The Role of an Analytics-Driven Pricing Model in Strategic Decision-Making: Evidence from a Multinational Manufacturing Case

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Abstract: ***This study examines whether an analytics-driven pricing model can support strategic decision-making in a multinational manufacturing setting. Using a qualitative single-case study design, the analysis focuses on a Netherlands-headquartered company operating manufacturing facilities in six countries (Türkiye, Bangladesh, Hong Kong, India, China, and Vietnam). The pricing model integrates product specifications with operational and cost data, including material consumption, machine and setup times, labor, scrap, packaging, exchange rates, and logistics. Cost structures for producing 1,000 units of the same product were compared across the six locations, and the resulting information was examined for its use in quotation preparation and production-location selection. Total costs varied substantially by location: USD 12.90 in Türkiye, USD 3.55 in Bangladesh, USD 2.10 in Hong Kong, USD 3.08 in India, USD 2.10 in China, and USD 4.09 in Vietnam. The model also reduced quotation preparation time from several weeks to approximately one hour by combining previously separate operational and cost data within a single analytical framework. These findings suggest that the primary managerial value of analytics lies less in cost calculation itself than in the transparency, comparability, and speed it brings to pricing and location decisions. Given the single-case design, the implications should be interpreted as practice-based evidence supporting analytical generalization rather than as statistically generalizable causal effects.***

Keywords: Data Analytics, Strategic Decision-Making, Pricing Model, Management Accounting, Multinational Manufacturing, Case Study

1. Introduction

The increasing complexities of global markets have significantly increased the kinds of information that decision-makers require for their strategic decisions. As a result of this increase in complexity, manufacturing companies operate across various countries, currencies, supply networks, and cost structures. Therefore, while managerial experience can still be an important factor, it is often insufficient on its own. For example, pricing, determining where to produce products or services, identifying required levels of production capability, selecting sources for goods or services, allocating resources all now rely upon a manager's ability to collect and analyze operational and/or financial data.

Data analytics has evolved into a key part of managerial decision-making. Rather than simply depending upon historical reports, firms may now utilize analytical tools in order to gain understanding of their current performance, to forecast potential trends that will occur, and to analyze different courses of action. Descriptive analytics provides insight into what has occurred or is currently happening, predictive analytics utilizes historical data to predict future outcomes, and prescriptive analytics allows for the comparison of alternative decisions. Together, these approaches enable managers to transform fragmented information into a more structured and systematic decision-making process.

The use of analytics at the managerial level extends beyond the adoption of technological applications. According to Davenport (2006) companies that compete effectively through analytics possess not only a high level of analytical capability but also the organizational commitment, structures, shared data, and culture necessary to support fact-based decision-making. As such subsequent studies also suggest that the positive impact of analytics will rely upon complementary organizational capability rather than some type of analytical technology used in isolation. For instance, Brynjolfsson et al. (2021) show that the strength of the relationship between the use of predictive analytics and improved productivity depends upon having sufficient worker skills and the accumulation of IT capabilities. Therefore, analytics should be viewed as a component of the broader managerial structure through which information is translated into action.

In this regard, it is especially significant for multinational manufacturers. For example, if a manufacturer produces the exact same product across multiple countries, then they will likely experience significantly varying labor expenses, machine expenses, set-up expense requirements, scrap rates, exchange rate variances and logistical issues for each country. As the various types of data are typically being entered into separate computer systems or analyzed manually; preparing a quote for an order, along with finding the best place to produce a specific item, will be both slow and complicated. More importantly, managers may struggle to identify the specific cost drivers behind differences between production alternatives. An integrated analytical pricing model can address this problem by bringing operational and financial variables into a common calculation structure.

Despite the growing literature on big data analytics, business intelligence, and data-driven decision-making, the practical use of analytics in management accounting and multinational pricing decisions deserves further attention. Much of the existing literature examines analytics at the level of organizational capability or firm performance. Less attention has been given to how operational and cost data from different

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countries can be integrated into a pricing model and then used directly in quotation preparation and production-location decisions. Examining this process at the case level can therefore provide useful insight into how analytics becomes embedded in an actual managerial decision process.

Against this background, this study examines an analytics-driven pricing model used by a Netherlands-headquartered manufacturing company with production operations in Türkiye, Bangladesh, Hong Kong, India, China, and Vietnam. The model integrates product specifications, raw material consumption, machine and setup times, labor, scrap, packaging, exchange rates, and logistics data. Using a common product specification and a production volume of 1,000 units, the study compares the resulting cost structures across the six production locations and examines how the model supports quotation preparation and production-location decisions.

The study makes two main contributions. First, it links the broader literature on data analytics and strategic decision-making with management accounting by showing how operational and cost data can be transformed into comparable information for a specific strategic decision. Second, this work offers practical evidence from a multi-national production setting that demonstrates how analytical pricing models can enhance cost transparency and accelerate quotation development while also supporting the comparison of alternative locations for manufacturing. The study therefore treats data analytics not as a substitute for managerial judgment, but as an information infrastructure that can make strategic alternatives more visible, comparable, and easier to reassess as conditions change.

2. Literature Review and Conceptual Framework

2.1 Big Data and the Emergence of Data-Driven Management

Competitive pressure has increased the importance of firms' ability to respond to customers with the appropriate product, price, quality, and delivery time. Likewise, digitalization has dramatically increased the velocity at which these data can be processed. As a result, data generated by production systems, supply chains, customer interactions, financial transactions, digital platforms, other forms of connected technology offer new avenues for more informed decision making; however, in addition to those new avenues, they also pose significant challenges to how we traditionally process information.

The term big data generally refers to datasets whose volume, variety, or complexity exceeds the practical capacity of conventional data-processing methods. Its significance is not limited to size. Big data may include structured numerical records as well as text, audio, images, social-media activity, point-of-sale data, RFID records, GPS information, and other forms of operational and behavioral information. As Sanders (2014) notes, the managerial value of such data does not arise simply from collecting it. Value is created when analytical methods are used to identify patterns, relationships, and information relevant to decisions.

The differentiation between data and actionable information is particularly important for management. As organizations continue to collect data from an increasing number of diverse sources, they also have an increased need to combine, interpret, and apply the collected data, which creates a unique managerial skill. According to Akter et al. (2016), this challenge can be addressed by a comprehensive framework encompassing management, technology, talent, data governance, model development, and organizational capabilities. Therefore, rather than treating big data simply as a technological resource, its potential value relies on the organization being able to convert the dispersed pieces of information into insights that can affect operational and strategic decision making.

2.2 Data Analytics

Data analytics provides an analytical process through which raw data are transformed into actionable information for managers. According to Davenport (2006), as product, technology and manufacturing processes become increasingly similar in nature, companies may create differentiation by virtue of their capability to use information in analytical ways. Companies that compete with analytics will thus take an additional step from individualized analytical uses toward incorporating data-based reasoning into a wider range of strategic and operational processes.

Analytics is found at three primary levels. Descriptive analytics organizes a company's past and present information to determine "what has occurred." The predictive analytics level determines probable future occurrences based on identified trends within a company's historical data. Finally, prescriptive analytics will compare alternatives and provide recommendations for course of action. Each category has its own purpose; however, there are increased opportunities for management to use each of the three categories for better decision-making processes if they work together as part of an overall decision process, instead of as independent analytical tools.

Developing this kind of ability requires more than investment in software. The ability to collect, store, integrate, access, analyze and use analytical information; as well as the level of management's "ownership" or acceptance of using this information to decide; and the organizational culture support will also determine if the analytical information will be used in deciding. Therefore, Davenport (2006), identified four key components to build an organization's analytical capability including centralized analytical leadership, shared data, common analytical tools, and a strong organizational commitment. Similarly, Cao et al. (2019) showed how building an organization's information processing capabilities can lead to creating a competitive advantage by enabling better decision making. Additionally, Mikalef et al. (2017), argued that the business benefits from using big data analytics depend upon developing firm specific capabilities that are difficult for other firms to replicate.

2.3 Business Intelligence and Analytical Infrastructure

Business intelligence (BI) delivers most of the information structure needed for an organization's ability to make decisions based on data. To generalize, BI represents an aggregation of the organizational data, analytical tools, metrics, technologies, and reporting processes which enhances managers' understanding of business activity and support future action The main idea behind BI is easy to grasp: decision-making can be improved when relevant data are systematically collected, integrated, analyzed, and presented in an accessible and actionable form.

The development of BI has thus been very much tied to various technological innovations which include data warehousing, ETL processes, OLTP systems, OLAP applications, data mining, and reporting platforms (Wixom & Watson, 2010; Bany Mohammad et al., 2022). Each of these technologies can provide unique capabilities or functionality in support of the others. Operational systems are used to process and store the day-to-day operations of an organization. Data extracted from each of the operational systems is cleaned, transformed and integrated through the use of ETL technology. Data warehouses allows organizations to consolidate information from different organizational sources; and OLAP and data-mining applications allow managers to analyze relationships, patterns, and trends.

It is also essential to understand the differences between operational data processing and analytical information processing. OLTP's primary focus is on supporting normal business functions and daily transactional processes while OLAP enables analysis of the data across dimensions such as time, product, customer, location, supplier, price, and quantity. Data mining extends this capability by identifying patterns and relationships that may not be apparent from conventional reports. These tools collectively enable organizations to make a transition from recording transactions to evaluating them economically and operationally (Pazarçeviren et al., 2015).

BI has a wide range of applications within all areas of organizations that relate to different business activities such as budgeting, forecasting, financial evaluation, managing employee performance, understanding customers, coordinating processes within the supply chain, making HR decisions and risk management (Ranjan, 2009). Therefore, BI cannot be thought of solely as an Information Technology (IT) architecture. Rather it provides a data platform from which managers can link day-to-day operational activities with long-term business goals.

2.4 Data Analytics and Innovation

The relationship between analytics and innovation has received increasing attention. Digital leadership and platform digitalization can strengthen innovation performance by improving the organization's capacity to identify and respond to new opportunities (Benitez et al., 2022). Similarly, big data analytics and machine-learning applications allow firms to analyze customer feedback, test assumptions, and incorporate market information into product-development decisions (Mariani & Fosso Wamba, 2020).

Business analytics can enhance environmental scanning capabilities, allowing organizations to identify emerging technological and market developments before making investment decisions (Duan et al., 2020). Research in SMEs has shown that there is a positive relationship between the use of big data analytics and both technological innovation and organizational performance (Saleem et al., 2020). However, it is not the accumulation of data as the common mechanism behind all these findings; rather, it is the process of converting data into quicker learning processes and better-informed experimental processes.

2.5 Data Analytics and Firm Performance

A core issue addressed in the analytics research is whether or not an organization's use of analytical capability will ultimately improve a firm's overall performance. Theoretical models grounded in organizational information processing and dynamic capability theory suggest that analytics may contribute to improved performance by providing organizations with enhanced insight into their own internal and external environment; as such, this theoretical work also supports the notion that organizations can potentially embed successful applications of analytic insight into operational systems to enhance firm level performance. For example, Wamba et al. (2017) demonstrate that big data analytics capability can impact firm performance directly, but it can also do so indirectly via the enhancement of an organization's dynamic capabilities.

This distinction is key for understanding how and why analytical technologies are not in themselves a guarantee of enhanced financial results. The ability to achieve economic value from analytics depends on many variables including system quality, information quality, and the presence of organizational competency, managerial interpretation, and management's capacity to act upon analytics. Business value derived from big data analytics has been found to be positively correlated with both financial performance and market performance, and also positively correlated with levels of customer satisfaction (Raguseo & Vitari, 2018; Vitari & Raguseo, 2020). Therefore, it can be argued that analytics is best described as an enabling capability rather than as an independent predictor of overall performance.

2.6 Data Analytics and Supply-Chain Decisions

Supply chain management is a particularly relevant context for analytics, as decision-making frequently involves large volumes of operational data across suppliers, production facilities, logistics networks, inventories, and customers. Big data and predictive analytics were emphasized by Hazen et al. (2016), with regard to their use in managing supply chain environments. In addition, Dubey et al. (2019) demonstrate that an organization's analytical capability enhances its supply-chain agility and ability to respond to disruptions.

Analytics can improve information-processing capacity by bringing together data concerning demand, inventory, supplier performance, production, and logistics. Chen et al. (2021) provide evidence that big data analytics contributes to supply-chain decision-making, while Yu et al. (2018) associate data-driven supply-chain capabilities with financial performance. For multinational manufacturing firms, this analytical capability is particularly important because production-location decisions cannot be based solely on direct manufacturing costs.

2.7 Data Analytics and Marketing Applications

Marketing has arguably been one of the organizational functions most influenced by the development of analytics. Traditional transactional data are combined with a variety of new forms of digital customer data, such as website interactions, social media activity, videos, images, and other digital content. As noted by Shah and Murthi (2021), analytics capabilities have increased firms' understanding of customer behavior at an individual level allowing for more tailored product/service offerings.

2.8 Data Analytics and Management Accounting

The connection between analytics and management accounting is at the heart of this study. Management accounting has historically provided planners and managers with data for a number of purposes, such as; planning, controlling, evaluating performance, allocating resources, cost analysis, and supporting management decision making. BI and analytics extend this role by allowing management accountants to work with larger datasets, integrate financial and operational information, and evaluate alternative decision scenarios.

The work of Rikardsson & Yigitbasioglu (2018), supports the idea that BI and analytics technologies are significant in terms of their impact on management accounting, as a lot of the tasks influenced by technology, such as reporting, planning, forecasting and decision support have historically fallen into the management accounting area. The issue is not whether or not analytics replaces management accounting; it is how analytical tools will change the information that can be made available to management accountants and through what means that information enters managerial decisions.

Appelbaum et al. (2017) provide a useful framework by linking management accounting data analytics with the Balanced Scorecard. Their approach integrates descriptive, predictive, and prescriptive analytics with financial, customer, internal-process, and learning-and-growth perspectives. The connection is especially important for costing and pricing. Traditional costing information may explain what a product has cost in a particular facility, whereas an analytical pricing model can combine cost data with operational assumptions and compare what the same product would cost under alternative production scenarios.

2.9 Data Analytics and Human Resource Management

Human resources represent another area in which analytics has expanded the range of information available to managers. The use of HR analytics can help inform manager decision making with regards to many aspects of employees including, but limited to; workforce planning, productivity, skill requirements, retention, and employee development. However, due to various organizational challenges associated with integration of analytics into HRM, there are also limitations associated with HRM analytics. Specifically, the quality of the input data and managerial perceptions/acceptance of HRM analytics output will limit the utility of HRM analytics for a given manager (Shet et al., 2021).

Research also highlights the complementary relationship between technology and human capability. Brynjolfsson et al. (2021) find that predictive analytics is associated with higher productivity when supported by workforce skills and accumulated IT capital. Wang et al. (2019) similarly emphasize the interaction between analytical skills and organizational resources.

2.10 Data Analytics and Dynamic Pricing

Pricing represents a tangible form of analytics applied directly to management decisions. The use of predictive analytics, customer segmentation, and dynamic pricing enable companies to adjust to changes in their demand for goods/services, local and global market dynamics, as well as competitive behavior. However, international pricing also adds another dimension of complexity with factors such as currency fluctuations, different country-specific costs associated with production and transportation (logistics), available capacity, tax structures, and various local operational issues affecting all countries (Schill & Nixon, 2024).

However, for this current study, dynamic pricing will be viewed as a specific type of managerial process. This study does not consider algorithmically based real time pricing based on individual consumers. It instead considers an analytical costing and pricing model which allows a global manufacturing company to revise its cost assumptions and review potential plant locations prior to generating quotations.

2.11 The Role of Data Analytics in Strategic Decision-Making

Strategic decisions typically have a wide-ranging impact on an organization as well as involve high degrees of uncertainty and require information that is drawn from numerous different sources. Data analytics may be used in supporting strategic decision-making processes as it increases the ability for managers to find trends or patterns, compare options, test hypotheses and respond to changes in the environment. Research has documented the use of big-data analytics for strategic planning, managing risk, optimizing operations, purchasing/marketing and supply chain related decisions (Chen et al., 2022; Intezari & Gressel, 2017; Patrucco et al., 2023).

The literature also makes clear that analytical information does not eliminate managerial judgment. Strategic decisions involve uncertainty, qualitative considerations, and factors that cannot always be represented numerically. Analytics therefore functions most effectively as decision support: it improves the visibility and comparability of alternatives while leaving responsibility for interpretation and choice with management.

2.12 Synthesis of the Literature and Research Gap

Taken together, the literature establishes several relationships relevant to this study. First, data analytics expands organizational information-processing capacity by transforming dispersed data into structured decision information. Second, the benefits of analytics depend on complementary managerial, technological, and organizational capabilities. Third, BI and analytics increasingly overlap with the traditional decision-support role of management accounting. Finally, analytics can support strategic decisions by improving the visibility, comparability, and speed with which alternatives are evaluated.

However, there is a large conceptual gap between these different theoretical perspectives on analytics and the actual use of analytics for particular aspects of management accounting. A lot of existing studies have researched the analytics capability of organizations as well as the relationship between organizational performance, innovation, supply chain development and data driven decision making. Nevertheless, empirical research that links business intelligence (BI) and analytics to the management accounting process has been relatively limited; especially when viewed as it relates to the various stages involved in the management accounting decision process.

This paper addresses this conceptual gap through an in-depth examination of an analytics-driven pricing model that is utilized across multinational manufacturing networks. Instead of investigating whether analytics contributes to improved performance of firms in general terms, this paper investigates a specific method or mechanism to see how heterogeneous operational and cost data from six production locations are standardized, converted into comparable cost information, and used in quotation preparation and production-location decisions.

3. Problem Statement

Decisions concerning pricing and production location for products produced by multinational manufacturers involve combining various types of data from different countries, systems, and cost structures. Factors influencing the total cost of the same product include product specification, material usage, equipment, set-up requirements, direct and indirect labor, material waste, packaging, exchange rates, and logistics. Managers will have difficulty comparing alternative production locations when this type of data is scattered over multiple sites or analyzed independently. Therefore, although the issue is not just how much data are available but rather transforming disparate operational and financial data into common terms that allow them to make an appropriate management decision.

This problem becomes particularly relevant during quotation preparation. If relevant variables are collected and calculated manually, quotation preparation may require repeated communication between locations, multiple calculations, and successive revisions. The resulting delay can reduce decision speed and make the underlying sources of cost differences less transparent to management.

Therefore, the central research question that has been investigated is how an analytics-driven pricing model can integrate dispersed operational and cost data from multiple production locations, convert these data into comparable management accounting information, and support quotation preparation and production-location decisions.

3.1 Conceptual Model

The conceptual model is developed around the proposition that the managerial value of analytics arises through the transformation of dispersed operational and financial data into structured and comparable decision information. In this study, the analytics-driven pricing model acts as the analytical mechanism connecting production-related inputs with management accounting information and strategic decision-support outputs.

Decision Inputs
Product specifications; materials; machine and setup times; labor; scrap; packaging; exchange rates; logistics
Analytics-Driven Pricing Mechanism
Data integration and standardization; country-level cost calculation; cost-driver analysis; scenario comparison
Comparable Management Accounting Information
Country-level total costs; cost-component visibility; comparable cost structures; major cost drivers
Strategic Decision-Support Outputs
Cost transparency; production-location comparison; faster quotation preparation; scenario-based flexibility

Figure 1: Conceptual Model of the Research

The model does not assume a deterministic relationship between analytics and firm performance. It examines a more immediate and observable relationship: whether the analytical model changes the information available to managers and the process through which pricing and production-location alternatives are evaluated. The relationships represented in Figure 1 are therefore treated as analytical relationships rather than causal hypotheses.

4. Method

4.1 Research Design

This study adopts a qualitative single-case study design to examine how an analytics-driven pricing model is used within a real organizational decision process. The unit of analysis is the analytics-driven pricing and production-location decision process used by a multinational manufacturing company. The study does not seek to estimate the statistical effect of analytics on firm performance. Instead, it examines how operational and financial data are integrated within the pricing model, transformed into comparable country-level costs, and used in quotation preparation and production-location decisions.

4.2 Case Selection and Research Context

The case company is headquartered in the Netherlands and operates manufacturing facilities in Türkiye, Bangladesh, Hong Kong, India, China, and Vietnam. The purposeful selection for this research case provided a unique opportunity to analyze an analytics-based pricing model that would be

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used within an actual multinational production setting. The presence of six alternative manufacturing locations allows the study to compare the cost of the same product using a common analytical structure.

4.3 Data Sources and Data Collection

The empirical analysis utilizes operational and financial data input to the company's current pricing model as well as the output of country level costs for each country. Inputs considered in this research include product technical specification, raw material type and amount used, time required to produce products and set up machines, cost per hour of machine usage, labor hours required and labor costs incurred, amounts of scrap or waste allowed, types and quantities of ink and other auxiliary materials used in the printing process, packaging requirements and associated costs, currency of quotations, information related to exchange rates and logistics costs. Additionally, the quotation process is evaluated both prior to implementing the analytical pricing approach and after the implementation of the analytical pricing approach.

4.4 Analytical Procedure

The research followed an analytic approach that consisted of four stages. Initially, the structure of the pricing model was studied for purposes of identifying both the primary input data as well as the logical base of the calculations. Subsequently, the six production sites were analyzed by means of a single product with a common production volume of 1,000 units. This stage served to demonstrate how the individual sites differ from one another on the basis of their costs. Next, the composition of total cost was investigated so that it could be determined which cost elements are responsible for cost differences at the national level. Finally, the implications of the model regarding production quotations (quotation preparation), transparent costs, comparable production alternatives, visible cost drivers and scenario-based decision making were evaluated. As such, the research combined a descriptive cost analysis with a case-based process analysis.

4.5 Research Questions

RQ1: How does an analytics-driven pricing model make the costs of different production locations comparable in a multinational manufacturing environment?

RQ2: How does an analytics-driven pricing model affect quotation preparation and support production-location decisions?

RQ3: Which cost components contribute to differences in total cost across alternative production locations?

RQ4: What observable managerial and decision-support benefits does an analytics-driven pricing model provide in pricing and production-location decisions?

4.6 Validity, Reliability, and Research Limitations

A number of design decisions were made to enhance the consistency of the within-case comparison. The country-level analysis uses the same product specifications as well as the same level of production volume (1,000 units), with the same main raw material being utilized at each location; as such, costs are separated out by component. These design decisions do not address the inherent problems of using an individual case study approach. In addition to the inability to generalize from a statistical perspective, it should also be noted that while we have some data available for this study; these are not longitudinal data which would allow us to establish cause-and-effect relationships with respect to tender success, contribution margin, profit margins and/or long-term financial performance.

5. Findings and Discussion

5.1 Case Description and Company Profile

The case company manufactures multi-national label products in the Netherlands and is operational with manufacturing facilities located within the countries of Türkiye, Bangladesh, Hong Kong, India, China, and Vietnam, employing an estimated 2400 employees. Prior to implementation of analytical pricing model, quotation preparation was accomplished through manual calculation processes. Additionally, the company would need to gather information from multiple production sites that were geographically dispersed across the world and repeatedly revise quotations. As a result, preparing a quotation could take several weeks. In the application examined in this study, the same process was completed in approximately one hour using the analytical pricing model.

This reduction is one of the clearest observable process outcomes in the case. It should, however, be interpreted as an improvement in process speed rather than evidence of higher tender success or profitability, neither of which is directly measured in this study.

5.2 Structure of the Analytics-Driven Pricing Model

The pricing model works as a multivariable decision-support tool which integrates product, operational, and cost information from alternative manufacturing locations into a single analytical structure. Its purpose extends beyond calculating a selling price. In addition to determining the sales price for a given product, this model also allows managers to determine what it will cost to produce the same product in different manufacturing locations and to identify the cost components underlying those differences.

Table 1: Data Input Table

Data Input	
Date	12.21.2025
Quotation Currency	USD
Horizontal Count	18
Vertical Count	3
Up Count	54
Gross Label Width (mm)	23
Gross Label Length (mm)	100
Printing Plate Width (cm)	35
Printing Plate Height (cm)	50
Hot-Foil / Lamination Area Width	20
Hot-Foil / Lamination Area Length	20
Click Count	4

5.3 Product Specifications and Material Selection

After establishing the initial quotation parameters, the next step involves incorporating the technical specification of the product into the model. Variables such as product width, length, dimensions, and lamination requirements influence material consumption, production requirements, and waste calculations. The next stage identifies the principal raw material. In the application examined, carta solida is used as the common basic material across the six production locations.

Table 2: Material Selection Table

Cost / 1,000 Units

Production Location	Türkiye	Bangladesh	Hong Kong	India	China	Vietnam
Paper / Cardboard						
Material (1) · Paper / Label	Carta Solida	Carta Solida	Carta Solida	Carta Solida	Carta Solida	Carta Solida
Material (2) · Paper / Label	Blank	Blank	Blank	Blank	Blank	Blank
Material (3) · Paper / Label	Blank	Blank	Blank	Blank	Blank	Blank
Material (4) · Paper / Label	Blank	Blank	Blank	Blank	Blank	Blank

5.4 Order Quantity and Production Structure

For the application analyzed in this study, calculations are based on a common production quantity of 1,000 units across all six production locations. Holding quantity constant is essential for the cross-country comparison because it ensures that observed cost differences are not simply the result of comparing different production volumes.

Table 3: Product Quantity Table

Cost / 1,000 Units

Production Location	Türkiye	Bangladesh	Hong Kong	India	China	Vietnam
Accessories						
Gloss lamination (USD)	-	-	-	-	-	-
Hook (USD)	-	-	-	-	-	-
Rope (USD)	-	-	-	-	-	-
Other accessories (USD)	-	-	-	-	-	-
Front ink coverage	Dark	Dark	Dark	Dark	Dark	Dark
Back ink coverage	Matte	Matte	Matte	Matte	Matte	Matte
Total ink cost (USD)	Blank	Blank	Blank	Blank	Blank	Blank
Pantone, total cost (USD)	-	-	-	-	-	-
Hot foil 1 / lamination	Black metallic	Black metallic	Black metallic	Black metallic	Black metallic	Black metallic
Hot foil 2 / lamination	-	-	-	-	-	-
Die-cutting cost (USD)	-	-	-	-	-	-
Hot-foil die (USD)	-	-	-	-	-	-
Number of dies	-	-	-	-	-	-
Die type	-	-	-	-	-	-
Die production cost (USD)	-	-	-	-	-	-

The model subsequently identifies the operations required to manufacture the product at each location, including the machines through which the product passes, the number and sequence of operations, and relevant setup requirements. Although the product specification is held constant, the production process does not necessarily have to be identical across countries.

Table 4: Operations Table

Cost / 1,000 Units

Production Location	Türkiye	Bangladesh	Hong Kong	India	China	Vietnam
Operation 1 · Machine	**HP2 Indigo 2C**	**HP2 Indigo 2C**	**HP2 Indigo 2C**	**HP2 Indigo 2C**	**HP2 Indigo 2C**	**HP2 Indigo 2C**
Setup time (s)	0.08	0.17	0.08	0.08	0.08	0.08
Setup cuts per 1,000 units	-	-	-	-	-	-
Estimated machine hours	0.00	0.01	0.00	0.00	0.00	0.00
Operation 2 · Machine	**-**	**-**	**-**	**-**	**-**	**-**
Setup time (s)	0.00	0.00	0.00	0.00	0.00	0.00
Setup cuts per 1,000 units	0	0	0	0	0	0
Estimated machine hours	0.00	0.00	0.00	0.00	0.00	0.00
Operation 3 · Machine	**Blank**	**Blank**	**Blank**	**Blank**	**Blank**	**Blank**
Setup time (s)	0.00	0.00	0.00	0.00	0.00	0.00
Setup cuts per 1,000 units	0	0	0	0	0	0
Estimated machine hours	0.00	0.00	0.00	0.00	0.00	0.00
Operation 4 · Machine	**Blank**	**Blank**	**Blank**	**Blank**	**Blank**	**Blank**
Setup time (s)	0.00	0.00	0.00	0.00	0.00	0.00
Setup cuts per 1,000 units	0	0	0	0	0	0
Estimated machine hours	0.00	0.00	0.00	0.00	0.00	0.00

5.5 Finishing and Packaging

The Model will include activities that occur at the latter portion of a manufacturing process. Examples include cost for packaging; average quantity packaged per item packaged; total packaging time; and all related cost. Adding finishing and packaging allows a broader and more detailed cost basis for comparing each location's cost structure.

Table 5: Finishing Table

Cost / 1,000 Units

Production Location	Türkiye	Bangladesh	Hong Kong	India	China	Vietnam
Finishing						
Average units per box	Avg. 10K	Avg. 10K	Avg. 10K	Avg. 10K	Avg. 10K	Avg. 10K
Units packaged per hour	Blank	Blank	Blank	Blank	Blank	Blank
Material	0.73	1.06	0.06	0.73	0.06	1.85
Scrap (setup, production)	-	-	-	-	-	-
Consumables	1.04	2.91	3.42	3.82	3.42	6.24
Total material cost	**1.77**	**3.96**	**3.48**	**4.55**	**3.48**	**8.09**
Production labor	2.47	0.28	0.15	0.18	0.15	-
Setup labor	7.37	0.84	0.45	0.54	0.45	-
Subcontract labor	-	0.01	0.01	-	0.01	-
Total labor cost	**9.84**	**1.12**	**0.61**	**0.72**	**0.61**	**-**
General scrap rate	**10%**	**10%**	**10%**	**10%**	**10%**	**10%**
Total cost, 1,000 units	**12.90**	**5.64**	**4.54**	**5.86**	**4.54**	**8.99**

5.6 Cost Calculation and Cross-Country Comparison

After the technical and operational inputs have been entered, the model calculates the relevant cost components for the common production quantity of 1,000 units. These include raw materials, production labor, setup labor, machine-related requirements, waste or risk allowances, ink, foil, and packaging. The resulting cost information is consolidated in the Pricing Model Summary.

Table 6: Pricing Model Summary

Cost / 1,000 Units

Production Location	Türkiye	Bangladesh	Hong Kong	India	China	Vietnam
COST SUMMARY						
Material	0.73	1.06	0.06	0.73	0.06	1.85
Setup material	-	-	-	-	-	-
Production labor	3.02	0.91	0.88	1.01	0.88	1.47
Setup labor	7.37	0.84	0.45	0.54	0.45	-
Die	-	-	-	-	-	-
Subcontract labor	-	-	-	-	-	-
Ink	0.41	0.30	0.41	0.41	0.41	0.28
Foil	0.07	0.07	0.07	0.07	0.07	0.07
Die cutting	-	-	-	-	-	-
Packaging	0.02	0.02	0.02	0.02	0.02	0.02
Risk / scrap	1.29	0.36	0.21	0.31	0.21	0.41
TOTAL COST	**12.90**	**3.55**	**2.10**	**3.08**	**2.10**	**4.09**

For the same product and a production quantity of 1,000 units, total costs were USD 12.90 in Türkiye, USD 3.55 in Bangladesh, USD 2.10 in Hong Kong, USD 3.08 in India, USD 2.10 in China, and USD 4.09 in Vietnam. Hong Kong and China therefore have the lowest calculated total cost in this application, while Türkiye has the highest. The managerial significance of the model, however, lies not only in identifying the lowest-cost location. It also makes the composition of these totals visible, allowing management to examine why one location produces a different calculated cost rather than relying solely on the final figure.

5.7 Logistics and the Production-Location Decision

The model subsequently incorporates transportation costs associated with delivering the product to the customer's location. This extends the analysis beyond the cost incurred within the manufacturing facility. The location with the lowest manufacturing cost does not necessarily have to be the preferred production alternative once logistics are considered. The model should therefore be interpreted as decision support rather than an automated mechanism for selecting the country with the lowest manufacturing cost.

5.8 Application Results and Observed Decision-Support Effects

Three findings emerge directly from the application. First, the model creates cross-country cost comparability by bringing data from six production environments into a common calculation structure. Second, it improves cost-driver visibility by allowing differences to be examined at the level of individual cost components. Third, it substantially changes quotation preparation speed in the case examined: a process that previously required several weeks was completed in approximately one hour. Taken together, these findings indicate that the model provides an information infrastructure for pricing and production-location decisions. They do not establish that the model increases profitability or tender success.

5.9 Discussion by Research Question

5.10 RQ1: Cross-Country Cost Comparability

Comparability is achieved primarily through the standardization of decision inputs and calculation logic. The same product specification and production quantity are applied across six locations, and country-level cost information is expressed within a common calculation structure. This finding is consistent with the BI literature, which emphasizes integrating information from different organizational sources before it can effectively support managerial decisions (Wixom & Watson, 2010; Bany Mohammad et al., 2022). Analytics does not create comparability simply because more data are available; comparability emerges because relevant data are structured according to common assumptions and calculation rules.

5.11 RQ2: Quotation Preparation and Production-Location Decisions

The most directly observable result concerns quotation speed. In the application examined, quotation preparation was reduced from several weeks to approximately one hour. The model also supports production-location evaluation by allowing management to compare alternatives using a common analytical structure. This illustrates the distinction between decision automation and decision support: the model structures the available evidence, but managerial judgment remains necessary when the final decision includes factors beyond the cost calculation (Intezari & Gressel, 2017; Chen et al., 2022).

5.12 RQ3: Visibility of Cost Drivers

The model does not restrict the analysis to a single total-cost figure. Materials, production labor, setup labor, machine-related requirements, ink, foil, packaging, and risk/waste allowances are represented separately. The present study does not conduct a formal statistical decomposition capable of assigning a precise percentage of country-level cost differences to each driver. The results therefore show the visibility and relevance of individual cost components rather than establishing that any single component statistically explains most of the variation. This finding is consistent with the expanding decision-support role of management

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accounting (Rikhardsson & Yigitbasioglu, 2018; Appelbaum et al., 2017).

5.13 RQ4: Managerial and Decision-Support Benefits

The case identifies four principal benefits: cost transparency, systematic comparability, decision speed, and scenario-based decision support. These findings support the conceptual sequence proposed in the study: Decision Inputs → Analytics-Driven Pricing Mechanism → Comparable Management Accounting Information → Strategic Decision-Support Outputs.

5.14 Theoretical and Managerial Implications

In addition to being useful research findings, the results of this study also have three contributions to existing research. Firstly, these findings provide an illustrative example at a process level about how analytical capabilities are actually used in real managerial decisions. Secondly, these findings further strengthen the relationship between data analytics and management accounting; specifically, by demonstrating how operational data can be converted into prospective costs for alternative production scenarios. Finally, the use of comparable information across multiple countries has shown to be important in multinational companies when making decisions. The strategic value of analytics may arise as much from standardization and integration as from analytical sophistication itself.

For managers, the case suggests that analytical pricing systems should be developed based on comparability, traceability, and adaptability to a greater extent than speed. In addition, multinational manufacturers should refrain from evaluating their production sites using only direct manufacturing costs. Other logistics or location-based factors may change the comparative value of what appears as a very low cost alternative.

6. Conclusion

This paper examined what an analytics-based pricing model contributes to quotation development and location selection for manufactured products across multiple countries. The findings show that the model's benefit is not merely providing a price; it changes how cost and operating data enter the decision-making process. When product specifications, equipment and set-up requirements, labor, scrap, packaging, currency information, and logistics are presented within a single analytical framework, comparison across production sites becomes easier and the sources of cost variation become clearer. Three results are evident in this case: standardization enabled consistent comparison among production sites, the use of analytics substantially reduced the time required for quotation preparation, and greater cost transparency supported managers' ability to compare production locations rather than relying on aggregate cost figures alone. Rather than measuring overall company-wide performance, this case illustrates an intermediate step in how analytics can create managerial value: operational data from multiple locations are standardized into comparable management accounting information and used by managers to evaluate strategic decisions. While this research cannot demonstrate that analytics leads to higher profit margins or identifies the objectively best production choice, its contribution lies in showing how analytics can support better information architectures for these decisions.

6.1 Limitations

The research focuses on one multinational manufacturer as well as the application of that firm's pricing strategy. Therefore, the results are limited to an inability for statistical generalization across different types of organizations; industries; or supply chains. In addition to the limitations imposed by the lack of a longitudinal data set which would measure organization-wide outcomes prior to and subsequent to the introduction of the pricing strategy, there is no direct evidence to support the proposition that the time it takes to prepare quotations (reduced from several weeks to approximately one hour) has a positive effect on either tender conversion rates; sales; contribution margins; profits; or other relevant measures of financial success. In addition, while the research analyzes differences in individual cost elements there is no formal statistical decomposition of cross-country cost variations.

7. Future Research

Further analysis of how analytic-driven pricing models function across a multitude of organizations, industry types and manufacturing network environments will provide valuable information for future research. Longitudinal studies could track quotation preparation time, bid conversion rate, contribution margin, logistics cost, production-location changes, and profitability before and after implementation. Analytical pricing systems may also be studied to identify what type of organizational environment allows them to be effectively implemented. These factors include data quality, top-management support, employees' analytical capabilities, company culture, data-governance policies and employee-acceptance of the new pricing model. Lastly, various pricing-models using simulation, optimization methods, predictive-analytics and machine-learning techniques can be analyzed against the pricing model used in this current study where sufficient historical data is available.

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