DATA ANALYTICS AS A DRIVER OF ECONOMIC GROWTH IN THE DIGITAL ECONOMY: EVIDENCE, MECHANISMS AND EMERGING CHALLENGES

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Abstract: The digital economy has increased the economic importance of data, making data analytics an important tool for transforming digital information into productive and innovative outcomes. This study examines the role of data analytics in economic growth through a review of recent academic and institutional literature published primarily between 2021 and 2026. It focuses on three key mechanisms: productivity improvement, data-driven innovation, and data-informed decision-making. The literature indicates that the economic value of data depends not only on its availability but also on analytical capabilities, digital infrastructure, organizational capacity, and appropriate institutional conditions. The study further identifies the evolution of research from firm-level data-driven innovation toward broader analyses of productivity and economic performance. It concludes that data analytics can contribute to economic growth when economies and organizations are able to effectively transform data into productive knowledge and innovation.

Keywords: data analytics, digital economy, economic growth, data-driven innovation, productivity, big data.

Introduction

The transition toward a digital economy has changed the way economic value is generated, organized, and measured. Digital technologies have enabled firms, governments, and consumers to generate and exchange unprecedented quantities of information, while analytical technologies have created new possibilities for transforming this information into economically useful knowledge. Consequently, data are increasingly integrated into production, innovation, management, and market processes. Within this environment, data analytics has become an important mechanism connecting the availability of digital data with economic decisionmaking and productive activity. The growing economic importance of data is closely related to the emergence of data-driven innovation. Gierten (2021), in an OECD study of firms' digitalization, examined the adoption of information and communication technologies and the activities through which firms collect, store, and use data, including big data analysis. Their analysis also provided firm-level microeconometric evidence concerning the relationship between big data analysis and different forms of innovation, including product, process, marketing, and organizational innovation. This work is important because it moves the discussion beyond the assumption that digitalization is inherently beneficial and instead examines how firms' use of data is associated with specific innovation outcomes. The subsequent literature has increasingly attempted to explain how data become a source of economic value. Luo (2022) conceptualized data-driven innovation as a

distinct innovation process and differentiated it from data-driven optimization and other data-related approaches. His framework emphasizes that data can influence the innovation process by helping organizations address uncertainty and enhance creativity. This distinction is relevant to economic growth because it suggests that the economic contribution of data is not limited to improving existing processes; data can also affect the creation of new products, services, and solutions. The development of this research stream can also be observed in systematic literature reviews. Samarasinghe and Lokuge (2022) conducted a systematic and comprehensive review of data-driven innovation research and identified gaps in the existing knowledge concerning the phenomenon and the development of organizational innovation capabilities. Their work therefore extends the discussion from the simple adoption of analytical technologies toward the organizational capabilities required to generate value from data. Wong and Ngai (2024) further developed this research trajectory through a systematic review of data-driven innovation literature covering studies published between 2009 and 2022. They classified the existing literature according to theoretical perspectives and levels of analysis and identified research gaps and directions for future research. Importantly, their study demonstrates that data-driven innovation had developed into a recognizable research field rather than remaining a collection of isolated applications of data technologies. More recent research has increasingly connected data and digital technologies with productivity and broader economic outcomes. Corrado et al. (2024), for example, examined data as a form of intangible capital and assessed its implications for productivity. Their analysis estimated that the greater relative efficiency associated with data capital contributed approximately 0.2 percentage points per year to labor productivity growth, while also identifying an appropriability effect that may have reduced measured total factor productivity growth by approximately 0.3–0.4 percentage points. This finding is particularly important for the present study because it demonstrates that the economic effects of data are not unambiguously positive: the productivity-enhancing effects of data can coexist with economic mechanisms that constrain broader productivity growth. The literature has continued to move toward more direct empirical examination of the relationship between digitalization and economic performance. Samariya, Bahl, and Sharma (2026), using panel data for 78 countries and a fixed-effects estimator, investigated the association between internet use and economic growth across different income levels. Their study illustrates the increasing use of cross-country quantitative methods to examine the economic consequences of digital connectivity. Although internet use is broader than data analytics itself, such research provides an important macro-level context for understanding the digital foundations upon which data-driven economic activity depends. Recent 2026 research has also begun to investigate the productivity consequences of data-related market institutions more directly. Zuo, Zeng, and Sun (2026) examined data-factor marketization and manufacturing firms' productivity, reporting that data-factor marketization was associated with higher levels of new-quality productive forces and that digital transformation mediated part of this relationship. This line of research extends the earlier firm-level literature by considering not only whether organizations use data, but also how institutional arrangements surrounding data affect productive outcomes.

Literature Review

1. From Data as a Digital Resource to Data-Driven Innovation. The recent literature demonstrates an important conceptual transition: data are increasingly understood not simply as information generated by digital activity, but as a productive resource whose value depends on the ability to analyze and apply it.

Gierten (2021) provide an important starting point for this transition. Their research examined firms' adoption of technologies that enable them to collect, store, and analyze data and investigated the relationship between big data analysis and different forms of innovation. The significance of their contribution lies in connecting data analytics to observable organizational outcomes rather than discussing digitalization only in technological terms.

Luo (2022) subsequently contributed to the conceptual development of this field by defining data-driven innovation as a distinct innovation paradigm. His analysis distinguishes data-driven innovation from data-driven optimization, emphasizing that the former concerns the use of data as part of the process through which new value is created. This distinction is important for economic analysis because productivity gains from optimization and growth generated through new innovation represent related but different economic mechanisms.

Samarasinghe and Lokuge (2022) continued this conceptual development through a systematic review of the data-driven innovation literature. Their work indicates that organizations increasingly seek to develop data-driven innovation capabilities, while researchers are still working to understand the phenomenon systematically. Thus, the literature begins to move from the question of whether data are valuable toward the more precise question of what organizational capabilities allow data to generate value.

This progression was further consolidated by Wong and Ngai (2024). Their systematic review of DDI research from 2009 to 2022 identified the principal theoretical approaches and levels of analysis used in the field and proposed a

framework for organizing the accumulated knowledge. Their findings are significant for the present research because they demonstrate that data-driven innovation has evolved into a structured research domain while also revealing areas requiring further empirical investigation. The literature therefore suggests a sequential relationship: data availability → analytical capability → data-driven innovation → productivity and economic value. However, this sequence should not be interpreted as automatic. The existence of data does not by itself guarantee innovation or economic growth. The analytical, organizational, technological, and institutional capabilities required to transform data into productive knowledge remain central to the process.

2. Data Analytics, Productivity, and Economic Performance. The productivity dimension provides a second major strand of the literature. Data analytics can affect productivity by enabling organizations to identify patterns, optimize processes, allocate resources more effectively, and make decisions using information that would otherwise remain difficult to interpret.

The OECD's 2021 firm-level analysis provides empirical support for the connection between big data analysis and innovation, thereby establishing an important microeconomic mechanism through which analytics can affect economic performance.

Corrado (2024) extend this discussion to the macroeconomic dimension by treating data as intangible capital. Their estimates suggest that the increased efficiency associated with data capital has contributed to labor productivity growth, while the concentration and appropriability of data-related intangible assets may simultaneously affect total factor productivity. This finding introduces an important qualification to the positive narrative surrounding data: the economic impact of data depends not only on how much data are available, but also on how data assets are organized, owned, and utilized.

Recent empirical research further reinforces the importance of digital foundations. Samariya, Bahl, and Sharma (2026) analyzed 78 countries and used a fixed-effects model to examine the relationship between internet use and economic growth across income groups. Although internet access cannot be equated with data analytics, it represents an enabling infrastructure for digital economic activity and therefore provides relevant macroeconomic context for the expansion of data-driven processes.

The 2026 study by Zuo, Zeng, and Sun provides another step in this progression by examining data-factor marketization and productivity at the manufacturing-firm level. The authors report a positive relationship between datafactor marketization and new-quality productive forces and identify digital transformation as a mediating mechanism. This finding shifts the analytical focus from technology adoption alone toward the institutional organization of data as an economic factor.

Consequently, recent literature increasingly supports a broader interpretation of data analytics: its economic contribution may emerge through multiple interconnected channels rather than through a single direct effect. Analytics can support innovation at the firm level, improve productivity through more efficient use of resources, and contribute to wider digital transformation when appropriate infrastructure and institutions are present.

3. From Firm-Level Innovation to the Digital Economy. A notable feature of the literature is its gradual movement across levels of analysis. The 2021 OECD study primarily examines firms and their use of big data analysis. Luo (2022) and Samarasinghe and Lokuge (2022) focus on the conceptual and organizational dimensions of data-driven innovation. Wong and Ngai (2024) then systematize the literature and identify the different theoretical and analytical levels represented within the field. More recent studies increasingly investigate productivity and economic growth at regional and cross-country levels. This progression creates an important research opportunity. If data analytics generates innovation and productivity improvements within organizations, and if digital infrastructure and data-related institutions influence those capabilities, then the relationship between analytics and economic growth should be examined as a multi-level process rather than as a simple direct correlation. The present study builds on this intellectual progression by connecting the microeconomic and macroeconomic perspectives. It proposes that data analytics can contribute to economic growth through three closely related mechanisms: productivity improvement, data-driven innovation, and datainformed decision-making. These mechanisms are not independent.

Materials and Methods

This study employs a mixed analytical approach combining a structured review of recent academic literature with descriptive analysis of internationally comparable digital-economy indicators. The literature review primarily covers studies published between 2021 and 2026, with particular attention to empirical research examining data analytics, data-driven innovation, productivity, digitalization, and economic performance. For the empirical component, the study relies on secondary data published by internationally recognized institutions, including the Organisation for

Economic Co-operation and Development (OECD), the International Telecommunication Union (ITU), and the United Nations Trade and Development (UNCTAD). These sources were selected because they provide internationally comparable indicators and transparent methodological documentation. The analysis focuses on several dimensions of digital economic development. First, enterprise adoption of big data analysis is examined as a direct indicator of the extent to which firms have developed data-analytical capabilities. Second, internet use and digital connectivity are considered as enabling conditions for data-driven economic activity. Third, evidence concerning productivity and economic performance is examined through recent empirical studies rather than treating digitalization indicators as direct substitutes for economic growth. The study uses descriptive comparison and literature-based synthesis rather than claiming a causal effect where the available data do not permit such identification. This distinction is important because digital transformation and economic growth are multidimensional processes affected by numerous factors, including investment, human capital, institutional quality, market structure, infrastructure, and technological capabilities.

Results and Discussion

1.The Expansion of the Digital Economy and the Foundations for Data Analytics. The global scale of digital connectivity demonstrates why data analytics has become increasingly relevant to economic activity. According to the International Telecommunication Union, approximately 6.0 billion people, or 74% of the world's population, were using the Internet in 2025. The corresponding figure was 5.8 billion in 2024, meaning that approximately 240 million additional people came online during 2025. Despite this expansion, 2.2 billion people remained offline. The digital divide is particularly pronounced across income groups: Internet use reached 94% of the population in high-income economies but only 23% in lowincome economies. These figures are important for interpreting the economic role of data analytics. A growing online population creates an expanding digital environment in which economic transactions, consumer interactions, business operations, and public services generate data. However, the same figures also demonstrate that the capacity to participate in the data economy remains unequally distributed. Consequently, the economic benefits of data analytics cannot be separated from the availability, affordability, and quality of digital infrastructure. The OECD provides a more direct measure of enterprise-level analytical capability. Its Digital Economy Outlook 2024 reports that, as of 2022, approximately 14% of enterprises with ten or more employees used big data analytics on average across the countries for which comparable data were available. National adoption rates ranged from approximately 3% to 40%. By comparison, the average share of firms using artificial intelligence reached 8% in 2023, with country-level rates ranging from 2% to 28%.

The relatively limited adoption of big data analytics is an important finding. It indicates that the existence of digital data does not automatically translate into analytical use. Even within economies with relatively advanced digital infrastructure, most enterprises had not yet adopted big data analytics by 2022. This supports the argument developed in the literature review that data availability and data value are different concepts: economic value emerges when organizations possess the technological and organizational capabilities required to transform data into usable information. The OECD's enterprise-level statistics also reveal substantial differences according to firm size. The technology-adoption tables distinguish small, medium-sized, and large enterprises and show that digital technology adoption generally increases with firm size. This difference is economically significant because large firms are typically better positioned to finance digital infrastructure, employ specialized analytical personnel, and integrate analytical technologies into organizational processes. Therefore, the diffusion of data analytics can itself become a source of heterogeneity in productivity and innovation capabilities.

2. Data Analytics and Innovation. The relationship between data analytics and innovation is one of the strongest mechanisms identified in recent literature. The

OECD's 2021 analysis of firm digitalization examined the relationship between the use of big data analysis and different forms of innovation. The study is particularly relevant because it evaluates data analytics at the firm level rather than assuming that digitalization automatically generates economic benefits. This empirical direction is consistent with the subsequent development of the data-driven innovation literature. Luo (2022) distinguishes data-driven innovation from datadriven optimization, emphasizing that data can contribute not only to improving existing activities but also to creating new forms of value. Samarasinghe and Lokuge (2022) subsequently reviewed the data-driven innovation literature and highlighted the importance of organizational capabilities in realizing value from data. Wong and Ngai (2024) further consolidated this research field through a systematic review covering studies published between 2009 and 2022.

The progression of these studies is important for understanding economic growth. If data analytics contributes to innovation, its economic effect does not necessarily appear immediately as an increase in GDP. Instead, the mechanism can operate through new products, improved processes, organizational changes, and new business models, which can subsequently affect productivity and market performance.

This interpretation is also supported by more recent evidence on data as intangible capital. Corrado (2024) estimated that the greater relative efficiency associated with data capital contributed approximately 0.2 percentage points per year to labour productivity growth. At the same time, their estimates suggest that an appropriability effect associated with data capital reduced measured total factor productivity growth by approximately 0.3–0.4 percentage points.

The findings are particularly significant because they challenge a purely positive interpretation of data-driven economic transformation. Data can increase productive efficiency, but the way data assets are controlled and appropriated can influence how those gains are reflected in broader productivity measures. Thus, the economic contribution of data analytics depends not only on technological adoption but also on the economic structure surrounding data.

3. Digital Connectivity as an Enabling Condition. The expansion of enterprise analytics cannot be considered independently from the broader digital ecosystem. Internet access, broadband infrastructure, cloud computing, digital skills, and data systems provide the foundations on which analytical capabilities operate. The ITU's 2025 estimates show that 74% of the world's population was online, while 2.2 billion people remained offline. The quality dimension of connectivity is also relevant: 5G networks covered approximately 55% of the world's population in 2025, but coverage was highly unequal, reaching 84% of the population in high-income countries compared with only 4% in low-income countries. The same report indicates that a typical Internet user in a high-income country generated nearly eight times more mobile data than a user in a low-income country. This difference illustrates that digital participation is not adequately measured by connectivity alone. The quantity and quality of digital activity also affect the amount of data available for economic analysis and the capacity of individuals and firms to participate in increasingly data-intensive economic activities. This finding has direct implications for the economic-growth argument. Economies with lower connectivity, limited affordability, weaker digital skills, and insufficient infrastructure may have access to the global digital economy without possessing comparable capabilities to generate value from data. The result can be a widening difference between being connected and being able to exploit data productively.

4. From Digitalization to Economic Growth. Recent research increasingly moves beyond firm-level adoption toward broader economic outcomes. Samariya, Bahl, and Sharma (2026), for example, examined 78 countries using panel data and a fixed-effects model to investigate the relationship between Internet use and economic growth across different income groups. This approach is important because it attempts to connect digital participation with macroeconomic performance rather than examining digitalization solely at the organizational level. A similar progression can be observed in research on data-factor institutions. Zuo, Zeng, and Sun (2026) examined the relationship between data-factor marketization and productivity among manufacturing firms and reported a positive association between data-factor marketization and new-quality productive forces, with digital transformation identified as a mediating mechanism. This evidence suggests that the institutional organization of data may influence whether data can be transformed into productive economic resources.

The combined evidence therefore points toward a multi-stage relationship rather than a simple direct equation: digital infrastructure → data generation → analytical capability → innovation/productivity → economic value.

Each stage represents a potential constraint. Weak infrastructure can restrict data generation; insufficient skills can prevent effective analysis; organizational limitations can prevent analytical results from being incorporated into decisionmaking; and weak institutional arrangements can limit the exchange and productive use of data.

5. The Unequal Economic Value of Data Analytics. The international evidence also demonstrates that the benefits of digital transformation are unevenly distributed. In 2025, Internet use reached 94% in high-income countries but only 23% in lowincome countries. Moreover, 96% of people who remained offline lived in low- and middle-income countries. The disparity extends beyond Internet access. According to ITU, 85% of the urban population was online in 2025 compared with 58% of the rural population. The gender gap also persisted, with 77% of men online compared with 71% of women. These differences matter because data analytics requires more than the physical ability to connect to the Internet. Organizations need computing resources, appropriate software, data governance systems, skilled employees, and the ability to integrate analytical outputs into economic decisions. Therefore, countries with limited digital capabilities may face a double disadvantage: they generate less economically usable digital data and have fewer capabilities for converting available data into productive knowledge. The UN Trade and Development's Digital Economy Report 2024 further emphasizes that digitalization creates both economic opportunities and costs. The report estimates that digital devices, data centres, and ICT networks account for approximately 6%–12% of global electricity use and stresses that developing countries often bear a disproportionate share of the environmental costs of digitalization while receiving fewer benefits. This evidence broadens the interpretation of data analytics as a driver of growth. Economic value should not be assessed solely in terms of technological adoption or output growth. A sustainable digital economy also requires consideration of resource consumption, inclusion, affordability, and the distribution of digital capabilities.

Conclusion

The analysis demonstrates that data analytics has become an increasingly important capability within the digital economy, but its contribution to economic growth should not be understood as an automatic consequence of digitalization. The evidence reviewed in this study suggests that the economic value of data emerges through a transformation process in which digital data are converted into information, knowledge, innovation, and more efficient economic decisions. Recent international evidence illustrates both the scale of this transformation and its limitations. In 2025, approximately three-quarters of the world's population was connected to the Internet, while 2.2 billion people remained offline. At the enterprise level, however, the adoption of big data analytics remained considerably lower: the OECD reported that approximately 14% of enterprises with ten or more employees used big data analytics on average in 2022. These figures indicate that digital connectivity and analytical capability represent different stages of digital economic development.

This evidence leads to an important conclusion: data analytics should be regarded as an economic capability rather than simply a technological instrument. Its contribution depends on whether firms and economies possess the infrastructure, human capital, organizational capabilities, and institutional conditions necessary to transform data into productive knowledge. The 2026 evidence on data-factor marketization provides further support for this interpretation, showing that institutional arrangements surrounding data can influence productivity through digital transformation. At the same time, the unequal distribution of digital infrastructure demonstrates that the economic benefits of analytics may also be unevenly distributed. In 2025, Internet use was substantially higher in high-income economies than in low-income economies, while 5G coverage and the intensity of mobile data use also showed significant differences between income groups. Therefore, expanding data analytics capabilities requires more than encouraging technology adoption. It also requires improving digital infrastructure, developing advanced analytical skills, strengthening data governance, and ensuring that organizations of different sizes and economic capacities can participate in the data economy.

Overall, the findings support the following conceptual relationship: Digital infrastructure → Data generation → Data analytics → Innovation and productivity → Economic value → Economic growth. The relationship is not linear or automatic. Each stage depends on capabilities and institutional conditions that determine whether data can be transformed into economic value. Future empirical research could strengthen this framework by using cross-country panel datasets to quantitatively estimate the relationship between enterprise-level data analytics adoption, productivity, innovation, and economic growth. Such research would help move the discussion from identifying associations toward establishing more robust causal evidence.

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