Journal of Business

Volume 10, Issue 03, 2025: 11-23
Article Received: 12-10-2025
Accepted: 30-10-2025
Available Online: 25-12-2025
ISSN 2380-4041(Print), ISSN 2380-405X(Online)
DOI: https://doi.org/10.18533/journal.v10i3.380

From automation to augmentation: AI-driven business analytics and the future of workforce productivity

Md. Mahedi Hasan[1], Md. Yeasir Arafat Bhuiyan[2], Abdullah Al Maruf[3], Sujit Kumer Deb Nath[4], Muhammad Belal Hossain Khan[5]

ABSTRACT

Artificial intelligence (AI) and advanced business analytics are reshaping how organizations allocate tasks, make decisions, and define productivity. Yet much of the AI–work debate still treats analytics as a primarily automation-oriented technology (replacement, monitoring, and headcount reduction). Building on a qualitative meta-synthesis of interdisciplinary research and policy evidence published between 2012 and 2025, this article develops the Automation-to-Augmentation Business Analytics (A2A-BA) framework as a socio-technical *process model* that explains when and how analytics moves from automation to augmentation and with what productivity consequences. The synthesis identifies four interdependent mechanisms (1) task re-bundling and workflow redesign, (2) decision support and organizational sense-making, (3) skills/AI literacy and hybrid roles, and (4) productivity metrics and governance and specifies their causal logic: skills and governance enable effective task and decision reconfiguration, while metrics and governance also institutionalize (or undermine) augmentation over time through feedback loops. The framework contributes by integrating task-based technological change, work design, sociotechnical systems, and dynamic capabilities into an empirically anchored explanation that yields testable propositions and explicit boundary conditions (e.g., low-data environments, small firms, and informal labor markets). Managerial and policy implications highlight augmentation-first strategy, inclusive reskilling, and accountable analytics governance for sustainable productivity gains.

Keywords: Business analytics, Artificial intelligence, Automation and augmentation, Workforce productivity, Digital transformation.
JEL Classifications: O33, M15, J24, O15, C55.

1.0 Introduction

The recent acceleration of the spread of artificial intelligence (AI) and data-driven business analytics has fueled the old arguments about technology, employment, and productivity. Initial accounts revolved around automation, the use of AI and algorithms in place of menial human work, and potentially killing jobs (Acemoglu

[1] Associate Professor, Department of Business Administration, Prime University, Dhaka, Bangladesh, Email: mismanipal245@gmail.com
[2] Assistant Professor, Department of Business Administration, Prime University, Dhaka, Bangladesh. Email: arafatprimes@gmail.com
[3] Lecturer, Department of Business Administration, Prime University, Dhaka, Bangladesh, Email: aamaruf.iu@gmail.com
[4] Assistant Professor, Department of Business Administration, Prime University, Dhaka, Bangladesh, Email: sujitprime21@gmail.com
[5] Assistant Vice President, Human Resources Services, SQUARE Hospitals Ltd. Email: belalhr2008@gmail.com

and Restrepo, 2019). More current data indicate a more complicated scenario: AI and sophisticated analytics have the promise of increasing labor and total factor productivity, though the realized benefits are dependent on complementary investments in skills, work design, and organizational capabilities (Damioli, Van Roy, and Vertesy, 2021; Czarnitzki, Fernandez, and Rammer, 2023; Filippucci et al., 2024).

This change is centered on business analytics. Within the last 10 years, companies have been spending massively on big data, cloud computing, and analytics, hoping to make superior decisions and improve their performance (Sharma, Mithas, and Kankanhalli, 2014; Wamba et al., 2017; Mikalef, Boura, Lekakos, and Krogstie, 2019). However, data infrastructures do not give rise to insight and productivity on their own. They rely on the integration of analytics into the work systems, employment positions, and managerial activities (Sharma et al., 2014; Dwivedi et al., 2021).

A powerful body of AI and work research has started to create a distinction between automation (technology taking over work) and augmentation (technology complementing and enhancing human performance) (Dwivedi et al., 2021; Zirar, Imran, and Islam, 2023; Bastida, Vaquero García, Vázquez Taín, and Del Río Araujo, 2025). Meanwhile, scholarly work on work-design emphasizes that the consequences of digital technologies on well-being and performance are moderated by the organization of tasks, autonomy, feedback, and social relations (Parker and Grote, 2020). Although the giant strides have been made, the junction point of business analytics, AI, and workforce productivity is still missing: we have not yet received a theoretically based account of how AI-inspired business analytics alters organizational logic beyond automation and how it transforms productivity at the work level (Latif, 2022).

Key constructs used in the paper are defined up front to improve precision. 'Workforce productivity' refers to the joint quantity and quality of work output per unit of labor input, including error reduction, decision quality, and innovation where relevant (not only speed/throughput). 'Automation' denotes AI/analytics substituting for human task execution or judgment; 'augmentation' denotes AI/analytics complementing human capabilities through redesigned roles and human-in-the-loop decision rights. 'AI-driven business analytics' refers to descriptive, predictive, and prescriptive analytics using machine learning and related techniques embedded in organizational routines. 'Governance' refers to the formal and informal structures that shape model development, deployment, monitoring, accountability, and worker voice in analytics-enabled work systems.

The paper will fill that gap answering three guiding research questions:

RQ1: How are organizations deploying AI-driven business analytics to move away with automation-oriented to augmentation-oriented approaches to work?

RQ2: How does AI-based business analytics transform the productivity of the workforce?

RQ3: What are the theoretical, managerial and policy implications of an augmentation-first analytics strategy?

To respond to those questions, this paper takes the methodology of a theoretical and qualitative approach. It performs a qualitative meta-synthesis of peer-reviewed articles, policy documents and case studies in the industry published during 2012-2025, about AI, business analytics, and work. The study determines the main mechanisms through which AI-enabled analytics enhances workers and creates a structure of Automation-to-Augmentation Business Analytics (A2A-BA) by using the concept of reflexive thematic analysis (Braun and Clarke, 2019).

The article has three key contributions. It, first, incorporates task-based conceptions of AI and work alongside business-analytics and dynamic-capabilities conceptions to theorize augmentation-oriented analytics. Second, it hypothesizes four processes, including task re-bundling, better sense-making, skills and AI literacy and new productivity metrics and governance, by which AI-enabled analytics transforms productivity. Third, it obtains policy and managerial implications in designing augmentation-first strategies that foster inclusive and sustainable productivity gains as opposed to limiting cost-cutting.

1.1 Positioning and novelty

Theories developed earlier shed some light on the puzzle, like task-based technological change, which is a description of how changing the content of tasks takes place, sociotechnical systems theory, which points to how joint optimization occurs, work design theory, which describes how autonomy/feedback influence results, and dynamic capabilities, which is how companies re-structure resources. Nevertheless, these literatures seldom identify how AI-driven business analytics works as a work-system configurable intervention that (i) ties analytics strategy with work redesign and decision rights, (ii) elucidates how skills and governance are enabling, and (iii) how the productivity measurement becomes itself a component of the mechanism. A2A-BA builds upon current automation-augmentation differences by providing an integrated causal process model at the work-system level, and posits explicit borderline conditions and propositions, which may be empirically tested across contexts.

The rest of the paper is structured in the following way. Section 2 examines the literature concerning automation versus augmentation, AI-powered business analytics and work design. The qualitative meta-synthesis methodology is described in Section 3. Section 4 provides and discusses the thematic findings and the

A2A-BA framework with the help of conceptual tables. Section 5 has given conclusions on policy and practice implications and given potential areas of future research.

2.0 Literature review and theoretical background

2.1 AI and work automation, augmentation and task based views of AI and work

Task-based frameworks of technological change postulate that digital technologies impacted jobs by changing the make-up of the task but not the occupation as a whole (Acemoglu & Restrepo, 2019). In this view, AI can:

a) Move work that was done manually towards automation,

b) Create new tasks, and

c) Alter relative productivity of the current human activities.

Simple robots will take our jobs stories are being contested by recent evidence. The macro-level and firm-level evidence demonstrates that the use of AI is connected with productivity gains and heterogeneous employment and wage outcomes, which vary according to institutions, skills, and organizational complements (Damioli et al., 2021; Czarnitzki et al., 2023; Filippucci et al., 2024). The workers with high skills and non-routine activities can be particularly vulnerable to AI but can receive wage premia in case AI assists them with analytical and creative work (Ozgul et al., 2024).

The concept of augmentation redefines AI as not just a replacement, but as a digital partner that can be used to augment human perception, reasoning, and coordination. Bastida et al. (2025) demonstrate how human resource functions are shifting towards more complex automation (e.g., payroll, tracking) to augmentation (e.g., AI-assisted talent analytics, personalized learning), and redefines HR functions and capabilities. Similar arguments are made by Zirar et al. (2023), who insist on the coexistence approach where humans and AI systems co-produce value, which will necessitate new work design, job crafting and governance.

According to this literature, AI will result in displacement or empowerment as a strategic, work-design, regulated and socially discussed, rather than a technologically determined consequence.

2.2 Big data, business analytics and firm performance

The development of business analytics shifted to a higher level of predictive and prescriptive systems based on big data, machine learning, and cloud computing. The conceptual framework of business analytics presented by Sharma et al. (2014) is a socio-technical system where the value creation is determined through a combination of human judgment, organizational mechanisms, and analytics competencies. They underscore the fact that data warehouses do not give rise to insights but through interaction between the analysts and the decision makers.

Empirical studies explain that analytics capabilities can be considered as strategic resources. Based on the resource-based perspective and dynamic-capabilities approach, Wamba et al. (2017) demonstrate that the big data analytics capability (BDAC) such as technology, human abilities, and organizational routines positively influence firm performance which is mediated by the process-oriented dynamic capabilities. According to Mikalef et al. (2019), the capabilities of big data analytics can be used to promote the competitive performance when they are associated with the presence of the appropriate governance and strategic alignment.

These studies however usually operate at the firm or process level (e.g., profitability, customer measures) and not at the level of workforce productivity, job design and worker experience. The paper builds upon the business-analytics literature by focusing in on the reconfiguring of the nature and measurement of work through AI-enabled analytics (Dube et al., 2025).

2.3 Artificial intelligence, human labor productivity, and human-artificial intelligence complements

An emerging number of studies investigate the impact of AI on productivity, inequality and growth. Damioli et al. (2021) discover that AI patents relate to increased productivity in labor-intensive sectors in which AI is applied, but the impacts vary based on absorptive capacity. Czarnitzki et al. (2023) demonstrate that the adoption of AI can increase the productivity of firms but can also enhance dispersion among leaders and laggards. Filippucci et al. (2024) review the evidence related to the effects of AI on productivity, distribution, and growth by stating that in the absence of complementary investments in skills and organizational change, AI can strengthen inequality despite increasing efficiency.

On the organizational scale, Dwivedi et al. (2021) mention both opportunities and threats of AI in all fields and the necessity to use human-centric and socio-technical strategies. Parker and Grote (2020) put work design in the center of the AI debate in that digital technologies have the potential to increase or decrease job resources (autonomy, skill use, social support), demands (monitoring, pace, complexity), and their impacts on well-being and performance.

The new wisdom is that complementarities between AI abilities and human capabilities are essential: human-AI teams perform better than humans or machines do, but they need to redesign work and clarify roles, distribute decision rights and responsibilities intelligently.

2.4 Coexistence and augmentation logic of workers and AI

Zirar et al. (2023) examine social-science literature on AI and work and find the themes of technological unemployment, algorithmic management, skill polarization, and new types of worker agency. They propose a research agenda of coexistence AI and human beings partake in tasks and responsibilities in changing workplace ecosystems.

Bastida et al. (2025) are human resource oriented and demonstrate a shift to automation logics (AI as a cost reduction, efficiency instrument) toward augmentation logics (AI as partner facilitating strategic, relational HR). They suggest that augmentation needs new data literacy, ethics, and change management skills in HR.

Combined, these sources argue that AI-based business analytics may pursue two opposite logic:

a) Automation-based logic: focus on replacement, cost savings, and surveillance.

b) Augmentation-based reasoning: focus on complementarity, empowerment and learning.

The theoretical shift in the center of the paper is to demonstrate that business analytics can be reconfigured intentionally to the second logic and how it modifies the workforce productivity.

2.5 Automation-to-Augmentation Business analytics (A2A-BA) perspective

By integrating the streams mentioned above, we formulate Automation-to-Augmentation Business Analytics (A2A-BA) as a socio-technical setup where:

a) AI-oriented analytics is integrated into processes to enhance and complement the human capabilities instead of substituting them completely.

b) Redesigning work enables humans to be occupied with tasks that require them to add special value (creativity, judgment, empathy, complex coordination), and the AI systems do data-heavy, pattern-recognition, optimization tasks.

c) New productivity indicators include learning, quality, inclusion, and sustainability besides output and efficiency.

d) The transparency, accountability, and fairness of algorithmic decision-making are guaranteed through the governance structures.

The ensuing part explains that we employed a qualitative and theory-oriented meta-synthesis of the available literature and examples to tighten and empirically anchor this model.

2.6 Causal logic of the A2A-BA framework: a process model

A2A-BA is designed as a process model rather than a static typology. The four mechanisms are conceptually distinct but causally linked, and they can operate sequentially with feedback loops. Figure 02 provides a visual summary of this causal logic.

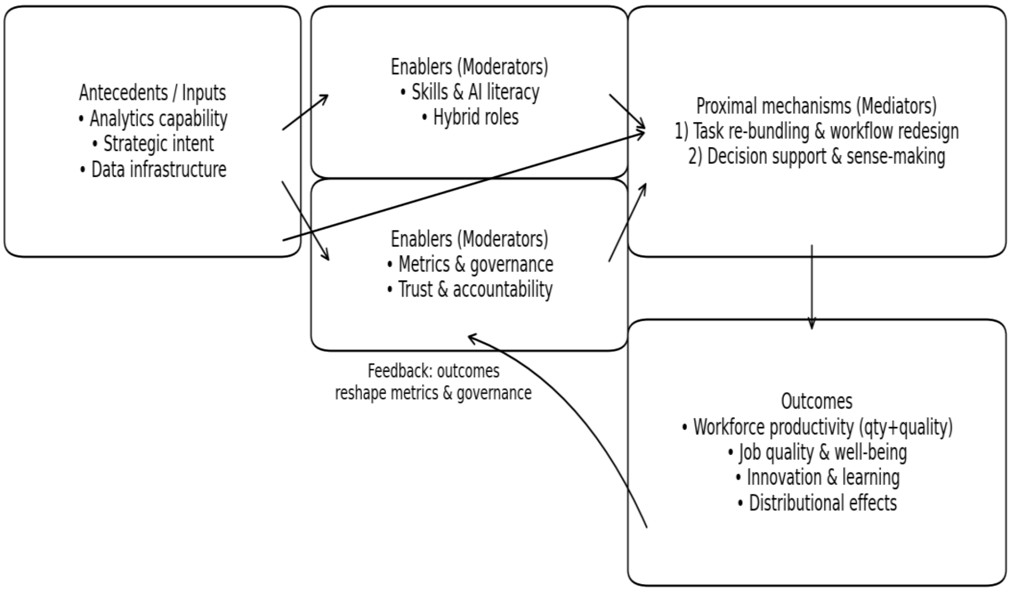

Figure 02. Causal process logic linking the four mechanisms in A2A-BA.

a) Antecedents (inputs): Analytics capability (data infrastructure, model quality, and integration) and strategic intent (automation-first vs augmentation-first) create the starting conditions for AI-driven work change.

b) Proximal mechanisms (mediators): Task re-bundling/workflow redesign and decision support/sense-making are the two "proximal" pathways through which analytics affects workforce productivity. They reallocate task bundles and reshape decision rights (who decide, with what information, and under what accountability).

c) Enabling conditions (moderators): Skills/AI literacy and hybrid 'translator' roles strengthen the productivity returns from the two proximal mechanisms by improving interpretation, error detection, and appropriate reliance on models. Metrics and governance also function as moderators by constraining surveillance-oriented uses and enabling explainability, contestability, and human oversight.

d) Institutionalization and feedback: Metrics and governance are additionally endogenized over time: as augmented workflows stabilize, organizations often codify new KPIs, audit routines, and accountability structures. These structures can reinforce augmentation (e.g., rewarding learning and quality) or push the system back toward automation (e.g., narrow speed metrics and punitive monitoring). This produces a recursive dynamic in which outcomes feed back into governance and capability investment.

Accordingly, the framework predicts that productivity gains are most sustainable when (i) an augmentation-first intent is matched with (ii) enabling skills and governance and (iii) proximal redesign of tasks and decisions; misalignment among these elements produces trade-offs (e.g., local efficiency with lower job quality or trust).

2.7 Boundary conditions and scope

A2A-BA is expected to apply most strongly in data-rich, digitally mediated work systems where tasks can be partially decomposed and recombined, and where organizations have the slack and leadership support to redesign jobs and invest in training. The framework is less likely to fit, or will operate differently, under the following conditions:

a) Low-data or low-digitization environments (e.g., small firms without reliable data pipelines, informal labor markets, and many micro-enterprises), where analytics cannot be embedded into routines at scale.

b) Highly tacit, craft-based, or relational work where performance is difficult to codify and model outputs are weak proxies for value, increasing the risk of harmful metric substitution.

c) High-regulation or high-liability settings where explainability and accountability requirements constrain model deployment, potentially slowing task re-bundling but increasing the importance of governance.

d) Organizations with weak change capability (limited managerial support, low trust, rigid job classifications) that constrain reskilling and workflow redesign.

e) Contexts of extreme labor precarity or coercive algorithmic management, where worker voice is limited and augmentation logics are less feasible.

These boundary conditions sharpen theoretical precision and guide empirical testing by indicating where mechanisms may be muted, reversed, or require adaptation.

3.0 Data and methodology

3.1 Overall design and rationale

The theoretical and qualitative approach adopted in the paper involves the following:

a) An AI, business analytics and work qualitative meta-synthesis of literature (2012-2025); and

b) An explanatory synthesis of descriptive cases in the industry based on published empirical research and policy publications.

It is an adequate design in a field whereby empirical data is spread among fields (information systems, management, economics, sociology, psychology) and where the theoretical integration is required (Dwivedi et al., 2021; Zirar et al., 2023).

Meta-synthesis is suitable when evidence is distributed across multiple disciplines and methods, and when conceptual development is as important as empirical generalization (Braun & Clarke, 2019). It allows the researcher to bring together conceptual, case-based, survey-based, and econometric studies under a coherent interpretive lens.

3.2 Data sources and selection

Our corpus construction followed a transparent, multi-stage search and screening procedure aligned with qualitative meta-synthesis practices.

3.2.1 Search strategy

We searched Web of Science, Scopus, ScienceDirect, and Google Scholar for 2012–2025 using combinations of terms such as ('artificial intelligence' OR 'machine learning') AND ('business analytics' OR 'big data analytics') AND ('work design' OR 'skills' OR 'labor productivity' OR 'workforce productivity'). Reference-list snowballing was used to identify additional foundational works and widely cited policy syntheses.

3.2.2 Screening and eligibility

Records were screened in three passes: (i) title/abstract screening for organizational relevance, (ii) full-text screening for explicit linkage to work, skills, job design, or workforce productivity, and (iii) synthesis eligibility for papers that provided mechanistic insight (not only correlations). Exclusion criteria removed purely technical model papers, consumer-only analytics studies, and items without organizational or workforce implications.

3.2.3 Quality and relevance appraisal

Peer-reviewed journal articles were prioritized. For policy and industry reports, we assessed credibility using an AACODS-style checklist (authority, accuracy, coverage, objectivity, date, and significance) and retained only sources that were methodologically transparent and widely referenced. Screening decisions and reasons for exclusion were logged to support an audit trail.

The search yielded an initial pool of approximately 150 items; after iterative screening, 45 core studies (peer-reviewed papers and high-quality reports) were retained for in-depth coding and synthesis.

3.3 Analytical approach

3.3.1 Coding and theme development

Analysis used reflexive thematic analysis with iterative cycles of coding and theory engagement (Braun & Clarke, 2019). First-cycle codes captured (a) the analytics application, (b) the locus of change (task, job, workflow, governance), (c) enabling conditions (skills, trust, regulation), and (d) productivity-related outcomes (throughput, quality, decision accuracy, innovation, job quality). Second-cycle coding clustered recurring patterns into four higher-order mechanisms. Theme boundaries were refined through constant comparison across disciplines (economics, IS, HRM, organizational behavior) and by actively seeking disconfirming evidence.

3.3.2 From themes to causal logic

To address explanatory power, we translated themes into a process model by specifying (i) antecedents, (ii) proximal mechanisms, (iii) enabling moderators, and (iv) feedback loops. This step supported the move from 'structured synthesis' toward a differentiated theoretical account of how augmentation-oriented analytics emerges and persists.

3.3.3 Reflexivity and trustworthiness

Consistent with reflexive thematic analysis, interpretation was treated as theory-informed and researcher-mediated rather than purely aggregative. Reflexive memos recorded how prior assumptions (e.g., a normative preference for augmentation-first designs) could shape coding choices; the analysis therefore explicitly searched for counter-cases where automation-centric analytics improved efficiency but degraded job quality or trust. Triangulation across academic and policy sources, a maintained audit trail of coding decisions, and transparent reporting of boundary conditions were used to strengthen credibility.

3.4 Qualitative and theoretical nature of the study

Notably, the paper does not imply primary fieldwork (e.g. original interviews) but rather provides a qualitative synthesis of the available empirical and conceptual evidence. It has a contribution in methodology in the sense that:

a) Combining interdisciplinary research of AI, analytics, and work;
b) Creating a unique A2A-BA model; and
c) Producing theoretically informed propositions and policy implications to be tested in future.

3.5 Nature and scope of the contribution

It is a clearly theoretical and qualitative study. It does not purport to offer estimates of AI effect on productivity that is statistically generalizable and it does not capture all the sectoral variations. Instead, it offers:

a) A conceptualization (A2A-BA) is based on available empirical and theoretical literature;
b) A system of processes and suggestions that may inform future primary study and policy trials;
c) An organizational policy discourse of augmentation-first approaches that makes linkage between corporate-level decisions and wider discussions about inclusive and sustainable productivity growth.

4.0 Results and discussion

4.1 From automation-centric to augmentation-centric analytics

In our analysis, we can see that the automation-focused and the augmentation-focused applications of business analytics are quite distinct. The key differences are summarized in Table 01.

Table 01.
Automation-centric vs augmentation-centric business analytics.

Dimension	Automation-centric analytics	Augmentation-centric analytics
Strategic logic	Cost reduction; headcount minimization.	Value creation; capability building; innovation.
Primary role of AI/analytics	Substitute for human judgment and manual tasks.	Complement human expertise; co-pilot and orchestration functions.
Focus of metrics	Efficiency, throughput, error reduction.	Productivity, learning, quality, inclusion, sustainability.
Work design implications	Task fragmentation, tighter monitoring, reduced autonomy.	Task re-bundling, enriched roles, human-AI collaboration.
Skill implications	Devaluation of routine skills; limited upskilling.	Investments in data literacy, domain expertise, hybrid "translator" roles.
Governance and ethics	Opaque algorithms; unilateral decisions.	Transparent models; shared oversight; worker voice and algorithmic accountability.
Likely workforce outcomes	Job insecurity, stress, polarization.	Enhanced productivity, employability, and job quality (if well governed)

The deployments based on automation are more likely to view analytics as a means of streamlining the current processes and eliminating human noise. Augmentation-based approaches, in contrast, view humans and AI as complementary resources, and work systems must be redesigned. Most organizations are caught between two worlds with pockets of both logics. According to our results, the balance and evolution of these two and net productivity and social outcomes are dependent (Sindhura et al., 2025 & Islam, Latif, Yasin, & Ali, 2025).

4.2 Mechanism 1: Task re-bundling and workflow redesign

Task re-bundling is the first process according to which AI-enabled business analytics reconfigures productivity. Instead of merely automating one task at a time, top organizations re-design workflows in such a way that humans and AI systems focus on what they do best.

Finance, healthcare, and customer service examples demonstrate that AI will replace high volume, data-heavy tasks, such as anomaly detection, triage, or basic query management, and humans will handle complex, relational or ambiguous cases (Dwivedi et al., 2021; Damioli et al., 2021). This tendency is consistent with the idea Parker and Grote (2020) provide, that digital technologies have a possibility to boost job resources in case the work is restructured in such a way that it does not destroy autonomy or skill utilization (Yasin & Latif, 2025).

In an A2A-BA configuration:

a) AI systems process data ingestion, feature extraction, pattern recognition and probabilistic forecasting;

b) Human workers make interpretations of patterns, trade-offs, exceptions and stakeholder engagements;

c) Re-sequencing of workflows is done to ensure that outputs of analytics go into collaborative decision points (e.g., AI-generated risk scores and human case conferences).

Regarding productivity, this mechanism enables organizations to:

a) Heavy workload Processes Reduce throughput by eliminating bottlenecks in analysis;

b) Enhance quality through a synthesis of machine and human contextualization;

c) Less mental load on employees, time saved on other value adding activities.

These gains are, however, not automatic. Without redesigning the jobs, to which AI is overlaid, employees can get information overload, divided work, and more surveillance which will affect their productivity and well-being (Parker and Grote, 2020; Zirar et al., 2023). Theoretical implication: analytics increases productivity when there is a joint optimum of technology and work design.

4.3 Mechanism 2: Decision support, sense-making, and analytical transparency

The second one is the decision support and sense-making, which can be provisioned with AI-driven analytics, instead of total decision automation. Business analytics offers dashboard, predictive models, and scenario simulators to inform people making human decisions in functions (marketing, operations, HR, finance).

The marketing research demonstrates how AI is able to tailor campaigns and pricing but the most successful systems are those that retain a human in the loop to analyze the results and adjust them to brand values and ethics (Davenport, Guha, Grewal, and Bressgott, 2020). Equally, the role of managerial judgment in interpreting the results of analytics and in transforming them into action is emphasized in large-scale studies (Wamba et al., 2017; Mikalef et al., 2019).

The main aspects of augmentation based decision support are:

a) Explainability and transparency: models that are created in such a way that users can gain knowledge about major drivers and constraints of the prediction;

b) Interactive analytics: software that enables personnel to experiment with assumptions and run what-if simulations, and question model results;

c) Sense-making practices: periodic meetings and rituals (e.g., analytics huddles) of cross-functional teams about the insights and implications.

Theoretically, the mechanism underpins the opinion that productivity is not only achieved through increased data but also more profound human sense-making through analytics (Sharma et al., 2014). It is also implied that the uptake and influence of AI systems are mainly based on trust and legitimacy (Dwivedi et al., 2021; Zirar et al., 2023).

4.4 Mechanism 3: Skills, AI literacy, and hybrid roles

The third mechanism is related to skills and AI literacy. The analytics based on augmentation assumes that employees can interpret the systems of AI and engage with them. Our analysis demonstrates that there are three general areas of skill:

a) Data and AI literacy: know how to use basic analytics concepts (e.g. correlation vs causation, prediction intervals, bias);

b) Domain expertise: thorough understanding of business processes, customers and regulations;

c) Hybrid translator skills: the capability to be the interface between data science and business, and is often a part of the analytics translator, product owner, or even augmented managers.

Analytics capabilities studies emphasize the importance of human skills and organizational culture in many cases is more significant than technology itself (Wamba et al., 2017; Mikalef et al., 2019 & Latif et al., 2016). Dwivedi et al. (2021) state that official upskilling and reskilling should be part of AI strategy to avoid exclusion and resistance.

Our analysis suggests that:

a) Companies with an otherwise technical view of AI tend to spend little on skills, which results in under-exploited systems and poor returns to productivity;

b) Companies investing in AI literacy of the wider workforce, as well as data scientists, can more effectively achieve the advantages of augmentation;

c) The new hybrid roles (e.g., human-AI coordinators, AI product managers) become the key nodes of the work system.

This mechanism has distributional consequences: employees who do not have access to training are at risk of leaving them, which increases inequality (Filippucci et al., 2024; Ozgul et al., 2024, Latif & Yasin, 2025).

4.5 Mechanism 4: New productivity metrics and governance

The fourth mechanism is the definition, measurement, and control of productivity in workplaces where AI is being enabled. Non-traditional measures like units per hour or cost per transaction might fail to reflect the value of augmented workers, i.e.:

a) Self-improvement in the level of decision and minimizing errors;

b)Experimentation, innovation derived through experimentation;

c) Satisfaction and trust by the customer;

d) When measuring inclusion, fairness and sustainability.

The policy aspect of AI and productivity indicates that measurement systems should be adjusted to consider intangible and systemic impacts (Filippucci et al., 2024; Vinuesa et al., 2019, Latif et al., 2024). In organizations, it follows as:

a) Multi-dimensional KPIs comprising of efficiency, learning, quality, as well as ethical indicators;

b) Structures of governance (ethics committees, algorithmic audit processes) that regulate the influence of analytics to work;

c) Mechanisms to enable workers to challenge or appeal AI-based evaluations.

The four mechanisms and implications are summarized in Table 02.

Table 02.

Mechanisms of AI-enabled augmentation and workforce productivity.

Mechanism	Description	Workforce productivity implications
1. Task re-bundling and workflow redesign	Redistributing tasks between humans and AI; redesigning processes.	Higher throughput, better quality, reduced cognitive load (if well designed)
2. Decision support and sense-making	Using analytics for interpretive, explainable decision support.	Better decisions, reduced uncertainty, stronger strategic alignment.
3. Skills, AI literacy, and hybrid roles	Investing in data literacy, domain expertise, and	Enhanced employability, reduced mismatch, more effective human–AI teams.

	translator roles.	
4. New metrics and governance	Updating productivity metrics and establishing AI governance.	Sustainable productivity, reduced risk, greater trust and legitimacy.

These processes are mutually necessary. To take an example, task re-bundling which boosts autonomy can end up failing, when workers are AI illiterate or the performance metrics only reward speed, but not quality (Latif & Yasin, 2025).

4.6 The A2A-BA conceptual framework

Bringing the mechanisms together we suggest the Automation-to-Augmentation Business Analytics (A2A-BA) framework, which may be outlined in the following three layers:

a) Inputs:

• AI/analytics/data infrastructure (data infrastructure, data models, data tools);
• Human capital (competency, AI literacy);
• Organizational culture and structure.

b) Configuration layer (A2A-BA design decisions):

• Logic of strategy (automation vs augmentation);
• Work structure and division of labor;
• Patterns of human-AI interaction (co-pilot, advisor, orchestrator);
• Governance and metrics.

c) Outcomes:

• Employee performance (effectiveness + quality + innovation);
• Employee health and labor conditions;
• Distributional impacts (wage dispersion, inclusion);
• Firm-level and macro-level performance.

The framework implies that it is not AI per se which dictates productivity results. Rather the results are determined by the way business analytics is designed at these layers. A more likely configuration is an augmentation-first configuration which:

• Create sustainable productivity improvements through exploiting complementarities;
• Develop employability and resilience by means of upskilling;
• Such policy goals as decent work (SDG 8) and less inequalities (SDG 10) (Vinuesa et al., 2019).

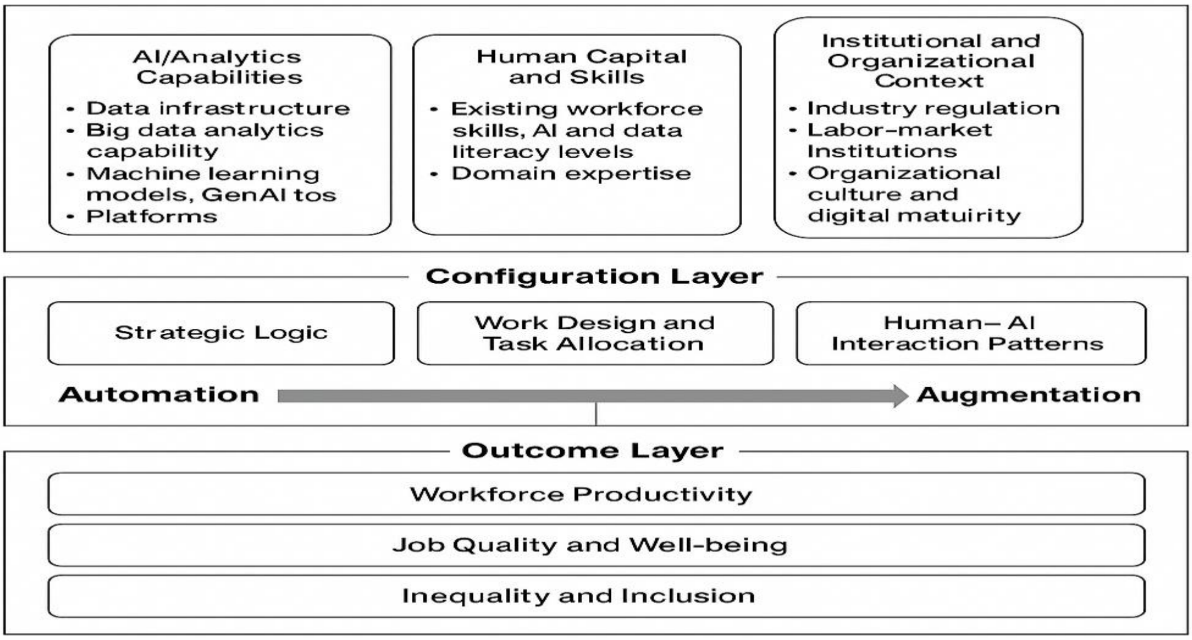

Figure 01. Automation-to-Augmentation Business Analytics (A2A-BA) Framework.

4.7 Theoretical Propositions

To enhance empirical testability, propositions are derived inductively from recurring patterns in the synthesis and organized to match the causal logic (antecedents → proximal mechanisms → moderators → outcomes).

4.7.1 Proposition 1 (Augmentation-first configuration and sustainable productivity)

a) Organizations that align an augmentation-first analytics intent with (i) task re-bundling/workflow redesign and (ii) human-in-the-loop decision support will realize larger and more durable workforce productivity gains than organizations pursuing end-to-end automation for cost reduction.

Synthesis basis: studies on analytics value creation stress socio-technical integration and human judgment in decision routines (e.g., Sharma et al., 2014; Wamba et al., 2017; Mikalef et al., 2019), while AI–work reviews highlight complementarity and coexistence logics (Dwivedi et al., 2021; Zirar et al., 2023).

4.7.2 Proposition 2 (Work design as a mediator)

b) Work design mediates the relationship between analytics capability and workforce productivity: human-centered redesign (autonomy, skill variety, feedback, and coordinated interdependence) strengthens positive productivity effects, whereas control-oriented redesign (fragmentation, surveillance, reduced discretion) attenuates or reverses them.

Synthesis basis: work design theory predicts that the same digital technology can raise or lower performance depending on job resources and demands (Parker & Grote, 2020), and coexistence perspectives emphasize redesigned roles and decision rights as central to outcomes (Zirar et al., 2023).

4.7.3 Proposition 3 (Skills and AI literacy as moderators):

c) Workforce AI literacy and hybrid 'translator' roles positively moderate the productivity effects of augmentation-oriented analytics by improving appropriate reliance on models, error detection, and the translation of insights into action.

d) Synthesis basis: analytics capability research repeatedly finds that human skills and routines are necessary complements to analytics infrastructure (Wamba et al., 2017; Mikalef et al., 2019), and policy evidence links productivity effects to absorptive capacity and skill investment (Damioli et al., 2021; Filippucci et al., 2024).

4.7.4 Proposition 4 (Governance and metrics as moderators and institutionalizers):

e) Multi-dimensional productivity metrics and accountable AI governance (transparency, auditability, contestability, and worker voice) strengthen augmentation outcomes by building trust and legitimizing human-in-the-loop practices; narrow efficiency-only metrics increase the likelihood of regression toward automation-centric monitoring.

Synthesis basis: governance and legitimacy are recurrent conditions for adoption and effective use of AI systems (Dwivedi et al., 2021), and productivity policy work emphasizes measurement and distributional trade-offs (Filippucci et al., 2024).

4.7.5 Proposition 5 (Distributional outcomes and boundary moderation):

These propositions support future empirical research designs (comparative case studies, longitudinal field studies, surveys, and quasi-experiments) and enable clearer falsification of the A2A-BA causal logic.

f) Synthesis basis: evidence on heterogeneous AI impacts points to dispersion between leaders and laggards and skill-based divergence (Czarnitzki et al., 2023; Filippucci et al., 2024), and studies of non-routine work suggest varying susceptibility and returns (Ozgul et al., 2024).

Even when augmentation-oriented analytics increases average productivity, benefits will be more unevenly distributed where access to training is unequal and worker voice is weak; inclusive reskilling and participatory governance moderate this inequality.

5.0 Conclusion and policy implications

5.1 Summary of main findings

This paper develops the Automation-to-Augmentation Business Analytics (A2A-BA) framework from a qualitative meta-synthesis of 2012–2025 interdisciplinary evidence. The central claim is that productivity effects are not determined by AI/analytics per se, but by how analytics is configured as a socio-technical work-system intervention.

a) Redesigning work and re-bundling tasks;
b) Decision support and sense-making;
c) Dexterity, artificially intelligent literacy and hybrid job titles;
d) New productivity indicators and controls.

The synthesis identifies four interdependent mechanisms—task re-bundling, decision support and sense-making, skills/AI literacy, and metrics/governance—and specifies their causal logic and boundary conditions. Automation-centric deployments may generate local efficiency gains but risk degrading job quality and long-run learning, whereas augmentation-centric configurations can produce more sustainable productivity improvements when skills investment and accountable governance are aligned with work redesign.

5.2 Policy implications

Since the study focuses on policy relevance, we point out implications on three categories of actors, which include policy makers, firms and workers/unions.

a) Policy makers

• Invest in AI prepared human capital. The national and regional skills strategies must focus on AI and data literacy in the whole workforce rather than the technical experts. Systems that facilitate transition to augmented roles may be facilitated by lifelong learning and micro-credentials.

• Revise measurement systems. Intangible capital, data resources, and the quality aspect of the work influenced by AI should be better reflected in official productivity statistics and other innovation indicators (Filippucci et al., 2024).

• Enhance open AI governance. The regulatory systems must enforce transparency, accountability, and human regulation in the AI systems that have a substantial impact on work and livelihoods (Dwivedi et al., 2021). The social partners (employers, unions, civil society) must be engaged in the development of the standards of algorithmic management.

b) Companies and organizational managers

• Use augmentation first approach. Managers need to inquire about where AI can cut jobs rather than asking where we can cut jobs. This demands explicit human-AI working patterns design and redesigned jobs.

• Invest in trans-lators and hybrid jobs. The companies are to identify and compensate positions that are cross-functional between data science and business, and incorporate them into the decision-making workflow (Mikalef et al., 2019; Wamba et al., 2017).

• Revisit KPIs and incentives. The performance indicators must be based on the overall goals of AI-driven change, such as innovation, learning, equity, and sustainability, rather than short-term cost savings.

• Intensify internal AI management. Such scenarios can be avoided by having ethics boards, algorithm-auditing routines, and worker consultation mechanisms to counter dangerous applications of analytics (e.g., intrusive surveillance, biased evaluations) that end up destroying trust and productivity.

c) Workers and unions

• Take initiative towards AI strategies. The worker representatives must be engaged in the debate surrounding the AI implementation by promoting augmentation-focused designs, reskilling pledges, and safeguarding against unjust algorithmic choices.

• Develop AI literacy. People can also enhance their bargaining power by developing the background data skills and learning how AI works and cannot work so they could be engaged in co-designing augmented work systems.

Table 03.

Policy and managerial implications of A2A-BA.

Stakeholder	Key challenge	Augmentation-oriented actions	Expected effects on productivity and inclusion
Governments / Regulators	Balancing innovation with worker protection.	Invest in AI-ready skills systems; set transparency and accountability standards for workplace AI; incentivize augmentation-first adoption.	Higher aggregate productivity with reduced social risk.
Firms / Managers	Capturing AI value while retaining talent.	Redesign jobs for human–AI collaboration; invest in AI literacy; adopt multi-dimensional KPIs; create AI governance boards.	Sustainable productivity gains, improved retention and engagement.
Education & Training Providers	Aligning curricula with emerging skills.	Develop programs on data literacy, ethics, and human–AI collaboration; micro-credentials for working adults.	Reduced skills mismatch; smoother transitions into augmented roles.
Workers & Unions	Preventing exclusion and erosion of job quality.	Engage in co-design of AI systems; negotiate training rights and algorithmic safeguards.	Stronger worker voice; more equitable sharing of productivity gains.

5.3 Direction and limitations to future research

The research has a number of limitations. To begin with, as a qualitative meta-synthesis, it relies on the quality and accessibility of the already existing research, which is uniformly distributed among nations, industries, and classes of workers. Second, we concentrated mainly on white-collar and data-rich settings; more studies are required on augmentation in manual and blue-collar and informal labor. Third, our A2A-BA paradigm is conceptual; empirical studies in the future should be able to test its propositions on a mixed-method basis in which longitudinal case studies, field experiments and large scale surveys are some of the methods that need to be used.

Suggestions and indications include:

a) Comparative research on automation-based and augmentation-based analytics strategies in and cross-industries;

b) Micro-level analysis of worker experience, identity, and job crafting of augmented role;

c) Studies on the dynamics between AI-based business analytics and gender or race or other dimensions of inequality;

d) Determination of the policy instruments (training subsidies, tax incentives, and regulatory sandboxes) to influence the adoption of AI-analytics towards inclusive productivity.

References

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives, 33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Bastida, M., Vaquero García, A., Vázquez Taín, M. Á., & Del Río Araujo, M. (2025). From automation to augmentation: Human resource's journey with artificial intelligence. *Journal of Industrial Information Integration, 46*, 100872. https://doi.org/10.1016/j.jii.2025.100872

Braun, V., & Clarke, V. (2019). Reflecting on reflexive thematic analysis. *Qualitative Research in Sport, Exercise and Health, 11*(4), 589–597. https://doi.org/10.1080/2159676X.2019.1628806

Czarnitzki, D., Fernández, G. P., & Rammer, C. (2023). Artificial intelligence and firm-level productivity. *Journal of Economic Behavior & Organization, 211*, 188–205. https://doi.org/10.1016/j.jebo.2023.05.008

Damioli, G., Van Roy, V., & Vertesy, D. (2021). The impact of artificial intelligence on labour productivity. *Eurasian Business Review, 11*(1), 1–25. https://doi.org/10.1007/s40821-020-00172-8

Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*, 24–42. https://doi.org/10.1007/s11747-019-00696-0

Dube, R., Agarwal, K., Rahman, A., Latif, W. B., & Balaji, V. (2025, February). *The impact of AI on economic forecasting: A case study of currency exchange rate prediction*. In *2025 International Conference on Technology Enabled Economic Changes (InTech)* (pp. 755–760). IEEE. https://doi.org/10.1109/InTech64186.2025.11198571

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., … Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Filippucci, F., Gal, P., Jona-Lasinio, C., Leandro, A., & Nicoletti, G. (2024). *The impact of artificial intelligence on productivity, distribution and growth: Key mechanisms, initial evidence and policy challenges* (OECD Artificial Intelligence Papers, No. 15). Organisation for Economic Co-operation and Development. https://doi.org/10.1787/8d900037-en

Islam, M. N., Latif, M. S. W. B., Yasin, I. M., & Ali, M. J. (2025). Trending research: Transforming applied medical sciences with EdTech innovations. *The Research Seer, 4*(1), 1–5. Retrieved from https://www.researchseer.com/volumes-issues/volume-4-issue-1/trending-research

Latif, W. (2022). Determinants of hotel brand image: A unified model of customer-based brand equity. *International Journal of Customer Relationship Marketing and Management, 13*(1), 1–20. https://doi.org/10.4018/IJCRMM.300834

Latif, W. B., & Yasin, I. M. (2025). From disparities to sustainability: Embedding artificial intelligence and digital health literacy into learning health systems—A critical review article. *Pacific Journal of Medical Research, 2*(4), 167–173. https://doi.org/10.70818/pjmr.v02i04.0122

Latif, W. B., & Yasin, I. M. (2025). The evolution of business models: How innovation is redefining strategic success. *Pacific Journal of Business Innovation and Strategy, 2*(2), 1–4. https://doi.org/10.70818/pjbis.2025.v02i02.039

Latif, W. B., Islam, M. A., Rahman, A., Mohamad, M., & Kongsompong, K. (2016). Conceptual framework of brand image for tourism industry: Tourism management and advertisement as moderators. *Journal of Tourism Management Research, 3*(1), 1–9. https://doi.org/10.18488/journal.31/2016.3.1/31.1.1.9

Latif, W. B., Yasin, I. M., Ali, M. J., Islam, M. N., & Forid, M. S. (2024). Transforming applied medical sciences: The impact of AI, VR, and AR on research, education technology, and clinical practices. *Integrative Biomedical Research, 8*(9), 1–8. https://doi.org/10.25163/angiotherapy.899862

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research, 98*, 261–276. https://doi.org/10.1016/j.jbusres.2019.01.044

Ozgul, P., Fregin, M.-C., Stops, M., Janssen, S., & Levels, M. (2024). High-skilled human workers in non-routine jobs are susceptible to AI automation but wage benefits differ between occupations. *Labour Economics*. Advance online publication. https://doi.org/10.48550/arXiv.2404.06472

Parker, S. K., & Grote, G. (2020). Automation, algorithms, and beyond: Why work design matters more than ever in a digital world. *Applied Psychology, 71*(4), 1171–1204. https://doi.org/10.1111/apps.12241

Sharma, R., Mithas, S., & Kankanhalli, A. (2014). Transforming decision-making processes: A research agenda for understanding the impact of business analytics on organisations. *European Journal of Information Systems, 23*(4), 433–441. https://doi.org/10.1057/ejis.2014.17

Sindhura, K., Rajagopal, N. K., Latif, W. B., Kumar, J. R., Kayande, R. A., & Sakthivel, S. (2025, February). *Leveraging big data and machine learning for real-time economic monitoring and forecasting*. In *2025 International Conference on Technology Enabled Economic Changes (InTech)* (pp. 789–794). IEEE. https://doi.org/10.1109/InTech64186.2025.11198446

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., … Fuso-Nerini, F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature Communications, 11*, 233. https://doi.org/10.1038/s41467-019-14108-y

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 70*, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

Yasin, I. M., & Latif, W. B. (2025). The strategic emergence of BRICS in business, policy and economics reimagining global trade and development. *Pacific Journal of Business Innovation and Strategy, 2*(3), 1–4. https://doi.org/10.70818/pjbis.2025.v02i03.074

Zirar, A., Imran, S., & Islam, N. (2023). Worker and workplace AI coexistence: Emerging themes and research agenda. *Technovation, 124*, 102747. https://doi.org/10.1016/j.technovation.2023.102747