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Assessing Innovation Strategies in the Digital Economy through Artificial Intelligence-Based Criteria Using CoCoSo method

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ABSTRACT

The digital economy, as the driving force of development in recent decades, has been directly affected by advances in Artificial Intelligence. The growing penetration of smart technologies has transformed business models while also reshaping decision-making structures. Therefore, the use of strategies that are evaluated and ranked based on AI-based criteria is an unavoidable necessity. This study ranked innovative strategies in the digital economy by reviewing previous studies and using the Combined Compromise Solution (CoCoSo) method. First, relevant criteria were identified through a review of previous studies; in this study, 10 AI-based criteria in the digital economy were identified, which were confirmed by experts. Then, innovative strategies were evaluated and ranked based on these criteria using the CoCoSo method. The results showed that "The expansion of AI in emerging sectors such as fintech (A4)" with a score of 0.291 and the first rank, plays a pivotal role in creating transformative innovations. In second place, "Investing in advanced cloud and computing infrastructure for AI (A5)" with a score of 0.259, serves as the foundation for robust processing capabilities and facilitates data transfer, without which the implementation of other strategies remains inefficient. Also, "Personalizing user experiences with AI (A2)" with a score of 0.194 and third place, focuses on optimizing decision-making and creating added value through customized experiences, which plays a key role in customer retention and increased engagement across digital platforms. From a managerial perspective, it is recommended that executives first focus on implementing the strategy A4 and launch innovative pilot models in collaboration with fintech and smart tech startups to accelerate the growth of the digital economy. While investment in A5 is needed to create scalable cloud infrastructures that facilitate SMEs' access to AI.

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1. Introduction

For over two decades, the digital economy has been examined from both theoretical and methodological perspectives [1]. The digital economy and the process of digitalization at the international level are among the most important issues that have been placed on the agenda of global institutions such as the World Trade Organization, the International Monetary Fund, the World Bank, and the Organization for Economic Cooperation and Development. Digital transformation strategies and programs have been formulated and implemented at the national, regional, and organizational levels, paving the way for profound changes in business patterns, supply and demand, and decision-making mechanisms [2].

The first stage of the evolution of the digital economy, known as the "information economy", began with the advent of the Internet and its rapid expansion. During this period, the volume of data circulating on the World Wide Web steadily increased, transaction costs decreased, and communication tools evolved from desktop computers to smartphones. This trend promoted a network pattern in economic activities, and “information” was introduced as the main strategic trend in this stage. In the following decades, the digital economy entered the stage of the knowledge economy, a stage in which knowledge and creative components played a central role in the creation of value. Focusing on intellectual work and the growth of creative industries, the knowledge economy created a platform for intangible products and technological innovations to become the main engines of growth [3].

The third stage is the formation of the contemporary digital economy, which began in the mid-2000s and was complemented by the development of ICT technologies, the Internet of Things, big data, and cloud computing. At this stage, the digital economy has become a field beyond the digitization of processes and is defined as an independent part of economic output: "That part of the economic output that comes solely or mainly from digital technologies with a business model based on digital goods or services". Although this definition has ambiguous boundaries, it provides the flexibility necessary to adapt to the innovations of the digital business model [4].

The digital economy is growing at a remarkable pace in emerging markets, which has led to the digital economy being raised as a catalyst for increasing capital and labor productivity, reducing transaction costs, and facilitating access to global markets [5,6]. The main drivers of this growth and transformation are economic and political factors, but in fact it is rooted in technological innovations. Continuous advances in digital technologies have led to the gradual erosion of the boundaries between the physical, digital, and biological spheres, and large-scale economic systems have undergone transformation. This transformation has been accelerated by the development of emerging technologies, especially in the field of artificial intelligence [7].

Artificial Intelligence (AI) has been touted as an effective and accelerator in the development of the digital economy. The literature defines artificial intelligence as "programs, algorithms, systems, or machines that demonstrate intelligence" and emphasizes that by using technologies such as machine learning and natural language processing, AI is able to interpret data, learn from it, and use these lessons to achieve specific goals [8]. AI, with its ability to analyze complex data, learn from patterns, and make intelligent decisions, has revolutionized the structure of production, distribution, and consumption, and has redefined the growth trajectory of the digital economy. With the expansion of the Internet of Things (IoT) and the production of big data, the platform for AI applications was developed and now AI has practical and proven applications in many areas such as marketing, customer service, finance, and supply chain management [4, 7, 9-11]. This trend demonstrates the pivotal role of AI in shaping innovations and improving efficiency in the digital economy.

In addition, the combination of AI and Big Data Economy has led to the evolution of the traditional economy towards a smart digital economy. This type of economy, using the capacities of AI as the main driving force, can reorganize and upgrade industrial structures through digital industrialization and digitization of production processes [12]. Also, with the help of data analysis and exploitation, it provides the ground for reducing information asymmetry and increasing efficiency in the allocation of production resources, and helps the flow of economic activities in the market more smoothly. For instance, in 2022, the size of China's core AI industry reached 508 billion yuan, marking an 18% year-on-year growth. During the same period, the value of the country's digital economy surpassed 50 trillion yuan, representing 41.5% of its GDP. The digital economy has thus become a central pillar of China's overall national development [1].

Due to the increasing acceleration of digital transformation and the expansion of the role of AI in various economic sectors, identifying and evaluating innovative strategies based on artificial intelligence criteria has become one of the topics of interest in the field of economic management and policy-making. In order to survive and grow in the dynamic environment of the digital economy, organizations need to make strategic decisions based on the analysis of intelligent and data-driven criteria. In this regard, relying solely on traditional approaches in the selection and implementation of innovation strategies is no longer responsive to the complexity and speed of technological developments. Therefore, the present study aims to evaluate and prioritize innovative strategies in the digital economy using AI-based criteria and using the CoCoSo multi-criteria decision-making method to provide a systematic framework for intelligent selection of strategies in organizations. The results of this study can help managers and policymakers chart the path to innovation development by focusing on key AI criteria and make more efficient and forward-looking decisions.

1.1 The Digital Economy and Its Benefits

The notion of the digital economy was first introduced in 1999 by American economist Don Tapscott [13]. A year later, the publication of the *Emerging Digital Economy Report* by the U.S. Department of Commerce marked the formal beginning of digital economy development. Despite its growing importance, the definition of the digital economy remains a subject of debate among scholars. A widely accepted explanation was later provided by *the G20 Digital Economy Development and Cooperation Initiative* at the 2016 G20 Hangzhou Summit, which defines the digital economy as a collection of productive activities that regard digital knowledge and information as key production factors, modern network technologies as essential media, and the effective use of information and communication technologies as the primary force driving efficiency improvement [1].

The digital economy can be defined as "that part of economic output derived solely or primarily from digital technologies with a business model based on digital goods or services". This definition emphasizes aspects such as the role of data as a factor of production, the role of information networks, and the use of information and communication technology as a driving force. Thus, the digital economy includes the digital core (activities that are inherently digital) and a broader range of digital activities that are gradually integrated into the structure of production and consumption. As shown in Figure 1, the digital economy encompasses both the digital core sector and a wider range of broad digital activities, without claiming that all digital activities are part of the digital economy [14].

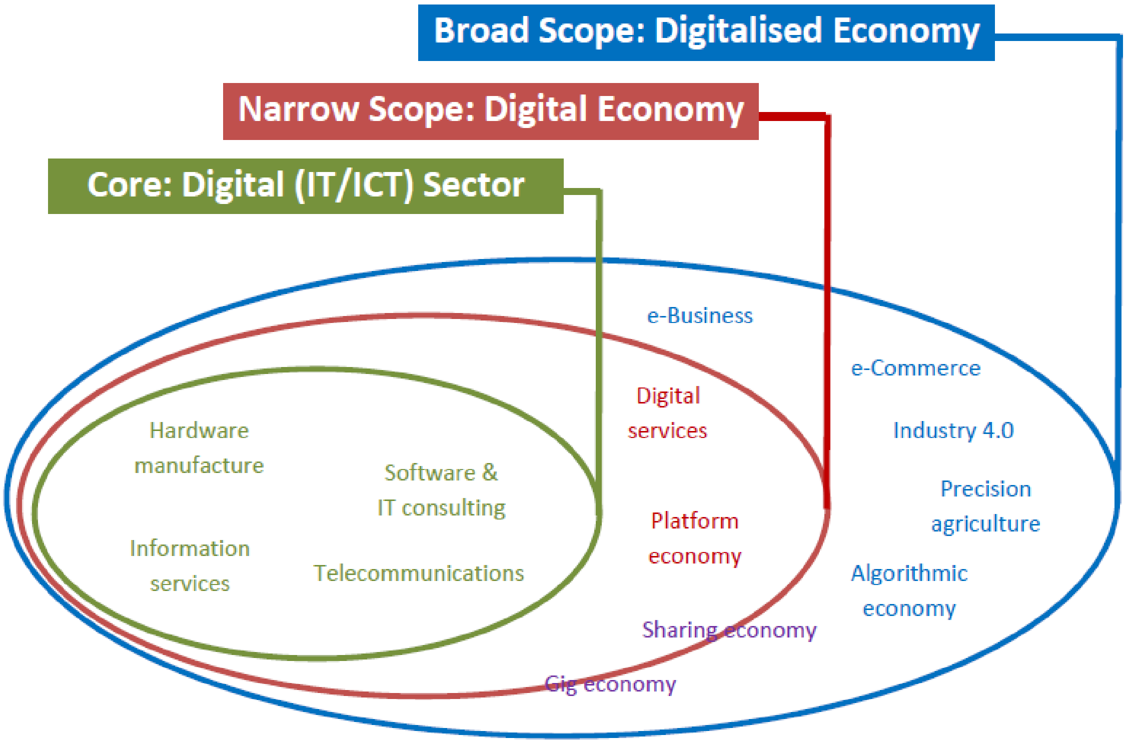

Fig. 1. Scoping the digital economy [14]

The digital economy can be described as a business activity that is carried out virtually, where value is created, exchanged, and transactions and interactions take place between economic actors using the Internet as the main tool. This means that, in general, the digital economy is based on the use of digital information and communication technologies in its operations. Changes in the behavior of people who increasingly rely on digital platforms in various sectors are the main drivers of the growth of the digital economy [15].

The digital economy has increasingly emerged as a major development trend across diverse spheres of society, such as politics, law, education, healthcare, and culture. Whereas a decade ago digital channels contributed little to GDP growth, their influence now extends far beyond the long-established domain of traditional goods trade. This evolution has greatly intensified global economic interactions and reshaped the framework of international communication [3].

In developing countries, the digital economy holds promise for faster and more dynamic growth, as it can increase capital and labor productivity, reduce transaction costs, and facilitate firms' access to global markets [6]. In addition, the tangible benefits of the digital economy in reducing economic inequalities are also evident, as the digital workforce in the Global South enjoys wages higher than the local average, which contributes to relative income convergence at the international level. The expansion of digital native startups and the development of online platforms in these countries have also provided a platform for firms and entrepreneurs to move beyond the inefficient and corrupt traditional market institutions and operate more effectively through the digital space [14].

The expanding presence of the digital economy across sectors such as e-commerce, financial technology, and healthcare has enhanced both the efficiency and competitiveness of businesses. Broader access to the Internet and digital tools has enabled firms to restructure their operations, leading to lower costs, greater transparency, and improved communication. At the same time, these advancements have generated new employment opportunities, particularly for younger individuals equipped with technological expertise. Furthermore, digitalization has simplified brand promotion and made product marketing more effective through online platforms. While finding suppliers once posed a significant challenge, today nearly all goods can be sourced via e-commerce systems. The digital marketplace, unrestricted by geography, has also created an enabling environment for micro, small, and medium-sized enterprises (MSMEs), allowing them to expand their activities and connect with both domestic and global consumers [15].

In addition to facilitating access to markets, digital transformation has improved productivity and increased efficiency in various economic sectors. The development of information technology and the expansion of digital platforms have led to the formation of new businesses in diverse fields such as trade and retail, accommodation and food services, automotive maintenance, mining, processing industries, transportation, and warehousing. Digital platforms have now become an efficient tool for companies to maximize the added value of products and services. Increasing the productivity of firms through digitalization has also paved the way for the creation of new jobs, especially with the proliferation of startups, e-commerce, and service platforms that have created diverse job opportunities on a large scale [16].

One of the most important positive effects of the digital economy is the facilitation and acceleration of economic transactions. Conducting transactions digitally has not only reduced the cost and time of transactions, but has also led to a boom in informal sectors and the emergence of social businesses. The use of social media such as Facebook and Instagram has led to an increase in the number of economic transactions and ultimately the growth of companies' revenues within the framework of e-business models. Increasing revenue from online activities helps businesses to sustain and maintain economic stability, especially since companies operating in the digital space have a higher ability to maintain economic stability on a macro scale due to greater financial flexibility [15].

The expansion of the digital economy has also paved the way for the development of financial inclusion. Digital financial services such as e-wallets have provided access to the financial system for companies and individuals who were previously deprived of traditional banking services. This has increased individual well-being and fostered more inclusive economic growth [17]. Along with this, digitalization has had a significant impact on strengthening micro, small, and medium-sized enterprises. By taking advantage of digital technology, these companies can penetrate international markets at a lower cost, increase their productivity, and perform more efficiently against the competition of foreign products. In addition to improving management, marketing, and inventory control processes, digital technologies have made it possible to operate extensively in the global market without the need for complex and costly infrastructure. Thus, the digital economy is recognized as one of the main pillars of contemporary economic growth and development by strengthening corporate competitiveness, expanding financial inclusion, and creating sustainable employment opportunities [2].

1.2 The Role of Artificial Intelligence in the Digital Economy

Artificial intelligence, as one of the transformative technologies of the present era, has found wide applications in various economic and social fields and has significantly improved efficiency, accuracy, and decision-making in various processes. In the healthcare sector, the ability of AI to analyze huge amounts of patient data, including medical records, X-ray and MRI images, and genetic information, has allowed for more accurate and timely diagnosis and improved patient treatment outcomes [18-22]. In education, AI-powered learning systems design personalized learning paths by analyzing student data that increases the engagement, understanding, and effectiveness of the learning process [23, 24]. In the financial sector, AI algorithms have added unprecedented speed and accuracy to financial trading by analyzing market data in real time and executing optimal trades, providing the ground for strategic and profitable decision-making [25]. In manufacturing industries, AI predicts the probable time of equipment failure by analyzing data from sensors such as temperature and vibration and allows for proactive maintenance planning, which reduces emergency costs and increases equipment lifespan [26-28]. In the field of transportation, AI systems propose optimal routes by examining real-time traffic data and environmental conditions and reduce travel time and fuel consumption [29-31]. Finally, in the agricultural sector, AI helps to optimize irrigation, fertilization, and pest control by processing data from sensors, satellites, and drones, thereby increasing productivity and reducing environmental impacts [32].

After experiencing the information age, consumer internet, and industrial internet, the digital economy has entered a new phase of the smart economy with artificial intelligence as the main driving force. Researchers and scientific and economic institutions increasingly emphasize the importance of digital infrastructure, innovation ecosystems, and AI readiness as key factors in improving economic and social performance [33]. This is due to the effective role of AI in supporting the digital economy; in other words, AI enables more rational decision-making and improves the level of development of the digital economy by optimizing the allocation of relevant production factors and extracting effective data from big data. Digital communication technology based on AI has also paved the way for the transformation and upgrading of traditional industries in the context of the digital economy through the influence and substitution effects. In fact, if we consider computers and the Internet as tools and data platforms for the development of digital technology, then artificial intelligence should be considered as a key link in transforming the indirect productivity of digital technology into direct productivity [1].

Economic growth, which focuses on increasing the efficiency of economic activities, improving labor productivity, and improving the quality of life, has been significantly affected by technological developments, especially the development of AI. Given the complex and multidimensional nature of economy, traditional analytical approaches have limited effectiveness in identifying patterns and predicting trends, while artificial intelligence technologies with their extensive data processing and analysis capabilities can overcome these limitations and pave the way for more accurate and efficient economic decision-making [34]. With its ability to extract patterns from complex data and provide decision recommendations, AI plays a facilitating and reinforcing role in the digital economy. AI can help increase the revenue of firms by increasing employee productivity, increasing consumer responses, setting competitive prices, and creating unique resources [35-37]. Also, AI can reduce costs by automating day-to-day processes and improving efficiency and reduce credit risks at the portfolio level through machine-based credit models [10].

Various studies have shown that AI significantly improves organizational performance by increasing employee productivity and facilitating their coordination with customers' changing needs. For example, Kim *et al.,* [38] emphasized that AI helps employees more effectively adapt to customer demands by providing them with detailed behavioral analytics, while Luo *et al.,* [39] also reported that AI enhances job performance by facilitating the flow of information and decision-making. Along with these benefits, AI can effectively help create healthier price competition; the findings of Miklós-Thal and Tucker [40] showed that machine learning-based demand forecasting algorithms can adjust prices to market fluctuations while reducing final prices and increasing consumer surpluses. In addition, Gregory *et al.,* [41] and Krakowski *et al.,* [42] believe that AI allows companies to create unique organizational resources that are difficult for competitors to emulate. This capability is particularly evident in digital platforms, where advances in AI have enabled systems to learn from users' data and provide personalized services that create specific value for each user.

Artificial intelligence has gained a prominent position, especially in the field of economic modeling and forecasting. The use of Machine Learning (ML) and Deep Learning (DL) methods has provided powerful and accurate tools for predicting regional GDP patterns and has made it possible to make forward-looking decisions in the field of development and economic policy [43]. Predictive economic models, relying on mathematics and learning algorithms, can predict economic growth, employment rates, industrial development, income distribution, and even environmental impacts on a regional scale [44]. Meanwhile, decision tree-based (DT) models, support vector machines (SVMs), and group methods such as random forest (RF) and gradient augmentation have significantly increased the accuracy of economic forecasts. Also, recurrent neural networks (RNNs) and their advanced types such as LSTM and GRU have shown high efficiency in analyzing local GDP trends due to their ability to process time-series data [45, 46].

In addition to supervised learning approaches, unsupervised learning models are also used to discover hidden relationships and new correlations between economic variables. These models, using clustering algorithms and dimension reduction, can reveal hidden structures in macroeconomic data and be effective in identifying new factors affecting economic performance. Advanced neural networks and autoencoders analyze large amounts of data to reveal complex relationships between economic indicators and help decision-makers to better understand economic dynamics. In particular, AI's ability to adapt to temporal changes and understand dynamic correlations has led to more accurate and reliable economic forecasts than traditional methods [34].

From the perspective of cost reduction, AI also plays a key role. This technology enables organizations to significantly reduce their operational costs by improving the efficiency of processes and reducing financial risks. Grennan & Michaely [47] stated that AI increases information efficiency and provides more accurate investment recommendations by simultaneously collecting and analyzing multiple data sources. Also, Costello *et al.,* [10] showed that machine-generated credit models can reduce credit risks at the future portfolio level compared to traditional models.

In addition to the direct economic benefits, AI allows for personalized experiences and enhanced customer engagement, which can lead to increased customer loyalty and lifetime value (CLV). These features make AI one of the most important drivers of product and service innovation in platform environments [41]. Artificial intelligence is playing an increasing role not only in economic data analysis but also in macro policy design and strategic decision-making. Utilizing advanced data mining, AI technology can identify patterns, hidden relationships, and indirect effects of economic variables and provide more accurate analyses of real-time statistics. This capability allows policymakers to simulate and evaluate the impact of fiscal decisions or monetary policy changes prior to implementation. In other words, AI has been able to move the economic planning process from empirical decision-making to data-driven analytics by providing a more comprehensive understanding of economic trends and the possible outcomes of strategic actions. As a result, this technology is not only a tool for economic forecasting and analysis, but it has also become a key factor in improving decision-making, increasing efficiency, and driving sustainable growth in the digital economy [34].

Finally, AI has paved the way for digital innovation and organizational transformation by automating daily tasks, increasing productivity, and creating new business models. In addition to improving the internal performance of organizations, this technology also helps increase customer loyalty and satisfaction by providing personalized and interaction-oriented experiences for customers. Organizations that take advantage of the capabilities of AI in the path of digital transformation gain new opportunities for growth, competition, and sustainable success in the dynamic environment of the digital economy, so that this trend can be considered as a symbol of AI-based innovation in the process of digital transformation [23].

2. Literature Review

Digital transformation and the development of smart technologies have led to the formation of a wide wave of research in the field of digital economy. In recent years, researchers have tried to investigate different dimensions of this phenomenon from the perspective of institutional, policy-making, innovation, and sustainability. In the following, some of the prominent researches in this field are reviewed.

In a study conducted by Miškufová *et al.,* [33], a comparison was made between digital competitiveness indicators in European countries to examine the impact of digital economy and artificial intelligence on countries' rankings. The study analyzed 29 European countries and used four valid indicators including the World Digital Competitiveness Ranking (WDCR), Network Readiness Index (NRI), AI Readiness Index (AIRI), and Digital Quality of Life Index (DQLI), showed that despite the high correlation, the rankings also have significant differences that are caused by the conceptual differences of the indicators. Countries such as Finland, Netherlands, and Denmark consistently ranked in the top rankings, while indices such as DQLI had more changes in the rankings. The results of this research show the importance of rank-based multidimensional assessments in measuring digital competitiveness and policies related to inclusive digital development.

In a study conducted by Lu *et al.,* [1], the interaction between the digital economy, artificial intelligence, and the development of the sports industry in China was examined. Using the panel vector autoregression (PVAR) model and panel data from 15 Chinese provinces during 2014-2020, they showed that the increasing level of the digital economy is increasing the use of artificial intelligence and the added value of the sports industry. The results of the research indicated that the digital economy has a short-term and weak effect on artificial intelligence, but it has a strong and significant impact on the development of the sports industry. Also, the internal driving force of the digital economy and artificial intelligence is higher and the self-dynamism of the sports industry is less, and the impact of artificial intelligence on the sports industry is greater than the level of development of the digital economy.

Wang *et al.,* [34] investigated the role of artificial intelligence and empirical models in predicting regional economic growth and transportation dynamics. Focusing on AI's abilities to manage complex data and analyze regional economic trends, the study found that the use of AI makes it possible to predict future patterns and support advanced economic decision-making. The research also investigated the relationships between types of transportation and regional economic growth and summarized the different empirical models and methods used in economic analysis. The results show that artificial intelligence can play a key role in the evolution of regional economic research and the development of data-based forecasting models, and can be applied in the design of economic policies and programs in accordance with the characteristics of each region.

Meidyasari [15] investigated the role and impact of the digital economy on Indonesia's economic growth and development. This study has been conducted with a qualitative approach and based on a systematic review of various sources including scientific articles, government reports, and case studies. The findings of the research showed that digital transformation in Indonesia has had a significant effect on increasing productivity, promoting innovation, and expanding access to markets in various economic sectors. The author emphasizes that efficient management and targeted policy-making in the digital field can make the digital economy one of the main drivers of the country's future economic growth. The research also emphasizes the importance of providing access to digital tools, financial resources, and specialized training for the success of micro, small and medium-sized enterprises (MSMEs) in the digital age, and suggests that the sustainable development of Indonesia's digital economy should be based on supportive policies and human and technological capacity-building.

Shafik [48] examined the role of artificial intelligence in the emerging era of the digital economy and pointed to the explanation of different dimensions of the impact of this technology on human life, work, and interactions with technology. This study has introduced different types of artificial intelligence, including rule-based systems, machine learning, and neural networks, and explained its applications in areas such as chatbots, predictive analytics, self-driving cars, image and speech recognition, and smart health services. The findings show that artificial intelligence increases productivity, efficiency, and quality of decision-making, although it also brings challenges such as job turnover, algorithmic bias, ethical issues, and data privacy.

Lee *et al.,* [49] investigated the role of artificial intelligence in the energy transition and its impact in the context of the digital economy. In this study, an indexing system was designed to assess the level of the digital economy to analyze its role in the relationship between artificial intelligence and the energy transition. The results showed that the advancements of artificial intelligence have a positive effect on improving the energy transition process, and the digital economy is also reinforcing this effect. In addition, the performance of countries varies based on income level, so that countries dependent on natural resources receive a greater impact from the AI-based energy transition. The findings of this study can be helpful for policymakers to accelerate the energy transition, reduce regional inequalities, and realize low-carbon development.

Aldoseri *et al.,* [23] investigated the relationship between artificial intelligence and innovation as two fundamental pillars in the framework of digital transformation. They stated that digital transformation systems provide a suitable platform for new innovations by producing a huge amount of data, and artificial intelligence can become the driving force of this process by relying on data analysis, continuous learning, and the development of innovative products. The findings of the research showed that the key pillars in fostering AI-based innovation include performance monitoring and evaluation, data analysis and forecasting, continuous learning, interdisciplinary collaboration, and the development of industrial partnerships.

Zhang [50] investigated the impact of the AI industry on the number and structure of employment in the context of the digital economy. By designing a theoretical model and analytical mechanism, he studied the dynamics of employment and structural changes in the labor market in industries related to artificial intelligence. The results showed that there has been a significant trend in the labor force in China, which is accompanied by a greater focus on education and increasing job opportunities. By analyzing the distribution of employment in different industries and the skill diversity of the workforce, this study provides a deeper understanding of the quantitative and qualitative changes in employment in the age of artificial intelligence.

Lim and Siripipatthanakul [51] explored the impact of artificial intelligence and ChatGPT on the digital economy in a qualitative systematic review. The results of the content analysis showed that these technologies are evolving the digital economy at a remarkable pace and have created numerous opportunities in areas such as health, finance, manufacturing, and transportation. Research states that ChatGPT and other AI tools are able to generate high-quality text, audio, and video content, saving time and money by automating the content creation process. Moreover, generative AI increases customer engagement, loyalty, and satisfaction by personalizing content and products based on users' preferences. The authors also suggested that the use of questionnaires and interviews in future research could lead to a more comprehensive understanding of the role of these technologies in the digital economy.

In a review study aimed at examining the role of artificial intelligence in the digital economy, Hang and Chen [52] tried to identify the capacities and barriers to the full realization of its potential in the fields of business and management. Their findings showed that AI can increase the revenue of organizations by increasing employee productivity, improving consumer evaluation, setting competitive prices, and creating unique resources. Also, this technology reduces operational costs by improving efficiency and reducing risks. However, the research emphasizes that factors such as the adoption of artificial intelligence, the nature of organizational tasks, and the way it is managed are the main obstacles to the full exploitation of the capabilities of artificial intelligence. According to the authors, one of the fundamental weaknesses of AI is the lack of interpersonal skills, and therefore it is recommended that future research focus on developing the interactive and social capabilities of AI to realize its more effective role in the digital economy.

Cheng and Huang [53] evaluated the factors affecting regional economic growth in the context of the digital economy using deep neural networks. The results of the simulations showed that the digital economy in provinces such as Guizhou, Beijing, Chongqing, Anhui, and Tibet is growing at a rapid pace, and in general, the gap between different regions of China is narrowing. According to the findings, for every 1% increase in investment in the digital economy, GDP grows by about 0.24%, while a 1% increase in the labor force leads to a growth of 0.22% in GDP. Research emphasizes that developing the infrastructure of the digital economy and attracting specialized manpower in China's western regions are essential for sustainable economic growth. In addition, the stability of the used model indicates the robustness of the obtained results.

Rong [7] provided a theoretical framework to better understand the developments and future prospects of the digital economy. Emphasizing the transition from the industrial economy to the digital economy, the study states that this transformation has led to the emergence of new factors of production, innovative organizations and models, and new economic fields. In this regard, the IBCDE conceptual framework was introduced, which examines the digital economy from five dimensions: digital infrastructure (I), to-B industry platforms (B), to-C two-sided platforms (C), data ecosystem (D), and economic contexts (E). The findings of the research have identified future research paths for the theoretical and applied development of the digital economy.

Zhu *et al.,* [54] investigated the impact of industrial accumulation on the regional economy in a simulated intelligent machine learning-based environment. In this study, using the industrial accumulation index, the degree of integration of the manufacturing industry in a city was evaluated and its relationship with regional economic development was empirically analyzed. The results showed that the integration of industries in intelligent environments based on simulation and machine learning has a positive and significant effect on the economic growth of the regions. In particular, a 1% increase in the level of cooperation between the manufacturing services and manufacturing industries will lead to a 0.025% growth in regional economic development. These findings highlight the importance of the use of intelligent technologies and machine learning in improving industrial convergence and improving the economic efficiency of regions.

Frolov and Lavrenteva [3] analyzed the nature and characteristics of the digital economy as a regulating phenomenon with an institutional approach. They investigated the logic of evolution and internal contradictions in the digital economy and explained its concepts, functions, and structures through comparative analysis. In this research, the conceptual framework and conceptual apparatus of digital economy theory have been redefined and completed. By presenting a conceptual model of the multi-level transition of the economy to digital development, the authors emphasized the importance of designing a regulatory system appropriate to different levels of digital transformation. In this regard, the distinction between "digitalized" and "digitized” sectors were proposed as two areas related to digital technologies and products, so that the first part includes inherently digital industries and the second part includes industries that have been affected by digitalization. The results of the research indicate that the creation of an appropriate institutional environment using hybrid institutions based on the combination of traditional and algorithmic law in the form of a multi-level structure can increase the effectiveness of regulatory policies in the digital economy. The authors also suggested the use of tools such as regulatory sandboxes, legal foresight, and public discussion to facilitate testing and policy modification in the real-world environment.

3. Methodology

The Combined Compromise Solution (COCOSO) method is a new multi-criteria decision-making method (MCDM) that operates as an integrated model of the Simple Additive Weighting (SAW) method (sometimes known as the Weighted Sum Model or WSM) and the Weighted Product Model (WPM). This method is based on the concept of compromise solutions and is designed to rank options in complex decision-making situations, focusing on the balance between positive and negative functions. COCOSO was introduced by Yazdani *et al.,* [55] and has gained attention in applications such as supplier selection, project evaluation, and risk management due to its simplicity of calculations, noise resistance, and ability to combine with fuzzy or gray methods.

In the original paper, the terms WSM and WPM are used to describe the combination of approaches. WSM operates on the basis of weighted summation of normalized scores, while WPM uses weighted multiplication to avoid compensation problems (such as strong criteria dominating over weak ones). By integrating these two models, COCOSO offers three ranking strategies that provide great flexibility in decision-making. Not only does this method increase the accuracy of the ranking, but it also makes the calculations simpler than traditional methods such as TOPSIS or VIKOR and facilitates sensitivity analysis to check the stability of the results.

Step 1: Forming the Initial Decision Matrix

In the MCDM methods, the first and fundamental step is the formation of the initial decision matrix. This matrix, represented by $X = [x_{mn}]_{m\times n}$, reflects the systematic evaluations of alternatives based on the criteria. In this matrix, each element x_{mn} represents the performance of alternative a_i over the criterion C_j, where $i = 1,2, \dots m$ and $j = 1,2, \dots n$ represent the number of alternatives and criteria respectively. Assessments can be based on quantitative (such as real numerical values) or qualitative (such as verbal or linguistic expressions) data, which makes the method suitable for a variety of applications, including fuzzy or grey environments.

$$x_{ij} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \tag{1}$$

These scales, often modeled as fuzzy numbers or grey numbers, allow for the processing of the inherent uncertainty in expert judgments. The criteria are further divided into two main categories: Benefit Criteria and Cost Criteria, a distinction that is influential in the subsequent normalization and weighting calculations. The precise formation of this matrix provides the basis for the validity and reliability of the final results in the COCOSO method, and is often collected through expert surveys or empirical data.

Step 2: Normalization of the Decision Matrix

Decision matrix normalization is carried out with the aim of unifying different scales of criteria and eliminating the impact of different units of measurement. This process generates the normalized decision matrix ($R = [r_{ij}]_{m\times n}$) and adjusts the values to the interval [0,1], which facilitates subsequent calculations and increases the accuracy of the results. The COCOSO method uses Min-Max Linear Normalization technique, which takes into account the distinction between Benefit Criteria, where higher values are more desirable, and Cost Criteria, where lower values are more desirable. Normalization is done using the following equations:

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}; \quad \textit{for benefit criterion} \tag{2}$$

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}; \quad \textit{for cost criterion} \tag{3}$$

This approach, by maintaining relative relationships between alternatives, avoids compensation issues and provides a solid foundation for calculating weighted scores in later stages of COCOSO. In the case of fuzzy or grey data, this normalization can be extended with appropriate generalizations (e.g., fuzzy normalization).

Step 3: Calculate the Weighted Sum and Weighted Product Values

In the third step of the COCOSO method, the Weighted Sum (S_i) and Weighted Product (P_i) scores for each alternative are calculated based on the normalized matrix and the weights of the criteria. These weights are entered as key inputs into the method and can be extracted through direct expert judgment methods or systematic approaches such as Analytic Hierarchy Process (AHP), Shannon Entropy, Best-Worst Method (BWM), or other weighting techniques. The calculation S_i is based on the Simple Additive Weighting Model (SAW, equivalent to the Weighted Sum Model or WSM), which provides linear weighted aggregation to evaluate overall performance. In contrast, P_i uses the Weighted Product Model (WPM), which is inspired by the multiplicative aspect of the WASPAS method. It also models nonlinear relationships between criteria using weight powers to avoid compensation effects. The values of S_i and P_i are obtained using Equations 4 and 5.

$$S_i = \sum_{j=1}^{n} w_j r_{ij} \tag{4}$$

$$P_i = \prod_{j=1}^{n} (r_{ij})^{w_j} \tag{5}$$

Step 4: Determining the Relative Weights of the Alternatives

In the fourth step of, the relative weights of the alternatives are calculated based on three aggregation strategies. These strategies, which are based on the weighted sum (S_i) and weighted product (P_i) scores from the previous step, increase the flexibility of the method in ranking the alternatives and allow the selection of a strategy that is appropriate for the decision-making situation. Each strategy strikes a different balance between linear (WSM) and nonlinear (WPM) aggregation, which makes COCOSO a powerful tool for dealing with uncertainty and multi-criteria complexities. The strategies are derived based on the following equations:

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} (P_i + S_i)} \tag{6}$$

$$k_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i} \tag{7}$$

$$k_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{\lambda \max_i S_i + (1-\lambda) \max_i P_i}; \quad 0 \le \lambda \le 1 \tag{8}$$

The value of λ in Equation 8 is determined by the decision maker, and at $\lambda = 0.5$, an equal balance is established between the two models. This approach allows for tuning based on specific preferences (such as greater emphasis on WSM or WPM) and increases the stability of the rankings in high-uncertainty environments.

The selection of the appropriate strategy is based on the nature of the problem (such as the presence of compensability or sensitivity to weak criteria), and often the average scores of the three strategies are used for the final ranking. This step, by incorporating trade-off aspects, improves the accuracy and generalizability of COCOSO compared to single-model methods.

Step 5: Determining the Final Ranking of the Alternatives

The final score of each alternative (k_i, for $i = 1, \dots, m$) is calculated based on the aggregation of three compromise strategies from the previous step. This aggregation, which is a combination of the geometric mean and the arithmetic mean, strikes a good balance between multiplicative (to emphasize overall agreement) and additive (for linear aggregation) relationships and increases the stability of the ranking against possible changes. The equation for calculating the final score is as follows:

$$k_i = (k_{ia} \cdot k_{ib} \cdot k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}) \qquad (9)$$

In this equation, the geometric mean highlights the sensitivity to the lowest performance, while the arithmetic mean ensures the overall balance. The alternatives are ranked based on k_i values, such that the higher the k_i value, the better the alternative. This approach improves the accuracy of decision-making by integrating trade-off aspects, and facilitates the possibility of sensitivity analysis on parameters such as λ in the third strategy to check the robustness of the results.

4. Results

In the era of digital transformation, the digital economy serves as the main engine of global economic growth. However, structural challenges such as inequalities in access to technology, growing cyber threats, and the need to quickly adapt business models to technological changes prevent it from fully exploiting its innovative potential. Artificial Intelligence AI as a key technology, can turn these challenges into competitive opportunities, but without strategic prioritization, investments will be fragmented and inefficient. In developing countries, the digital divide and infrastructural constraints exacerbate this issue, and necessitate the need for a data-driven approach to prioritization.

The main issue in this research is to prioritize AI-driven strategies in the digital economy that create sustainable added value based on the key criteria in Table 1. These criteria include “ Cost Optimization (C1)”, “Decision-Making Optimization (C2)”, “Facilitating Access and Data Transfer (C3)”, “Reducing the Digital Divide (C4)”, “Creating Added Value (C5)”, “Adapting Business Models to Changes (C6)”, “Cybersecurity (C7)”, “Strong Processing Capabilities (C8)”, “ Interaction with Emerging Technologies (C9)”, and “Customization of Goods and Services (C10)”. Table 1 provides each criterion with its corresponding references and Table 2 lists the alternatives.

Table 1
AI-based Criteria in the Digital Economy

Symbol	Index
C1	Cost Optimization
C2	Decision-Making Optimization
C3	Facilitating Access and Data Transfer
C4	Reducing the Digital Divide
C5	Creating Added Value
C6	Adapting Business Models to Changes
C7	Cybersecurity
C8	Strong Processing Capabilities
C9	Interaction with Emerging Technologies
C10	Customization of Goods and Services

Table 2
Alternatives under Consideration

Symbol	Alternative
A1	Integrating AI into supply chain and process automation
A2	Personalizing user experiences with AI
A3	Investing in AI-driven training and workforce
A4	The expansion of AI in emerging sectors such as fintech
A5	Investing in advanced cloud and computing infrastructure for AI
A6	Strengthening data security and digital trust

First, based on the first step in the COCOSO method, the alternatives were compared based on 10 key criteria. A quantitative evaluation was performed on a scale of 1 to 10, with a score of 10 indicating the maximum score of the alternative and a value of 1 indicating the minimum score. For normalization, the range was limited to 3 to 10 to make subsequent analyses more accurate (see Table 3).

Table 3
Evaluation of alternatives in each criterion

Symbol	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	9	8	7	5	8	7	6	9	6	4
A2	7	9	6	4	9	6	5	7	7	10
A3	4	5	4	9	7	9	4	5	8	5
A4	6	8	7	6	9	9	8	8	10	9
A5	8	7	9	7	7	8	7	10	9	5
A6	5	6	6	4	6	5	10	6	6	4
min	3	3	3	3	3	3	3	3	3	3
Max	10	10	10	10	10	10	10	10	10	10

In the next step, the decision matrix was normalized based on the maximum and minimum values of each criterion. Table 4 shows the normalized decision matrix.

Table 4
The Normalized Decision Matrix

Symbol	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.857	0.714	0.571	0.286	0.714	0.571	0.429	0.857	0.429	0.143
A2	0.571	0.857	0.429	0.143	0.857	0.429	0.286	0.571	0.571	1.000
A3	0.143	0.286	0.143	0.857	0.571	0.857	0.143	0.286	0.714	0.286
A4	0.429	0.714	0.571	0.429	0.857	0.857	0.714	0.714	1.000	0.857
A5	0.714	0.571	0.857	0.571	0.571	0.714	0.571	1.000	0.857	0.286
A6	0.286	0.429	0.429	0.143	0.429	0.286	1.000	0.429	0.429	0.143

Next, using Equations 4 and 5, the S_i and P_i values were obtained as shown in Tables 5 and 6. In these calculations, the weights of the criteria were considered equal.

Table 5
Weighted Sum Values (S_i)

Symbol	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	Yes
A1	0.086	0.071	0.057	0.029	0.071	0.057	0.043	0.086	0.043	0.014	0.557
A2	0.057	0.086	0.043	0.014	0.086	0.043	0.029	0.057	0.057	0.100	0.571
A3	0.014	0.029	0.014	0.086	0.057	0.086	0.014	0.029	0.071	0.029	0.429
A4	0.043	0.071	0.057	0.043	0.086	0.086	0.071	0.071	0.100	0.086	0.714
A5	0.071	0.057	0.086	0.057	0.057	0.071	0.057	0.100	0.086	0.029	0.671
A6	0.029	0.043	0.043	0.014	0.043	0.029	0.100	0.043	0.043	0.014	0.400

Table 6
Weighted Product Values (P_i)

Symbol	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	pi
A1	0.985	0.967	0.946	0.882	0.967	0.946	0.919	0.985	0.919	0.823	9.337
A2	0.946	0.985	0.919	0.823	0.985	0.919	0.882	0.946	0.946	1.000	9.349
A3	0.823	0.882	0.823	0.985	0.946	0.985	0.823	0.882	0.967	0.882	8.998
A4	0.919	0.967	0.946	0.919	0.985	0.985	0.967	0.967	1.000	0.985	9.638
A5	0.967	0.946	0.985	0.946	0.946	0.967	0.946	1.000	0.985	0.882	9.568
A6	0.882	0.919	0.919	0.823	0.919	0.882	1.000	0.919	0.919	0.823	9.005

In the last step, three strategies were used for the final ranking. In the third strategy, the λ was considered to be 0.5. These strategies were combined using Equation 9 and the final ranking was obtained.

Table 7
Final Ranking of Alternatives

Symbol	k_{ia}	Ranks	k_{ib}	Ranks	k_{ic}	Rranks	k_i	Final Ranks
A1	0.167	4	2.431	4	0.956	4	0.188	4
A2	0.167	3	2.468	3	0.958	3	0.194	3
A3	0.159	5	2.071	5	0.911	5	0.127	5
A4	0.175	1	2.857	1	1	1	0.291	1
A5	0.173	2	2.742	2	0.989	2	0.259	2
A6	0.159	6	2.001	6	0.908	6	0.120	6

5. Conclusion

In the present study, with the aim of determining innovative priorities in the digital economy through the use of AI-based criteria, key criteria were identified in order to provide a systematic framework for ranking AI-driven strategies. In this study, 10 key criteria including “Cost Optimization (C1)”, “Decision-Making Optimization (C2)”, “Facilitating Access and Data Transfer (C3)”, “ Reducing the Digital Divide (C4)”, “Creating Added Value (C5)”, “Adapting Business Models to Changes (C6)”, “Cybersecurity (C7)”, “Strong Processing Capabilities (C8)”, “Interaction with Emerging Technologies (C9)”, and “Customization of Goods and Services (C10)” were identified. Next, six alternative strategies were identified and ranked, including “Integrating AI into supply chain and process automation (A1)”, “Personalizing user experiences with AI (A2)”, “Investing in AI-driven training and workforce (A3)”, “The expansion of AI in emerging sectors such as fintech (A4)”, “Investing in advanced cloud and computing infrastructure for AI (A5)”, and “Strengthening data security and digital trust (A6)”.

The results showed that the alternative A4 (The expansion of AI in emerging sectors such as fintech) with a score of 0.291 and the first rank, plays a pivotal role in creating transformative innovations. Because by utilizing AI in high-growth areas, it redefines business models and creates significant added value in interacting with emerging technologies and customizing services. This facilitates access to global markets, especially in developing economies. In second place, A5 (Investing in advanced cloud and computing infrastructure for AI) with a score of 0.259, serves as the foundation for robust processing capabilities and facilitates data transfer, without which the implementation of other strategies remains inefficient. Also, A2 (Personalizing user experiences with AI) with a score of 0.194 and third place, focuses on optimizing decision-making and creating added value through customized experiences, which plays a key role in customer retention and increased engagement across digital platforms.

At the lower ranks, A1 (Integrating AI into supply chain and process automation) with a score of 0.188 and a fourth rank, helps optimize cost consumption and adapt business models, although its impact is more operational than innovative, and can serve as a complement to superior strategies. With a score of 0.127 and 5th place, A3 (Investing in AI-driven training and workforce) plays a supportive role in bridging the digital divide and preparing the workforce for change, which will lead to the sustainability of innovations in the long run, but the need for high initial investment reduces its priority. Finally, A6 (Strengthening data security and digital trust) with a score of 0.120 and sixth place, emphasizes cybersecurity and maintains user trust, regardless of which other strategies face serious risks, though its low score indicates a greater focus on the defensive aspects than the innovation driver.

As a result, the present study, focusing on prioritizing AI-driven strategies in the digital economy, showed that the expansion of AI in emerging sectors such as fintech and smart tech (A4) with the first rank, has emerged as the main driver of innovation and has a high potential in interacting with emerging technologies and creating added value, while investing in advanced cloud and computing infrastructure (A5) with the second rank, has an infrastructural role in strengthening capability. It facilitates the processing and access to data. In contrast, supportive strategies such as investing in AI-driven training and workforce (A3) and strengthening data security (A6) are given lower priority (fifth and sixth), although necessary. This ranking provided a framework for policymakers and managers to direct attention to high-yield strategies and prevent resource fragmentation.

From a managerial perspective, it is recommended that executives first focus on implementing the strategy A4 and launch innovative pilot models in collaboration with fintech and smart tech startups to accelerate the growth of the digital economy. While investment in A5 is needed to create scalable cloud infrastructures that facilitate SMEs' access to AI. For intermediate strategies such as A2 and A1, Short-term hybrid applications (such as personalized automation in the supply chain) are proposed to improve decision-making and cost optimization. Finally, for A3 and A6, long-term support budgets should be allocated, such as AI-driven training programs and national security standards, to ensure digital sustainability and trust, and to keep the economy competitive in the global arena.

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Conflicts of Interest
The authors declare no conflicts of interest.

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