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Adoption of Business Analytics as a Data-Driven Approach to Process Optimizations in Mechanical Manufacturing Companies' Operational Performance: Moderating role of Mechanical Technology Utilization

Muhammad Awais Bhatti[1*], Anvar Absamatov[2]
[1] Department of Management, School of Business, King Faisal University, Al-Ahsa 31982, Saudi Arabia
[2] Department of Economics, Termez University of Economics and Service, Uzbekistan

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ABSTRACT

The study objective was to test the adoption of business analytics as a data-driven approach to process optimizations in mechanical manufacturing companies' operational performance. The study also tested the moderating role of mechanical technology utilization. Data was collected from 320 employees of mechanical production manufacturing companies and analyzed using Structural Equation Modeling (SEM) with Smart PLS 4. The results showed that data acquisition and tool acquisition have positive and significant influence on the adoption of business analytics. Furthermore, perceived ease of use and perceived usefulness also positively and significantly influence adoption of business analytics. Adoption of business analytics also had a positive and significant influence on operational performance. Furthermore, mechanical technology utilization also positively moderates between adoption of business analytics and operational performance. The study with its specific findings strengthens the technology adoption theories by showing that data acquisition, tool acquisition, perceived ease of use, and perceived usefulness collectively drive business analytics adoption. They also extended operational performance theory by confirming that analytics adoption improves operational performance. Additionally, the moderating effect of mechanical technology utilization offers new theoretical insight into how digital mechanical integration enhances performance relationships. Furthermore, managers should invest in proper data and tool acquisition to support successful analytics adoption. Training employees to enhance ease of use and understanding of analytics tools will further increase adoption levels. Organizations should integrate mechanical technologies with analytics systems to maximize operational performance. These insights help mechanical firms design effective digital transformation and performance improvement strategies.

Corresponding Author:

Muhammad Awais Bhatti
Department of Management, School of Business, King Faisal University, Al-Ahsa 31982, Saudi Arabia
Email: mbhatti@kfu.edu.sa

1. Introduction

Operational performance (OP) refers to how companies efficiently and effectively use their resources to produce highly quality goods through minimizing waste, cost, and downtime (Truong et al., 2017). OP directly affects to the companies in compromising their ability through effectively managing their resources, and products that increase the customers' expectations in terms of their cost with compromising cost (Kenyon, 2025). In other ways, OP also enhances the internal process efficiency through reducing waste management and improving cost management, which increases companies sustainability in the competitive market (Oteri et al., 2023). Additionally, OP also serves as a critical link between organizational strategy and execution, which is ensuring that strategic goals are translated into tangible outcomes such as increased market share, customer satisfaction, and innovation capacity (Al Najjar & Qandeel, 2025). Furthermore, OP also increases the firm's ability to adapt the internal and external pressures, such as technological disruptions, fluctuating demand, and supply chain uncertainties, which enhances the long-term sustainability (Zhou et al., 2024). One of the most prominent factors to improve the OP is the adoption of business analytics (BA), which enables organizations to convert vast amounts of operational and production data into actionable insights for better decision-making (Chowdhury, 2024a). In the context of mechanical manufacturing, where operations rely heavily on machines, BA offers the potential to improve machine utilization, reduce downtime, and enhance overall operational performance (Chatterjee et al., 2024).

The adoption of BA in manufacturing companies is being influenced by various factors because the improvement of BA enhances the companies' OP (Chatterjee et al., 2024). Among factors, data acquisition refers to the systematic collection of structured and reliable data from machines, sensors, and production systems, which serves as the foundation for analytics processes (Chatterjee et al., 2024; Liu & Li, 2016). In addition, the tool acquisition means is providing and utilizing advanced analytics software, dashboards, and modeling platforms that allow firms to extract actionable insights from collected data (Liu & Li, 2016). In other words, perceived ease of use (PEOU) and perceived usefulness (PU) reflect the human and behavioral aspects of analytics adoption, emphasizing that systems must be intuitive and demonstrate clear operational benefits to ensure successful implementation (Isiaku & Adalier, 2024; Sandema-Sombe, 2019). These indicators improve the adoption of BA, which is integrating it into daily production and operational workflows. As the literature supported that when the companies have stronger BA adoption then it leads to improved OP, especially in the manufacturing companies (Chowdhury, 2024a). It is also supported that BA adoption enables companies to implement predictive maintenance, optimize production scheduling, monitor machine to improve the OP (Riipa et al., 2025). In addition, the effectiveness of BA adoption is also often contingent upon the utilization of mechanical technology, where high utilization of these resources ensures that analytics insights can be applied effectively, which increases the OP (Hossain et al., 2024). Therefore, study focused on moderation of mechanical technology utilization.

Despite the growing interest in the data acquisition, tool acquisition, PEOU and PU to improve operational performance but these studies still have various gaps that need to be addressed in the current study. Firstly, most of the prior studies on PEOU and PU have mainly concentrated on intention to use internet banking while a limited attention on the adoption of BA (Alshammari & Babu, 2025; Hussain et al., 2025; Nuralam et al., 2024; Yao & Wang, 2024). Also, perceived of ease of uses and PU have limited attention on OP. Therefore, this study extended the previous gaps to test impact on OP. Furthermore, prior studies also have major focus of data acquisition and tools acquisition on OP with a limited attention on adoption of BA (Mali, 2024; Paramita et al., 2024; Sahoo et al., 2025; Saraswat & Choudhari, 2025; Wong & Ngai, 2025). Therefore, this study extended prior gaps in current to test influence on BA adoption in improving OP.

In addition, prior studies also have often examine the factors like as data or tool acquisition (analytics capability) or PEOU and PU (from the Technology Acceptance Model, TAM), but rarely integrate these factors into a unified framework (Alshammari & Babu, 2025; Hussain et al., 2025; Nuralam et al., 2024; Sahoo et al., 2025; Yao & Wang, 2024). Therefore, this study combined these factors in a unified model. On the other hand, the relationship between BA adoption and OP is also inconsistent (Fowowe & Adedapo, 2025; RAHANUMA et al., 2025; Riipa et al., 2025; Saeed et al., 2025). These inconsistent findings highlight the need for an integrated model that can capture multiple dimensions of analytics adoption and their impact on performance in production-intensive environments. Therefore, this study added mechanical technology utilization as a moderating variable in the current study. Prior studies have paid limited attention to the moderating role of mechanical technology utilization, which could enhance or weaken the effect of analytics adoption on operational performance. While moderators such as data-driven culture have been studied (Wong & Ngai, 2025), the impact of machinery sophistication remains underexplored.

Lastly, prior studies also conducted on other sectors with a limited focused on the mechanical department manufacturing companies. To address this gap is integral because manufacturing companies are operated in those environment where the machine utilization directly effects to the companies competitiveness (Akhmetova, 2025) that is only possible when the companies have stronger OP. Therefore, this study tested the influence to influence of data acquisition, tools acquisition, PEOU, and PU as a data-driven approach to optimize the mechanical production operational performance. The moderating role of mechanical technology utilization was also tested in the current study. Through focusing on this relationship, theoretically, this study contributed an integrated model of analytics adoption that combines data and tool acquisition, PEOU and PU to improve OP through examining the moderating role of mechanical technology utilization, addressing gaps in prior research that focused either on single factors or general organizational contexts. From the practical point of view, this research also contribute to provide the significant insights for the mechanical manufacturing department managers which is highlighting how strategically leveraging analytics alongside advanced machinery could enhance production efficiency, machine utilization to OP which is enabling firms to remain competitive in increasingly technology-driven manufacturing environments.

The study was further divided into four chapters. Literature review was second chapter. Research methodology was third chapter. Forth chapter was the data analysis and results. The last chapter was study results discussion.

2. Literature Review

2.1 Theoretical Framework

Research framework of the study is being formulated primarily from the Technology Acceptance Model (TAM) and Resource-Based View (RBV) theory. According to the TAM, which provides a foundation on PEOU, and PU to influence to the business analytics (BA) (Liew et al., 2025; Olubiyi & Akinlabi, 2025). From the mechanical production context, PEOU reflects how the user-friendly tools help operators and managers in analyzing through using different software's which increases the company's operational performance (Cao et al., 2025)**.** PU represents the perceived value of analytics in improving operational efficiency, reducing downtime, and optimizing production processes (Cao et al., 2025). On the other hand, according to RBA company's operational performance could enhance through companies resources that are unique like as advanced analytics tools, robust data acquisition systems, and skilled personnel (Hussain et al., 2025). Both of RBA and TAM model theories explained that why the companies adopt to the BA to improve the operational performance particularly when the these are integrated with the mechanical production technologies (Thanabalan et al., 2025).

In addition to previous, contingency theory also incorporated for capturing the mechanical technology utilization as moderating role in between BA adoption and operational performance (Hentati et al., 2025). According to this theory, management practices are effectively depends on contextual factors in the mechanical production which increases the companies analytics insights that could implemented effectively adoption of BA to improve operational performance (El Arif & Tahiri, 2025). High mechanical technology utilization allows firms to act on predictive maintenance alerts, optimize machine scheduling, and improve product quality to improve the operational performance through improve the adoption of BA (Pang et al., 2025). The study focused on three theories namely TAM, RBV, and contingency theory where the proposed model not only explains the BA adoption drivers but also tested impact on the OP through highlighting the moderating role of mechanical technology utilization that is filling a notable gap in the literature where prior literature particularly in the mechanical operational department. The above relationship variables are depicted in Figure.1.

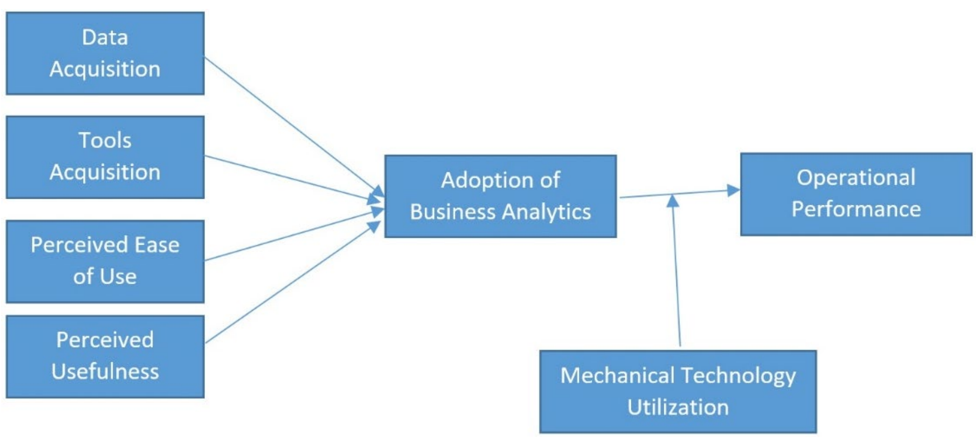

Figure 1: Study Model

3. Hypothesis Development

3.1 Data Acquisition and Business Analytics Adoption

Data acquisition that is being referred to the process and systems through which firms collect and manage data from the diverse operational sources (Xu et al., 2020). In manufacturing, particularly mechanical production environments, a robust data acquisition infrastructure is crucial because machines continuously generate vast amounts of data; if this data is not captured or is of poor quality, analytics outputs will be unreliable (Downey et al., 2015). The ability to acquire accurate data enables companies to build predictive models that anticipate machine failures, optimize scheduling, and maintain consistent production quality (Mali, 2024). Literature also supported the importance of data acquisition for increasing the BA adoption (Xia et al., 2023), because companies without accurate, timely, and integrated data, analytics platforms may produce low-value insights, leading to user distrust and resistance (Liu & Li, 2016; Yun et al., 2021). Furthermore, companies with the efficient data acquisition also support to real time monitoring that is important in mechanical operations to prevent equipment downtime and ensure production continuity. In addition, Liu and Li (Liu & Li, 2024) found that data acquisition is one of the most critical enablers for BA adoption, because poor data quality can introduce significant barriers to implementation and scaling. Liu and Li (Liu & Li, 2024) empirically found that data infrastructure and data collection capability significantly predict BA adoption in firms. Furthermore, Chatterjee et al. (Chatterjee et al., 2024) study also demonstrated in a manufacturing setting that analytics applied to machine sensor data led to improved operational efficiency, reinforcing that effective data acquisition is a foundational capability for BA adoption. These prior studies highlighted that in the mechanical production, data acquisition enhances companies' adoption of BA and accordingly study has hypothesis below,

H1: Data Acquisition significantly influence to adoption of business analytics.

3.2 Tool Acquisition and Business Analytics Adoption

Tool acquisition, which referred to the procurement and deployment of analytical platforms, software, and infrastructure. From the RBV perspective, these tools helps to represent the valuable assets which are properly integrated and aligned, which allow organizations to extract strategic value from their data (Chatterjee et al., 2024). In mechanical production, tools need to integrate with machine controls and sensor systems to translate insights into actionable production adjustments, such as modifying cutting speeds or machine operating sequences (Chaudhuri et al., 2024). Prior literature also highlighted that companies with stronger tools acquisition also improves the adoption of BA (Bauskar, 2024). In addition, advanced tools also increase the scenario analysis and various simulations which are improves to increase the mechanical production in the BA adoption (Chatterjee et al., 2024). Other study also highlighted that when tools are well-matched to business processes and provide clear, actionable insights adoption rates rise then it increase the company's adoption of BA (Chaudhuri et al., 2024) OP. Min and Lea (Min & Lea, 2024) empirically also found that analytics tools positively influence BA adoption in manufacturing firms. Furthermore, real-world frameworks in manufacturing highlight how machine utilization and analytics tools together enhance BA which increases the operational performance (Alanudin, 2024). This underscores that tool acquisition in mechanical production is both a technical and strategic necessity and accordingly hypothesis is,

H2: Tool Acquisition significantly influence to adoption of business analytics.

3.3 Perceived Ease of Use and Business Analytics Adoption

PEOU refers to the degree to which the potential user believes that using a system will be free of effort (Isiaku & Adalier, 2024). In a BA context, PEOU refers to how simple and intuitive users find analytics tools to increase the operational performance. High PEOU reduces anxiety and frustration among operators and managers, which is particularly important in mechanical production environments where operators may not have advanced data analytics training (Gharaibeh & Md Kassim, 2024). PEOU is important for the BA adoption because when the users perceive analytics are easy to use then they are engaged with more effective analytical skills, which increases the company's performance (Chaudhuri et al., 2024). Companies with lower perceived efforts reduces the resistance, training costs, and uncertainty, which helps to accelerate adoption across teams (Putro & Takahashi, 2024). Further, empirical studies highlighted that usability of analytics tools and the intuitiveness of dashboards are cited in practitioner and case-study literature as key challenges when implementing analytics in operations (Luo et al., 2024). Moreover, advanced manufacturing research emphasizes that ease of use in real-time monitoring tools is essential for shop-floor operators to trust and act on analytics insights (Nuralam et al., 2024). This highlights that PEOU is not only a usability concern but also a critical determinant of adoption success in production environments and accordingly hypothesis is.

H3: Perceived ease of use significantly influences to adoption of business analytics.

3.4 Perceived Usefulness and Business Analytics Adoption

Perceived usefulness (PU) is being defined through the extent where a user believe that using a system could increase the BA. PU is being reflected the beliefs where they found that analytical tools are significantly improves the production performance through improve the companies the analytical capabilities (Nuralam et al., 2024). Companies with the stronger PU increase the motivation of employees and managers to increase their engagements towards the BA that could improve the companies operational performance (Hussain et al., 2025). PU also enhances the rational for the management in management and allocation of resources in integration the BA in their mechanical production operations through increasing investment in the training and complementary technology (Năstase et al., 2024; Raman et al., 2024). In o other way, PU is also critical because the perception that analytics will deliver tangible benefits increases both initial adoption and sustained use (Raman et al., 2024). In the setting of mechanical production department perspectives, where production processes involve complex machines and precise tolerances, the perceived benefits of BA are often highly visible and measurable (Khashan et al., 2025). Thus, PU serves as a bridge between technical capabilities and practical operational gains. Alshammari and Babu (Alshammari & Babu, 2025) empirically found that PU significantly predicts adoption in manufacturing firms, which highlighting the role of value perception in shaping user behavior. Similarly, Yaseen et al. (Yaseen et al., 2025) illustrates in mechanical engineering production that when predictive analytics are perceived as valuable in improving quality and efficiency, employees are more likely to integrate them into their routines. These studies demonstrate that perceived usefulness is both a psychological motivator and a practical facilitator for BA adoption in the mechanical production context and accordingly hypothesis is,

H4: Perceived usefulness significantly influences to adoption of business analytics.

3.5 Adoption of Business Analytics and Operational Performance

Adoption of BA is being referred to the degree where the organizations has institutionalized analytics within the operations in their daily decision-making, process optimization, and resource allocation (Chaudhuri et al., 2024). The adoption of BA also means to embedding analytics into machine operation, scheduling, maintenance planning, and quality control (Riipa et al., 2025). Organizations that have fully adopted BA can respond quickly to production anomalies, anticipate equipment failures, and optimize throughput efficiently (Chowdhury, 2024a). In response to this, prior studies have also found that BA adoption increases the company's OP (Chaudhuri et al., 2024). Other research also identified that BA also minimizes unplanned downtime, process optimization improves throughput and consistency, and data-driven scheduling maximizes utilization of mechanical resources (Chaudhuri et al., 2024). BA also supports organizations' capabilities that could can incrase operational inefficiencies through integrating analytics insights directly with machine operations. Firms in mechanical production can achieve measurable gains in efficiency, quality, and responsiveness. (Chowdhury, 2024b) empirically found that BA applied to machine sensor data improved manufacturing efficiency through reducing unplanned downtime and increasing throughput. Similarly, Komolafe et al. (Komolafe et al., 2024) also found positive influence of BA adoption on operational efficiency. These studies collectively indicate that BA adoption translates into concrete operational benefits, though most research has focused on general manufacturing rather than mechanical production specifically, leaving a gap in context-specific empirical evidence and accordingly hypothesis is below,

H5: Adoption of business analytics has significant influence on operational performance.

3.6 Moderating Role of Mechanical Technology Utilization

Prior studies have shown that the relationship between the adoption of business analytics and operational performance is not clear, highlighting that further study need to address gap. Therefore, this study used mechanical technology utilization as a moderating variable. Mechanical technology utilization, which consisted of the intensity and effectiveness of mechanical production technologies in an organization (Bayraktar et al., 2024; Chaudhuri et al., 2024). Companies with highly utilization of machine technology implies that companies have greater level technology that could be used efficiently and integrated in the production processes in ways that allow analytics insights to be operationalized. Chen et al. (Chen et al., 2024). It has been found in the literature that BA alone could not effectively improve the OP unless insights can be applied directly to machines (Riipa et al., 2025). Therefore, the level of mechanical technology utilization is critical in determining the ultimate impact on OP (Mohammed et al., 2024). Because when the companies' machine technology utilization is high then the analytics insights can be executed promptly to enhance OP (Chowdhury, 2024a). Companies that have poorly maintained machines, then the company's potential of BA adoption to enhance OP is constrained, as analytics insights cannot be fully translated into physical actions (Alonge et al., 2024). In other perspectives, study on BA and OP was conducted and found positive and significant relationship and further they highlighted that further relation needs to be addressed with moderating effect. Despite theoretical and empirical importance, the moderating role of mechanical technology utilization has been largely underexplored. Various studies have been explored the predictors of BA, while these studies have not investigated how physical production technology intensity affects the adoption–performance link. Chen et al. (Chen et al., 2024) noted that predictive maintenance and real-time analytics maximize OP only when mechanical systems are adequately utilized. This represents a clear gap in the prior literature that mechanical technology utilization could be used moderating variable and accordingly a hypothesis is formulated below,

H6: Adoption of business analytics and operational performance is significantly moderated by mechanical technology utilization.

4. Research Methodology

To test the study hypothesis, the researchers employed the deductive quantitative approach. It provides objective, measurable, and generalizable results through systematic data collection and statistical analysis (Strunk, 2024). Furthermore, there are two cross-sectional and longitudinal research designs. From these, with respect to cross-sectional design, data was collected on one point while using survey instrument. While, in longitudinal research design data is being collected through using multiple time periods (Hunziker & Blankenagel, 2024). It is cited in the literature that when the researchers have a survey-based study then the cross sectional research design is considered to be effective for the hypothesis testing more significantly (Ventura & Köbis, 2024).

4.1 Survey instrument and data collection

The survey instrument was taken from existing literature. Data acquisition comprised four items, and tool acquisition comprised 3 items, and these items were drawn from the study of (Chaudhuri et al., 2024). Perceived ease of use was comprises 4 items, and perceived usefulness was comprises from four items, and these items were comprises from (Rejikumar et al., 2020). Adoption of business analytics were comprises from 5 items of (Chaudhuri et al., 2024). Operational performance were comprised from seven items of (Wong & Ngai, 2025). Lastly, technology acquisition was comprised from 4 items of (Qureshi et al., 2023). Each of the above items was measured on five point Likert Scale**.**

Study population was comprised employees which were working in the mechanical department of various manufacturing companies. From the non-probability sampling techniques, researchers employed the convenience sampling technique which was employed due to its accessibility in reaching respondents who were readily available and willing to participate (Golzar et al., 2022). The actual sample size was 390 questionnaires, which were distributed among the employees of the mechanical department of manufacturing companies. Out of the 390 questionnaires disseminated, a total of 320 comeback which is representing a sufficiently robust sample size for ensuring reliable and meaningful statistical insights into the operational performance dynamics within the selected organizations (Golzar et al., 2022).

5. Data Analysis and Results

Data was analyzed in both descriptive and inferential perspectives. Descriptive analysis was conducted through SPSS and inferential analysis was conducted using Smart PLS 4.

5.1 Demographic Profile

The demographic characteristics (Table 1) of the mechanical production department of the manufacturing companies have been highlighted in this section. Results shown that there are 81.9% respondents are belongs to the males while 17.2% respondents are female. Within the age group, majority of the respondents are in the age of 30–39 age group (44.1%), followed by those aged 20–29 (26.3%) and 40–49 (22.5%). From the educational perspectives, more than half hold a bachelor's degree (52.8%), while others possess diplomas (22.8%), master's degrees (18.1%), or additional certifications (6.3%). Job roles are mainly concentrated among mechanical engineers (49.4%) and technicians (30.0%), with supervisors (13.1%) and managers (7.5%) representing smaller segments. Respondents also show varied experience levels, with the largest group having 3–7 years of experience (37.2%), followed by those with 8–12 years (27.8%), more than 12 years (17.8%), and less than 3 years (17.2%). The participants come from different types of manufacturing companies, predominantly automotive manufacturing (36.9%), heavy machinery (23.8%), electronics/equipment production (20.9%), and metal fabrication (18.4%).

Table 1(a): Demographic Profile

Category	Sub-Category	Frequency	Percentage
Gender	Male	262	81.9%
	Female	58	17.2%
Age Group (YRs)	20 to 29	84	26.3%
	30 to 39	141	44.1%
	40 to 49	72	22.5%
	Above 50 years	23	7.2%
Education Level	Diploma in Mechanical Engineering	73	22.8%
	Bachelor's Degree	169	52.8%
	Master's Degree	58	18.1%
	Other Certifications	20	6.3%
Job Position	Technician	96	30.0%
	Mechanical Engineer	158	49.4%
	Supervisor	42	13.1%
	Manager	24	7.5%

Table 1(b): Demographic Profile

Category	Sub-Category	Frequency	Percentage
Years of Experience	Less than 3 years	55	17.2%
	3–7 years	119	37.2%
	8–12 years	89	27.8%
	More than 12 years	57	17.8%
Type of Manufacturing Company	Automotive Manufacturing	118	36.9%
	Heavy Machinery	76	23.8%
	Metal Fabrication	59	18.4%
	Electronics / Equipment Manufacturing	67	20.9%

5.2 Measurement Model

5.2.1 Convergent Validity

The study employed Partial Least Squares (PLS)-Structural Equation Modeling (SEM) using Smart PLS 4. The analysis was conducted in two measurement and structural models. The measurement model (Figure 2) results highlight that the survey fulfilled the requirements of the measurement model. Hair et al. (Hair et al., 2019) highlighted that composited reliability (CR) values must be higher than 0.70. Furthermore, the average variance extracted (AVE) construct values are recommended from above 0.50. In other words, Hair et al. (Hair et al., 2019) also recommended that factor loadings must also be greater 0.50, and results showed that values are greater than the recommended values, which indicates that the measurement model exhibits acceptable reliability and convergent validity in Table 2. Furthermore, variance inflation factor (VIF) values are also less than 5 which shown that there is no issue of multicollinearity (Hair et al., 2019). Results are predicted in Table.2 below,

Table 2: Convergent Validity

Variable	VIF	Cronbach's Alpha (α)	CR	AVE
DTA	1.341	0.862	0.881	0.632
PU	1.432	0.873	0.892	0.671
PEOU	1.672	0.854	0.873	0.643
MTU	…….	0.862	0.882	0.664
DA	1.732	0.783	0.783	0.732
TA	2.432	0.893	0.782	0.681
OP	……	0.882	0.901	0.702

Note: DTA-Adoption of Data Analysis, PEOU-Perceived Ease of Use, Perceived Usefulness, Mechanical Technology Utilization, Operational Performance.

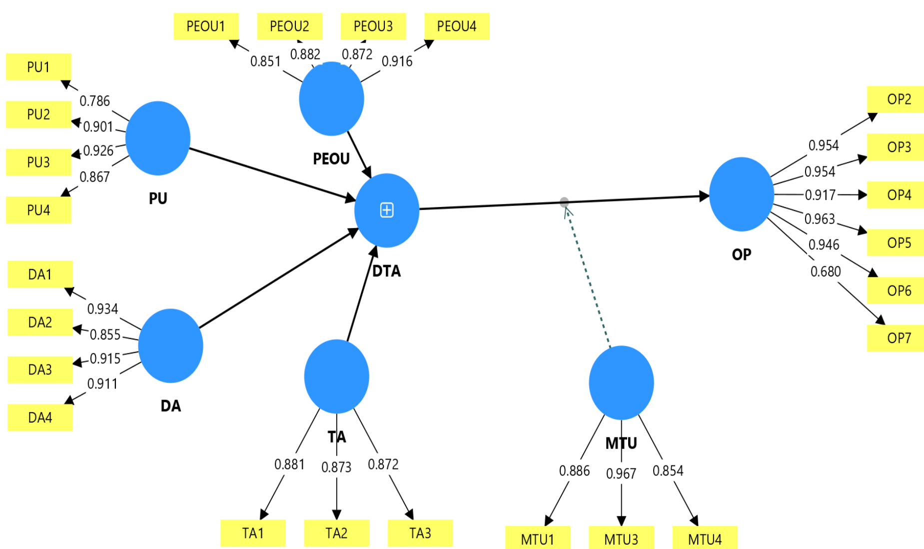

Figure 2: Factor Loadings

5.2.2 Discriminant Validity

The Fornell–Larcker criterion results demonstrate satisfactory discriminant validity among all constructs. According to Fornell and Larcker (Fornell & Larcker, 1981), the square root of AVE must be greater than the diagonal values, which shows the constructs' discriminant validity. Table 3 diagonal values are higher than the values below, which highlights discriminant validity.

Table 3: Discriminant Validity

Construct	DTA	SU	POB	MTU	OP
DTA	0.794				
PU	0.612	0.819			
PEOU	0.581	0.632	0.800		
MTU	0.553	0.573	0.602	0.812	
OP	0.492	0.542	0.564	0.533	0.836

5.3 Hypothesis Results

Next process after testing the validity of the construct is hypothesis testing. From the hypothesis testing, DA has positive (β = 0.421, t = 5.121) influence on DTA in manufacturing companies. Furthermore, TA also positively (β = 0.362, t = 4.283) influence to DTA. PEOU also positively (β = 0.293, t = 3.654) influence to DTA. PU also exhibits positive influence (β = 0.454, t = 5.785) influence to DTA. Furthermore, DTA also positively (β = 0.512, t = 6.246) effect to OP. Mechanical technology utilization significantly positively (β = 0.331, t = 3.973) moderates the relationship between DTA and OP. Above results are depicted in Table 4 and Figure 3.

Table 4: Regression Results

Relationship	B	SE	t-value	p-value	Result
DA → DTA	0.421	0.082	5.121	0.000	Supported
TA→ DTA	0.362	0.084	4.283	0.000	Supported
PEOU→ DTA	0.293	0.079	3.654	0.001	Supported
PEOU→ DTA	0.454	0.078	5.785	0.000	Supported
DTA→ OP	0.512	0.082	6.246	0.000	Supported
DTA*MTU → OP	0.331	0.083	3.973	0.000	Supported

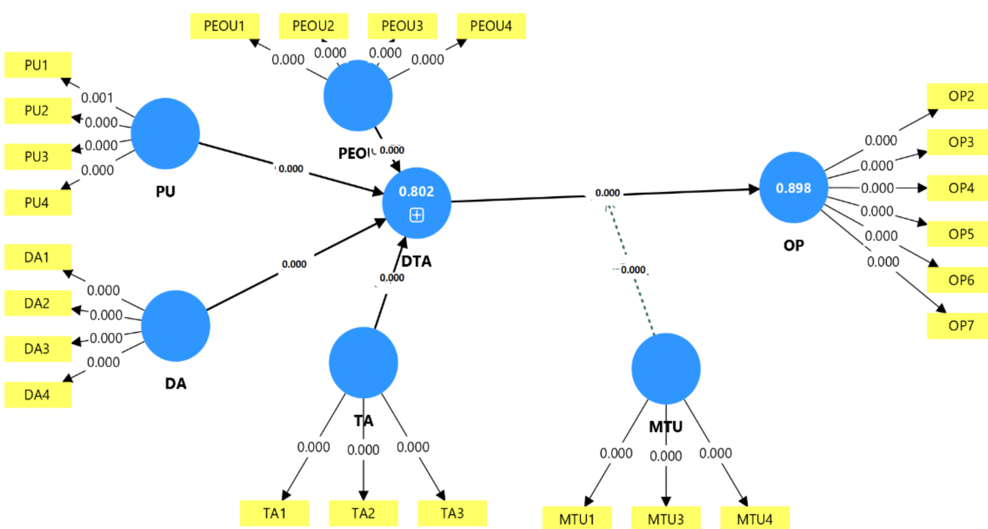

Figure 3: Structural Model

6. Discussion

The study objective was to test the DTA as a data-driven approach to process optimizations in mechanical manufacturing companies' OP. The study also tested the moderating role of MTU. Objective results indicated that data acquisition has a positive and significant influence on the DTA in the manufacturing companies. These results shown that companies with the better data collection mechanism are able to implement analytics effectively because it increases the quality of structured data which ensures that better decision making can be applied efficiently, reducing downtime and improving production reliability. Liu and Li (Liu & Li, 2016) found the same results where they emphasized that firms with systematic data acquisition infrastructure experience smoother analytics integration, while (Thanabalan et al., 2025) also reported that manufacturing companies with robust data systems achieve higher operational efficiency. Prior studies and current study results indicated that manufacturing companies should focus on integrating data acquisition across all mechanical processes, including machine status, energy consumption, and production rates, to provide a strong foundation for analytics adoption. Moreover, training employees to collect, interpret, and utilize this data ensures better alignment between technological infrastructure and operational objectives which could improve their analytical skills to improve companies' competitive advantage.

Further, study demonstrated that tool acquisition significantly effects to DTA. These results shown that availability of advanced analytics platforms, dashboards, simulation software, and predictive modeling tools enables manufacturing firms to process complex operational data efficiently and derive actionable insights. Accordingly, companies with the stronger tools allows a real time monitoring, performance tracking and decision-making optimization, which is particularly critical in mechanical production with multiple machines and operations running concurrently. The result is consisted with prior study of (Gangwar, 2020) where they highlighted that without appropriate analytical tools, even high-quality data may remain underutilized. Thanabalan et al. (Thanabalan et al., 2025) study also further argued that firms with flexible, user-friendly tools reduce barriers to adoption, improving collaboration between production managers, engineers, and shop-floor operators. These study emphases that manufacturing companies should invest in analytics solutions that are compatible with their mechanical systems, scalable to production complexity, and customizable to specific operational metrics. Tool acquisition also encourages experimentation with advanced analytics techniques, such as predictive maintenance and process simulation, which can improve quality, reduce waste, and optimize machine utilization.

Further results highlighted that PEOU also played a significant role in increasing the DTA. In manufacturing environments, where operators often have varying levels of technical expertise, user-friendly and intuitive analytics platforms significantly reduce resistance to adoption. When employees perceive that these tools are easy to use then they explore analytics insights into production decision-making to improve OP. The results is consisted with the following study of Gharaibeh and Md Kassim (Gharaibeh & Md Kassim, 2024) where they found that easiness in technology increases the perception BA techniques of the business. In the same vein, PU also significantly increases the DTA by demonstrating tangible benefits, such as improved machine efficiency, reduced downtime, cost savings, and enhanced product quality. This is aligned with the studies of (Alshammari & Babu, 2025; Hussain et al., 2025; Nuralam et al., 2024; Yao & Wang, 2024), who highlighted that employee perceptions of usability and operational value strongly influence technology acceptance. They also emphasized that in manufacturing, aligning analytics tools with operator capabilities ensures higher adoption rates and better utilization of insights. These prior studies emphasize that the manufacturing companies should implement training programs, provide user manuals, and offer ongoing support to increase the PEOU which could encouraging long-term adoption across production teams.

Further study confirmed that DTA also positively and significant increase the OP in manufacturing companies. Firms implementing analytics experience measurable improvements in efficiency, through put, quality, and resource utilization. Analytics enables predictive maintenance to reduce machine downtime, optimal scheduling to maximize productivity, and real-time process monitoring to ensure consistent product quality. (Aprijal et al., 2024) supported above findings where they highlighted that manufacturing firms applying predictive analytics achieved higher machine utilization and efficiency. Dias et al. (Dias et al., 2025) also emphasized that analytics adoption allows firms to adopt data-driven operational strategies, such as adjusting machine parameters dynamically based on production feedback, minimizing defects, and improving energy efficiency. Manufacturing companies should therefore integrate analytics into core operational processes, linking insights directly to mechanical production activities. In addition, fostering a culture of data-driven decision-making ensures that analytics outputs are consistently used to improve daily operations, creating a continuous cycle of performance enhancement. Therefore, it is enforcing that manufacturing companies should has have stronger predictors of business analytics that could increase the OP to increase the company's competitive advantage.

Lastly, the moderating effect results shown that mechanical technology utilization also has significantly moderated between the DTA and operational performance. This result indicated that companies along the usage of modern technology are able to translate analytics insights into operational improvements which ensures that technology is an effective way to improve the company's overall operational performance. Wolniak (Wolniak, 2024) also highlighted the same view that analytics alone is insufficient unless physical production systems are efficiently used. Min (Min, 2021) also emphasize that manufacturing firms with high-intensity machine utilization can fully leverage predictive insights, resulting in increased throughput, reduced operational costs, and improved quality. Prior literature also found that information significantly moderates. This result highlighted that companies must not only adopt analytics but also optimize machine scheduling, maintenance, and operational practices to maximize the impact of analytics insights. Ensuring high machine utilization allows predictive analytics to anticipate failures, optimize production flow, and reduce idle time, creating tangible performance gains. Therefore, aligning analytics adoption with effective mechanical technology usage is crucial for achieving sustainable competitive advantages in manufacturing operations.

7. Implications and Future Directions

This study contributes theoretically to how businesses adopt business analytics in their mechanical manufacturing processes. Firstly, by extending the technology acceptance model through the significant influence of PU and PEOU on DTA in manufacturing firms. This confirms the significance of human perception of system usability and operational benefits for the successful adoption of technology. Secondly, the current study supports the resource-based view, which considers technological resources as analytics tools, and the data acquisition system as a strategic asset for companies, which plays a key role in the optimization of the production process to achieve sustainable competitive advantage. Thirdly, this study also validated the factors that contribute towards the successful adoption of business analytics by emphasizing the significance of IS constructs in the industrial environment where humans interact with mechanical systems. Lastly, this study also contributes to the moderation theory by signifying the role of mechanical technology utilization in operational performance and DTA, which shows that the operational context poses the significance of technology adoption and physical resources in manufacturing operational performance.

From the practical perspective, study also contributed that companies should have proper investment on the robust data acquisitions which is important to provide a strong and accurate production data which always facilitates to the companies for predictive maintenances and real time decision making. Study also contributed that companies should acquire and implement an effective tool which allows to the engineers and operators to derive actionable insights from operational data, optimize machine performance, and improve quality and energy efficiency. Ensuring that analytics platforms are user-friendly and supported by training programs enhances adoption among operators and engineers, reduces resistance, and promotes consistent utilization of insights in mechanical production processes. Finally, study also contributed to optimize the mechanical technology which essential for the firms to ensure that machines, robots, and automated lines are fully utilized and integrated with analytics insights to maximize operational performance, minimize downtime, and improve throughput. Mutually, these theoretical and practical implications provide a roadmap for mechanical manufacturing companies to leverage business analytics effectively and enhance operational performance.

Study with significant contributions still have various gaps that need to be addressed in future research. Firstly, the study did not test the mediating effect of the DTA, which limited the predictive relevance of the study. Therefore, future research could test the mediating effect of the DTA to increase the model's predictive relevance. Secondly, the study did not employ a longitudinal research design for data collection, which would have allowed for testing in multiple time frames. A key strength of a longitudinal research design is its ability to track changes over time, allowing stronger insights into cause-and-effect relationships. Therefore, future research needs to be addressed on a longitudinal research design. Lastly, the study focused on a quantitative approach while ignoring a qualitative approach. Therefore, further research needs to be conducted on a mixed methods approach to increase the study scope.

8. Conclusion

The study objective was to test the DTA as a data-driven approach to process optimizations in mechanical manufacturing companies' OP. The study also tested the moderating role of MTU. The regression results shown that DTA and TA increase the DTA. Furthermore, PEOU and PU also increase the DTA. In addition, DTA also increases the OP. Furthermore, MTU also positively moderates between DTA and OP. The study with the specific findings strengthens the technology adoption theories through showing that DA, TA, PEOU, and PU collectively drive BTA. They also extended the OP theory by confirming that analytics adoption improves operational performance. Additionally, the moderating effect of mechanical technology utilization offers new theoretical insight into how digital mechanical integration enhances performance relationships. Furthermore, managers should invest in proper DA and TA to support successful analytics adoption. Training employees to enhance ease of use and understanding of analytics tools will further increase adoption levels. Organizations should integrate mechanical technologies with analytics systems to maximize operational performance. These insights help mechanical firms design effective digital transformation and performance improvement strategies.

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