Journal of Soft Computing and Decision Analytics, Volume 3, Issue 1 (2025) 72-95

SCIENTIFIC OASIS

Journal of Soft Computing and Decision Analytics

Journal homepage: www.jscda-journal.org
ISSN: 3009-3481

Examining the Importance of AI-Based Criteria in the Development of the Digital Economy: A Multi-Criteria Decision-Making Approach

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ARTICLE INFO

Article history:
Received 22 September 2024
Received in revised form 9 December 2024
Accepted 24 January 2025
Available online 9 February 2025

Keywords:
Digital Economy; Artificial Intelligence; Best Worst Method (BWM); Multi Criteria Decision Making; Digital Transformation.

ABSTRACT

As one of the main pillars of global transformation in the contemporary world, the digital economy helps create new economic and business opportunities through new technologies. In addition to improving efficiency and reducing costs, this transformation plays a vital role in the economic growth and development of various countries. Artificial intelligence, as one of the key technologies in the development of the digital economy, has a profound impact on optimizing processes, increasing productivity, and enhancing customer experience. By processing big data and providing advanced analytics, this technology makes economic decisions faster and more accurately and affects various sectors of the digital economy. In this regard, 20 key AI-based criteria in the development of the digital economy were extracted from a review of previous studies and were placed in four general categories. The four general categories include structural, organizational, technological and economic. Hesitant Fuzzy Best Worst Method (HF-BWM) was used to rank the AI-based criteria in the development of the digital economy. “Investing in innovation (C16)”, “Potent processing capabilities (C1)”, “Process automation and intelligence (C11)”, “Identifying growth opportunities (C6)” and “Adapting business models to changes (C7)” ranked one to five, respectively. Managers in the digital economy should pay attention to investing in innovation and strengthening processing infrastructure to exploit new technologies and make more accurate decisions. Process intelligence, identifying new areas of growth and adapting the business model to market changes also help improve efficiency, reduce costs, exploit new opportunities and make organizations stable in the face of rapid changes and increasing competition.

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https://doi.org/10.31181/jscda31202555

1. Introduction

Global economies are undergoing significant restructuring, with platform owners now wielding influence that could surpass that of factory owners during the early industrial revolution. Digital technology has become a powerful driver of societal transformation and economic advancement. Consequently, it is essential for nations to understand and adapt to the architecture of the digital economy [1]. In recent years, the digital economy (DE) has catalyzed a major shift, reshaping traditional industries and fostering societal development. As an emerging economic paradigm, the DE utilizes data resources as key production factors, technological innovation as its driving force, and the Internet as a fundamental enabler [2]. Moreover, the digital platform economy encompasses a growing array of digitally facilitated commercial and social interaction activities [3].

The digital economy has emerged as the "new engine" propelling global economic growth in the information age, holding a significant role in the fiscal policies of nations worldwide. In the era of the new economy, the level of digital economy development serves as a crucial indicator of a country's overall national strength. However, competition and conflicts of interest within the digital domain have grown increasingly intense. Challenges such as digital technology barriers, disparities in digital infrastructure, and differences in economic and educational levels across nations further amplify inequalities and imbalances in the development of the digital economy. As a result, analyzing the development levels and the factors influencing the digital economy across countries has become increasingly complex [4].

Starting with the fundamental concept of the digital economy, its development relies on the presence of robust digital economy infrastructure as the most essential prerequisite. The development of economic systems is deeply intertwined with global trends, particularly those emerging in the technological domain. Technologies frequently serve as catalysts for building competitive advantages, enhancing economic efficiency, and sustaining the stability and success of organizations [5]. The digital economy thrives on diverse economic activities that heavily rely on digitally transformed knowledge and information. Key technologies driving the digital economy include data analytics, artificial intelligence (AI), blockchain, the Internet of Things (IoT), cloud computing, and other internet-based services. These cutting-edge digital tools enable the collection, storage, analysis, and distribution of information in digital formats [1].

The “digital core” is the center of the digital economy, serving as the foundation for technology platforms and applications that enable organizations to transform into digital enterprises and meet the demands of the digital economy. This core integrates next-generation technologies, such as advanced analytics, IoT, AI, and machine learning (ML), which are often incompatible with traditional IT infrastructures. As technologies like IoT, AI, virtual reality, blockchain, and self-driving vehicles continue to evolve, the digital economy is anticipated to become indispensable. The modern concept of the digital economy extends to the digitalization of all economic and social spheres, necessitating the extensive development of digital infrastructure across industries, services, public administration, social domains, and entertainment. This digital infrastructure operates on two levels: the basic ICT infrastructure, which includes terminals for data collection, transmission networks, and data storage centers, and the secondary information infrastructure, encompassing platforms, advanced AI technologies, and functional AI applications [6].

A key component of the digital economy, which is structured around platforms, is the integration of artificial intelligence (AI) technologies. A defining characteristic of these AI technologies is their capacity for self-learning, which relies heavily on the availability of vast amounts of data and its continuous generation. Artificial Intelligence (AI) has become a critical driver of a new wave of technological advancements and industrial transformation. Innovations like machine learning and deep learning have significantly accelerated digital transformation, enabling the integration of emerging technologies across various industries and enhancing their ability to meet the demands of the digital economy [7]. In the context of the Fourth Industrial Revolution, AI serves as a technological cornerstone of the digital economy. Its role in smart automation not only extends the functionality of other digital technologies but also enhances their overall efficiency. Alongside AI, smart automation encompasses a range of digital technologies and specialized software, including cloud computing, databases, big data, and blockchain. These advanced tools are deeply embedded within the modern digital economy, shaping its progression in the era of the Fourth Industrial Revolution [8].

The continuous advancement of artificial intelligence (AI) technologies enhances their capabilities, positioning AI to tackle increasingly complex tasks that surpass the potential of other digital technologies. As a key driving force in the digital economy, AI facilitates industrial restructuring, the transformation, and modernization of traditional industries through processes like digital industrialization and industrial digitization. Moreover, it effectively minimizes information asymmetry by leveraging data as a critical resource. Big Data and AI technologies possess unique characteristics that significantly enhance the effectiveness and potential of management systems within the digital economy [9], [10].

However, as the DE continues to evolve, its development relies not only on technological progress but also on the strategic identification and prioritization of relevant criteria that ensure its sustainable growth and effective integration across diverse sectors. While AI has gained significant attention as a cornerstone of the DE, there remains a critical gap in systematically evaluating and prioritizing the AI-based criteria that influence its development. Existing research primarily focuses on individual technologies or provides broad overviews, failing to address the complex interplay of factors that shape the DE. This lack of a structured, multi-criteria decision-making (MCDM) approach limits the ability of policymakers, industry leaders, and researchers to comprehensively identify and prioritize the most influential criteria. Consequently, the potential of AI to drive digital transformation and economic sustainability remains underutilized. The absence of a robust framework for prioritizing AI-based criteria poses several challenges. Without a clear understanding of which criteria are most significant, stakeholders may struggle to make informed decisions that align AI technologies with the DE’s demands. This misalignment can hinder efforts to fully harness AI’s capabilities in reducing information asymmetry, enhancing management systems, and promoting societal progress. Furthermore, as the DE encompasses a wide range of applications across industries, the lack of a standardized approach to criteria prioritization creates inconsistencies in how AI is deployed and utilized.

To address these challenges, this study aims to examine the importance of AI-based criteria in the development of the DE using a multi-criteria decision-making approach. By systematically identifying and prioritizing these criteria, the research seeks to bridge the existing gap and provide actionable insights for stakeholders. Such an approach is essential to ensure that AI technologies are strategically leveraged to drive industrial transformation, foster digital industrialization, and support economic sustainability. The findings of this study will contribute to the creation of a comprehensive framework that guides the integration of AI into the DE, enabling stakeholders to align technological advancements with global economic and societal needs. In doing so, this research will not only advance theoretical understanding but also offer practical solutions for policymakers, industry practitioners, and researchers seeking to navigate the complexities of the DE.

2. Literature Review

2.1 Digital Economy Development

The concept of the digital economy was first introduced by American economist Don Tapscott in 1997. The following year, the US Department of Commerce's report “Emerging Digital Economy” formally marked the beginning of the digital economy's development. Despite its growing prominence, the definition of the digital economy remains a subject of debate within academic circles. A widely accepted definition is provided by the G20 Digital Economy Development and Cooperation Initiative, which was released during the G20 Hangzhou Summit in 2016. According to this definition, the digital economy encompasses a series of production activities that rely on digital knowledge and information as key production factors, modern network information as a vital medium, and the strategic use of information and communication technology (ICT) as the primary driver to enhance economic efficiency [9]. The digital economy includes any business or activity that utilizes data analytics, artificial intelligence (AI), blockchain, IoT technologies, cloud computing, or other internet-based services. It is a multifaceted and dynamic concept, constantly evolving [10–13]. Broadly, the digital economy refers to any economic activity conducted online or enabled by digital technology. This definition includes traditional “tech” sectors such as data centers and software development, as well as the diverse applications of digital technologies in various industries, including online banking, energy, digital marketing, and logistics automation. Additionally, the digital economy extends beyond commerce to include economic, social, cultural, and other activities that rely on the Internet and digital communication systems [1].

The development of the digital economy has emerged as a strategic priority for nations worldwide, serving as a critical avenue for improving economic development quality and strengthening their influence in the global economy. Organizations such as the EU and OECD, along with countries like China, the United States, Germany, France, Canada, and India, have made the development of the digital economy a central element of their national economic strategies [4]. The digitization of the economy generates substantial benefits and efficiencies, with digital technologies fostering innovation, creating new job opportunities, and driving economic growth. Moreover, the digital economy permeates every aspect of society, transforming the way people connect and sparking profound societal changes. The global economy has greatly benefited from the commercial opportunities offered by the digital economy. The digital economy has dismantled the limitations of the traditional economy in areas such as production, marketing, and trade. It has compelled businesses to improve their offerings and better meet consumer demands. By creating new avenues for business and employment, the digital economy has ushered both the global and local economies into a digital age. Traditional economic processes, goods, and services have been converted into digital formats, forming the foundation of the digital economy. This system, driven by technology and reliant on the internet, represents the integration of business operations with electronic technology [5].

Scholars have increasingly focused on studying the digital economy's impact across various aspects in regions or countries, providing constructive insights from different perspectives. Du et al., [2] investigate the role of the digital economy (DE) in promoting carbon emission efficiency amid the global push for green transformation and sustainability. Using panel data from 49 cities within the Beijing-Tianjin-Hebei (BTH), Yangtze River Delta (YRD), and Pearl River Delta (PRD) regions between 2011 and 2022, the study reveals a U-shaped relationship between the digital economy and green development. Initial investments in digital infrastructure exhibit a rebound effect, delaying the carbon efficiency benefits of digital applications. Thresholds for the DE's effectiveness vary across regions—0.158 in BTH, 0.199 in YRD, and 0.467 in PRD. Efficient resource allocation enhances carbon performance in BTH and YRD but remains limited in PRD. Additionally, industrial structure upgrades in BTH and YRD improve carbon emission efficiency, with shape-flip thresholds at 6.104 and 6.470, respectively. However, the PRD region struggles to achieve similar emission reduction outcomes due to weaker synergies between industrial upgrading and the digital economy. The authors highlight the importance of region-specific strategies to address disparities in urban green development [2].

Chen [7] investigated the impact of the digital economy (DE) on the evolution of the global industrial structure (IS) by analyzing data from 280 Chinese cities spanning 2007 to 2020. The study revealed that DE plays a significant role in optimizing IS, with human capital (HC) identified as a crucial mediating factor in this process. This finding aligns with prior research emphasizing the relationship between higher education and industrial upgrading. Using spatial econometric methods, the study highlighted the spillover effects of DE, demonstrating its positive influence on the industrial upgrading of neighboring regions. The research also uncovered the nonlinear impact of DE on IS upgrading, characterized by an inverted U-shaped relationship—a novel discovery in this field. Moreover, it was found that regions with advanced artificial intelligence technologies experience a more pronounced impact of DE on industrial optimization, underlining the influence of regional disparities in digital transformation. Based on these findings, this study provided policy recommendations aimed at fostering DE development and enhancing IS levels, ultimately contributing to high-quality economic growth [7].

Ruan et al., [11] examined the impact of digital economy development on regional income disparities within Chinese provinces, emphasizing underlying mechanisms and multidimensional threshold effects. Analyzing provincial panel data from 2011 to 2021, the study revealed a U-shaped relationship where digital economy development initially reduces income gaps but eventually widens them. Key contributors to inequality include internet penetration and digital transaction growth. Moderate multidimensional inequality enhances the digital economy's ability to narrow income gaps, whereas excessive inequality diminishes or reverses this effect. The findings underscore the need to manage inequality to promote balanced regional development through the digital economy.

Wang et al., [4] developed a multidimensional and dynamic indicator system to evaluate the development level of the digital economy, focusing on the value creation dimension through the global digital value chain, alongside access and usage dimensions. The findings highlight significant disparities in digital economy development between nations, with notable advancements in some developing countries. Utilizing the Barro Rule and the Cobb-Douglas production function, the study explored the relationship between asymmetric fiscal policies and digital economy development during downturns, showing that proactive fiscal expenditure policies play a key role in advancing national digital economies. Policy recommendations are provided to guide future research and policymaking in this area [4]. Wang and Shen [12] analyzed the impact of digital economy development on income inequality across 97 countries. The findings revealed that while digital economy development generally exacerbates income inequality, globalization mitigates this effect on a global scale. In lower-middle-income and low-income countries, digital economy development worsens inequality, whereas its impact is insignificant in high-income and upper-middle-income countries. Mechanisms for reducing inequality include fostering industries with low entry barriers, reducing labor market information asymmetries, and promoting human capital equalization [12]. Sun et al., [13] investigated the impact of digital economy development on China's export upgrading using provincial-level panel data from 2012 to 2019. The findings reveal that the digital economy significantly enhances the technical complexity of exports, particularly in regions with higher resource allocation efficiency. Mediation analysis identified the development of the technology market and human capital improvement as key pathways for this effect. Robustness tests, including variable replacement and instrumental variable analysis, confirmed the validity of the conclusions [13].

Wang et al., [14] examined the intersection of digital technology, security, and the digital economy, focusing on patient rights, genetic testing, and cloud computing within legal frameworks. The study highlighted the importance of individuals' ability to engage with health-related information and understand the economic aspects of digital platforms, particularly in areas where genetic testing and cloud computing overlap, addressing challenges such as data privacy, security, regulatory compliance, and intellectual property rights. Using the Hainan Free Trade Port as a case study, the research explored how digital technologies can enhance healthcare services while emphasizing ethical considerations and security measures for sustainable development. It also examined the use of genetic data for individualized economic outcomes and the roles of artificial intelligence and privacy in these domains. Furthermore, the study analyzed the transformative impact of Web 2.0 in enabling individuals, businesses, and communities to leverage advanced technologies for social, economic, and environmental benefits. By addressing these opportunities and challenges, the research emphasized the need for robust legal frameworks, ethical standards, digital inclusivity, and global collaboration to promote sustainable progress through innovative practices in the digital economy [14].

Zhang et al., [15] examined the development and trends of enterprise social media research in the context of the digital economy. Their study identified research hotspots, including themes such as knowledge sharing, communication, and organizational performance, while observing a transition from singular to more diverse research topics over time. The analysis revealed that although enterprise social media research is gaining attention, the volume of literature remains relatively limited, with weak collaboration among researchers, particularly those from higher education institutions in China and the United States. Additionally, the study outlined future research directions in three key areas: human–computer collaborative models in the age of artificial intelligence, privacy disclosure and protection for users, and the mental and physical health impacts of enterprise social media use on employees. These proposed directions aim to enrich the academic discourse and guide further exploration in this evolving field [15].

Akhtar et al., [16] provide a comprehensive overview of the intersection between social media analytics and the digital economy, using bibliometric analysis of 1,539 articles published from 1996 to 2022 and sourced from the Scopus database. Employing VOSviewer, the study maps trends and relationships within the literature, analyzing keyword co-occurrence, co-citation, co-authorship, and journal influence. The findings highlight the most influential journals, articles, authors, and countries contributing to the research, with content analysis identifying broad thematic clusters through bibliographic coupling. A conceptual quadrant model is devised to explore the interrelation between social media analytics and the digital economy. The study reveals a shift in research focus from developed countries to emerging economies, including China, India, Pakistan, Bangladesh, and Ukraine. Furthermore, density visualization of keywords shows that topics like "digitalization," "artificial intelligence," "blockchain," "cryptocurrency," and "bitcoin" dominate the research trends in this field. This work sheds light on the evolving landscape of digital economy research and its integration with social media analytics, emphasizing its growing importance in developing nations [16].

Ding et al., [17] explore the impact of the digital economy on high-quality economic development (HQED) in China, focusing on its mechanisms, effects, and regional heterogeneity. Using data from 30 Chinese provinces between 2011 and 2019, the study employs a mediating effects model and a spatial Durbin model for empirical analysis. Findings indicate that both the digital economy and HQED levels remain relatively low, exhibiting high and low agglomeration regions with evident spatial path dependence and lock-in effects. The digital economy significantly promotes HQED, with notable spatial spillover effects. However, its impact weakens progressively across eastern, central, and western regions. Technological innovation emerges as a critical pathway through which the digital economy enhances HQED. The authors recommend strengthening digitalization efforts to bridge the digital divide and implementing dynamic, region-specific strategies to address imbalances and promote sustainable, high-quality development across China [17].

Bertani et al., [18] explore the long-term economic implications of intangible digital technologies, including software, artificial intelligence, and algorithms, using an agent-based modeling approach. By integrating the concept of intangible digital technology into the Eurace macroeconomic model, the study investigates its effects at both micro and macro levels. The results reveal critical business phenomena, such as increasing returns, winner-take-most dynamics, and market lock-in. On a macroeconomic scale, the findings highlight a rise in unemployment driven by a significant reduction in employment within the mass-production system, as higher productivity from digital assets is insufficiently offset by job creation in the digital sector. This study provides valuable insights into the transformative economic impacts of the ongoing digital technological wave [18].

Sidorov and Senchenko [19] propose a model for constructing a composite index to evaluate the development level of the digital economy across regions of varying sizes. The model leverages a functional network structured as a directed graph, adhering to principles of hierarchy, modularity, and balance, while utilizing available data on digital economy development. The composite index's scalar value is determined through additive convolution, eliminating subjective biases by replacing expert-determined weights with calculations based on standard deviation. The approach was tested to analyze regional disparities in the digital economy's development across Russia and to compare Russian and European practices. The model offers a systematic and objective method for assessing and comparing digital economy development levels [19].

2.2 Artificial Intelligence in Digital Economy

The rapid development of internet information technology has ushered in a new wave of technological revolution and industrial transformation. At this pivotal juncture, artificial intelligence (AI) technologies, which integrate data with systems, algorithms, and computational capabilities, are advancing on a global scale. AI has found extensive applications across various domains, revolutionizing industries and enhancing efficiency. In healthcare, AI-driven diagnostic tools assist in early disease detection, personalized treatment planning, and robotic surgeries [20], [21]. In finance, AI algorithms optimize risk assessment, fraud detection, and algorithmic trading [22], [23], [24], [25], [26], [27]. The manufacturing sector benefits from AI-powered automation, predictive maintenance, and quality control. In transportation, AI enables autonomous vehicles, smart traffic management, and route optimization [28], [29], [30], [31]. Additionally, AI plays a crucial role in education through personalized learning platforms and intelligent tutoring systems [32]. Its widespread adoption continues to transform businesses, streamline operations, and improve decision-making processes across multiple sectors [33], [34], [35], [36]. The synergy between AI and the Big Data Economy has transformed the traditional statistical economy into an intelligent digital economy, enabling robust economic connections and precise data sharing for accurate economic statistics and mathematical analysis [37]. The foundation of the digital economy lies in advanced technologies such as AI, big data analytics, and cloud computing. It thrives on the interconnectivity of individuals, enterprises, and governments across borders, leveraging massive data collection, analysis, and application. This fosters innovation and disrupts traditional industries, necessitating a technologically skilled workforce to maximize its potential [38].

The transformative impact of AI is deeply intertwined with the rapid expansion of the digital economy in recent years. Hong and Xiao [39] examined the role of digital technologies in promoting sustainable development in the context of environmental degradation and resource constraints.

They emphasized the potential of blockchain and artificial intelligence (AI) to decouple economic growth from carbon emissions by enhancing supply chain coordination and reducing environmental impacts. These technologies were highlighted as tools to incentivize recycling, support circular business models, and enable carbon accounting and offsetting. The study stressed the need for deploying blockchain and AI within inclusive and collaborative frameworks that integrate social and ecological priorities. Their findings indicated that incorporating blockchain and AI into supply chains can significantly improve transparency, traceability, accountability, and efficiency, as demonstrated through numerical analysis. Moreover, the study offered policy recommendations for leveraging digital innovations to support smart and green industrial transformations. While these technologies present substantial opportunities to optimize production systems and reduce environmental externalities by addressing information imbalances in global supply chains, Hong and Xiao underscored the importance of inclusive governance. They argued that democratic participation in decision-making processes is crucial to mitigating potential negative consequences, particularly for vulnerable communities, and ensuring these technologies achieve maximum positive impact for society and the environment [39].

Lu et al., [9] explored the interaction between the digital economy, artificial intelligence (AI), and the sports industry within the framework of China’s "dual-carbon" goal. Using a panel vector autoregression (PVAR) model and panel data from 15 Chinese provinces between 2014 and 2020, their study provided key insights into this dynamic relationship. The findings revealed that a 1-unit increase in the lagged level of the digital economy leads to a 0.008-unit increase in AI application at a 10% significance level, indicating a short-term but weakly facilitating effect of the digital economy on AI. Additionally, a 1-unit increase in the lagged level of the digital economy contributes 9.539 units of value added to the sports industry at a 1% significance level, demonstrating a short-term but strong impact on sports industry development. The study further showed that the internal driving forces primarily drive the growth of the digital economy and AI, with self-contribution rates of 72.7% and 91.5%, respectively. In contrast, the sports industry exhibits a weaker self-driving force, with a self-contribution rate of 68.2%. Moreover, the contribution rates of the digital economy and AI to the sports industry are 12.3% and 19.6%, respectively, suggesting that the sports industry is more influenced by AI application than by the digital economy's overall development. These findings offer valuable insights into promoting low-carbon development and structural upgrades in the sports industry [9].

Wang et al., [40] examined the role of artificial intelligence (AI) models within the digital economy in driving the transformation of the manufacturing industry in the Internet of Things (IoT) environment. The study proposed an optimized AI model specifically designed to address the performance limitations of traditional AI models in resource-constrained environments. The research first analyzed the pivotal role of the IoT in the manufacturing revolution and its integration with AI, followed by an exploration of the IoT’s core role in the digital economy and manufacturing transformation. The study then focused on optimizing the AI model for IoT applications. A comprehensive evaluation of the optimized model was conducted by comparing it with the standard Convolutional Neural Network and the lightweight Mobile Neural Network across indicators such as energy consumption, running time, prediction accuracy, and recall. The findings demonstrated that the optimized model outperformed traditional models, particularly excelling in energy efficiency. Case analyses of manufacturing enterprises further validated the model’s ability to enhance production efficiency, improve product quality, and reduce costs in practical applications. The study also addressed research limitations and proposed future directions, including expanding the model’s applicability to diverse scenarios and improving its generalization capabilities. By offering a novel perspective on AI deployment in the IoT context, this research provides significant theoretical and practical insights for advancing intelligent manufacturing and fostering growth in the digital economy [40].

Javaid et al., [1] reviewed the transformative impact of the digital economy, which encompasses economic activities driven by digital technologies, including online transactions and innovations such as IoT, AI, Blockchain, Virtual Reality, and autonomous vehicles. This study analyzed key trends, enablers, features, and challenges of the digital economy, emphasizing its role in shaping the Industry 4.0 environment. Unlike traditional economies, the digital economy relies on hyper-connectivity—linking individuals, organizations, and devices through the Internet, mobile technologies, and IoT—facilitating the shift to intelligent manufacturing practices and innovative industrial operations. The paper highlights how Industry 4.0 technologies, including cloud computing, robotics, big data, and AI, drive automation, data exchange, and customer engagement, supporting industrial objectives and digital transformation. Additionally, the study discusses the growing reliance on integrated ecosystems within the digital economy, where software platforms generate value, enhance resilience, and foster innovation, replacing traditional linear value chains with networked interactions involving goods, assets, and people. These insights provide a roadmap for industries adapting to digital technologies, underlining the evolving nature of production and consumption in a digitally interconnected world [1].

Lee et al., [41] investigate the economic and environmental impacts of artificial intelligence (AI), focusing on its role in driving energy transitions amidst global warming concerns. The study develops an evaluation index system to assess the digital economy's level and its influence on AI and energy transition. The findings reveal that advancements in AI significantly enhance the energy transition, with the digital economy acting as a catalyst that amplifies AI's positive impact. Additionally, the study highlights disparities among countries, noting that AI-driven energy transitions are more pronounced in resource-dependent nations and exhibit differing effects between high-income and middle- to low-income countries. These results provide valuable insights for policymakers aiming to promote energy transition, address regional energy inequities, and support low-carbon development strategies [41].

Zhang [42] explores the multifaceted impact of AI-related industries on labor employment and the evolving job market structure. By constructing a mechanism and theoretical model, the study examines labor dynamics and structural transformations within the AI sector. The findings highlight a shift in China's labor force, emphasizing education and creating new employment opportunities. This research contributes significantly to understanding employment trends and structural changes by analyzing employment distribution, skill diversity, and digital economy policies. The study proposes recommendations to promote national economic growth and digital transformation, leveraging insights from China's advancements in digital technologies. A key innovation lies in applying a Marxist theoretical perspective to assess the AI industry's influence on labor structures, offering both theoretical and practical value for addressing employment challenges in the digital era [42].

Liu and Wang [43] explore how digital technologies, including artificial intelligence, big data, and blockchain, are transforming the business models of Chinese manufacturing firms by reshaping their resources and capabilities. The study investigates the relationship between market orientation (MO), entrepreneurial orientation (EO), and firm performance, with a particular focus on the mediating effect of business model process formalization (PF). Using a sample of 369 firms, the study identifies three distinct mediation paths through which strategic orientation impacts firm performance: ‘MO→PF→firm performance,’ ‘EO→PF→firm performance,’ and ‘the interaction term of the two orientations→PF→firm performance.’ The findings show that both MO and EO contribute positively to firm performance, with the interaction term having a synergistic effect. Among the three pathways, the indirect effect of 'MO→PF→firm performance' is the most significant, accounting for 12.29%. These results enrich the understanding of strategic orientations in the context of the digital economy and offer practical guidance for Chinese firms seeking to align their business models with digital transformation [43].

Hang and Chen [44] examined the role of artificial intelligence (AI) in creating competitive advantages for firms in the digital economy while identifying barriers to its full potential. They found that AI can enhance revenue by improving employee productivity, consumer evaluation, competitive pricing, and resource creation, while also reducing costs through efficiency improvements and risk reduction. However, key barriers include AI adoption challenges, task nature, and AI management issues, particularly due to AI's lack of interpersonal skills. The authors advocate for future research to address these interpersonal skill limitations to maximize AI's potential benefits [44].

Bencsik [45] investigates the influence of Industry 4.0, digitalization, and artificial intelligence on the competitiveness of companies, focusing on the management challenges faced by industrial organizations. The study examines organizational preparedness for the digital future, comparing the issues encountered by multinational companies (MNCs) and small and medium-sized enterprises (SMEs). Through structured deep interviews with 195 senior managers, analyzed using NVivo 12, the findings reveal that while managers recognize the urgency of digital challenges, their efforts are primarily concentrated on technical developments, neglecting human-related issues. The handling of human problems emerges as the most pressing concern, yet decisions on these matters are often deferred. The study concludes that even large companies are inadequately prepared for leadership changes and organizational adjustments needed for the digital era [45].

2.3 Multi-Criteria Decision-Making (MCDM) Approaches in the Digital Economy

The digital economy's rapid expansion has introduced complex decision-making scenarios involving numerous conflicting criteria. Multi-Criteria Decision-Making (MCDM) methods have become essential tools for navigating these complexities, enabling stakeholders to evaluate various factors systematically and make informed choices. Techniques such as the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Fuzzy TOPSIS are widely utilized to assess and prioritize elements within the digital economy, ensuring balanced and effective decision outcomes. In recent years, there has been a growing body of research applying MCDM methods to various aspects of the digital economy.

Liang et al., [46] introduced DCMSort, a novel multiple criteria sorting method based on the deck of cards approach, designed to classify alternatives into pre-defined and ordered categories. Unlike traditional methods, DCMSort derives criteria weights and utility functions using personalized preferences through comparisons of consecutive levels, requiring fewer comparisons due to the ordinal relationship. The method incorporates reference levels and representative profiles to enhance flexibility in preference representation and allows for an uncertain number of blank cards between positions. A case study on assessing digital economy development in China demonstrated DCMSort's practicality, with sensitivity and comparative analyses confirming its stability and effectiveness [46].

Guo et al., [38] introduced a hierarchical framework for constructing a Digital Economy Development Index (DEDI) and developed a robust method for determining the optimal weights for aggregating sub-indicators. The H-DEA model was transformed into a parametric linear programming problem, and the improved golden section algorithm was used to find approximate optimal solutions. Applying this method, they assessed the DEDI for 30 provinces in China from 2015 to 2020. The results revealed a clear digital economy development gradient from east to west, with the East leading. The study suggests strategies for regional development, such as fostering digital industry clusters in the central region, enhancing competitiveness in the northeast, and strengthening innovation and infrastructure in the west [38].

Huo et al., [47] explore the energy efficiency of urban districts using the Malmquist–DEA model, analyzing the spatial effects of the service trade and digital economy on green urban development. The study emphasizes the AI service trade's role in advancing the digital intelligence industry and enhancing urban energy efficiency through innovation and positive externalities. Cluster analysis is employed to investigate green development across city districts, incorporating AI-driven programming for green communication and cooperation mechanisms, leveraging quantum computation via QUBO modeling. The findings highlight the synergistic impact of the service trade and digital economy on energy efficiency and the potential of quantum-based AI advancements to foster new productivity paradigms for green cities. This interdisciplinary research offers valuable insights into the integration of green AI technologies within social computing science, contributing to sustainable urban development [47].

Baydaş et al., [48] propose a novel approach for comparing multi-criteria decision-making (MCDM) methods by evaluating their association strength with real-life rankings, particularly focusing on the economic performance of G-20 countries. The study explores the impact of different data structures, normalization techniques, and decision-making components on MCDM results. Using ten periodic decision matrices, the authors employ ten crisp-based MCDM methods (e.g., COPRAS, CODAS, MOORA, TOPSIS, MABAC, VIKOR, FUCA, and ELECTRE III) to provide a comprehensive analysis. CODAS demonstrates the highest correlation with real-life anchors in most periods, and the maximum normalization technique is identified as the most effective among various alternatives. Additionally, the study compares crisp-based and fuzzy-based CODAS results, finding consistent outcomes. The authors propose the "Maximum normalization-based fuzzy integrated CODAS procedure" as a robust framework for decision-makers assessing the economic performance of countries [48].

Wang [49] investigates the influence of the digital economy on urban tourism, emphasizing its role in facilitating economic growth through seamless financial transactions. The study introduces a Multi-Criteria Fuzzy-based Decision-Making Method (MCFDMM) to assess the impact of the digital economy on tourism. A novel framework, DLFDSS-RRM, integrates deep learning with fuzzy decision support systems to enhance resource allocation, security, and resident satisfaction in urban residential communities. Key criteria, such as expenses, positive responses, and repeated payments, are evaluated based on tourist reviews and their alignment with economic growth. Using a fuzzy process, the study validates economic growth across two successive financial quarters and identifies factors contributing to minimal growth. By addressing these limitations with "hiking conditions," the framework mitigates hindrances to economic advancement. Comparative analysis demonstrates growth rates between 0.263 and 0.4055, condition satisfaction percentages between 53.747 and 74.351, and analysis rates between 0.275 and 0.4662, underscoring the model's efficacy in promoting urban tourism and economic growth [49].

Deng et al., [50] addressed the issue of insufficient indicators in digital economy research, which can impede data-driven decision-making for governments. To resolve this, they proposed a digital economy indicator evaluation system, classifying the digital economy into four categories: "basic," "technology," "integration," and "service," with five indicators selected for each category. Using an improved entropy method inspired by the Analytical Hierarchy Process (AHP), the weights of these indicators were calculated. The method compared the differences between paired indicators, mapped these comparisons to a 1–9 scale, and constructed a judgment matrix based on information entropy, mitigating the traditional entropy method's limitation of large weight disparities. The study found that the digital economy in Guangdong Province experienced relatively balanced development from 2015 to 2018, with prospects for future improvement. However, rural e-commerce remained underdeveloped, and a significant digital divide between urban and rural areas was observed. To simplify future analyses, the authors used principal component analysis and factor analysis to extract two variables that retained the informational integrity of the original 20 indicators. Finally, Deng et al. provided actionable recommendations to enhance the digital economy in Guangdong Province during the study period [50].

2.4 Research Gap

The digital economy (DE) has been widely recognized as a transformative force, driving global industrial transformation and economic sustainability through the integration of advanced technologies such as artificial intelligence (AI). Numerous studies have explored the role of AI in enhancing automation, optimizing resource allocation, and fostering innovation within the DE. Researchers have also highlighted the critical importance of data-driven technologies, including AI, IoT, blockchain, and big data, in shaping the architecture of the DE. However, while significant progress has been made in understanding the technological dimensions of the DE, there remains a notable gap in identifying and systematically prioritizing AI-based criteria that are pivotal to the DE's sustainable growth and strategic development. Existing literature primarily focuses on individual AI applications or generalized overviews of digital transformation processes, often neglecting the complex interplay of factors that influence the effectiveness and adoption of AI within the DE. Furthermore, while multi-criteria decision-making (MCDM) approaches have been applied to various domains [16], [51], [52], [53], [54], their use in evaluating and prioritizing AI-based criteria specific to the DE remains underexplored. This lack of structured frameworks limits policymakers, industry leaders, and researchers in effectively leveraging AI technologies to align with economic and societal objectives.

To address this gap, this research adopts a systematic approach to identifying and prioritizing AI-based criteria critical to the development of the DE. These criteria have been derived from a comprehensive review of the literature and then screened through expert opinions to ensure that they reflect the most relevant and impactful aspects of AI integration in the DE. The identified criteria are presented in four categories: structural, organizational, technological and economic. Table 1 shows these categories and criteria. By employing a multi-criteria decision-making approach, this study aims to fill the existing gap by offering a robust framework that not only highlights the importance of these AI-based criteria but also provides actionable insights for stakeholders to strategically harness AI's transformative potential. This approach is expected to guide future developments in the DE, ensuring that AI technologies are optimally aligned with global economic and societal needs.

3. Methodology

3.1 Hesitant Fuzzy Sets

The Hesitant Fuzzy Set (HFS) is a tool used for modeling uncertainty and hesitation in decision-making processes. This concept was first introduced by Torra in 2010 to represent situations where a decision-maker is unable to assign a specific value to their preferences. Instead, they provide a set of possible values for membership degrees or preferences. In this approach, each value represents one of the potential states of preference. Subsequently, concepts such as the score function are utilized to determine the relative importance and compare these values. By employing HFS, the preferences of decision-makers are modeled more comprehensively, preserving information that would otherwise be lost due to hesitation during the decision-making process [55].

This approach, due to its high capability in modeling complex conditions and human uncertainties, has found widespread applications in multi-criteria decision-making (MCDM) methods such as HF-TOPSIS, HF-VIKOR, and HF-BWM. The primary advantages of hesitant fuzzy sets (HFS) include their ability to more accurately represent uncertainty, avoid oversimplification of preferences, and provide flexibility in analyzing decision-makers' preferences. This approach also enables more precise comparisons among alternatives and empowers decision-makers to make optimal decisions even in the presence of incomplete information or existing uncertainties. For these reasons, HFS is recognized as an innovative tool in decision-making management and the analysis of uncertain data [56].

Table 1
AI-based Criteria for Digital Economy Development

Code	Category	Criteria	Reference
C1	structural	Potent processing capabilities	[1], [15], [44]
C2		Cyber-security	[43], [57], [58]
C3		Reducing the digital gap	[1], [44], [59]
C4		Data accessibility	[14], [19], [38], [57]
C5		Immediate transfer of data	[2], [14], [60]
C6	organizational	Identifying growth opportunities	[1], [7], [9], [61]
C7		Adapting business models to changes	[5], [12], [43]
C8		Knowledge management	[15], [19], [40]
C9		Education and learning of digital technologies	[5], [44], [62]
C10		Decision-making optimization	[17], [42], [44], [45]
C11	technological	Process automation and intelligence	[42], [43], [57], [63]
C12		Minimizing system errors	[41], [43], [47]
C13		Identifying trends and patterns	[40], [43], [61]
C14		Interaction with emerging technologies	[15], [61], [64]
C15		Automating repetitive processes	[15], [40], [44]
C16	economic	Investing in innovation	[1], [15], [42], [57]
C17		Developing emerging markets	[14], [65]
C18		Creating added value/value creation	[42], [66]
C19		Cost management	[15], [57], [67]
C20		Customization of goods and services	[7], [15], [43]

3.2 Hesitant Fuzzy Best Worst Method (HF-BWM)

The Best-Worst Method (BWM) is a multi-criteria decision-making technique used to determine the relative weights of evaluation criteria. In this method, the decision-maker first identifies the most important (best) and least important (worst) criteria. Then, pairwise comparisons are conducted between these criteria and the remaining criteria to establish their relative priorities. BWM is preferred for its efficiency in reducing the number of pairwise comparisons while maintaining accuracy. In economic studies, BWM has been applied in various domains, including evaluating firms' R&D performance [68], [69], supply chain management [70], supplier selection [71], and energy-related decision-making [72].

This section outlines the steps of the HF-BWM method utilized in this study, which are as follows: Step 1: Identify the evaluation criteria, Step 2: Determine the best and worst criteria, Step 3: Conduct pairwise comparisons by assessing the best criterion to others and others to the worst criterion, Step 4: Transform hesitant fuzzy preferences into score values, Step 5: Incorporate the slack variable, and Step 6: Solve the linear optimization model [73].

3.2.1 Defining the Criteria

In the first step of implementing the HF-BWM method for analyzing AI-based digital economy criteria, the identification of indicators was conducted in two stages. Initially, primary criteria were extracted through a thorough review of previous studies. Then, to ensure the comprehensiveness and relevance of these criteria to the specific context of the research, the opinions of experts in the fields of artificial intelligence and the digital economy were utilized. The experts, by screening these criteria, removed irrelevant or redundant items and integrated them to produce a final set of key and effective criteria. This scientific and integrative process not only preserves the theoretical foundation but also establishes credibility based on the practical perspectives of experts.

3.2.2 Selecting the Best and Worst Criteria

In the second step, the criteria identified as the final ones in the first step are examined. At this stage, the experts in the group carefully analyze these criteria to identify the best and worst ones. After conducting discussions and exchanges of opinions among group members and reaching a collective agreement, two criteria were selected as the best and worst. These selections were made based on the relative importance of each criterion and its impact on the evaluation process, so that they could serve as a basis for prioritization and analysis in the subsequent application of the BWM.

3.2.3 Pairwise Comparisons

In the third stage of the BWM method, structural comparisons are performed, the results of which are in the form of Hesitant Fuzzy Best-to-Others (HFBO) and Hesitant Fuzzy Others-to-Worst (HFOW) vectors. First, the best criterion identified in the previous stage is compared with the other criteria. The result of this comparison is the HFBO vector, which indicates the degree of preference of the best criterion over the other criteria and reflects the values determined by the experts. Similarly, comparing the other criteria with the worst criterion creates the HFOW vector. This vector also indicates the degree of preference of the other criteria over the worst criterion [74]. As a result, the comparison of the experts forms the initial HFBO and HFOW vectors (Equation 1).

$$\begin{aligned} HFBO &= (h_{B1}, h_{B2}, ..., h_{Bj}, ..., h_{Bn}) \\ HFOW &= (h_{1W}, h_{2W}, ..., h_{jW} ..., h_{nW}) \end{aligned} \tag{1}$$

It should be noted that these comparisons were made by the experts using linguistic terms and their hesitant fuzzy equivalents. Figure 1 shows the values corresponding to the linguistic terms. Overall, this step provides the key data for the final weighting of the indicators through 2n-3 comparisons, forming a more accurate basis for decision-making. The reason for eliminating secondary comparisons lies in the transitive property of pairwise comparisons. Each secondary comparison can be derived using the known reference comparisons.

3.2.4 Pairwise Comparisons

After determining the HFBO and HFOW vectors, the comparison scores are calculated using Equation 2. These scores are then aggregated to construct the integrated score vectors $s(HFBO)$ and $s(HFOW)$ (Equation 3). For each element within these vectors, Equation 4 is utilized, forming the core foundation for deriving the criteria weights in the BWM approach.

$$s(h) = \frac{1}{\# h} \sum_{\gamma \in h} h \tag{2}$$

$$\begin{aligned} s(HFBO) &= (s(h_{B1}), s(h_{B2}), \dots, s(h_{Bj}), \dots, s(h_{Bn})) \\ s(HFOW) &= (s(h_{1W}), s(h_{2W}), \dots, s(h_{jW}), \dots, s(h_{nW}))^T \end{aligned} \tag{3}$$

$$\begin{aligned} \omega_B / (\omega_B + \omega_j) &= s(h_{Bj}) \\ \omega_j / (\omega_j + \omega_W) &= s(h_{jW}) \end{aligned} \tag{4}$$

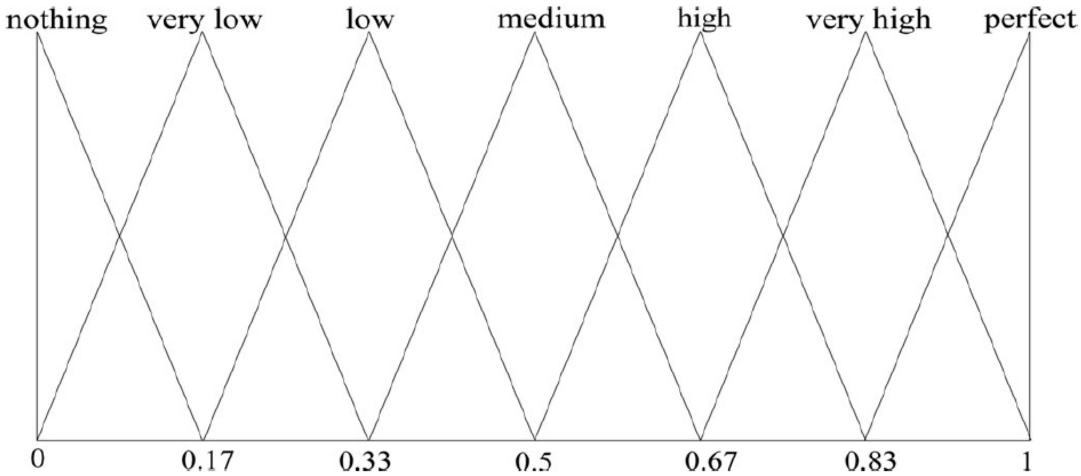

Fig. 1. Set of seven terms with its semantics [75], [76], [77]

3.2.5 Introduction of the Slack Variable

Since hesitant fuzzy preferences may not be fully consistent, a slack variable (S) is introduced. This variable represents the maximum absolute deviation between the reference comparisons and the corresponding ratio of weights. If the preferences are fully consistent, the value of ‘S’ will be zero. Otherwise, the value should be minimized as much as possible to ensure maximum consistency with the experts’ preferences.

3.2.6 Solving the Linear Optimization Model

In the final step, a linear optimization model is constructed with the primary objective of minimizing the maximum deviation (Model 1). This model determines the final weights of the criteria by leveraging the score values and relationships established in the earlier steps. The goal is to align the derived weights as closely as possible with the experts’ preferences, minimizing any inconsistencies or deviations in the process. By integrating hesitant fuzzy logic, this approach offers an effective and straightforward framework for multi-criteria decision-making, reducing uncertainty and enhancing the reliability of the evaluations.

By solving this model, the crisp weights of the criteria are extracted, representing the relative importance of each criterion. These weights are presented in a numerical and deterministic form and are normalized to ensure consistency. The crisp weights, as the output of the weighting model, play a key role in aggregating the preference vectors provided by the experts and assist in prioritizing the criteria based on their importance.

Model 1

$$\begin{aligned} &\min \quad \psi_S \\ s.t: \quad &\left|\omega_B - (\omega_B + \omega_j) \times s(h_{Bj})\right| \le \psi_S \\ &\left|\omega_j - (\omega_W + \omega_j) \times s(h_{jW})\right| \le \psi_S \\ &\sum_{j=1}^{n} \omega_j = 1, \ \omega_j \ge 0 \end{aligned} \tag{5}$$

4. Results

In this study, 20 AI-based criteria related to digital economy development were identified and ranked. These criteria provide a valuable foundation for evaluating and improving performance in the digital economy domain. They were ranked from 1 to 20 based on their level of importance and impact. The HF-BWM was employed to perform this ranking, enabling the integration and analysis of expert opinions with high precision and reliability. To this end, the best criterion and the worst criterion were selected based on expert opinions. “Investing in innovation” (C16) was identified as the best criterion by the experts, while “Customization of goods and services” (C20) was recognized as the worst criterion. The experts conducted pairwise comparisons between the best criterion and the other criteria, as well as between the other criteria and the worst criterion. Subsequently, the opinions of the experts were synthesized using Equation 2. The synthesized expert opinions, which form the score vector, are presented in Table 2.

In the next step, using the score vectors s(HFOW) and s(HFBO) in Table 2, a linear optimization model, which is shown as Equation 6, was developed to determine the weight of each criterion. This model was designed to ensure the accuracy and consistency of the analysis results while integrating the diverse opinions of experts in a structured and scientific manner.

Table 2
Score Vector of Criteria

Code	Criteria	s(HFOW)	s(HFBO)
C1	Potent processing capabilities	0.73	0.53
C2	Cyber-security	0.88	0.62
C3	Reducing the digital gap	0.57	0.57
C4	Data accessibility	0.67	0.77
C5	Immediate transfer of data	0.53	0.73
C6	Identifying growth opportunities	0.87	0.59
C7	Adapting business models to changes	0.81	0.60
C8	Knowledge management	0.63	0.72
C9	Education and learning of digital technologies	0.43	0.76
C10	Decision-making optimization	0.53	0.88
C11	Process automation and intelligence	0.90	0.57
C12	Minimizing system errors	0.72	0.67
C13	Identifying trends and patterns	0.60	0.70
C14	Interaction with emerging technologies	0.67	0.81
C15	Automating repetitive processes	0.60	0.90
C16	Investing in innovation	0.94	0.06
C17	Developing emerging markets	0.73	0.63
C18	Creating added value/value creation	0.72	0.69
C19	Cost management	0.70	0.87
C20	Customization of goods and services	0.06	0.94

$$
\begin{aligned}
&\min \quad \psi_S \\
&s.t: \\
&\left|\omega_{16}-(\omega_{16}+\omega_{1})\times 0.53\right| \le \psi_S \quad \left|\omega_{1}-(\omega_{20}+\omega_{1})\times 0.73\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{2})\times 0.62\right| \le \psi_S \quad \left|\omega_{2}-(\omega_{20}+\omega_{2})\times 0.88\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{3})\times 0.57\right| \le \psi_S \quad \left|\omega_{3}-(\omega_{20}+\omega_{3})\times 0.57\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{4})\times 0.77\right| \le \psi_S \quad \left|\omega_{4}-(\omega_{20}+\omega_{4})\times 0.67\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{5})\times 0.73\right| \le \psi_S \quad \left|\omega_{5}-(\omega_{20}+\omega_{5})\times 0.53\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{6})\times 0.59\right| \le \psi_S \quad \left|\omega_{6}-(\omega_{20}+\omega_{6})\times 0.87\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{7})\times 0.60\right| \le \psi_S \quad \left|\omega_{7}-(\omega_{20}+\omega_{7})\times 0.81\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{8})\times 0.72\right| \le \psi_S \quad \left|\omega_{8}-(\omega_{20}+\omega_{8})\times 0.63\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{9})\times 0.76\right| \le \psi_S \quad \left|\omega_{9}-(\omega_{20}+\omega_{9})\times 0.43\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{10})\times 0.88\right| \le \psi_S \quad \left|\omega_{10}-(\omega_{20}+\omega_{10})\times 0.53\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{11})\times 0.57\right| \le \psi_S \quad \left|\omega_{11}-(\omega_{20}+\omega_{11})\times 0.90\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{12})\times 0.67\right| \le \psi_S \quad \left|\omega_{12}-(\omega_{20}+\omega_{12})\times 0.72\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{13})\times 0.70\right| \le \psi_S \quad \left|\omega_{13}-(\omega_{20}+\omega_{13})\times 0.60\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{14})\times 0.81\right| \le \psi_S \quad \left|\omega_{14}-(\omega_{20}+\omega_{14})\times 0.67\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{15})\times 0.90\right| \le \psi_S \quad \left|\omega_{15}-(\omega_{20}+\omega_{15})\times 0.60\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{17})\times 0.63\right| \le \psi_S \quad \left|\omega_{17}-(\omega_{20}+\omega_{17})\times 0.73\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{18})\times 0.69\right| \le \psi_S \quad \left|\omega_{18}-(\omega_{20}+\omega_{18})\times 0.72\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{19})\times 0.87\right| \le \psi_S \quad \left|\omega_{19}-(\omega_{20}+\omega_{19})\times 0.70\right| \le \psi_S \\
&\left|\omega_{16}-(\omega_{16}+\omega_{20})\times 0.94\right| \le \psi_S \quad \sum\nolimits_{j=1}^{n} \omega_j = 1,\ \omega_j \ge 0
\end{aligned}
\tag{6}
$$

Based on the formulated equations and the utilization of the values s(HFOW) and s(HFBO), the weight of each criterion was calculated. These weights represent the relative importance of each criterion within the framework of the intended analysis. To enhance clarity and emphasize the differences in the importance of the criteria, all calculated weights were multiplied by 100, making the relative importance of each criterion more noticeable. For precise presentation of the results, the weights of the criteria, their weighted percentages, and their rankings are provided in Table 3.

Table 3
Final Ranking of Criteria

Code	Criteria	Weights	Weight Percentage	Rank
C1	Potent processing capabilities	0.08137	8.137	2
C2	Cyber-security	0.06755	6.755	6
C3	Reducing the digital gap	0.04508	4.508	12
C4	Data accessibility	0.03814	3.814	14
C5	Immediate transfer of data	0.03987	3.987	13
C6	Identifying growth opportunities	0.07523	7.523	4
C7	Adapting business models to changes	0.07258	7.258	5
C8	Knowledge management	0.04658	4.658	11
C9	Education and learning of digital technologies	0.03004	3.004	16
C10	Decision-making optimization	0.02294	2.294	18
C11	Process automation and intelligence	0.08080	8.080	3
C12	Minimizing system errors	0.05628	5.628	8
C13	Identifying trends and patterns	0.04968	4.968	10
C14	Interaction with emerging technologies	0.03214	3.214	15
C15	Automating repetitive processes	0.02058	2.058	19
C16	Investing in innovation	0.08343	8.343	1
C17	Developing emerging markets	0.06515	6.515	7
C18	Creating added value/value creation	0.05223	5.223	9
C19	Cost management	0.02417	2.417	17
C20	Customization of goods and services	0.01615	1.615	20

4. Conclusions

The digital economy, as one of the main drivers of economic growth in the present era, has gained significant importance. In this context, artificial intelligence, as one of the transformative technologies, plays a key role in shaping and developing the digital economy. The impact of artificial intelligence on areas such as improving productivity, accelerating data analysis, and creating new opportunities for businesses highlights its significance in this field. Therefore, identifying and evaluating criteria related to the digital economy that are influenced by artificial intelligence is of vital importance for policymakers and business managers. In this research, AI-driven digital economy criteria were extracted based on previous studies and then screened through expert opinions. Finally, 20 key criteria were identified in four categories: structural, organizational, technological and economic. The ranking of these criteria was conducted using the HF-BWM method, which is a scientific and precise approach for prioritizing criteria in uncertain conditions. This method allows for the incorporation of expert doubts and uncertainties in the ranking process, making the results closer to reality. The ranking results indicated that the criteria, including "Investing in innovation" (C16), "Potent processing capabilities" (C1), "Process automation and intelligence" (C11), "Identifying growth opportunities" (C6), and "Adapting business models to changes" (C7), have the highest priorities in sequence. This ranking helps decision-makers optimally allocate their resources and take steps towards the sustainable development of the digital economy.

The criterion of "Investing in innovation" (C16) has secured the top rank among all the criteria. This prominent position underscores the critical importance of innovation in this field, which has emerged through the close interaction between artificial intelligence technologies and the digital economy. Investment in innovation serves as the main driver of development and transformation, providing the necessary foundation for advancing technological capabilities, creating new products and services, and enhancing competitiveness within this complex ecosystem. This criterion has far-reaching impacts on the AI-based digital economy. First, investment in innovation accelerates the development of AI tools capable of processing vast amounts of data and providing intelligent solutions. Second, such investment creates conditions for traditional business models to evolve into advanced, digital models that can quickly adapt to market changes. Third, increased investment in innovation strengthens economic and technological infrastructures, enabling the creation of dynamic and sustainable ecosystems.

The criterion of “Potent processing capabilities” (C1), which ranked second among the key criteria for AI-based digital economy in this study, is one of the most important factors in the development and sustainability of this type of economy. The AI-based digital economy is based on processing vast amounts of data and executing complex algorithms, both of which require high computational power. This criterion, in addition to the technical infrastructure required for big data analysis and executing AI models, helps in the rapid and accurate decision-making of managerial and operational processes. In the absence of powerful processing capability, the utilization of AI and large-scale data analysis, and consequently the development of the AI-based digital economy, would face significant challenges. Potent processing capability has a wide-ranging impact on the development of digital economy. On one hand, this criterion enables the implementation of advanced deep learning models, predictive analytics, and optimization of business processes. On the other hand, increased processing power can lead to reduced processing costs, faster analysis and response to market changes, and the creation of technological innovations.

The criterion of “Process automation and intelligence” (C11) ranks third among the 20 identified criteria in this study. This criterion reflects the ability of systems and organizations to leverage advanced AI technologies for optimizing business processes and reducing resource waste. Process automation and intelligence can enhance productivity, reduce costs, and enable quicker responses to environmental changes. For development of digital economy, process automation and intelligence not only contributes to better business performance but also creates a foundation for greater innovation and competitiveness. By using AI techniques such as machine learning, natural language processing and advanced data analytics, organizations can automate repetitive and manual processes, accelerate decision-making and increase operational accuracy. This is especially valuable in industries such as banking, healthcare, logistics, and manufacturing, which require the fast and precise processing of large volumes of data. Process automation and intelligence also lays the groundwork for creating smart supply chains and delivering personalized services.

In the ranking of criteria affecting AI-based digital economy, “Identifying growth opportunities” (C6) achieved the fourth position. This criterion refers to the ability to discover new opportunities in the market, analyze technological changes and predict future needs. In the AI-based digital economy, this criterion plays a key role in fostering innovation, guiding investments toward high-potential areas and accelerating the achievement of strategic objectives. By utilizing AI-based data analysis tools, organizations can identify emerging trends in the market and create new growth opportunities. This capability enables businesses to enter new markets ahead of competitors, optimize their business models and respond to the changing needs of customers.

“Adapting business models to changes” (C7) ranks fifth. In the dynamic environment of the digital economy, which is intertwined with transformations brought about by advancements in artificial intelligence, businesses must have the ability to quickly adapt to changes in technology, markets and customer behaviors. Artificial intelligence, by creating widespread changes in business models and providing tools for advanced data analysis, trend prediction and process optimization, reinforces this necessity. This criterion not only impacts the competitiveness of businesses but also ensures their survival in an AI-based digital economy. Adapting business models to changes means constantly revisiting the structures, strategies and value chains of businesses. This adaptation may involve the use of emerging technologies, leveraging advanced AI algorithms for decision-making and identifying new opportunities in the market. For example, when AI enables the precise analysis of customer data and prediction of their behavior, businesses must optimize their models based on this information and offer personalized services. This ability leads to business growth and sustainability in the face of future challenges.

Acknowledgement
This research was not funded by any grant.

Conflicts of Interest
The authors declare no conflicts of interest.

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