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The Impact of AI-BA Opacity on Operational Inefficiency: Examining the Mediating Roles of AI Utilization Inefficiency and Organizational Resistance to AI

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Abstract
Despite the growing adoption of Artificial Intelligence–Integrated Business Analytics (AI-BA) in organizational processes, empirical evidence reveals that such technological integration can inadvertently lead to operational inefficiencies. This study investigates the paradoxical relationship between AI-BA and operational inefficiency by examining the mediating roles of AI utilization inefficiency and organizational resistance to AI. Anchored in the Technology-Organization-Environment (TOE) framework, the study adopts a quantitative, cross-sectional design, surveying 343 senior professionals from manufacturing firms registered with the Lahore Chamber of Commerce and Industry (LCCI), Pakistan. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to test the hypothesized relationships. The findings demonstrate that AI-BA significantly contributes to operational inefficiency, both directly and indirectly. Notably, AI utilization inefficiency and organizational resistance to AI emerge as significant mediators, revealing that underutilization of AI tools and institutional resistance hinder the realization of expected operational benefits. These results challenge deterministic assumptions of AI-driven performance improvements, emphasizing instead the critical importance of organizational readiness, cultural alignment, and effective change management.

Keywords: AI-Integrated Business Analytics, AI Utilization Inefficiency, Operational Inefficiency, Organizational Resistance to AI

Introduction
The infusion of artificial intelligence (AI) into business systems has emerged as a transformative force in reshaping organizational practices. Scholars and practitioners alike have increasingly turned their attention to the integration of intelligent technologies in enterprise decision-making processes, recognizing their potential to streamline operations, enhance strategic agility, and unlock competitive advantage (Elia et al., 2022). Yet, the practical realities of implementing AI technologies remain far from straightforward. Across industries, there is growing evidence of organizational friction and unintended consequences stemming from the rushed or ill-conceived adoption of AI systems. As organizations seek to automate workflows, derive predictive insights, and optimize resource allocation through AI-enabled business analytics, they often encounter barriers that hinder the realization of anticipated gains. These barriers are not purely technological; rather, they reflect a complex interplay of institutional resistance, strategic

misalignment, and inefficiencies in AI deployment (Tarafdar et al., 2023). The scholarly debate has shifted from whether AI should be adopted to how it can be effectively integrated within business environments without exacerbating operational inefficiencies. This growing concern highlights the need to understand the nuanced dynamics between AI integration, internal resistance, and organizational outcomes.

Recent literature highlights the paradox of AI adoption: while the integration of AI in business processes promises operational excellence, many organizations struggle to extract value from these technologies (Ghosh et al., 2022; Waizenegger et al., 2023). Studies indicate that AI-infused analytics systems often fail to deliver intended performance improvements due to underutilization, poor alignment with organizational routines, and resistance from employees and middle management. Organizational scholars have documented how digital transformation efforts tend to falter when AI technologies are introduced without sufficient cultural, structural, or strategic preparation (Li et al., 2022). Moreover, it is increasingly evident that AI implementation is not a purely technical endeavor, it necessitates coordinated behavioral and managerial change. Although a growing body of work explores AI's role in decision-making and innovation, limited attention has been paid to understanding the mechanisms by which AI misuse, underuse, or resistance leads to operational inefficiencies across different organizational layers.

The global race for AI adoption has intensified in recent years, spurred by governments, investors, and industry stakeholders seeking to enhance productivity and global competitiveness. According to the International Data Corporation (IDC, 2024), global AI spending is projected to surpass USD 500 billion by 2027, with a significant portion allocated to business analytics. However, the anticipated performance dividends are often undermined by unintended operational bottlenecks, especially in low- and middle-income economies where AI infrastructure and institutional readiness remain uneven (OECD, 2023). In Pakistan, for instance, while public and private sector firms are eager to embrace AI tools for process automation, many faces systemic challenges, such as employee apprehension, lack of technical know-how, and insufficient change management strategies, that derail successful integration (Ahmed & Noor, 2023). Organizational resistance to AI remains an underreported but growing concern in digital transformation efforts. Employees often view AI systems as threats to job security, while decision-makers struggle with aligning AI outputs with core business goals (Chen et al., 2022). These issues not only reflect a misalignment between AI capabilities and organizational realities but also raise critical questions about whether AI-enhanced business analytics may inadvertently exacerbate operational inefficiencies rather than resolve them.

The proliferation of AI-based business tools, the assumption that AI integration directly improves organizational performance has been increasingly contested. A significant research gap persists in understanding the indirect and sometimes counterproductive consequences of AI adoption, especially within the domain of operational performance. While existing literature emphasizes the strategic benefits of AI in enhancing forecasting accuracy, customer personalization, and workflow optimization (Singh et al., 2023), less attention has been paid to the unintended inefficiencies that emerge when AI is poorly utilized or met with internal resistance. Moreover, prior studies tend to adopt a technology-centric lens, often overlooking how organizational behavior, culture, and resistance mediate or moderate the effects of AI on performance outcomes (Narayan & Dutta, 2022). This gap is particularly pressing in emerging economies, where AI integration is frequently pursued without adequate infrastructure, employee training, or leadership support. Scholars have called for more context-sensitive models that examine not just AI implementation but the behavioral and systemic obstacles that arise in real-world settings (Al Mahmud et al., 2022). Therefore, this study seeks to unpack how AI-integrated business analytics may contribute to operational inefficiencies through two critical but underexplored channels: AI utilization inefficiency and organizational resistance to AI. Addressing this gap is essential for moving beyond simplistic success-failure dichotomies in AI research, and toward a more nuanced understanding of how AI systems can sometimes inhibit, rather than enhance, organizational functioning.

Understanding the unintended consequences of AI adoption holds significant relevance for both academic inquiry and managerial practice. At the organizational level, AI systems are increasingly embedded in strategic decision-making processes, and their malfunction or misalignment can lead to cascading inefficiencies, ranging from flawed analytics and redundant workflows to employee disengagement and increased costs (Günther et al., 2023). From a policy perspective, governments in developing economies are investing heavily in digital infrastructure and AI policy frameworks without a full appreciation of the barriers that impede effective utilization. Without a clear understanding of these impediments, such investments may fail to yield productive outcomes. Academically, the field of information systems and operations management requires models that do not treat AI as a deterministic solution, but instead consider the sociotechnical context in which AI operates. Identifying the drivers of AI inefficiency and resistance is critical to developing more realistic and implementable AI strategies. Addressing this issue aligns with global calls for responsible and sustainable AI implementation, emphasizing not just the capabilities of technology, but the readiness of organizations to adapt and govern these technologies effectively (Brennen et al., 2023).

This study contributes to the emerging discourse on the dark side of digital transformation by offering an empirically grounded model that explains how AI-integrated business analytics can unintentionally lead to operational inefficiencies. By investigating AI utilization inefficiency and organizational resistance to AI as mediating mechanisms, this research adds conceptual clarity to the conditions under which AI fails to generate expected benefits. It further provides practical insights for managers seeking to align technological capability with organizational preparedness. The study is grounded in the Technology-Organization-Environment (TOE) framework, which provides a holistic lens to examine the adoption and consequences of technological innovations. The TOE framework accommodates the technological sophistication of AI, organizational readiness, and contextual challenges that influence outcomes. By integrating this framework, the study links AI capabilities, internal inefficiencies, and operational consequences in a theoretically cohesive model. The findings have the potential to inform both academic theory and managerial policy on how to optimize AI integration for operational performance.

Theoretical Foundation

The present study is underpinned by the Technology-Organization-Environment (TOE) framework, a comprehensive theoretical lens that captures the multifaceted dynamics surrounding technological adoption within organizational contexts. The TOE framework as it was first described and published by Tornatzky and Fleischer in 1990 presents a systematic method of viewing the determinants of innovation adoption, by categorizing them into three domains which are interconnected and they are; technological domain, organizational domain, and environmental domain. Originally presented as a model to explain the process of the diffusion of innovation in general, the framework was adapted to the current moment in modern times, and it would apply to the existing digital changes, particularly the most complex and dynamic aspects, such as the implementation of the artificial intelligence (AI) (Martins et al., 2022).

The TOE framework posits that the successful adoption and implementation of technology within firms is not solely dependent on the capabilities of the technology itself. Rather, adoption outcomes are at the mercy of the synergy between technological (including the complexity, compatibility, and relative advantage), as well as organizational (including size, structure, culture, and resources) features and the environmental factors (including the competitive pressure and the regulatory environment) (Yadegaridehkordi et al., 2023). Such a cross-dimensional thinking allows scholars and practitioners to discard the frames of technologically determined thinking and to appeal to the socio-organization cloth, in the context of which innovations are integrated. The application of the TOE framework to the study of digitalization of different sectors was actively investigated in the past decade by the researchers, and the effectiveness of the framework and its establishing as highly stable and capable of working in the rapidly changing technological world were proved (Pellizzoni et al., 2022). The framework has gained more of an application to study the digital technologies of cloud computing, blockchain, and AI, all of which not only entail their technical difficulties but also organizational resistances and strategic misalignments (Lee & Han, 2023). The TOE framework is especially appropriate in explaining the journey of organizations through the advanced analytics in the specific context of the application of AI. It focuses on internal forces that may diminish the gains derived through operations such as institutional inertia, cultural resistance, abilities deficits, as examples of what can halt the operational advantages that AI is projected to bring.

The framework's relevance is amplified in settings where digital maturity is uneven and institutional support structures are underdeveloped. The up-and-coming economies, e.g., encounter unique environ mentality restrictions, poor regulatory ecosystems, poor digital infrastructure, and horizontalized supply chains, and it complicates the adoption journey further (Wamba et al., 2023). The TOE framework allows us to interpret the reasons why organizations can miss the opportunities provided by the digital innovations at hand even in a scenario where the organization has state-of-the-art technologies. Modern studies also emphasize the modeling capability of this framework to integrate behavior and organizational constructs which influence the technological results. The framework allows exploring unintended consequences and performance bottlenecks of technology use in theory because it locates such phenomena as utilization inefficiency and organizational resistance in a larger TOE architecture (Raja et al., 2022). Instead of posing a linear process between adoption and impact, TOE advocates investigating recursion and feedback loops, as well as friction, of organizational response to innovation.

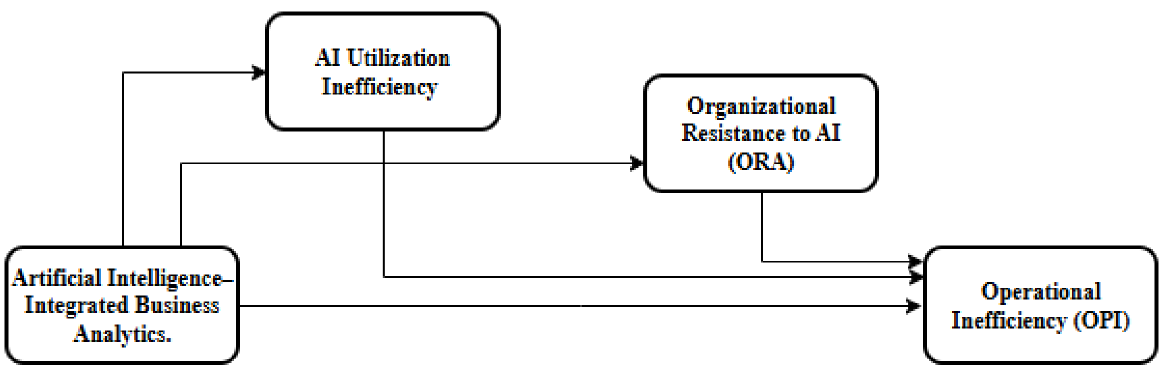

Figure 1: Research Model

Hypotheses Development

The rapid diffusion of Artificial Intelligence–Integrated Business Analytics (AI-BA) has significantly reshaped how organizations collect, analyze, and act upon data to inform decision-making. Such tools will allegedly allow increased responsiveness, flowing operation, and less inefficiency that is brought about by automating routine work, along with improved accuracy in forecasting. Nevertheless, theory alone is not enough to point to the high potential of AI-BA the evidence is much more ambivalent. Many studies emphasize the fact that the mere use of AI-powered analytics systems does not imply the corresponding enhancement of the performance outcomes (El Khatib et al., 2022). They are extremely dependent on the internal preparedness, levels of the organization, and its strategic fit, and its capability to properly integrate AI intelligence in operations (Lee & Han, 2023).

Drawing on the Technology-Organization-Environment (TOE) framework, it becomes evident that AI-BA operates within a broader socio-technical system, where organizational culture, processes, and resources collectively shape its effectiveness (Pellizzoni et al., 2022). Some of the disadvantages of AI to organizations are failure to achieve the desired returns on investment, failure to capitalize on the cost efficiency of AI due to a variety of internal limitations that may include lack of good data governance, an inability to operate integrated systems, and human unwillingness to have key decisions made out of algorithms. Such obstacles are capable of derailing the smooth process of AI-BA by causing redundancies, delays, or, indeed, improper decision-making, and adding to operational-based shortcomings (Raja et al., 2022). The latest empirical studies also highlight that under conditions of less technologically mature, or change-driven leadership, the introduction of AI is likely to disrupt even otherwise well-established routines, with little to provide in the way of replacements, potentially causing more friction in operations (Wamba et al., 2023). The lack of an enabling organizational structure and the coordination across different functions will make such insights delivered by AI-BA unusable, leading to reinforcing inefficiency rather than improving it in the daily operations (Ghosh et al., 2023). These side effects raise the bias according to the over-optimistic perspective of AI adoption and imply that AI-BA, unless used effectively, might adversely affect the performance of operations. Based on this reasoning, it is hypothesized that:

H1: The implementation of AI-integrated business analytics is positively associated with operational inefficiency.

Organizations increasingly deploy AI-integrated business analytics to improve decision-making and streamline operations; questions have emerged regarding their actual effectiveness in day-to-day execution. While the strategic value of AI in generating insights is widely recognized, its success depends heavily on how effectively it is utilized within existing workflows (Lee & Han, 2023). Many organizations fall into what has been termed the "AI implementation trap", where sophisticated analytics tools are procured and introduced without the parallel development of internal capabilities or integration strategies (Pellizzoni et al., 2022). This results in a scenario where AI systems are underused, misused, or poorly aligned with the specific operational needs of the firm.

Evidence suggests that such misalignments are not simply technical oversights, but indicative of broader inefficiencies in utilization practices. Ghosh et al. (2023) maintain that in the absence of a well-outlined approach to the use of AI, as well as training, cultural preparation, and operational reorganization, organizations are likely to develop what they call an analytic silo, which makes decision making even more complex. In this scenario, AI-BA turns into more of a burden than an enabling technology, makes operations extra-complicated, and hinders performance flexibility (El Khatib et al., 2022). The TOE framework points out that the technology aspect, which is done by system functions, should be addressed by organizations practices that guarantee the proper use and application (Yadegaridehkordi et al., 2023). Underperformance of this alignment does not only negate any possible benefits of the AI tools but also introduce friction into processes, further increasing operational inefficiencies. Inefficiency of AI Utilization acts as a vital process to define how the prospect of AI-BA could be converted to less than the ideal payoff. It is hypothesized that:

H2: AI Utilization Inefficiency mediates the relationship between AI-integrated business analytics and operational inefficiency.

The integration of artificial intelligence into organizational systems is often accompanied by deep-rooted behavioral and structural challenges. As the technical process of business analytics integration with AI took place rather fast, its integration into organizational practice often comes across the resistance of people or organizations. It is not an emotional or psychological response to a change but institutionalized, built through formal structures of power and legacy systems, cultural norms and imagined threats to autonomy and job security (Ghosh et al., 2023). This kind of resistance can interfere with the implementation of AI insights, blur the purpose of strategic goals, and break the continuity of decisions.

Contemporary studies reveal that even in technologically capable firms, resistance from middle managers, IT staff, or frontline employees often slows down or misdirects the use of AI-based systems (Wamba et al., 2023). This resistance can also be non-compliance through inaction, selective adherence or active resistance to algorithmic outputs, actions which end up causing inefficiencies in the course of operations. Technology-Organization-Environment (TOE) constructs are important to postulate considering that successful integration of technology largely depends on organizational considerations, such as leadership support, training, and culture alignment (Raja et al., 2022). Without such enablers, AI systems, no matter how much sophisticated their analysis results are, will likely be met with resistance that will cancel any potential advantage. This kind of organizational resistance may result increase in decision cycles and decoupling of insights in the strategic work and operational ability increasing operational inefficiencies. Resistance is an important mediating process in turning technological potential to disruption of operations, especially in the contexts where change management is weak and unheeded. Therefore, it is hypothesized that:

H3: Organizational Resistance to AI mediates the relationship between AI-integrated business analytics and operational inefficiency.

Methodology

This study adopts a quantitative, cross-sectional research design to investigate the influence of Artificial Intelligence–Integrated Business Analytics (AI-BA) on operational inefficiency, with AI utilization inefficiency and organizational resistance as mediating constructs. The cross-sectional potential, consisting in collecting data at a specific moment, is suitable when it is necessary to consider the current structure of the attitudes, practices, and outcomes in a particular organizational environment (Creswell & Creswell, 2023). The quantitative design is suitable approach to demonstrate the explanatory goals of the research since it enables to formulate and test the potential relationships between variables based on statistically-defined models. As the process of digital transformation and the incorporation of AI within the companies is quite dynamic, the approach will guarantee a timely and concentrated overview of the relations which shall be examined.

The target population of the study comprises managers and senior professionals employed in manufacturing sector firms registered with the Lahore Chamber of Commerce and Industry (LCCI), Pakistan. The said population consists of people who make strategic decisions, adopt technology, and run the operation of the organization, which will be able to determine key insights on the practice of AI-BA or its influence on organizational performance. The reason behind selecting the LCCI manufacturing industry is the level of its involvement in the process optimization, data analytics, and recent steps toward digitalization using AI. Therefore, the state of manufacturing companies as the ones that are highly vulnerable to the problems of operational inefficiency makes this environment suitable to investigate the forms of the interaction between technological interventions, including AI analytics, and organizational processes (Ahmed & Noor, 2023). A stratified random sampling was the method used to obtain the respondents to be used so that they are represented across the sizes of the manufacturing industry (e.g., textile, electronics, pharmaceuticals, machinery, etc.). The stratification increases the degree of representativeness of the sample because it helps to measure the possible variations in AI adoption practices in various industry segments (Hair et al., 2022). A random number of respondents was chosen by sampling/searching in publicly available directories and company lists submitted by the LCCI database. The sample size was determined using principles from Item Response Theory (IRT), which emphasizes the need for sufficient respondent-to-item ratios to ensure stable and reliable parameter estimates. IRT especially applies to structural equation modeling (SEM), in which latent variables are defined in terms of multiple observed indicators. According to the recommendation provided by Linacre (2022), at least 20 respondents per item can be regarded as sufficient. The present tool consists of 28 items that assess AI-BA, inefficiency of AI usage in practice, and organizational as well as operational resistance. According to IRT principles, the validity of the model would be no less than 560 responses meaning 560 questionnaires were handed out and 343 valid answers remained in the final data after screening and cleaning.

Measurement of Variables

All items were measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree), unless stated otherwise. The constructs include AI-Integrated Business Analytics (AI-BA), Organizational Resistance to AI (ORA), and Operational Inefficiency (OPI) and AI Utilization Efficiency (AIU).

AI-Integrated Business Analytics was operationalized to assess the extent to which organizations embed artificial intelligence within their data-driven decision-making systems. It contained six items based on the scale developed by Mikalef et al. (2023). Examples included "Our company has access to AI-based tools helping to predict trends" and "AI algorithms help us with real-time decision-making processes.". Organizational Resistance to AI is what cognitive, behavioral, and organizational impediments to the effective introduction of AI technologies constitute in an organization. It was based on a six-item scale taken after Gok et al. (2022) and Alkhatib and Abdalla (2022). Example included "Employees are unwilling to embrace AI-based technologies" and 'Our organizational culture will not support transformation toward AI." Operational Inefficiency was used to determine the impacts that technology implementation. The scale was taken as prepared by Leung and Zhang (2022) and Baig et al. (2023) and it comprised of five items. Such examples can be found in the following statements: "Our operations are delayed because our systems are not well integrated" and "Implementation of AI has created a problem with workflow efficiency." The construct evaluates the unintended dark side effects of not effective operational implementation of AI systems. AIU has 8 items developed by Lee et al. (2022).

Data analysis:

Regression Weights

Table 1: Factor Loadings

Variables	Items	AIB	AIU	OP	ORA
AI-Integrated Business Analytics	**AIB1**	0.888			
	AIB2	0.867			
	AIB3	0.850			
	AIB4	0.825			
	AIB5	0.868			
	AIB6	0.894			
	AIB7	0.823			
	AIB8	0.913			
AI Utilization Inefficiency	**AIU2**		0.784		
	AIU3		0.765		
	AIU4		0.808		
	AIU5		0.867		
	AIU6		0.786		
	AIU7		0.813		
Operational Inefficiency	**OP1**			0.863	
	OP2			0.910	
	OP3			0.874	

	OP4			0.910	
	OP5			0.850	
	OP6			0.866	
Organizational Resistance to AI	**ORA1**				0.810
	ORA2				0.813
	ORA3				0.809
	ORA4				0.858
	ORA5				0.854
	ORA6				0.800

Factor loadings are essential indicators used to assess the degree to which observed items represent their underlying latent constructs in structural equation modeling (SEM). Within reflective measurement models, the factor loadings measure the correlation between the observed indicator and latent variable. A high loading will also indicate that an item will be a good representative of the construct it will be measuring and will boost its reliability and validity (Hair et al., 2022). The literature generally accepts the lowest loading requirement at 0.40 in exploratory research whereas higher loadings above 0.70 are desirable in confirmatory research within which items exhibit a significant importance to the measurement of constructs (Henseler, Hubona, & Ray, 2022). Factor loadings that are below such thresholds could be related to measurement error but also to unclear conceptual relationships and lack of eminent relationship and can interfere with the general precision of the model and forecasting. Factor loadings denote how well an observed measure is related to a latent construct, and are an important measure of validity of measurement in structural model. In confirmatory research, it is preferable to have loadings greater than 0.70, manifesting a high dependency of each element on a corresponding construct (Hair et al., 2022). The values are used in establishing the convergent validity and reliability of constructs in the model.

Convergent Validity

Table 2: Validity Statistics

	Cronbach's alpha	(rho_a)	(rho_c)	(AVE)
AI-Integrated Business Analytics	0.952	0.955	0.960	0.751
AI Utilization Inefficiency	0.891	0.895	0.917	0.647
Operational Inefficiency	0.941	0.943	0.953	0.773
Organizational Resistance to AI	0.905	0.906	0.927	0.680

In structural equation modeling, internal consistency reliability and convergent validity are essential to ensure the robustness of latent construct measurements. Coherent measures of internal consistency are cronbach alpha (alpha), rhoA (rhoA) and composite reliability (rhoC). Hair et al. (2022) argued that the values of 0.70 and more indicate acceptable reliability in the cases of 6, 6 and 6A. Similarly, the convergent validity is tested using Average Variance Extracted (AVE) whereby a numeric value of 0.50 or greater implies that construct represents over 50 percent of variance within indicators (Sarstedt et al., 2022). The construct AI-Integrated Business Analytics proves highly reliable, with 0.952, 0.955, 0.960 being the 0 respectively, which are quite superior to include standard marks. Convergent validity is also strong as its AVE value is 0.751. The same happens with AI Utilization Inefficiency which demonstrates high internal consistency (alpha = 0.891; rho-A = 0.895; rho-C = 0.917) and is also good in terms of convergent validity (AVE = 0.647), suggesting proper construct measurement. The construct precision of Operational Inefficiency can be attested by an excellent reliability (alpha = 0.941; RA = 0.943; RC = 0.953), as well as the highest AVE of 0.773. Organizational Resistance to AI also satisfies all reliability requirements (alpha = 0.905; RFA = 0.906; RCA = 0.927) and has the acceptable AVE (0.680).

Taken together, this set of measures certifies the empirical sufficiency and theoretical validity of the constructs.

Discriminant Validity

Table 3: HTMT Ratio

	AIB	AIU	OP	ORA
AI-Integrated Business Analytics				
AI Utilization Inefficiency	0.440			
Operational Inefficiency	0.577	0.475		
Organizational Resistance to AI	0.620	0.480	0.612	

Discriminant validity refers to the extent to which a construct is empirically distinct from other constructs in a model, ensuring that each measures a unique concept. The assessment of discriminant validity which is largely supported continues to be the Heterotrait-Monotrait correlation of correlations (HTMT) and it examines the levels of correlations between the latent factors. The strict thresholds give the value of less than 0.85 and 0.90, respectively, as evidence of adequate discriminant validity via the value of HTMT (Hair et al., 2022). It is indicated that higher values could indicate overlap in concepts between constructs, which may present a problem of multicollinearity or redundancy (Sarstedt et al., 2022).

The presented HTMT matrix confirms acceptable discriminant validity across all construct pairs. For instance, the HTMT between AI-Integrated Business Analytics and AI Utilization Inefficiency is 0.440, well below both thresholds. AI-Integrated Business Analytics with Operational Inefficiency (0.577) and Organization Resistance to AI (0.620) also meet the requirements of the acceptable range. The HTMT values of AI Utilization Inefficiency to Operational Inefficiency (0.475) and Organizational Resistance to AI (0.480) are not beyond recommended range. The maximum value of the correlation is 0.612 between Operational Inefficiency and Organizational Resistance to AI which is also less than the liberal value of 0.90. The aggregation of these results points towards the fact that there is a conceptual difference between the constructs and the discriminant validity of the measurement model is satisfied.

R Square

Table 4: R Square

	R-square	R-square adjusted
AI Utilization Inefficiency	0.168	0.165
Operational Inefficiency	0.423	0.417
Organizational Resistance to AI	0.338	0.336

The R-square (R^2) and adjusted R-square values provide insight into the explanatory power of the structural model. R^2 represents the proportion of variance in the dependent variable explained by its predictors, while the adjusted R^2 accounts for model complexity and sample size, offering a more accurate estimate (Hair et al., 2022). AI Utilization Inefficiency has an R^2 of 0.168, indicating weak explanatory power. Operational Inefficiency ($R^2 = 0.423$) and Organizational Resistance to AI ($R^2 = 0.338$) demonstrate moderate explanatory power. These values suggest that the model moderately explains key outcomes while maintaining acceptable parsimony.

Model Fitness Indicators

Table 5: Model Fitness Indicators

	Saturated model	Estimated model
SRMR	0.059	0.073
d_ULS	1.239	1.872

d_G	0.720	0.734
Chi-square	1409.520	1412.896
NFI	0.826	0.825

The model fit indices collectively indicate an acceptable structural model fit. Both SRMR values (0.059 for saturated and 0.073 for estimated) fall below the 0.08 threshold, confirming good fit (Hair et al., 2022). The small differences in d_ULS (1.239 vs. 1.872) and d_G (0.720 vs. 0.734) suggest minimal model deterioration, despite lacking strict cutoffs (Henseler et al., 2016). The Chi-square values (1409.520 vs. 1412.896) are expectedly high due to sample size but remain close, indicating stability. NFI values (0.826 and 0.825) exceed the 0.80 minimum, reflecting a moderately acceptable model fit. Overall, the model demonstrates satisfactory structural adequacy

Findings:

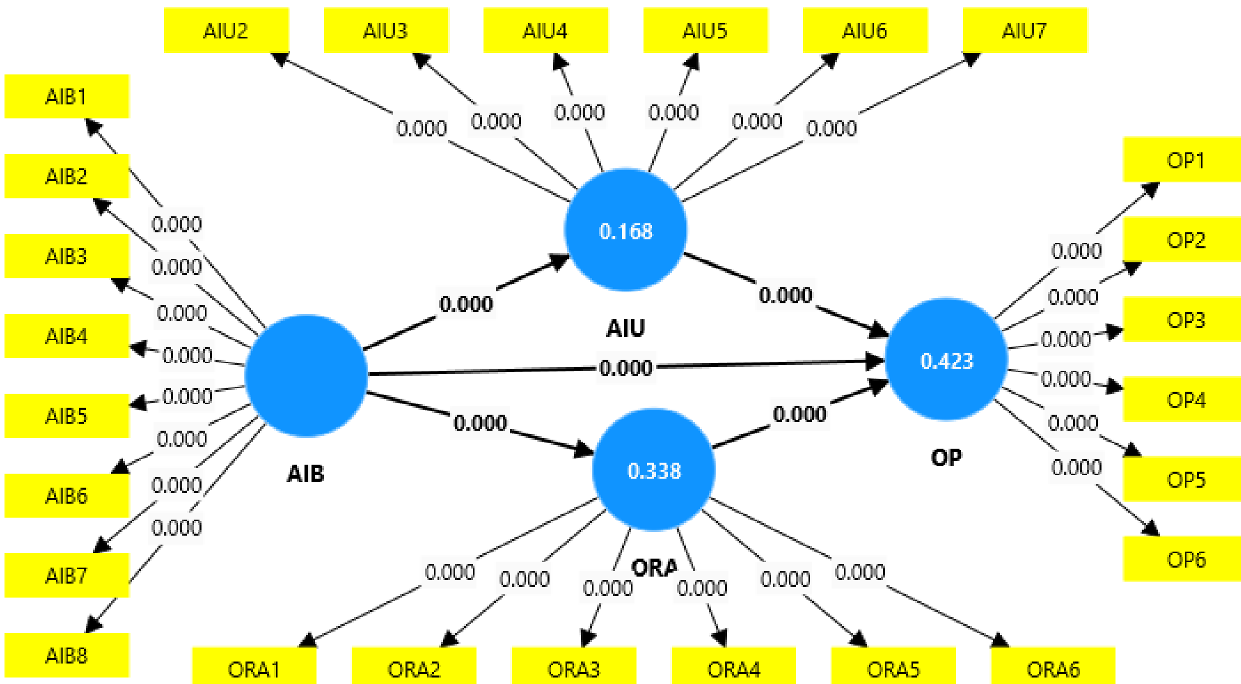

Table 6:Results

Hypotheses	Original sample	(M)	Standard deviation	T statistics	P values
AIB -> OP	0.289	0.289	0.053	5.409	0.000
AIB -> AIU -> OP	0.077	0.078	0.022	3.452	0.001
AIB -> ORA -> OP	0.184	0.184	0.036	5.144	0.000

The structural model results indicate that AI-Integrated Business Analytics (AIB) significantly and positively influences Operational Inefficiency (OP), with a direct effect of 0.289 ($t = 5.409$, $p < 0.001$), confirming a strong and statistically significant relationship. This suggests that the way AI is integrated into business analytics processes can directly shape operational outcomes, aligning with prior findings that AI's transformative effect on operational structures (Dwivedi et al., 2023). The mediating role of AI Utilization Inefficiency (AIU) between AIB and OP is significant, with an indirect effect of 0.077 ($t = 3.452$, $p = 0.001$). This indicates that inefficiencies in the utilization of AI tools partially mediate the relationship, implying that technological integration, underutilization can hinder operational efficiency (Mikalef et al., 2022). Organizational Resistance to AI (ORA) mediates the AIB–OP relationship, with a significant indirect effect of 0.184 ($t = 5.144$, $p < 0.001$), suggesting that internal resistance can substantially dampen AI's operational benefits.

Discussion

The hypothesis tested whether the implementation of AI-integrated business analytics (AI-BA) positively associates with operational inefficiency. The findings supported an insightful positive relationship, meaning that the convergence of AI-BA does not necessarily improve operation effectiveness and it is quite the contrary; the following of such practice is related to inefficiencies. Such an observation is consistent with analogous reports in the literature suggesting that the introduction of any AI system cannot result in the overall success as long as there is no appropriate organization infrastructure and readiness (Lee et al., 2022). This perspective is reinforced within the context of the TOE that states that the successful technology adoption must be effective to meet organizational and environmental contexts to work efficiently (Yadegaridehkordi et al., 2023). In the absence of alignment, the insights that the AI tools will provide may not be readily implementable, and workflows may be redundant because they have to be slowed down by the performance bottleneck (Ghosh et al., 2023). The situation when the speed of AI implementation exceeds the rate at which employees could adapt, or the integration strategies are underdeveloped, the additional complexity of decisions and the hindrance of work processes could occur, leading to the further friction of operations (El Khatib et al., 2022). Motivated by the positive relationship between AI-BA and operational inefficiency, the study shows the unintended results of the premature or unorganized introduction of AI, particularly in novice economies where digital maturity is still unequal (Ahmed & Noor, 2023).

The hypothesis examined whether AI utilization inefficiency mediates the relationship between AI-BA and operational inefficiency. The findings affirmed the moderator effect which means that low use of AI systems was a key intermediate link through which AI-BA has an impact on outcomes of operations. This result fits the current literature, which asserts that improper utilization of AI resource, i.e., default configuration of AI resource, non-personalization, or integration with the decision-making process, may dissipate the AI value proposition (Chen et al., 2023). Utilization inefficiency serves as a mediating factor based on theoretical error that is found in the TOE framework, which determines that internal organizational capabilities, such as personnel competencies and adaptive business processes, are necessities to ensure that technology has not only positive but also performance effects (Pellizzoni et al., 2022). In cases of these capacities being underdeveloped, the AI systems might only be relegated to shallow roles or even left to lay idle leading to disconnection between what it can potentially do and what it does. According to Ghosh et al. (2023), this case is referred to as the analytic disconnect because highly sophisticated AI platforms are not matched with the organizational cadence and therefore, they produce rather than eliminate inefficiencies. When it comes to resource-constrained environments, it is only compounded by the absence of constant technical education and strategic integration, which leads to stagnation and inappropriate use of AI insights (Alahakoon & de Silva, 2023). Thus, the importance of such a mediation effect implies that the utilization efficiency is an indispensable factor on the path to AI success, and failure may make AI systems counterproductive.

The hypothesis proposed that organizational resistance to AI mediates the relationship between AI-BA and operational inefficiency. The data also supports this relationship through the realization of the fact that resistance in the organization is enormously directed into negative operations effects of AI-BA. This observation supports the previous research that identifies resistance, both cognitive, behavioral, and structural, as a barrier to the process of AI technology integration into everyday processes (Gokalp Saner, 2022). Fear of redundancy, the feeling that one is losing control, or disbelief in algorithmic decision-making are commonly the causes behind reducing organizational resistance (Ghobakhloo & Iranmanesh, 2022). Such feelings may be manifested as passive (rejection of AI recommendations) or active (undermining the system or lobbying against AI programs). Both types interrupt the movement of AI-enhanced procedures, leading to the bottleneck that hinders the efficiency. Similarly to the TOE framework, the framework also allows attaining a valuable perspective because it helps to state that cultural and managerial aspects cannot go without saying the extent of the technological adoption success (Raja et al., 2022). Resistance becomes institutionalized when the leaderships fail to communicate the strategic advantage of AI or engage the employees in the process of the transformation journey, whereby this builds a large part of the blockage to operational coherence. Such an outcome also supports the evidence presented by Baig et al. (2023) who state that the current opposition is often expressed as fractured AI implementation and poor data utilization, which, in turn, leads to a low degree of operational flexibility. Such a powerful mediation effect indicates the necessity of both proactive change management and inclusive leadership and cultural alignment as the preconditions to utilize the AI technologies properly.

Limitations and Future Directions

While the present study offers valuable insights into the unintended consequences of AI-integrated business analytics (AI-BA) on operational inefficiency, it is important to acknowledge certain limitations that may affect the interpretation and generalizability of the findings. The study design is cross sectional and this limits the establishment of causal relationships among variables. Even though structural equation modeling offers precise measurements of the anticipated paths, the chronological follow-ups of effects cannot be strictly deduced. Longitudinal studies would be more suitable to consider the dynamic process of the introduction of AI in the field and its implications on operations in the course of time (Dwivedi et al., 2023). The sample of the examination report was selected only among the manufacturing companies under the Lahore Chamber of Commerce and Industry (LCCI) in Pakistan. Although the operational inefficiencies are observed in this sector in particular, the regional and sector-specific emphasis might constrain the conclusion that the results may have in other countries. Differences in cultural, institutional and technological maturity industry-wise and geographically may buffer the relationships that were found to exist. As a future research direction, it is possible to expand the scope to a variety of industries including banking, healthcare, logistics, and cross-country comparisons to accommodate the variability in the result of AI assimilation (Amankwah-Amoah, 2023).

A limitation lies in the reliance on self-reported data collected through structured questionnaires. Despite the fact that validated measurement scales were utilized, the issue of common method bias and social desirability effects cannot be absolutely excluded. The integration of a multi-source, such as performance metrics of organizations, use logs, and qualitative data about the system obtained by interviewing people, may increase the accuracy of measurements and provide more insights on interpretation (Hair et al., 2022). Although the existing framework considers the inefficiency of AI usage and resistance to the organization as two mediating mechanisms, it lacks such moderating potentials as leadership style, organizational learning culture, and digital maturity. Based on the Technology-Organization-Environment (TOE) model, such factors might strongly influence the way in which AI systems are adopted in practice and regarded within organization settings (Lee & Han, 2023). Researchers are invited to explore between which effects transformational leadership or digital ambidexterity act as moderators, either to attenuate the adverse impact of resistance or boost the efficiency of AI use (Bag & Wood, 2023). Investigating psychological constructs that focus on such areas as technostress, perceived job insecurity, or algorithmic trust would allow seeing into the nature of employee reaction towards AI technologies in a more detail-oriented manner (Golk et al., 2022). Factors at the environmental level, such as the regulatory pressure, the competition in the industry or AI readiness indices in a certain country, may be incorporated in future models to add insights. Such additions would enable the researchers to better chart the multilevel forces affecting the results of AI-enabled transformations. As AI systems are moving towards higher levels of autonomy, the problem of ethical concern and data governance should be given more attention on the scholarly level. An investigation of the impact of a framework of ethical AI and responsible innovation practices on employee acceptance and operational outcomes could be conducted in the future (Brennen et al., 2023).

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