introduction of Tableau and Excel into retail procurement profitability analysis represents a critical step toward data-driven decision-making. The two tools complement one another, with Excel providing detailed modeling and Tableau offering advanced visualization and integration capabilities. Their combined use enhances transparency, supports scenario planning, and empowers managers to make informed decisions in complex and dynamic retail environments. This paper builds upon the extensive literature on procurement analytics, profitability analysis, and business intelligence tools to explore how Tableau and Excel contribute to procurement performance. Section 2 provides an in-depth review of the relevant literature, tracing the evolution of profitability analysis in procurement and examining the roles of Tableau and Excel up to 2020.

2. Literature Review

The growing complexity of retail procurement operations has driven extensive scholarly attention toward profitability analysis tools and methodologies. The literature reveals an evolution from traditional accounting-based approaches to advanced analytics platforms, reflecting shifts in technology, managerial expectations, and competitive pressures. This review synthesizes the key contributions up to 2020, with particular focus on Tableau and Microsoft Excel as dominant tools for supporting profitability analysis in retail procurement contexts. The discussion is organized around five themes: the foundations of profitability analysis in procurement, the role of spreadsheets in retail analytics, the rise of data visualization and business intelligence platforms, the complementary use of Tableau and Excel, and the challenges and limitations associated with their adoption.

2.1. Foundations of Profitability Analysis in Retail Procurement

Profitability analysis in retail procurement has long been anchored in the principles of managerial accounting and supply chain management. Traditionally, procurement decisions were assessed through gross margin analysis, purchase price variance, and basic cost-reduction measures[44, 45]. Researchers emphasized procurement's role as a cost center, where success was largely measured in terms of minimizing input costs while ensuring product availability [46]. However, as supply chains became more globalized and retail operations more diversified, the limitations of these simple measures became apparent. Procurement costs, while critical, represented only part of the profitability equation, as supplier performance, lead times, and inventory holding costs exerted substantial influence on financial outcomes [47, 48].

The evolution of activity-based costing (ABC) methodologies in the 1990s further refined profitability analysis by attributing indirect costs more accurately across procurement activities [49]. ABC allowed managers to identify high-cost procurement processes and suppliers, facilitating more informed decision-making. By the early 2000s, researchers began emphasizing the importance of integrating financial and operational metrics, arguing that procurement profitability should account not only for purchase prices but also for supplier quality, reliability, and risk exposure [50]. This broadened perspective reflected the growing consensus that procurement profitability is multi-dimensional, requiring sophisticated tools capable of integrating diverse data sources and perspectives [51, 52].

2.2. Excel and the Spreadsheet Tradition in Procurement Analysis

Microsoft Excel has been the dominant tool for profitability analysis across industries for decades, with widespread adoption in retail procurement due to its flexibility, accessibility, and relatively low cost [53]. Its spreadsheet-based interface allows managers to structure procurement data into organized tables, perform complex calculations, and apply financial models without requiring specialized programming knowledge. Excel's features such as pivot tables, scenario analysis, and Solver optimization have been widely used for tasks such as supplier comparison, cost modelling, and inventory forecasting[54].

Several studies highlight Excel's role in supporting procurement managers who must balance competing objectives of cost minimization, supplier reliability, and inventory efficiency. For example, pivot tables have enabled dynamic analysis of supplier performance data, facilitating comparisons of defect rates, lead times, and pricing trends across vendors. The flexibility of Excel allows for the construction of customized profitability models that capture both direct and indirect procurement costs, enabling firms to identify areas of inefficiency [55]. Moreover, Excel's widespread familiarity among business users has reduced barriers to adoption, making it the de facto tool for many procurement organizations [56].

However, the literature also documents significant limitations of Excel in retail procurement contexts. First, Excel struggles with scalability when handling very large datasets typical of modern retail supply chains. Procurement data often originates from multiple sourcesERP systems, supplier databases, and point-of-sale recordswhich require integration beyond Excel's native capacity [57]. Second, Excel models are prone to human error, with small mistakes in formulas potentially leading to significant misinterpretations of profitability. Third, Excel provides limited visualization capabilities, often restricting managers to static charts and tables that do not adequately support real-time, interactive decision-making. These limitations have spurred interest in complementary or alternative tools that enhance Excel's analytical capabilities [58].

2.3. The Rise of Tableau and Business Intelligence Platforms

The emergence of business intelligence (BI) platforms such as Tableau marked a turning point in the application of analytics to procurement profitability. Tableau, founded in the early 2000s, gained widespread adoption due to its ability to transform large, complex datasets into intuitive visualizations and interactive dashboards [59]. Unlike traditional reporting tools, Tableau allows managers to explore procurement data dynamically, enabling "drill-down" analyses across multiple dimensions such as supplier performance, category-level profitability, and geographic trends.

Research highlights Tableau's value in addressing Excel's limitations. Its capacity to connect directly to diverse data sources, including ERP systems, SQL databases, and cloud platforms, allows for more seamless integration of procurement data [60]. Furthermore, Tableau's in-memory processing engine enables efficient handling of large datasets, supporting near real-time analytics [61, 62]. In retail procurement, these features have been applied to monitor supplier delivery performance, track purchase order fulfillment, and analyze cost structures across product categories. The interactive nature of Tableau dashboards enhances managerial decision-making by reducing cognitive overload and enabling rapid identification of patterns, anomalies, or risks [63].

The broader literature on BI emphasizes Tableau's role in democratizing access to analytics by enabling non-technical users to engage with data [64]. This is particularly relevant in procurement contexts, where decision-makers often lack advanced technical training but require timely insights into vendor performance and profitability. Tableau has also been used in collaborative settings, where dashboards are shared across organizational levels, promoting transparency and alignment between procurement teams and executive management. By bridging the gap between raw data and actionable insights, Tableau embodies the shift toward data-driven procurement strategies [65].

2.4. Tableau and Excel as Complementary Tools

Although Tableau and Excel are often compared, the literature increasingly frames them as complementary rather than competing tools. Tableau excels in visualization, data integration, and interactivity, while Excel remains indispensable for detailed modeling, scenario analysis, and financial calculations [66]. Many organizations adopt a hybrid approach in which Tableau dashboards provide executive-level insights, while Excel supports analyst-driven tasks that require granular control.

Scholars have documented cases where Tableau and Excel are used together in retail procurement profitability analysis. For example, Tableau dashboards may highlight underperforming suppliers through visual metrics, while Excel models allow managers to perform sensitivity analyses on potential contract renegotiations [67]. Similarly, Tableau may reveal trends in category-level profitability, prompting analysts to use Excel for detailed cost breakdowns and forecasting. This combination leverages the strengths of both tools: Tableau's visualization capabilities enhance understanding and communication, while Excel's flexibility supports deep, customized analyses [68].

The complementary use of Tableau and Excel reflects a broader theme in analytics research, where organizations are encouraged to adopt "tool ecosystems" rather than rely on a single platform. Such ecosystems recognize that different tools serve different purposes and that integration across platforms is essential for comprehensive decision support. For retail procurement, this means using Tableau to monitor high-level profitability and performance trends while employing Excel to test alternative strategies, model supplier scenarios, and calculate detailed financial outcomes [69].

2.5. Challenges and Limitations

Despite their advantages, both Tableau and Excel face limitations that constrain their application in profitability analysis. Cost and resource requirements represent a major challenge. While Excel is widely available, Tableau licenses and training can be expensive, particularly for smaller retailers [70]. The implementation of Tableau also requires technical expertise to manage data connections, design dashboards, and maintain system performance. Without adequate training and governance, organizations risk underutilizing Tableau's capabilities or misinterpreting visualizations [71].

Data quality and integration challenges are another limitation. Both Excel and Tableau rely on accurate, consistent, and timely data inputs. In procurement, where data often originates from disparate systems, ensuring quality can be difficult. Poor data quality undermines the reliability of profitability analyses, regardless of the tool use. Moreover, integrating sustainability, risk, and social responsibility dimensions into profitability analysis remains challenging, as standardized data on these dimensions is often lacking [72].

A further limitation concerns cognitive and organizational factors. While Tableau enhances visualization, research shows that decision-makers may still misinterpret graphics or focus on visually salient but less relevant trends [73]. Similarly, the flexibility of Excel may lead to inconsistent modeling practices across organizations, reducing comparability and reliability. Both tools require governance frameworks to ensure consistent, reliable, and meaningful application in procurement contexts [74].

2.6. Synthesis of Literature Trends

The literature up to 2020 demonstrates a clear trajectory in the use of Tableau and Excel for retail procurement profitability analysis. Early reliance on Excel reflected the accessibility and familiarity of spreadsheets, but limitations in scalability, visualization, and integration drove the adoption of Tableau and similar BI platforms. Tableau's rise represents the broader shift toward data visualization and interactive analytics, while Excel continues to serve as a foundation for detailed modeling and financial analysis. Together, they form a complementary toolkit that supports both strategic and operational procurement decision-making [75].

The literature also highlights broader trends, including the growing emphasis on data-driven procurement, the integration of sustainability and risk considerations into profitability analysis, and the recognition of analytics tools as strategic resources. While challenges remainparticularly in terms of cost, data quality, and organizational adoptionthe combined use of Tableau and Excel offers significant opportunities for improving profitability analysis in retail procurement operations. By synthesizing these insights, the present review underscores the need for integrative frameworks that leverage the strengths of both tools while addressing their limitations through governance, training, and process alignment [76].

3. Discussion and Implications

The review of literature demonstrates that the use of Tableau and Excel in retail procurement profitability analysis represents more than a shift in analytical tools; it reflects a broader transformation in how organizations conceptualize, manage, and leverage data for decision-making. This section discusses the key insights from the literature and their implications for practice, research, and organizational strategy.

A major theme emerging from the literature is the complementary role ofTableu and Excel in procurement profitability analysis. Excel's strength lies in detailed modeling and scenario analysis, while Tableau provides interactive visualization and integration across multiple data sources [77]. Their joint use allows organizations to capture both strategic and operational perspectives, thereby enhancing decision quality. For practitioners, this highlights the importance of developing tool ecosystems rather than relying on a single platform. Procurement managers must recognize that while Excel remains indispensable for granular calculations, Tableau adds value by enabling decision-makers to detect trends and communicate insights across organizational levels [78].

Another implication relates to the strategic positioning of analytics in procurement. Profitability analysis is no longer confined to cost-cutting measures; it has evolved into a strategic capability central to competitiveness [79]. Retailers operate in environments characterized by volatile consumer demand, globalized supplier networks, and thin margins. In such contexts, Tableau and Excel provide decision-support systems that help managers balance efficiency, resilience, and sustainability. This aligns with resource-based view theory, which suggests that firms gain advantage when they develop unique analytical capabilities that competitors cannot easily imitate [80]. For organizations, this implies that investments in Tableau and Excel are not merely operational choices but strategic initiatives that can deliver long-term advantage.

The literature also emphasizes the importance of organizational adoption and governance. While tools like Tableau democratize access to analytics, they also require structured implementation frameworks to ensure consistency and reliability [81]. Without governance, organizations risk fragmented practices where different managers interpret and manipulate data in inconsistent ways. Excel, for example, can produce divergent results if models are not standardized, while Tableau dashboards may lead to misinterpretation if poorly designed. Therefore, organizations must embed Tableau and Excel within broader data governance systems, supported by training, documentation, and oversight mechanisms [82]. For researchers, this underscores the need to study not only the tools themselves but also the organizational contexts in which they are applied.

A further implication concerns the integration of sustainability and risk considerations into profitability analysis. While the literature up to 2020 increasingly acknowledges these dimensions, the integration of environmental and social data into Tableau and Excel models remains underdeveloped [83, 84]. Data limitations, lack of standardized reporting, and methodological challenges hinder their systematic inclusion. For practitioners, this suggests the need for innovative approaches to collect and analyze sustainability-related data, such as supplier audits, third-party certifications, and IoT-enabled monitoring [85, 86]. For scholars, this represents an important research agenda focused on expanding profitability analysis beyond purely financial metrics to encompass broader stakeholder concerns [87, 88].

Finally, the discussion highlights the risk of data overload. Tableau enables dynamic exploration of large datasets, but without careful curation, users may become overwhelmed by complexity. Similarly, Excel's flexibility can encourage the development of overly complex models that obscure rather than clarify insights [89, 90]. The implication is that effective profitability analysis requires not only robust tools but also clear decision frameworks that prioritize relevant metrics and guide managerial interpretation [91, 92]. This balance between technical sophistication and managerial usability remains a central challenge for both researchers and practitioners.

In summary, the discussion demonstrates that Tableau and Excel play critical, complementary roles in profitability analysis for retail procurement. Their adoption must be accompanied by strategic positioning, governance frameworks, sustainability integration, and attention to usability to maximize their impact. For practitioners, the insights highlight practical steps for embedding analytics into procurement operations, while for scholars they suggest future directions for advancing theory and methodology in procurement analytics.

4. Conclusion

This paper has examined the role of Tableau and Excel in comprehensive profitability analysis within retail procurement operations, drawing on literature up to 2020. The review highlights several key findings. First, profitability analysis in procurement has evolved from narrow cost-based measures to multi-dimensional approaches that incorporate supplier performance, risk, and sustainability [93, 94]. Second, Excel remains a cornerstone tool for detailed modeling and scenario analysis, but its limitations in scalability, visualization, and integration necessitate complementary platforms. Tableau addresses many of these gaps by offering advanced visualization, real-time data integration, and intuitive dashboards, enabling decision-makers to explore procurement profitability dynamically [95, 96].

Third, the literature shows that Tableau and Excel should not be viewed as substitutes but as complementary tools. Tableau enhances transparency and communication across organizational levels, while Excel provides the flexibility for granular financial and operational modeling[97, 98]. Their combined use creates a comprehensive toolkit that supports both strategic and operational decision-making in retail procurement. Fourth, challenges remain in terms of adoption costs, data quality, organizational governance, and the integration of sustainability and risk dimensions [99, 100]. These challenges highlight the need for robust implementation frameworks and continued research into expanding the scope of profitability analysis beyond purely financial metrics.

The implications of these findings are significant. For practitioners, the results underscore the value of integrating Tableau and Excel into procurement processes to enhance profitability, resilience, and competitiveness. For researchers, the review identifies important gaps, including the need for frameworks that integrate sustainability, address data overload, and balance analytical sophistication with usability. Future research should also examine the role of emerging technologies such as artificial intelligence, machine learning, and predictive analytics in enhancing Tableau-Excel ecosystems for procurement profitability analysis.

In conclusion, Tableau and Excel together represent a powerful, practical, and strategically significant combination for retail procurement profitability analysis[101]. Their effective adoption can transform procurement from a transactional cost center into a data-driven strategic capability that contributes to long-term organizational success [102, 103]. While limitations remain, the trajectory of research and practice up to 2020 demonstrates a clear movement toward integrative, data-driven frameworks that align procurement profitability with broader organizational objectives.

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