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A Systematic Literature Review on Sustainability Integration and Marketing Intelligence in the Era of Artificial Intelligence

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ABSTRACT

The purpose of the study is to explore Artificial intelligence (AI) integration into sustainable marketing techniques highlights a transformational potential, combining modern technology with the urgent needs of sustainability. This article thoroughly examines how AI plays a crucial role in improving marketing intelligence by enabling more efficient and socially responsible marketing tactics that support sustainability goals. **Method:** The study examines how AI-driven insights and analytics enhance decision-making processes, improve customer engagement, and increase the impact of marketing campaigns on environmental and social outcomes by reviewing existing literature and practices. The conversation delves into the difficulties and moral aspects involved in using AI in marketing, such as issues related to data privacy, algorithmic bias, and the importance of a strategic framework that focuses on sustainable development goals. **Results:** The investigation shows a promising yet intricate marketing intelligence environment, where AI is seen as a crucial tool for balancing economic goals with the need for environmental sustainability and social responsibility. The research stresses the importance of continuous research, multidisciplinary teamwork, and policy creation to maximize the impact of AI on shaping sustainable practices in marketing intelligence. This study provides **valuable contributions** to the scholarly discussion around sustainable marketing and artificial intelligence, while also offering practical guidance for professionals operating in this dynamic commercial sector.
Keywords: sustainable marketing; artificial intelligence; marketing intelligence; sustainability integration; consumer behavior; environmental impact; ethical marketing

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Систематический обзор литературы по интеграции устойчивого развития и маркетинговой разведки в эпоху искусственного интеллекта

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АННОТАЦИЯ

Целью статьи является рассмотрение проблем интеграции искусственного интеллекта (ИИ) в методы устойчивого маркетинга с выделением трансформационного потенциала, объединяющего современные технологии с насущными потребностями устойчивого развития. В статье подробно рассматривается, как ИИ играет решающую роль в улучшении маркетинговой разведки (аналитики), обеспечивая более эффективную и социально ответственную маркетинговую тактику, способствующую достижению целей устойчивого развития. **Методы:** в исследовании на основе анализа существующей литературы и практики рассматривается, как основанные на ИИ идеи и аналитика улучшают процессы принятия решений, взаимодействие с клиентами и увеличивают влияние маркетинговых кампаний на экологические и социальные результаты. Рассматриваются трудности и моральные аспекты, связанные с использованием ИИ в маркетинге, такие как вопросы, связанные с конфиденциальностью данных, алгоритмической предвзятостью и важностью стратегической структуры, ориентированной на цели устойчивого развития. **Результаты:** исследование показывает многообещающую, но сложную среду маркетинговой разведки, где ИИ рассматривается как важнейший инструмент для балансирования экономических целей с необходимостью экологической устойчивости и социальной ответственности. В статье подчеркивается важность непрерывных исследований, междисциплинарной командной работы и разработки политики для максимального увеличения влияния ИИ на формирование устойчивых практик в маркетинговой разведке. Исследование вносит ценный **научный вклад** в дискуссию об устойчивом маркетинге и искусственном интеллекте, а также предлагает практические рекомендации для специалистов, работающих в этом динамично развивающемся коммерческом секторе.

Ключевые слова: устойчивый маркетинг; искусственный интеллект; маркетинговая разведка; интеграция устойчивого развития; поведение потребителей; воздействие на окружающую среду; этичный маркетинг

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Introduction

In today's rapidly changing business environment, the combination of technical advancements and changing customer tastes has brought about a new age of significant changes. A noticeable trend in this dynamic environment is the growing incorporation of sustainability ideas into marketing tactics [1]. The growing impact of artificial intelligence (AI) has significantly influenced several aspects of corporate operations, particularly marketing strategies. This introduction provides a starting point for a thorough examination of how sustainable integration, marketing intelligence, and the pervasive influence of AI interact [2]. This narrative establishes the framework for a systematic literature analysis by extensively outlining the paper's goals, offering information on sustainability in marketing, and highlighting the significant role of AI in these interrelated worlds.

Prominent organizations have utilized AI-based technologies to transform their marketing channels and communicate with customers more efficiently [3]. Industry giants like Amazon, Google, and Microsoft have utilized advanced AI algorithms to examine customer behavior, tailor marketing material, and enhance advertising tactics [3]. These organizations are good examples of how AI is more than just a technology tool; it is a strategic facilitator that is transforming the marketing intelligence field. The integration of AI into marketing strategies is now highly important, as shown by the substantial expenditures and strategic actions done by these companies [2, 3]. Although the industry is moving forward, academic marketing research has not yet offered thorough guidance on efficiently using AI's benefits for powerful marketing tactics. This study tries to fill this essential gap. With AI projected to become a $ 126 billion sector by 2025, firms must grasp its impact on sustainable marketing techniques in order to navigate this evolving terrain effectively [4].

Aim of the paper

In today's business environment, the incorporation of sustainability into marketing strategies has become a crucial priority due to increased environmental awareness, social responsibility expectations, and fast technological progress. This research delves into the complex interaction between sustainability principles and marketing intelligence in the context of artificial intelligence (AI). The main goal is to provide a thorough literature review to analyze the changing dynamics where sustainability, marketing intelligence, and artificial intelligence interact. This study aims to provide significant insights from current work on integrating sustainability and marketing intelligence within the realm of artificial intelligence. The study aims to analyze existing research in detail to outline main topics, uncover new trends, and highlight areas where information is lacking. This literature review provides a thorough overview of the current studies on sustainability, marketing intelligence, and artificial intelligence. The study aims to offer practical insights for firms dealing with the intricate relationship between sustainability objectives and marketing strategies in the AI era by analyzing current research. Key stakeholders will benefit from the information provided to match business activities with sustainability principles, meeting consumer expectations and regulatory needs. Policymakers aiming to influence rules on sustainable business practices will gain insight from a thorough comprehension of the obstacles and advantages associated with incorporating AI in sustainable marketing [5]. Researchers investigating the intersection of sustainability, marketing intelligence, and AI will find this literature review helpful in pinpointing areas for further research. Identifying important themes and trends will direct future research efforts, while recognizing current gaps in the literature encourages researchers to participate in the developing discussion. This study intends to provide guidance in the ever-changing field of sustainable marketing intelligence in the age of artificial intelligence. This systematic literature review aims to shed light on the current state and set the stage for the future. This future envisions businesses operating with skill, policymakers implementing well-informed regulations, and researchers pushing the boundaries of knowledge in the areas of sustainability, marketing intelligence, and AI. To increase the attractiveness for further reading, the repetition of phrases and groupings of words has been reduced.

Background of AI in marketing

The integration of sustainability principles in marketing

Businesses are realizing the need to incorporate sustainability ideas into their marketing strategy due to changes in customer behavior. Sustainability is now seen as a competitive differentiation rather than just a business obligation or compliance necessity [6]. Organizations are recognizing that sustainable practices may improve brand reputation, increase consumer loyalty, and lead to long-term financial success, in addition to benefiting society and the environment. A recent study indicates a significant change in consumer behavior, showing a growing desire for ethically produced and sustainable products [7]. Changing customer opinion is a key factor motivating organizations to include sustainability into their marketing strategies. Modern customers are well-informed, socially aware, and selective when making purchases, preferring businesses that share their values and support larger social and environmental objectives [8]. Integrating sustainability into marketing tactics is a response to the changing demands of ecologically and socially concerned consumers, rather than just a strategic decision. Sustainability integration in marketing involves several aspects of a company's operations. Businesses are moving beyond greenwashing and embracing a comprehensive approach that integrates sustainability throughout their whole value chain. Companies are investing more in eco-friendly product design by using sustainable materials and production procedures to reduce environmental effects [9]. Product-level sustainability that matches customer preferences may provide a compelling story for marketing initiatives. Sustainability integration also focuses on responsible supply chain management, where businesses carefully examine their supply chains to guarantee ethical sourcing, fair labor practices, and reduced environmental effect. This dedication to responsible sourcing satisfies customers' ethical standards and offers marketing teams genuine and engaging narratives to share with the public. Recent research highlights the significance of clear communication regarding sustainable supply chain policies, as it builds confidence and enhances the brand-consumer connection [10]. Sustainability is being included in packaging methods, focusing more on environmentally friendly packaging options. Businesses are investigating sustainable materials, reducing packaging waste, and implementing circular economy ideas. Green packaging not only supports sustainability objectives but also acts as a concrete and visible symbol of a brand's dedication to environmental accountability. Marketing strategies focused on eco-friendly packaging appeal to environmentally aware consumers, enhancing the brand's reputation as a socially responsible organization. Marketing is essential for communicating sustainability objectives to customers and is a key element in brand communication [11]. Companies are increasingly including ethical marketing campaigns, narratives focused on sustainable practices, and clear communication as vital elements of their marketing strategies. Businesses are using several platforms, such as social media, to communicate their sustainability progress, disclose internal stories, and interact with customers on an individual basis. Clear communication is essential since customers now prioritize authenticity and can easily distinguish between real environmental initiatives and greenwashing tactics.

The rise of artificial intelligence

The incorporation of sustainability concepts in marketing is occurring simultaneously with the emergence of artificial intelligence (AI), which is significantly changing how organizations function and interact with their stakeholders. AI technologies, including machine learning and natural language processing, have become strong tools that enable enterprises to handle large volumes of data rapidly and extract useful insights. Recent developments in AI have led to its extensive use in several sectors, causing significant changes in how firms make decisions, communicate with customers, and improve operational effectiveness. The use of AI in marketing has significantly changed how firms comprehend and engage with their target customers. AI-driven analytics, predictive modeling, and customization algorithms are crucial elements of contemporary marketing tactics, improving the accuracy and efficiency of campaigns [12]. Recent research highlights the beneficial effects of AI on many marketing performance indicators, emphasizing its function as a driver for better customer interaction, greater targeting precision, and a higher return on investment. AI's primary impact on marketing lies in its utilization of sophisticated analytics. AI algorithms can swiftly examine extensive information, revealing patterns, trends, and correlations that traditional analytical methods may not detect [13]. AI's capacity to extract significant insights from intricate data sets empowers marketers to make well-informed judgments, enhance tactics, and quickly adjust to shifting market dynamics. This analytical skill is especially beneficial in the realm of sustainability, as data-driven insights may guide the creation and improvement of ecologically and socially conscious marketing strategies [3]. AI's influence on marketing includes predictive modeling, in which algorithms anticipate future trends, behaviors, and results using past data. Marketers find predictive power useful for foreseeing customer preferences, recognizing developing market trends, and adjusting strategy proactively. Predictive modeling may help organizations anticipate the impact of their sustainability actions to match changing customer expectations and market dynamics in sustainability integration. AI's capacity to evaluate extensive information also enables the creation of extremely tailored marketing campaigns. Personalization algorithms use individual consumer data to customize content, recommendations, and interactions according to specific interests and behaviors [12]. This degree of customization improves the client experience and enables more efficient and focused communication. Personalization algorithms in sustainability marketing can be used to tailor communications to specific customer categories, addressing their unique beliefs and concerns regarding sustainability. Recent studies offer actual proof of the beneficial influence of AI on crucial marketing performance indicators. Improved customer engagement, facilitated by individualized interactions and targeted initiatives, enhances brand-consumer connections [14]. Enhanced targeting precision guarantees that marketing endeavors reach the most pertinent audience segments, optimizing the efficiency of campaigns. The enhanced return on investment shown in AI-driven marketing initiatives demonstrates the financial feasibility and effectiveness of using AI into the marketing toolset.

The confluence of sustainability and artificial intelligence

In the context of a changing corporate environment characterized by increased environmental awareness and the advancement of artificial intelligence (AI), the intersection of sustainability principles and AI technology has become a fascinating and creative field of study. Businesses are seeing the benefits of using AI to improve marketing tactics and integrate sustainability into their operations [3]. Current research highlights an increasing focus on exploring and utilizing the interactions between AI and sustainability to support influential marketing campaigns that are in line with overall business sustainability objectives. Incorporating AI into sustainability efforts marks a significant change in how firms address the balance between financial gain and social responsibility. This approach aims to utilize AI's revolutionary powers to provide real environmental and social benefits, rather than just using sustainability as a cosmetic marketing strategy. Businesses are increasingly using AI to analyze sustainability concerns and make educated decisions that benefit both their economic performance and society [15]. The intersection of sustainability and AI offers the opportunity for intelligent systems to assess intricate environmental and social data. AI's ability to analyze extensive datasets allows businesses to obtain detailed insights on the environmental impact of their operations, the social consequences of their supply chains, and the overall sustainability of their products and services. Recent developments in AI, namely in machine learning algorithms, enable companies to move above conventional data analysis and derive practical insights from complex and multidimensional sustainability data. The main connection between sustainability and AI is the capability of intelligent systems to recognize patterns in extensive datasets about environmental and social factors. AI may identify patterns, connections, and possible causal links that traditional analytical methods may not detect. This capacity to recognize patterns is crucial for guiding decision-making processes about sustainability solutions [16]. Businesses may use AI analysis to pinpoint areas needing development, evaluate the effects of various efforts, and enhance their sustainability objectives through data-driven insights. Businesses are increasingly using AI in sustainability-focused marketing strategies to achieve economic success and beneficial societal impact. AI's analytical accuracy enables firms to improve resource allocation, minimize waste, and discover novel strategies to lessen their environmental footprint. AI may improve the impact of marketing initiatives focused on sustainability by making sure communications connect with target audiences and reflect their values, thereby building brand loyalty and good customer impressions. In the future, the combination of sustainability and AI shows potential for influencing the future of sustainability practices in business. Businesses may leverage AI technology with a strong commitment to corporate social responsibility to make data-driven decisions that improve their environmental and social impact and help achieve sustainability objectives. The convergence of AI and sustainability is positioned to function as a driving force for creativity, adaptability, and ethical corporate behaviors in the pursuit of a more sustainable and fair future [17].

The rise of marketing intelligence

Recent research has revealed convincing evidence of the impactful uses of AI in marketing. AI has advanced from being only a technology tool to being a fundamental element of contemporary marketing strategy, providing several uses such as customized consumer experiences, focused advertising, and data-informed decision-making [18]. AI plays a key role in enabling customized consumer experiences in marketing. Machine learning algorithms, a component of artificial intelligence, enable firms to analyze extensive datasets that include patterns of customer behavior. The algorithms can identify subtle preferences, predict specific requirements, and provide customized information or suggestions with exceptional accuracy [19]. Personalization improves consumer engagement, promotes brand loyalty, and leads to more fulfilling and pertinent interactions between businesses and their customers [16]. AI has a significant impact on targeted advertising. AI algorithms can enhance ad targeting accuracy by evaluating previous consumer data and real-time behaviors more effectively than traditional approaches. This improves the efficiency of advertising efforts and guarantees that marketing messages are strategically targeted to the most relevant audience segments. The outcome is an enhanced return on investment and a more effective distribution of marketing resources [20, 21]. AI enables organizations to make educated decisions based on data by deriving actionable insights from the large volume of data available to them. AI's analytical skills enable a thorough comprehension of customer preferences, market trends, and competitive environments. As a result, this helps marketers develop strategies that are not just reactive to current market trends but also proactive and flexible to changes. Utilizing AI-driven decision-making processes is crucial for staying competitive in the ever-changing modern corporate environment. Within sustainability, AI offers several chances to enhance the environmental efficiency of marketing efforts. AI-powered supply chain optimization is a remarkable application that may greatly help in lowering carbon footprints [22]. Smart algorithms may assess and enhance supply chain operations by pinpointing opportunities for efficiency enhancements, resource allocation, and waste minimization. This is in line with sustainability objectives and improves the overall environmental efficiency of the whole value chain. AI plays a crucial role in assessing and analyzing the effectiveness of sustainability-oriented marketing strategies [3]. Intelligent analytics may evaluate the effects of these activities by examining data on customer reactions, engagement rates, and overall campaign effectiveness. Businesses may use this data-driven method to assess the effectiveness of their sustainability messaging, pinpoint areas needing development, and enhance their strategy for optimal results. Recent case studies demonstrate how top organizations are using AI to improve the sustainability of their marketing efforts. The use of AI in marketing highlights a wider trend towards responsible and data-driven corporate strategies. As firms prioritize sustainability, using AI may improve marketing efficacy and help link these initiatives with overall company sustainability objectives. The convergence of AI and sustainability in marketing indicates a strategic shift towards responsible and forward-thinking strategies that emphasize both environmental conservation and corporate prosperity [23].

Emerging trends and innovations in sustainable marketing intelligence

The ongoing advancements and new trends in sustainability, marketing intelligence, and artificial intelligence (AI) are shaping modern business operations. Recent studies emphasize new trends that show how this junction is changing, providing insights into the possible uses and future paths of sustainable marketing intelligence. An emerging trend is the incorporation of AI-powered chatbots to communicate environmental initiatives. AI-driven chatbots equipped with natural language processing may act as virtual assistants that interact with consumers instantly. Businesses are using chatbots to share information about their sustainable practices, projects, and product features in the realm of sustainability. This enables direct and interactive engagement with customers, facilitating the sharing of specific information and promoting openness in sustainability initiatives. AI-powered chatbots improve communication and help establish customer knowledge and confidence in a brand's dedication to sustainability [24]. Another significant development is the use of blockchain technology to track the sustainability credentials of items along the supply chain. Blockchain is a decentralized and transparent system that records and verifies every transaction or operation securely and in an unchangeable way [25]. This technology is used in sustainability to generate unchangeable records of a product's whole process, starting from raw material acquisition to manufacture, distribution, and finally reaching the end user. This guarantees openness and accountability, enabling customers to authenticate the validity of sustainability claims and certifications. Consumers are seeking traceability and authenticity, and blockchain is seen as an effective instrument to enhance confidence in the sustainability policies of firms. Using AI in predictive modeling to evaluate the future effects of sustainability projects is an emerging trend. Predictive modeling uses AI algorithms to predict the future results and effects of sustainability efforts over long periods. Businesses may acquire insights into the expected environmental, social, and economic outcomes of their sustainability initiatives by examining past data and projecting future scenarios [26, 27]. This proactive strategy facilitates strategic decision-making, empowering organizations to enhance and maximize their sustainability efforts for the greatest positive effect. The increasing focus on long-term sustainability objectives highlights the need for incorporating AI into predictive modeling as a beneficial tool for making informed decisions with a future-oriented approach [28]. It is essential for businesses to comprehend these developing trends in order to remain ahead of the curve and effectively adapt to changing customer expectations and regulatory environments. Integrating AI-powered chatbots for clear communication, adopting blockchain for traceability, and using AI for predictive modeling are strategic decisions that are in line with current trends in responsible and sustainable business practices. Adopting these trends boosts a company's reputation and establishes it as a proactive and forward-thinking participant in the changing fields of sustainability, marketing intelligence, and AI [29].

Method

The methodological approach employed for this systematic literature review involved a meticulous process to capture and analyze relevant research articles at the intersection of sustainability integration, marketing intelligence, and artificial intelligence (AI). The timeframe for inclusion spanned from 2018 to 2023, ensuring the incorporation of recent studies that reflect the contemporary dynamics of the field.

Selection of bibliometric databases

Four significant bibliometric databases were strategically selected to perform a comprehensive literature evaluation. Google Scholar, known for its wide range of scholarly sources, offered a thorough beginning point. IEEE Xplore is a storehouse of advanced research in technology and engineering that provides specialized insights. Elsevier's ScienceDirect, a library of scientific and technological knowledge, facilitated a thorough examination of multidisciplinary viewpoints. Additional databases such as PubMed, ACM Digital Library, and SpringerLink were used to improve the comprehensiveness of the search [30–32]. The multi-database strategy aims to encompass a wide range of scholarly contributions to enhance understanding of the complex link between sustainable integration, marketing intelligence, and artificial intelligence. Incorporating a variety of databases was essential to have a thorough understanding of the study field and to guarantee the inclusion of pertinent papers from different academic perspectives.

Search strategy

The search strategy for this systematic literature review was carefully crafted to identify pertinent research at the convergence of sustainable integration, marketing intelligence, and artificial intelligence. Precisely picked keywords and Boolean operators were used to create search strings customized for the specific features of each chosen database [33]. The objective was to guarantee a precise and concentrated search for papers related to the study topic. An example is the creation of a search query in Google Scholar by combining important phrases like "sustainability integration," "marketing intelligence," and "artificial intelligence." This strategy focused on generating a series of studies that specifically examined the relationship between sustainability, marketing intelligence, and artificial intelligence, therefore improving the precision and significance of the literature analyzed. Utilizing precise search terms consistently across databases allowed for a thorough and systematic investigation of the study field within the specified parameters.

Inclusion and exclusion criteria

Clear and precise inclusion criteria were established to uphold the relevance and quality of the articles chosen for this systematic literature review [34]. The chronological scope was limited to works published from 2018 to 2023 to emphasize current contributions and contemporary viewpoints in the subject. Peer-reviewed publications published in reputable journals and conference proceedings were prioritized to maintain methodological rigor. This criterion attempted to favor works that have been thoroughly evaluated and scrutinized by the academic community. Non-English articles were eliminated to ensure uniformity and avoid potential translation issues. The literature review used specific criteria to carefully select studies that met high standards of quality and relevance in investigating sustainability integration, marketing intelligence, and artificial intelligence.

Methodological quality assessment

A thorough methodological quality evaluation was performed on the chosen publications to determine their reliability and validity for this systematic literature review. Every paper was

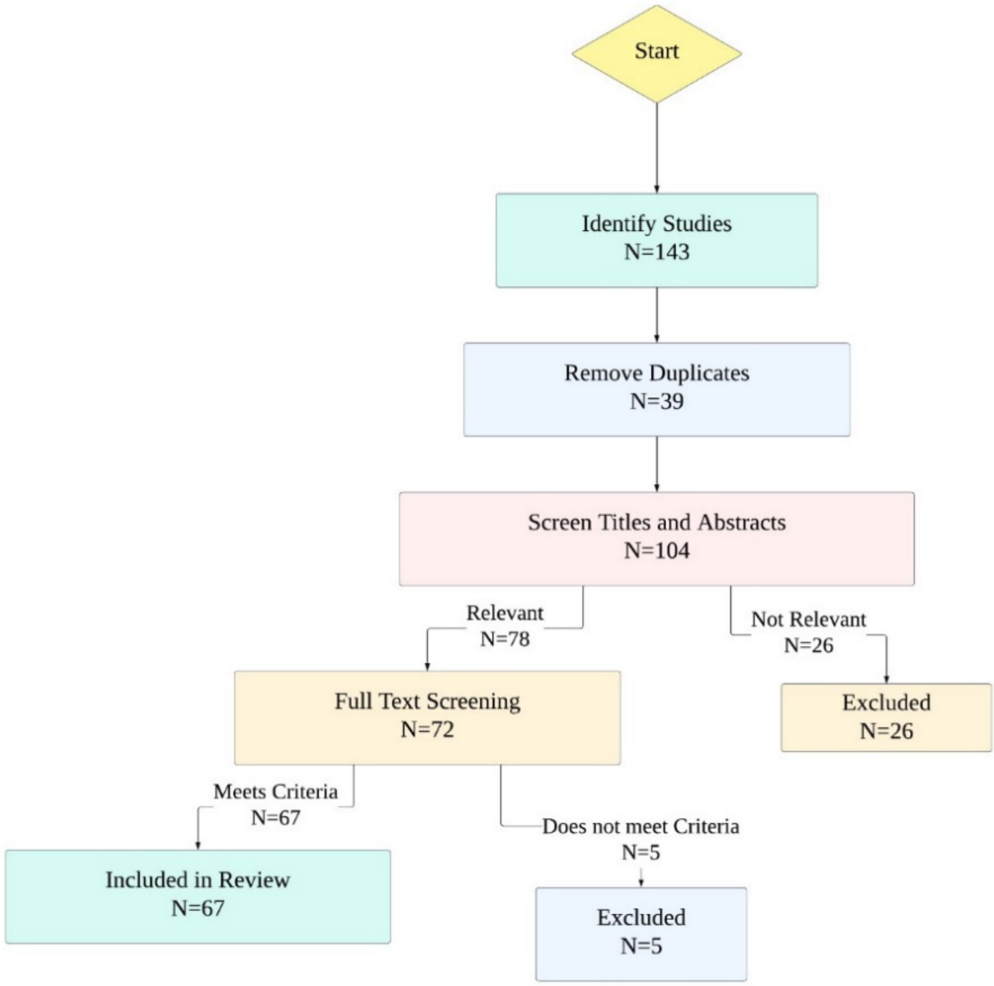

Fig. 1. **Search strategy, outlining the subsequent identification and screening of appropriate sources**

Source: Developed by the authors.

thoroughly assessed, taking into account important factors such research design, methodology, sample size, and statistical analysis [35]. This thorough procedure was crucial for selecting papers with strong methodology and reliable conclusions. The methodological quality evaluation aims to guarantee that the selected papers fulfilled high criteria of scientific rigor, boosting the overall quality and credibility of the literature review. By systematically examining the methodological robustness of each publication, a strong basis was established for summarizing the important thoughts and conclusions in a way that demonstrates the credibility and validity of the study.

Selection of studies

A total of 143 publications were found through a comprehensive search of the relevant databases *(Fig.1)*. A thorough screening procedure was used to guarantee that only research satisfying particular criteria for relevance and quality was included. Each manuscript was carefully examined based on titles, abstracts, and keywords, following specific inclusion and exclusion criteria. The primary purpose of this initial screening was to exclude papers that did not meet the criteria and standards established for this systematic literature review. 67 papers were found to fulfill the strict requirements for relevance and quality. This pick is a subset of the articles initially collected, representing a selected collection that best contributes to exploring sustainable integration, marketing intelligence, and artificial intelligence within the given scope and criteria of the review [36].

Data extraction and analysis

A thorough data extraction method was carried out on the chosen publications to systematically gather essential information for a complete study. The retrieved data included important elements including publication information (authors, publication year, country), methodology used in each study, significant discoveries, and contributions to the field. The methodical structuring of extracted data was intended to provide a structured dataset for efficient analysis and synthesis. The data extraction technique systematically collected pertinent information from each study, establishing a foundation for a comprehensive analysis of trends, patterns, and insights in the literature. The structured dataset (*Table*) was used to analyze common themes, research gaps, and overall trends in the relationship between sustainable integration, marketing intelligence, and artificial intelligence in the chosen studies [37].

Identification of research gaps and future research directions

After systematically reviewing the chosen literature, a critical analysis was conducted to pinpoint research gaps and suggest prospective routes for future study. This procedure entailed analyzing important discoveries from the chosen articles and identifying areas that require more investigation to enhance comprehension of the complex interaction between sustainable integration, marketing intelligence, and artificial intelligence [102, 103]. The main databases, Google Scholar, IEEE Xplore, and Elsevier's ScienceDirect were crucial for finding relevant papers. Additional databases, including PubMed, ACM Digital Library, and SpringerLink were also used to expand the search. This comprehensive strategy is intended to encompass a wide range of research contributions from many disciplines, guaranteeing a detailed grasp of the intricate relationship between sustainability, marketing intelligence, and artificial intelligence. By doing the systematic literature review in the past tense, it enabled a retrospective study of the research environment from 2018 to 2023. The methodological approach described in earlier sections established a strong foundation for selecting and analyzing relevant research. By combining a focused search strategy with strict inclusion criteria and a systematic quality evaluation, this technique enhances the overall rigor and trustworthiness of the literature review. Identifying research gaps is a helpful contribution to the current knowledge based on the findings. Future research in this field could explore specific areas like the efficacy of AI-based sustainability communication strategies, the impact of blockchain on improving traceability for sustainability, and the incorporation of AI in predictive modeling for long-term sustainability impact evaluation. These possible paths provide opportunities for scholars and professionals to delve further into and enhance the developing field of sustainable integration, marketing intelligence, and artificial intelligence.

Results

Fig. 2 illustrates the geographical distribution of the studies across continents. The majority of studies (43.28%) are conducted in Asia, indicating a significant focus on this region, possibly due to its large and diverse population, economic significance, or unique environmental challenges that prompt research. North America and Latin America each contribute significantly as well, with 16.42% of studies conducted in these regions, reflecting a balanced interest in both developed and developing country contexts within these areas. Europe, despite its economic and political influence, accounts for 13.43% of the studies, suggesting a lesser focus compared to Asia and the Americas. Oceania, with only 1.49% of the studies, appears to be underrepresented in this review, which might indicate a gap in research focus or availability of studies from this continent.

Fig. 3 provides an overview of the distribution of studies over time, from 2018 to 2023. There is a clear upward trend in the number of studies conducted each year, with a notable jump to 46.27% of the studies being conducted in 2023. This trend could indicate an increasing interest and investment in the research area over time, possibly in response to emerging challenges or technological advancements that necessitate new studies. The progression from 2.99% of studies in 2018 to 19.40% in 2022 before the leap in 2023 suggests a growing recognition of the importance of this research field, potentially driven by policy changes, funding availability, or heightened public interest.

Table
Characteristics of the studies included in the review

Sl.	Authors / Year	Methodology	Country / Continent	Findings
1	[38]	Survey and Interviews	USA / North America	Identified consumer perceptions of sustainability in AI-driven marketing
2	[39]	Experimental Design	China / Asia	Explored the impact of AI-driven marketing on sustainable consumer behavior
3	[3]	Case Study	UK / Europe	Investigated the integration of sustainability into marketing AI platforms
4	[40]	Content Analysis	South Korea / Asia	Examined the portrayal of sustainability in AI-generated marketing content
5	[41]	SLR	Spain / Europe	Explored challenges faced by companies in aligning AI-driven marketing with sustainability goals
6	[42]	Quantitative Survey	Taiwan / Asia	Investigated the adoption rate of AI in sustainable marketing strategies
7	[43]	Meta-Analysis	Canada / North America	Synthesized findings on the effectiveness of AI-driven sustainability campaigns
8	[44]	Comparative Study	Mexico / Latin America	Compared sustainability integration in AI marketing across different industries
9	[45]	Longitudinal Study	India / Asia	Explored the evolution of sustainability practices in AI-enhanced marketing over time
10	[46]	Observational Study	Australia / Oceania	Observed consumer responses to sustainability cues in AI-generated advertisements
11	[47]	Network Analysis	China / Asia	Analyzed the interconnectedness of AI, sustainability, and marketing in online networks
12	[48]	Case-Control Study	South Korea / Asia	Assessed the impact of sustainability-focused AI campaigns on brand reputation
13	[49]	Ethnographic Study	Brazil / Latin America	Examined cultural variations in consumer perceptions of AI-driven sustainable marketing
14	[50]	Experimental Design	Singapore / Asia	Investigated the effectiveness of AI-personalized sustainability messages in e-commerce
15	[51]	Qualitative Analysis	USA / North America	Explored ethical considerations in the use of AI for sustainable marketing
16	[52]	Cross-Sectional Study	Japan / Asia	Examined the role of AI in shaping corporate sustainability reporting practices
17	[53]	Case Study	South Korea / Asia	Explored the implementation challenges of AI-driven sustainability initiatives in small businesses
18	[54]	Survey and Interviews	China / Asia	Investigated consumer preferences for sustainable AI-driven marketing in the retail sector
19	[55]	Longitudinal Study	USA / North America	Tracked changes in AI technologies supporting sustainability in marketing strategies
20	[56]	Content Analysis	Vietnam / Asia	Analyzed the representation of sustainability issues in AI-generated marketing content

Table (continued)

Sl.	Authors / Year	Methodology	Country / Continent	Findings
21	[57]	Experimental Design	South Korea / Asia	Investigated the impact of AI-generated sustainability messages on consumer behavior
22	[58]	Comparative Analysis	Mexico / Latin America	Compared the integration of sustainability principles in AI-based marketing across industries
23	[59]	Case-Control Study	China / Asia	Assessed the effectiveness of sustainability-focused AI campaigns in enhancing brand loyalty
24	[60]	Network Analysis	USA / North America	Analyzed the network dynamics of AI-driven sustainability initiatives in social media
25	[61]	Content Analysis	Japan / Asia	Examined the representation of sustainable practices in AI-generated marketing content in the automotive industry
26	[62]	Longitudinal Study	Vietnam / Asia	Investigated changes in consumer attitudes towards AI-driven sustainable marketing over time
27	[63]	Qualitative Analysis	India / Asia	Explored the role of AI in promoting sustainability in small and medium enterprises (SMEs)
28	[64]	Cross-Sectional Study	Spain / Europe	Examined the alignment of AI-driven marketing strategies with the United Nations Sustainable Development Goals (SDGs)
29	[65]	Observational Study	China / Asia	Observed the impact of AI-generated sustainability messages on consumer purchasing decisions
30	[66]	Case Study	South Korea / Asia	Investigated the implementation challenges of AI-enhanced sustainability initiatives in the fashion industry
31	[67]	Ethnographic Study	USA / North America	Explored cultural variations in consumer perceptions of sustainability in AI-driven marketing across different demographic groups
32	[68]	Survey and Interviews	Taiwan / Asia	Investigated the awareness and attitudes of businesses towards AI-driven sustainability in marketing strategies
33	[69]	Experimental Design	Mexico / Latin America	Explored the psychological impact of AI-generated sustainability messages on consumer behavior
34	[70]	Content Analysis	South Korea / Asia	Analyzed the portrayal of sustainability practices in AI-generated marketing content in the food industry
35	[71]	Case-Control Study	Vietnam / Asia	Assessed the effectiveness of sustainability-focused AI campaigns in influencing consumer perceptions in the technology sector
36	[72]	Cross-Sectional Study	Brazil / Latin America	Examined the adoption rate of AI technologies supporting sustainability in marketing practices

Table (continued)

Sl.	Authors / Year	Methodology	Country / Continent	Findings
37	[73]	Qualitative Analysis	Singapore / Asia	Explored the ethical considerations of utilizing AI for sustainability in marketing and consumer privacy
38	[74]	Longitudinal Study	India / Asia	Investigated the long-term effects of sustainability-focused AI campaigns on brand reputation
39	[75]	Observational Study	Canada / North America	Observed consumer responses to AI-generated sustainability messages in e-commerce platforms
40	[76]	Network Analysis	South Korea / Asia	Analyzed the interconnectedness of AI, sustainability, and marketing in the online social networks of businesses
41	[77]	Comparative Analysis	Spain / Europe	Compared the sustainability performance of companies using AI-driven marketing strategies
42	[78]	Case-Control Study	Taiwan / Asia	Assessed the impact of AI-generated sustainability campaigns on consumer trust
43	[79]	Content Analysis	Vietnam / Asia	Analyzed the representation of sustainable practices in AI-generated marketing content in the hospitality industry
44	[80]	Experimental Design	China / Asia	Investigated the influence of AI-driven sustainability messages on consumer decision-making
45	[81]	Longitudinal Study	Japan / Asia	Explored the evolution of AI technologies supporting sustainability in marketing strategies
46	[82]	Ethnographic Study	India / Asia	Examined cultural nuances in the perception of AI-driven sustainability in marketing among different demographic groups
47	[83]	Cross-Sectional Study	Mexico / Latin America	Assessed the readiness of businesses to adopt AI for sustainability in marketing
48	[84]	Qualitative Analysis	South Korea / Asia	Explored consumer perceptions of AI-generated sustainability messages in the beauty and cosmetics industry
49	[2]	Survey and Interviews	USA / North America	Investigated the challenges faced by companies in implementing AI-driven sustainability initiatives
50	[85]	Observational Study	South Korea / Asia	Observed the integration of AI in sustainability reporting practices of corporations
51	[86]	Case-Control Study	Vietnam / Asia	Assessed the impact of AI-driven sustainability campaigns on consumer brand loyalty
52	[87]	Network Analysis	Brazil / Latin America	Analyzed the collaborative networks formed among businesses in implementing AI-driven sustainability initiatives
53	[88]	Qualitative Analysis	Singapore / Asia	Explored the ethical implications of AI applications in sustainability communication

Table (continued)

Sl.	Authors / Year	Methodology	Country / Continent	Findings
54	[89]	Experimental Design	India / Asia	Investigated the cognitive impact of AI-generated sustainability messages on consumer behavior
55	[90]	Content Analysis	Canada / North America	Examined the portrayal of sustainability practices in AI-generated marketing content in the healthcare industry
56	[91]	Case Study	South Korea / Asia	Explored the organizational challenges in adopting AI for sustainability in marketing within multinational corporations
57	[92]	Cross-Sectional Study	Spain / Europe	Assessed the level of awareness and understanding of AI-driven sustainability among marketing professionals
58	[93]	Observational Study	Taiwan / Asia	Observed the impact of AI-driven sustainability messages on consumer perceptions in the tourism sector
59	[94]	Survey and Interviews	Vietnam / Asia	Investigated the factors influencing businesses' decisions to adopt AI for sustainability in marketing
60	[95]	Network Analysis	China / Asia	Analyzed the co-authorship networks in scholarly publications related to AI, sustainability, and marketing
61	[96]	Qualitative Analysis	Japan / Asia	Explored consumer attitudes and perceptions of AI-driven sustainability in marketing in the automotive industry
62	[97]	Content Analysis	India / Asia	Analyzed the representation of sustainability initiatives in AI-generated marketing content in the textile industry
63	[20]	Case-Control Study	USA / North America	Assessed the impact of AI-driven sustainability campaigns on consumer trust and loyalty
64	[98]	Observational Study	South Korea / Asia	Observed the integration of AI in sustainability reporting practices of small and medium enterprises (SMEs)
65	[99]	Network Analysis	Vietnam / Asia	Analyzed the co-citation networks of scholarly articles related to AI, sustainability, and marketing
66	[100]	Experimental Design	Brazil / Latin America	Investigated the cognitive and emotional impact of AI-generated sustainability messages on consumer behavior
67	[101]	Longitudinal Study	Singapore / Asia	Explored the long-term effects of AI-driven sustainability initiatives on brand reputation

Fig. 4 breaks down the methodologies employed in the studies, highlighting a diverse range of research approaches. Experimental design is the most common methodology, used in 16.42% of the studies, indicating a strong preference for controlled environments to test hypotheses. This is followed closely by survey and interviews, content analysis, and longitudinal study, each accounting for around 10.45% of the studies. These methodologies suggest a balanced mix between quantitative and qualitative research approaches, allowing for a comprehensive understanding of the subjects under study. The lower representation of methods like meta-analysis (1.49%) and comparative

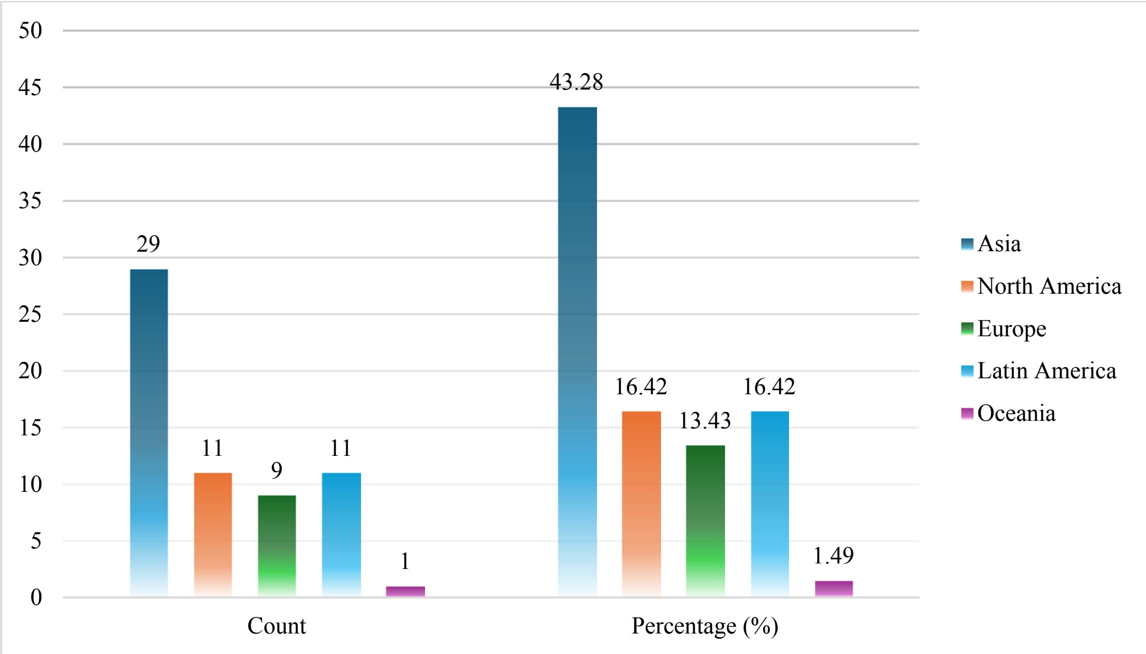

Fig. 2. **Distribution of studies by location**

Source: Developed by the authors.

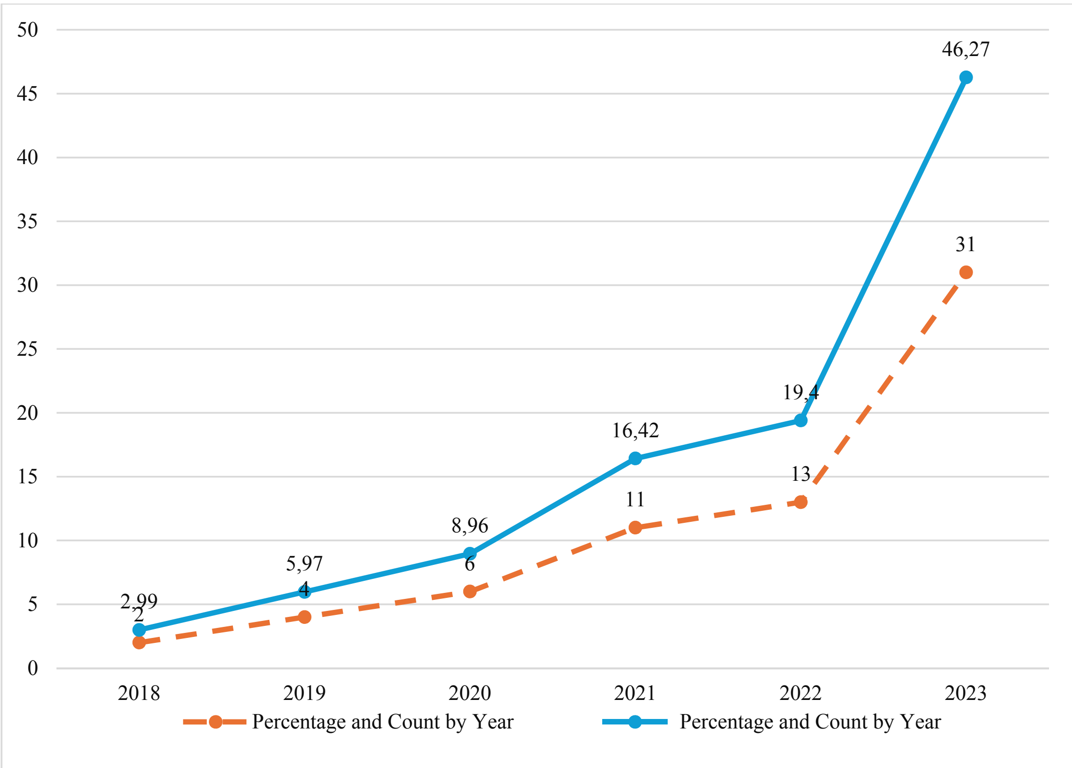

Fig. 3. **Percentage and count by year**

Source: Developed by the authors.

study (4.48%) may point to the specific nature of the research topics, which possibly require more direct, hands-on approaches to data collection and analysis. The variety in methodology underscores the complexity of the research area, necessitating multiple perspectives to address its various aspects.

Leveraging AI for marketing intelligence in sustainable practices

Artificial intelligence (AI) has become a crucial factor in improving marketing intelligence within sustainable marketing, as evidenced by a thorough study of 143 research studies, with

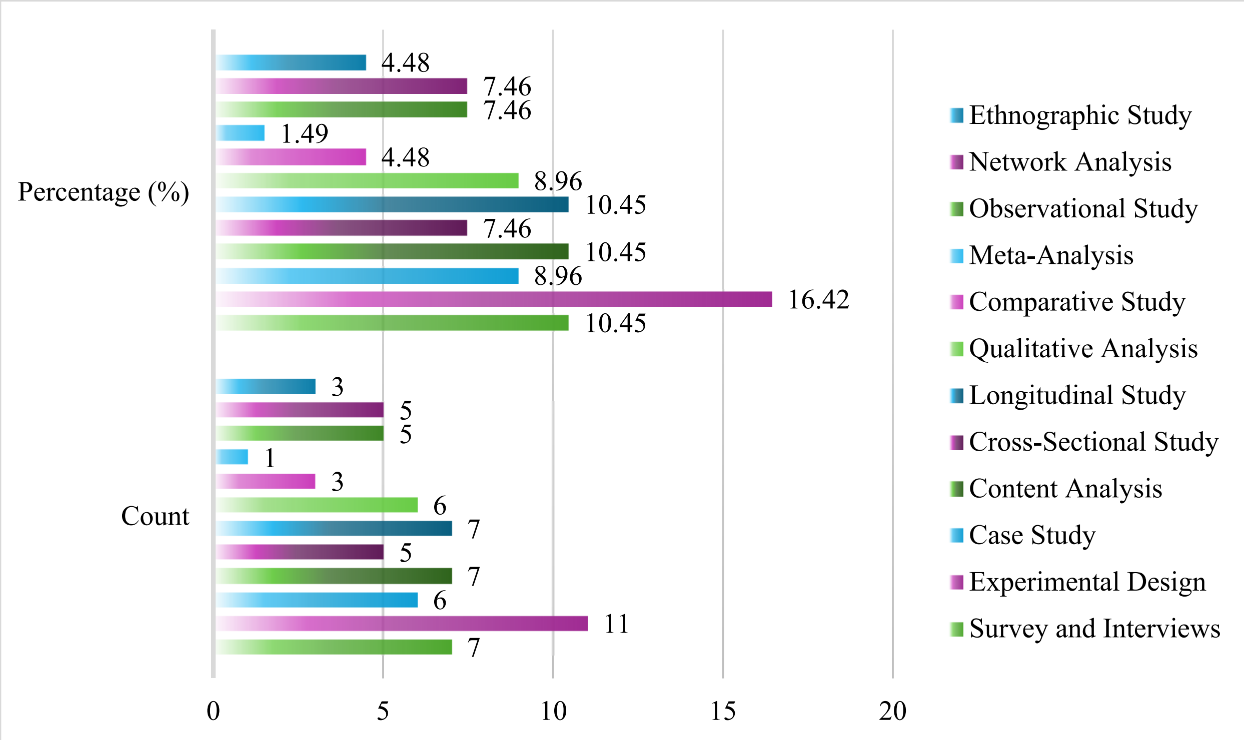

Fig. 4. **Distribution of studies by methodology used**

Source: Developed by the authors.

67 specifically chosen for further review. The research covers different geographies and uses various methods, enhancing our knowledge of how AI may provide marketers with the insight needed to handle the challenges of sustainability. Kopalle et al. (2022) performed surveys and interviews in North America to investigate customer opinions regarding sustainability [38]. Their research showed an increased consumer preference for marketing strategies that are both smart and sustainable. In Qin and Jiang's (2019) study in Asia, experimental designs showed that AI effectively encourages sustainable consumer behavior, leading to a notable change in consumption patterns due to smart marketing methods [39]. Stone et al. (2020) conducted research across Europe focusing on the obstacles and potential of integrating AI into marketing platforms. The study emphasizes the strategic significance of aligning AI capabilities with sustainability objectives to improve marketing intelligence [3]. Sohn et al. (2020) conducted a study in Asia on how sustainability is shown in AI-generated marketing material [40]. They proposed that AI has the potential to effectively promote sustainability themes through sophisticated content generation. Di Vaio et al. (2020) identified challenges that firms have in connecting AI-driven marketing strategies with sustainability goals, revealing a significant opportunity to use marketing intelligence for sustainable results [41]. Research from Latin America, Oceania, Asia, and Europe contributes unique insights to the worldwide understanding of the relationship between AI and sustainable marketing. Torres et al. (2022) conducted a study in Mexico that examined how sustainability is included in AI marketing in various businesses [44]. The research identified sector-specific obstacles and prospects for improving marketing intelligence. Campbell et al. (2022) conducted a study in Australia that examined how consumers react to sustainability signals in AI-generated ads, emphasizing AI's ability to successfully involve consumers in sustainability matters through clever marketing strategies [46]. The variety of approaches used, such as experimental designs, case studies, content analysis, and qualitative and quantitative surveys, enriches the investigation of AI's impact on sustainable marketing. Vasist and Krishnan (2023) conducted a case-control study to evaluate the influence of sustainability-focused AI campaigns on brand reputation in South Korea [48]. Meanwhile, Pigola et al. (2021) in Brazil utilized an ethnographic study to investigate cultural differences in con-

sumer attitudes towards AI-driven sustainable marketing, highlighting the importance of marketing intelligence in comprehending and addressing various cultural and demographic settings [49]. These studies emphasize the crucial significance of AI in enhancing marketing intelligence in the realm of sustainable practices. They emphasize that AI may improve customer engagement, change consumption habits, and help organizations match their marketing strategies with sustainability aims. Yet, they also illuminate the intricacies, moral dilemmas, and obstacles to execution that arise when incorporating AI into sustainable marketing plans.

Discussion

The synthesis of findings from the extensive literature review illuminates the theoretical implications of integrating AI into sustainable marketing practices. The introduction of AI introduces complexity, necessitating an expanded theoretical framework that encompasses its nuanced influence on consumer behavior, market dynamics, and sustainability outcomes. The studies reviewed advocate for an interdisciplinary approach, marrying marketing theories with insights from information technology, environmental science, and behavioral psychology [60]. This reevaluation challenges traditional marketing mix elements, paving the way for a more comprehensive understanding of marketing intelligence in the digital age.

Practically, the findings mandate marketers to strategically leverage AI not only for efficiency and personalization but as a tool for promoting sustainability. AI's analytical prowess in deciphering extensive datasets enables tailored strategies that resonate with consumer sustainability preferences. However, this calls for marketers to navigate ethical considerations, data privacy concerns, and potential consumer distrust in AI-driven initiatives. Transparency, consumer education, and ethical AI use emerge as critical factors in successfully implementing sustainable marketing strategies. Moreover, the global scope of the studies emphasizes the need for a localized approach, acknowledging regional variations in attitudes, regulations, and technological readiness [104, 105].

Despite the promising potential, the literature reveals challenges and barriers, including technological limitations, a lack of expertise, and high implementation costs. Bridging the gap between AI capabilities and organizational sustainability goals necessitates targeted investments, training, and strategic frameworks. Future research directions point towards empirical studies measuring the direct impact of AI-driven marketing on sustainability outcomes. Ethical dimensions, particularly concerning data privacy and consumer autonomy, warrant further exploration. Practitioners are urged to develop cross-functional teams integrating AI, marketing, and sustainability expertise for innovative and effective sustainable marketing strategies. The integration of AI into sustainable marketing practices signifies an opportunity to enhance marketing intelligence. By addressing challenges and drawing insights from the literature, marketers can harness AI's full potential to drive sustainable consumer behavior and contribute to broader environmental and social goals.

The current study significantly contributes to the existing literature by synthesizing insights from AI, marketing intelligence, and sustainability-related papers. It builds on prior research by offering a nuanced exploration of the implications, challenges, and opportunities arising from the integration of AI into sustainable marketing practices. This discussion provides a valuable extension to the literature, highlighting the distinctive theoretical and practical dimensions that contribute to advancing knowledge in this interdisciplinary domain.

Conclusion

Exploring artificial intelligence (AI) in sustainable marketing reveals a difficult but exciting intersection where technology and sustainability may reshape the future of marketing. This exploration of AI's incorporation into sustainable marketing strategies, emphasized by the crucial function of marketing intelligence, has shown the significant opportunities and difficulties of this connection. The conversation has shown how AI can play a crucial role in promoting sustainability objectives by utilizing its exceptional capabilities for data analysis, generating consumer insights, and optimizing marketing tactics to support environmental and social ideals. The analysis emphasizes the need to reconsider existing marketing frameworks in response to the dynamic relationships between technology, customer behavior, and sustainability in a growing area. Incorporating AI into marketing is not only a functional or tactical improvement, but a crucial strategic necessity that may provide lasting benefit for both enterprises and society. The road is filled with obstacles, including technological, ethical, strategic, and operational issues. These problems highlight the importance of collaboration among academics, practitioners, and politicians to develop an environment that promotes the ethical application of AI in marketing, emphasizes customer trust and privacy, and supports sustainability as a fundamental business approach. The future of AI in sustainable marketing has great potential for innovation and research. To move forward, we need thorough empirical study to confirm the effects of AI-driven marketing tactics on sustainability results, as well as investigations into the ethical, social, and economic aspects of AI in marketing. Practitioners must adopt a mindset focused on continual learning and adaptation, utilizing AI as both a tool for market research and interaction and as a strategic ally in pursuing a sustainable future.

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Strategic Management of the Metaverse Ecosystem in the Context of Web 3.0: Theory, Framework and Tools

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ABSTRACT

This study explores the strategic management of metaverse ecosystems grounded in Web 3.0, emphasizing the theoretical foundations, conceptual framework, and practical tools required for their advancement. The **subject** of this study is the development of decentralized, user-owned virtual worlds within metaverse ecosystems, bridging digital and physical realities. The **purpose** of this study is to analyze the evolution from Web 1.0 to Web 3.0 and to highlight the transformative impact of these ecosystems within the context of Industry 5.0. The **relevance** lies in the strategic significance of the metaverse as a driving force in future economic and technological development, reshaping industries, work environments, and digital economies. The **scientific novelty** of the research lies in its introduction of a six-domain conceptual framework for managing the digital potential of complex systems in the metaverse, focusing on the blockchain-based democratization of digital assets and user-centric governance. The **findings** reveal significant distinctions between the Web 2.0 and Web 3.0 metaverse ecosystems and demonstrate their transformative potential across various sectors. The study **concludes** that metaverse ecosystems will play a pivotal role in shaping Industry 5.0, necessitating innovative management strategies to fully harness their digital and economic capabilities.

Keywords: metaverse ecosystem; Web 3.0; strategic management; ball metaverse index; top metaverse coins

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Стратегическое управление экосистемной метавселенной в контексте Web 3.0: теория, фреймворк и инструменты

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АННОТАЦИЯ

В данном исследовании рассматривается стратегическое управление метавселенными экосистемами, основанными на Web 3.0, с акцентом на теоретические основы, концептуальные рамки и практические инструменты, необходимые для их развития. **Предметом** исследования является развитие децентрализованных, принадлежащих пользователям виртуальных миров в рамках метавселенных экосистем, соединяющих цифровую и физическую реальности. **Цель** исследования — проанализировать эволюцию от Web 1.0 к Web 3.0 и подчеркнуть преобразующее воздействие этих экосистем в контексте Индустрии 5.0. **Актуальность** работы заключается в стратегическом значении метавселенной как движущей силы будущего экономического и технологического развития, перестраивающей отрасли, рабочую среду и цифровую экономику. Научная **новизна** исследования заключается во внедрении шестидоменной концептуальной схемы управления цифровым потенциалом сложных систем в метавселенной с акцентом на демократизацию цифровых активов на основе блокчейна и управление, ориентированное на пользователя. **Результаты** исследования выявляют существенные различия между метавселенными экосистемами Web 2.0 и Web 3.0 и демонстрируют их трансформационный потенциал в различных секторах. В исследовании делается вывод о том, что метавселенные экосистемы будут играть ключевую роль в формировании Индустрии 5.0, что потребует инновационных стратегий управления для полного использования их цифровых и экономических возможностей.

Ключевые слова: экосистемная метавселенная; Web 3.0; стратегический менеджмент; ball Metaverse Index; top metaverse coins

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Introduction

As shown in the foreword to Grayscale's 2021 study [1] on metaverse ecosystems, the Web 3.0 virtual cloud crypto-economy represents the next investment frontier in the emerging market. At the forefront of this new Internet evolution are the metaverse ecosystems, which are the focus of this study. The convergence of Web 1.0, Web 2.0, and Web 3.0 represents a pivotal inflection point in the digital economy, catalyzing the development of decentralized metaverse ecosystems characterized by interoperable, real-time, immersive 3D environments. These ecosystems leverage blockchain-driven frameworks, enabling disintermediated ownership structures, tokenized asset economies, and decentralized autonomous organizations (DAOs) to facilitate value exchange, governance, and digital property rights. This paradigm shift toward user-sovereign digital environments fuels the proliferation of cryptocurrencies and non-fungible tokens (NFTs), which underpin the metaverse's socio-economic fabric. As technological incumbents capitalize on this emergent frontier, hybridized virtual-physical economic models are redefining market dynamics, fostering a decentralized, participatory, and resilient economic architecture that transcends traditional centralized control [1–3].

Literature review

The metaverse represents a paradigmatic evolution in the cyber-physical continuum, transcending traditional ecosystem constructs by exponentially amplifying immersiveness and actor integration [4]. Within the cybernetic modality of hyperspatial architectures, metaverse ecosystems form an intricate subdomain of the intelligent cyber-social meta-ecosystem, a foundational element of Industry 5.0 [4–17]. As decentralized frameworks underpinned by distributed ledger technologies and cognitive automation, these ecosystems facilitate seamless interoperability, asset tokenization, and real-time socio-economic convergence across virtual and tangible domains. While still nascent, core components such as decentralized governance protocols, interoperable asset economies, and AI-driven experiential design are crystallizing, signaling the metaverse's trajectory toward a resilient, user-owned, and cognitively adaptive meta-economy [4]. The purpose of this study is to make the concept of metaverse ecosystems in the context of Web 3.0 more tangible.

Methodology

The objective was achieved through three steps:

- To describe the evolution of the transition from Web 1.0 to Web 2.0 and Web 3.0.
- To develop a conceptual framework for Web 3.0 metaverse ecosystems.
- To classify the existing and prospective tools for strategic management of the digital potential of complex systems based on the concept of Web 3.0 metaverse ecosystems.

The methods used in this study include system analysis, historical analysis, general scientific methods, and the comparison of data from domestic and foreign studies, as well as materials from the World Economic Forum and technology companies in the Web 2.0 and Web 3.0 domains.

Table 1
Key features of the three stages of Web 1.0 — Web 2.0 — Web 3.0 evolution

	Web 1.0	**Web 2.0**	**Web 3.0**
Main idea	Virtual networks	Online communities	Virtual worlds of communities
Interaction	Reading	Reading-Writing	Read-Write-Possess
Core	Static text	Interactive content	Virtual cloud economy
Organisation	Companies	Platforms	Networks
Infrastructure	Personal computers	Cloud and mobile technologies	Cloud blockchain
Control	Decentralised	Centralised	Decentralised
Key company	Netscape	Facebook	Decentraland
Metaverse ecosystems	None	Closed corporate	Open crypto

Source: Developed by the authors based on [1].

Results and discussion

Evolution of the transition from Web 1.0 to Web 2.0 and Web 3.0

Over the past three decades, from 1990 to the present, Internet technology has evolved, transforming the way we interact with the web. This continuous process can be divided into three major eras in the development of online communities [1]:

- Web 1.0: Bringing users together based on virtual networks.
- Web 2.0: Creation of online communities.
- Web 3.0: Formation of a virtual world belonging to communities.

The key features of the three stages of Web 1.0 — Web 2.0 — Web 3.0 evolution are presented in *Table 1*.

The conceptual foundations of Web 3.0, rooted in decentralization, user sovereignty, and blockchain interoperability, have evolved in parallel with advances in virtual reality and immersive digital ecosystems [18]. From early experiments with immersive interfaces such as the Sensorama Simulator of the 1960s to Neal Stephenson's seminal portrayal of a decentralized "metaverse" in "Snow Crash" (1992) [19], the trajectory of digital interaction has continually leaned toward disintermediated, user-empowered paradigms. The advent of Bitcoin in 2009 and the proliferation of NFTs (non-fungible tokens) have facilitated cryptographic asset ownership, enhancing liquidity and enabling programmable digital scarcity within metaverse economies. These innovations promise to underpin a new era of cyber-physical convergence, where tokenized assets fuel decentralized autonomous organizations (DAOs) and peer-to-peer value exchanges. However, to mitigate systemic risks like market manipulation and fraudulent NFTs, robust regulatory frameworks and decentralized verification protocols remain paramount for fostering a resilient and equitable Web 3.0 economy [18].

The evolutionary trajectory of Web 1.0, Web 2.0, and Web 3.0 underscores a paradigm shift in the economic architectures underpinning digital interaction, catalyzing the emergence of metaverse ecosystems predicated on decentralized ownership and blockchain technology [1]. This metamorphosis encompasses a transition from hierarchical, platform-centric networks to peer-to-peer, trustless infrastructures that facilitate disintermediated value exchange and user sovereignty [1]. Enabled by distributed ledger technologies and tokenized digital assets, Web 3.0 fosters an endogenous digital economy where smart contracts automate transactions, non-fungible tokens (NFTs) confer immutable property rights, and decentralized autonomous organizations (DAOs) operationalize governance structures [1]. Consequently, metaverse ecosystems hold the potential to dismantle legacy gatekeeping mechanisms, engendering a heterarchical model of economic activity that harmonizes virtual and physical realms [1].

Metaverse ecosystems 2.0 vs metaverse ecosystems 3.0

The key differences between Web 2.0 metaverse ecosystems and Web 3.0 metaverse ecosystems are as follows [1]:

• Closed corporate Web 2.0 metaverse ecosystems are centrally owned and controlled by big tech companies.

• Open crypto Web 3.0 metaverse ecosystems are democratically owned and controlled by global users.

One of the fundamental limitations of Web 2.0 metaverse ecosystems lies in their monopolistic architecture, where developers impose structural capital constraints and inhibit asset liquidity, thus creating walled-garden economies devoid of interoperability. This results in a rent-seeking environment where participants' digital labor and capital cannot be converted into fungible economic value within external markets. Web 3.0 metaverse frameworks, leveraging decentralized blockchain infrastructures, dismantle these restrictions by facilitating asset ownership through non-fiat tokens (NFTs) and enabling seamless peer-to-peer exchange across digital ecosystems. This paradigm fosters an open, disintermediated market structure where digital capital can achieve full liquidity, thereby introducing an efficient mechanism for transmuting virtual wealth into tangible economic assets within the broader macroeconomy [1].

Web 3.0 conceptual framework of metaverse ecosystems in strategic management

The metaverse, as a transcendent virtual economy, is underpinned by the triadic principles of presence, interoperability, and standardization, which collectively drive its economic scalability and cross-platform viability [3]. Presence leverages immersive VR technologies to engender a hyper-realistic perception of spatial engagement, thus augmenting transaction utility and enhancing socio-economic interactions within virtual marketplaces [3]. Interoperability, facilitated by blockchain infrastructures and tokenized assets, ensures seamless transferability of digital capital — avatars, NFTs, and cryptocurrencies — across heterogeneous platforms, thus creating a unified, frictionless economic space [3]. Standardization, championed by international consortia such as the Open Metaverse Interoperability Group, institutionalizes uniform protocols, ensuring platform-agnostic compatibility and accelerating the metaverse's adoption curve by mitigating technological fragmentation [3].

The conceptual framework of Web 3.0 metaverse ecosystems in strategic management of digital potential is illustrated in *Fig.*

As illustrated in *Fig.*, it is appropriate to consider metaverse ecosystems through seven interrelated cognitive domains [2]:

— The domain of *AI and the Metaverse* investigates the convergence of artificial intelligence and immersive virtual environments, highlighting AI as the cognitive substrate for adaptive systems, autonomous agents, and real-time content generation. This domain further explores the ethical and regulatory dimensions of AI, incorporating blockchain-based financial systems, governance frameworks, and socio-cultural dynamics in digital entertainment and media ecosystems. It is an increasingly prominent subfield within artificial intelligence: generative AI enables not just analysis but also the creation of seemingly new information, based upon the dataset with which the model has been trained. Generative AI can perform content creation of different types (its images and music have drawn particular attention), easily prompted by typing in brief instructions using natural language. Foundation models like GPT (or BERT) are now a recognized paradigm for building AI systems — in which a model trained on a large amount of unlabelled data can be adapted to many different applications. At a time when the virtual worlds soon to populate the metaverse need content, generative AI will be increasingly looked to for scaling up digital creation. In a similar way to what happens in the current version of the internet, AI applications will be used to automate, moderate, and organize content within immersive spaces — or to power hardware capabilities (like capturing physical environments and rendering them in 3D, or adjusting the passthrough in virtual and augmented reality devices).

Ethics will be key; AI should be considered in light of its potential impact on social, economic, and ethical issues as it is increasingly applied in the metaverse. As a field, AI ethics is comprised of many different dimensions stemming from its

Fig. **Web 3.0 conceptual framework of metaverse ecosystems in strategic management**

Source: World Economic Forum. The Metaverse. Global Issue. URL: https://intelligence.weforum.org/topics/a1G680000004EbNEAU (accessed on 10.12.2024).

pervasive nature, from the bias in datasets, to the potential lack of transparency in how models are trained or developed, or the lack of a clear explanation on how it makes decisions. Large language models present significant challenges, not least the inexplicable errors and inconsistencies dubbed "AI hallucinations." Biased models will become biased metaverse content, amplifying existing inequalities and discrimination while reinforcing a lack of diversity and harmful stereotypes (for example, by providing representations of "beauty" tied only to certain, limited parameters including skin colour or age), and erasing cultural context. The "echo-chambers" that already exist in social media could become even more harmful in immersive environments; the potential long-term effects on human cognition are as yet unknown. In addition, new devices to interface with the metaverse may rely on neurotechnology in ways that raise questions about human agency and identity.

— *Industries and the public sector within the Metaverse* focus on the transformative potential of virtual environments for industrial production, entrepreneurship, and public governance. It covers the reconfiguration of supply chains, digital twins, and innovation ecosystems, examining the role of the metaverse in reshaping manufacturing, disinformation management, and capital markets. This domain also addresses the challenges of integrating traditional industries with digital infrastructure to enhance productivity and governance efficiency. In much the same way that the internet and mobile computing have in the past, metaverse technologies are now beginning to affect just about every industry imaginable. The dimensions of this impact have spread beyond gaming and entertainment, and begun to transform enterprise verticals like manufacturing, healthcare, automotive, aerospace, tourism, training and education, architecture, and real estate. The opportunities within each range from creative and design, to collaboration, to maintenance and customer support. Some of the most interesting applications of metaverse technology concern the public sector; governments worldwide are exploring its potential to bolster virtual collaboration, diplomatic engagement, and policy simulations. As the metaverse evolves, its relevance to shaping the future of governance and international relations becomes increasingly apparent. For example, the United Arab Emirates' Ministry of Economy has established what it has called a "third address" located in the metaverse to provide an immersive experience at its virtual headquarters — and, while hailing the metaverse as a great leveller, the island nation of Barbados announced plans to establish a new, virtual embassy there.

Meanwhile, industries such as education, gaming, retail, fashion, and entertainment have all started to refine their approach to the metaverse. The pharmaceutical firm Novartis, for example, has trained employees on labelling using the technology, while US retailer Walmart has used it for customer service training. For fashion retailers, "virtual dressing rooms" have enabled customers to see themselves in items from different angles and in different environments — revamping the online shopping experience while addressing sizing challenges. The manufacturing, healthcare, financial services, and tourism industries have also developed metaverse applications. The large US bank JPMorgan Chase and Co. opened a lounge in the "Decentraland" virtual world in 2022, while BMW and other carmakers are using augmented reality (AR) to accelerate design and prototyping. In 2020, orthopaedic surgery was performed using AR via the Microsoft HoloLens, enabling the surgeon to view necessary images and records without stepping away from the operating table. The technology also served a tourism purpose during the pandemic; the Dubai World Expo 2020 drew a larger number of virtual attendees than in-person visitors.

— *The Metaverse's social and economic impacts* domain evaluates the intersection of virtual technologies with mental health, social equity, and economic transformation. It considers the psychological and sociological implications of prolonged virtual engagement, global governance structures, and ethical concerns related to inequality, disinformation, and mental well-being. The focus is on ensuring that digital ecosystems foster social inclusion, mental health resilience, and sustainable development. As a virtual ecosystem enabling users to interact with each other and the world in new and innovative ways, the metaverse has the potential to impact social stability and revolutionize economic growth. Its social impact can already be seen in the ways it fosters connections and collaboration across geographical and cultural boundaries, while its economic impact may yet manifest in the creation of new markets and industries. However, the metaverse also raises concerns about privacy, security, and social inequality. Connection and collaboration are key benefits related to social interaction; the technology creates a shared virtual space, where people can communicate and cooperate in ways previously impossible. For example, the metaverse can be used to create virtual classrooms, conferences, and events — enabling people to learn, work, and socialize in a shared space. It also provides opportunities for health and well-being, such as relaxation spaces, virtual therapies, artificial intelligence-assisted counselling, and real-time biometric feedback therapies. New related markets and industries will prove to be key benefits for broader economic growth — opportunities for commerce and entrepreneurship abound, as users spend more time and money in virtual spaces.

Examples of these metaverse-based opportunities include the creation of virtual real estate, and digital goods and services that enable users to buy, sell, and trade virtual assets and experiences. Key social and economic development-related challenges relate to privacy, security, manipulation, and social inequality; the metaverse creates new risks for personal data, not to mention virtual assets and social cohesion, as users share more information and resources in virtual spaces. Criminal activity is a possibility — it could be used for money laundering or cyberattacks, as well as for impersonation or the perpetuation of harmful social discrimination. In addition, potential addiction and other cyber-psychological effects on users need to be addressed. The metaverse is a complex and exciting ecosystem with the potential to change the world. To ensure that it is developed in a way that maximizes benefits and minimizes risks, it is crucial to develop a research agenda that focuses on its social and economic impact. This agenda should include studies on the privacy, security, and psychological implications of the technology, its potential impact on social inequality, and it possible benefits for social interaction, economic growth, and general well-being.

— *Metaverse governance* encompasses frameworks and principles essential for maintaining order, fairness, and accountability within virtual spaces. This domain examines global governance, agile regulatory mechanisms, and ethical standards required to manage justice, law, and illicit activities. It underscores the need for adaptive governance systems capable of responding to the complexities and disruptions inherent in decentralized digital environments. Effective governance structures and mechanisms for the metaverse are needed now, in order to help ensure a more responsible, safe, equitable, inclusive, and interoperable future spread of the technology. The governance being applied should take into full account the specific challenges related to operating virtual economies and creating (and occasionally losing) value there, to adequate rights and protections for its users, and to evenly balanced regulatory frameworks that are satisfactory to all of the relevant stakeholders. Protecting the rights of users will inevitably involve issues related to privacy, data protection, safeguards against manipulative and negatively persuasive content, support for health and wellness, adequate levels of content moderation, proper identity verification to prevent fraud and future harm, and guarantees against fraudulent transactions.

The regulatory frameworks for the metaverse need to balance user freedom with protection from illicit and harmful activity — particularly as it relates to children. True value creation in virtual economies requires mechanisms to enable investment with accountability — where competition creates better experiences and pricing for users while spurring a broad ecosystem where businesses, startups, and creators cannot just participate but flourish. Some potential governance frameworks include decentralized models, cross-sector collaboration, transparency in reporting, ethical guidelines and auditing, sustainable practices and policies, workforce rights for health and safety, and user-centric design and feedback. Technical standards are also crucial, to ensure interoperability and security. It's additionally important to consider the tradeoffs in governing the metaverse, as prioritizing some stakeholders' preferences may come at a cost to others.

— *Infrastructure and the Metaverse* address the foundational technological systems supporting the seamless operation of virtual environments. This domain includes the digital economy, AI integration, cybersecurity, and communication networks essential for maintaining resilient and scalable virtual infrastructure. It explores the symbiotic relationship between physical and virtual infrastructure, emphasizing the importance of energy transition, blockchain, and advanced computing technologies in sustaining the Metaverse's growth. With each major evolution in computing, there has been a corresponding leap in technological infrastructure. The initial adoption of telecommunications, for example, necessitated the creation of a new user interface device — the telephone — and extensive supporting networks. Later, modern computers changed how we interface with information and one another from a distance, and birthed many companies that supported the evolution of computers from behemoths to small personal computers and laptops perched on desktops. Now, the metaverse and spatial computing are in a similarly foundational phase. Some related technologies, such as Web 3, blockchain, and cryptocurrencies, have had ups and downs in terms of public perception; as demonstrated by overinvestment in fibre optic cable infrastructure in the US in the 2000s (much of it went unused for decades), it is challenging to determine which technologies will be worthy of extensive time and resources at an initial stage. However, it is clear that new consumer devices for interfacing with the metaverse will be necessary, alongside related chips and sufficient backend infrastructure.

As time passes, the ways in which users want to transact — be it through blockchain, or fiat currency, Web 3 or Web 2 experiences, or across different levels of bandwidth — will become clearer. Both startups and large companies continue to invest heavily in related infrastructure. Apple's 2024 launch of the Vision Pro headset, enabled by the custom M2 chip, was a key moment for that company's entry into the space. The metaverse is not evolving in isolation; it is increasingly intersecting with other, high-growth sectors like artificial intelligence. The chipmaker NVIDIA's stock has hit all-time highs that underscore this synergy and the demand generated by both the metaverse and AI (Sam Altman, the CEO of OpenAI, said during a 2023 interview that the metaverse will be a major convergence point for users to interface with AI). The continued growth of the metaverse indicates that foundational technologies like consumer hardware, chips, and enabling software are not only important pillars, but also fertile ground for the emergence of entirely new, trillion-dollar companies.

— *Metaverse access and equity* emphasize inclusivity, sustainability, and the mitigation of systemic biases within virtual ecosystems. This domain explores issues of digital communications, virtual and augmented reality, and equitable access to Metaverse resources. The focus lies on addressing systemic racism, inequality, and human rights within digital environments, ensuring that the Metaverse promotes ethical, inclusive, and sustainable development on a global scale. The metaverse presents a significant opportunity for progress and greater prosperity, so it is imperative that access is recognized as a fundamental human right. This calls for a concerted effort to include more diverse voices in shaping its future, to expand participation generally, and to have global conversations about its governance and standards. This will enhance the metaverse experience, by ensuring that it evolves to satisfy a wider range of perspectives and needs. Core to this inclusive vision is investment in critical infrastructure, to support the metaverse's growth and accessibility, ideally creating a universal access situation where device distribution is not restricted by geography. This will require prioritizing the development of affordable metaverse technology, and making it available regardless of socioeconomic status. Generally expanding internet connectivity is key, particularly in under-served regions, to enable truly global metaverse participation. There is also a need to invest in scalable, distributed computing solutions — which could support the metaverse's expansion in ways that ensure everyone can enjoy real-time, seamless experiences free of technical lags.

The commitment to sustainable development within this digital domain is also important. This will mean channelling resources to data centres powered by sustainable energy sources, aligning the growth of the metaverse with proper environmental stewardship. The potential benefits of metaverse technologies run the gamut of the UN's Sustainable Development Goals; in order to achieve them, we must do away with the status quo and embrace a transformative approach that discards harmful ways of engaging with (and developing) any new technology. This is a multistakeholder endeavour, where cooperation will be necessary among governments, private sector professionals, civil society groups, academia, international organizations, industries, and users — in order to forge a way forward. It will require convening at national and global levels, and making an unprecedented commitment to implementation. In that way, we can potentially foster a metaverse that is not only technologically advanced and engaging, but also socially responsible and accessible to everyone. This approach could lay the foundation for a metaverse that both drives global prosperity and ensures equitable participation in an increasingly digital era.

— *The future of work in the Metaverse* investigates how immersive digital technologies are redefining labor markets, education, and organizational dynamics. This domain examines cybersecurity, corporate governance, and advanced manufacturing processes within virtual environments. It highlights the implications for workforce dynamics, remote collaboration, and skill development in a hyper-digitalized economy, underscoring the importance of resilience, adaptability, and human rights in the evolving landscape of work. The metaverse heralds a new direction for the future of work, in ways that promise to interweave advanced digital constructs with profound societal shifts. The technology has triggered a reimagining of learning paradigms, as classrooms are potentially transformed into immersive spaces where students from around the world can participate in shared, enriched experiences enhanced by virtual and augmented reality — potentially democratizing access to valuable STEM (science and technology)-based curricula and other practical tools. Both virtual classrooms and other immersive learning experiences facilitated by augmented and virtual reality have the potential to transform pedagogical approaches, in ways that make education more accessible and engaging. Traditional, related business models are being reimagined, as companies integrate virtual spaces, digital assets, and metaversal strategies into their operational frameworks. As the metaverse gains traction, it has the potential to catalyse the emergence of entirely new industries, professions, and economic models.

The nascent development of everything from virtual real estate to digital asset management has created potential avenues for job creation and new wealth generation that are vast and varied. Some of the novel industry positions and job roles being fashioned in the metaverse include virtual asset managers and digital architects, carving increasingly unique paths to professional development, economic contributions and greater diversification. The metaverse embodies the essence of the Fourth Industrial Revolution, which has been underpinned by the convergence of physical, digital, and biological realms. Augmented and virtual reality technologies, in tandem with artificial intelligence and the Internet of Things, are pivotal. As they move beyond gaming and entertainment, AR and VR have become handy for professional training, design, and general collaboration. On the precipice of what will likely turn out to be a transformative era, a fuller understanding the multifaceted impact of the metaverse on work, education, and manufacturing is crucial for businesses and people everywhere.

Strategic management tools in the concept of Web 3.0 metaverse ecosystems

Table 2 systematizes the toolkit for strategic management within the Web 3.0 metaverse concept across seven areas of the conceptual framework.

The emergence of metaverse ecosystems is intrinsically dependent on the confluence of advanced semiconductor technology and decentralized financial architectures. Companies like Nvidia are pioneering the fabrication of specialized GPUs and silicon architectures capable of rendering hyper-realistic, high-resolution 3D environments essential for immersive virtual economies. Concurrently, sophisticated peripherals, such as motion-tracking controllers and haptic feedback headsets, facilitate seamless user interaction, creating the experiential fidelity necessary for metaverse adoption [21]. At the core of the metaverse's economic infrastructure lies the proliferation of cryptocurrencies and blockchain protocols, which establish a trustless, decentralized mechanism for asset tokenization, cross-platform value exchange, and smart contract-driven governance. These distributed ledgers ensure immutability, scarcity verification, and user sovereignty over digital assets, which are indispensable for maintaining liquidity, market stability, and transactional efficiency in this emerging hybrid economy [21].

Market valuation of Web 3.0 metaverse ecosystems: Ball Metaverse Index

The major players in the Web 3.0 market are [25]:

- Companies developing the infrastructure required for metaverse ecosystems, such as Cloudflare and Nvidia.
- Game engines responsible for creating virtual worlds, including Unity and Roblox.
- Pioneers in content, commerce, and social services for metaverse ecosystems, such as Tencent, Sea, and Snap.

The top 10 companies in the metaverse market as of 20.08.2024 are summarized in *Table 3*.

The metaverse, an emergent socio-digital construct, is predicated upon robust computational infrastructures and decentralized economic paradigms. Nvidia's advancements in high-performance GPUs and proprietary virtual-world design software serve as linchpins for rendering hyper-realistic 3D environments, while auxiliary hardware — such as motion-tracking controllers and immersive headsets — facilitates real-time, kinesthetic interactivity [21]. Concurrently, cryptocurrencies and blockchain technologies constitute the metaverse's financial substrate, enabling frictionless peer-to-peer transactions and immutable asset verification within decentralized autonomous economies [21]. The Ball Metaverse Index operationalizes a taxonomical framework for categorizing firms contributing to the metaverse's techno-economic scaffolding, encompassing computational power provision, high-bandwidth networking, virtual platform development, interoperability protocols, digital payment infrastructures, and identity-linked asset management [25]. This confluence of advanced hardware, cryptographic economic systems, and standardized interchange protocols undergirds the metaverse's scalability, fostering an intricate ecosystem that amalgamates digital and physical economic modalities.

The rapid proliferation of Web 3.0 metaverse ecosystems has catalyzed an exponential increase in user adoption, now exceeding 50,000 lifetime participants, with active wallets serving as key performance indicators for engagement and economic activity [1]. This represents a tenfold increase since the early stages of 2020, underscoring a trajectory of accelerated digital asset penetration and decentralized user participation [1]. Despite its nascency compared to entrenched Web 2.0 platforms, the metaverse's growth trajectory reflects the maturation of decentralized finance (DeFi) frameworks, smart contract interoperability, and tokenized asset ownership models [1]. If the current adoption velocity persists, these metaverse ecosystems may evolve into economically dominant spheres, reshaping digital commerce and network economies through user-centric, decentralized governance [1].

The metaverse, characterized by decentralized virtual economies and the convergence of digital and physical realms, represents an evolving frontier of economic potential. ARK Research projects that revenues derived from virtual worlds, including platform infrastructure and content layers, could surge to $ 400 billion by 2025, reflecting expansive growth in immersive digital experiences [25]. Concurrently, Bloomberg Intelligence forecasts a market opportunity reaching $ 800 billion by 2024, driven by the proliferation of

Table 2

Toolkit for strategic management of digital potential in the concept of Web 3.0 metaverse ecosystems by seven areas of the conceptual framework

Conceptual Framework Area	Tools and Technologies of Web 3.0 Metaverse Ecosystems
AI and the Metaverse [18]	Arts and Culture Media, Entertainment and Sport Blockchain Financial and Monetary Systems Internet Governance The Digital Transformation of Business The Digital Economy Infrastructure
Industries and the Public Sector in the Metaverse [20]	Innovation Entrepreneurship Disinformation Banking and Capital Markets Future of Consumption Retail, Consumer Goods and Lifestyle Data Policy Fourth Industrial Revolution
The Metaverse's Social and Economic Impacts [21]	Mental Health Global Governance Agile Governance Leadership Illicit Economy Values Justice and Law
Metaverse Governance [22]	Health and Healthcare Pandemic Preparedness and Response Advanced Manufacturing and Production Education Human Rights Inequality Systemic Racism
Infrastructure and the Metaverse [23]	Artificial Intelligence Digital Communications Virtual and Augmented Reality Energy Transition Sustainable Development Corporate Governance Cybersecurity Future of Work Future of Computing Behavioural Sciences
Metaverse Access and Equity [24]	Artificial Intelligence Digital Communications Virtual and Augmented Reality Energy Transition Sustainable Development Systemic Racism Inequality Human Rights
Future of Work in the Metaverse	Education Cybersecurity Corporate Governance Future of Work Health and Healthcare Pandemic Preparedness and Response Advanced Manufacturing and Production Justice and Law

Source: Developed by the authors based on [18, 20–24].

Table 3
Top 10 companies in the metaverse market as of 20.08.2024

Name	Ticker	Weight
ROBLOX Corp	RBLX	9.02%
Apple Inc	AAPL	8.51%
Meta Platforms Inc	META	5.69%
CI Galaxy Ethereum ETF	ETHX/U CN	5.01%
NVIDIA Corp	NVDA	4.38%
Unity Software Inc	U	4.07%
Sony Group Corp	6758 JP	3.97%
Microsoft Corp	MSFT	3.35%
Nintendo Co Ltd	7974 JP	3.34%
Alphabet Inc	GOOGL	2.91%

Source: Roundhill Investments. METV: The Metaverse ETF. URL: https://www.roundhillinvestments.com/etf/metv/ (accessed on 21.08.2024).

virtual commerce, social interactions, and decentralized assets, though excluding categories such as hardware, networking, compute, and payment systems [25]. Despite these optimistic projections, recent valuations show the metaverse market cap at a mere $ 7.21 billion as of August 21, 2024, exhibiting a volatile 2.1% fluctuation within a 24-hour period [26]. This disparity underscores the speculative nature of metaverse investments, shaped by evolving adoption rates, regulatory frameworks, and technological scalability.

Web 3.0 metaverse ecosystems represent a paradigmatic shift in digital economies, creating decentralized, crypto-driven virtual worlds where value generation transcends traditional online boundaries. These ecosystems leverage blockchain-based tokenomics, smart contracts, and non-fungible tokens (NFTs) to enable disintermediated transactions and transparent asset ownership, fostering free-market capitalism beyond the constraints of centralized Web 2.0 platforms. The sale of virtual assets — including land, digital commodities, and services — has surpassed $ 200 million, underpinned by dynamic primary and secondary markets that empower developers, third-party creators, and users alike [1]. By dismantling capital controls and introducing immutable, trustless systems, these crypto-virtual environments catalyze rapid innovation, productive efficiency, and new modalities of e-commerce. This convergence of digital assets and decentralized finance (DeFi) augments the metaverse's economic architecture, promoting the seamless integration of commercial activities such as NFT art exhibitions, virtual corporate collaboration, play-to-earn gaming, and programmatic advertising, thus redefining the contours of digital economic sovereignty [1].

The emergence of metaverse ecosystems, driven by the convergence of decentralized Web 3.0 principles and immersive virtual environments, presents a transformative potential for global economic paradigms by reshaping labor markets, vocational training, and industrial manufacturing processes [3, 21]. Virtualized economies facilitate decentralized value creation through blockchain-enabled ownership models, empowering users to monetize digital assets and participate in play-to-earn frameworks, thus broadening income-generation avenues beyond traditional economic constraints [21]. Concurrently, industries such as healthcare and education are poised to benefit from scalable virtual training modules and telepresence solutions, mitigating geographical and socio-economic disparities. In manufacturing, digital twins and AI-driven collaboration tools optimize the lifecycle of product development and smart factory operations, enhancing productivity and reducing costs [3]. Despite these advancements, concerns surrounding the psychosocial impacts of prolonged virtual immersion, including potential exacerbation of anomie, cognitive fatigue, and circadian disruption, necessitate a critical evaluation of the metaverse's implications on socio-economic well-being [21].

Conclusions and policy implications

In the course of the study, through the systematization of various interpretations of the concept of the "metaverse ecosystem" and the identification of key characteristics, the authors' vision of metaverse ecosystems as part of the cybermodality of the Industry 5.0 ecosystem was formed. The metaverse, as a version 2.0 of the traditional ecosystem, with a significant increase in the degree of immersiveness and integration of actors, will bring new values and become more human-centered [27]. A conceptual framework for Web 3.0 metaverse ecosystems has been proposed, focusing on six key areas, within which a toolkit for the strategic management of the digital potential of complex systems has been systematized.

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Assessing the Level of Employment in the Informal Sector of the Economy of Russian Regions Using Modern Machine Learning Methods

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ABSTRACT

The global trend is mass employment of the population in the informal sector of the economy. At the same time, only in economically developed countries of the world such workers have relatively good working conditions. At the current stage of development, Russia is among the group of actively economically developing countries of the world. Therefore, the improvement of the mechanism of state social protection of those employed in the informal sector of the economy remains an **urgent relevant issue** for our country, which, in turn, implies monitoring of the situation. **The purpose** of this study is to develop tools for such monitoring with the help of artificial intelligence (more precisely, modern machine learning **methods**). According to the results of cluster analysis carried out using the k-means **method** in the Python programming language, it was found that in modern Russia there is a high degree of differentiation of regions by the level of employment in the informal sector of the economy. At the same time, most of the subjects of the Russian Federation are characterised by the same situation as in economically developing countries of Eastern Europe (Bosnia and Herzegovina, Serbia, Czech Republic). Four regions of Russia (from the North Caucasus Federal District) have an abnormally high level of employment in the informal sector of the economy comparable only with economically developing countries of Asia, Africa, North and South America. In the course of solving the classification problem using a modern machine learning method (LightGBM), the key factors affecting the level of employment in the informal sector of the economy of Russian regions were identified. According to the classification results, we can **conclude** that a cardinal change in the current situation is not expected in the future. Therefore, for modern Russia, it is necessary to improve the state social policy for a significant part of the regions. **The results** of the empirical study can be applied to improve the effectiveness of the state social policy of the Russian Federation. Thus, in particular, it will be possible to specify the amount of financial resources required for additional social support of the employed population of certain regions of our country.

Keywords: regions of Russia; employment level; informal sector of the economy; precariat; machine learning; clustering; classification; forecasting

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Оценка уровня занятости в неформальном секторе экономики регионов России с помощью современных методов машинного обучения

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АННОТАЦИЯ

Общемировой тенденцией является массовая занятость населения в неформальном секторе экономики. При этом только в экономически развитых странах мира такие занятые имеют относительно хорошие условия труда. На современном этапе развития Россия входит в группу активно экономически развивающихся стран мира. Поэтому для нашей страны **актуальным** вопросом остается совершенствование механизма государственной социальной защиты занятых в неформальном секторе экономики, что, в свою очередь, предполагает мониторинг ситуации. **Целью** данного исследования является развитие инструментария для такого мониторинга с помощью искусственного интеллекта (точнее, современных **методов** машинного обучения). По итогам кластерного анализа, проведенного с помощью **метода** k-means на языке программирования Python, было установлено, что в современной России наблюдается высокая степень дифференциации регионов по уровню занятости в неформальном секторе экономики. При этом для большей части субъектов РФ характерна ситуация, что и в экономически развивающихся странах Восточной Европы (Боснии и Герцеговине, Сербии, Чехии). В четырех регионах России (из Северо-Кавказского федерального округа) наблюдается аномально высокий уровень занятости в неформальном секторе экономики, сопоставимый только с экономически развивающимися странами Азии, Африки, Северной и Южной Америки. В ходе решения задачи классификации с помощью современного **метода** машинного обучения (LightGBM) были выявлены ключевые факторы, влияющие на уровень занятости в неформальном секторе экономики регионов России. По итогам классификации можно сделать **вывод**, что кардинальное изменение сложившейся ситуации в перспективе не ожидается. Поэтому для современной России необходимо совершенствование государственной социальной политики в отношении значительной части регионов. **Результаты** эмпирического исследования могут быть применены для повышения эффективности государственной социальной политики РФ. Так, в частности можно будет уточнить объем финансовых ресурсов, необходимых на дополнительную социальную поддержку занятого населения определенных регионов нашей страны.

Ключевые слова: регионы России; уровень занятости; неформальный сектор экономики; прекариат; машинное обучение; кластеризация; классификация; прогнозирование

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Introduction

Currently, more than 2 billion people, or 60% of the world labor market, are covered by informal employment [1]. One worldwide trend is that a sizable portion of the working population in various nations is frequently classified as informally employed. The indicator is also marked by abnormally high readings in some countries. For example, in 2021, the level (in percent of the working-age population) of informally employed in Angola was 69.3%, in Vietnam — 68.3%, in Guatemala — 89.3%, Zambia — 73.5%, Zimbabwe — 75.7%, India — 71.3%, Comoros — 91.4%, Pakistan — 67.5%, Paraguay — 70.1%, Peru — 68%, Rwanda — 74.7%, El Salvador — 70.6% and Uganda — 97.8%. The most favorable situation on the level of informal employment was observed in a number of economically developed countries in Europe: in Austria the value of the indicator was 5.1%, Belgium — 2.9%, Germany — 2.8%, Ireland — 1.7%,

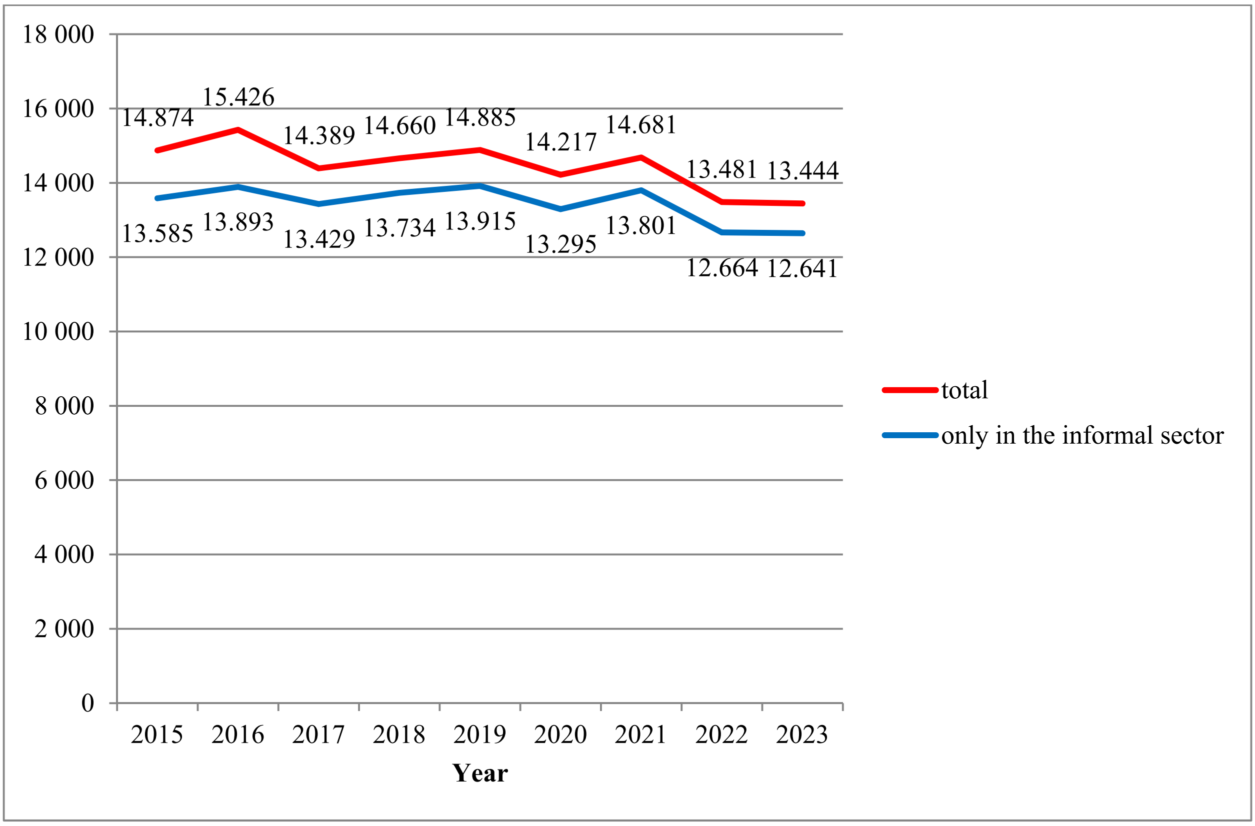

Fig. 1. **Change in the number of employees in the informal sector of the Russian economy (by the type of employment) for 2015–2023, thousand people**

Source: Compiled by the authors according to the data of the Labor Force, Employment and Unemployment in Russia (based on the results of sample labor force surveys). 2024 Stat.sb. Moscow: Rosstat; 2024.

Spain — 5.1%, Finland — 5%, France — 3.5% and Sweden — 2.6% in 2021 [2].

In Russia, this phenomenon is widespread as well as in a number of other countries of the world. It is known that most of the informally employed in modern Russia also work in the informal sector of the economy [3]. Therefore, within the framework of this study, we will limit ourselves to the study of employment in the informal sector of the national economy. Based on the data of official statistics, let us independently draw up a "portrait" of the employed in the informal sector of the economy of modern Russia. In *Fig. 1,* we visualize the change over the last 9 years for our country, both the total number of employed in the informal sector of the economy and their part with the only appropriate type of work.

As shown in *Fig. 1*, there was no definite trend of change in the values of the indicator for 2015–2023. However, over the entire analyzed period of time, the number of people employed in the informal sector of the Russian economy decreased from 14874 to 13444 thousand people (historical minimum), i.e., by almost 10%. At the same time, for about 90–91% in 2015–2016 and 93–94% throughout the rest of the period, such compatriots worked exclusively in the informal sector of the national economy.

Fig. 2 shows the change in the share of working Russians in the informal sector of the national economy by age groups.

According to *Fig. 2*, during the first 7 years of the analyzed period, the value of the indicator averaged about 20% in the country, except for 2016 (exceeded 21%). At present (as of 2023), the value of the share of those employed in the informal sector of the national economy has reached a historical minimum and is about 18%.

At the same time, the bulk of employed Russians in the informal sector of the economy is concentrated in two age groups: the youngest (from 15 to 19 years) and the oldest (70 years and older). Thus, the share of such workers was respectively about 42–49 and 36–39% of the total number of the employed of a certain age in different years of the analyzed period.

Fig. 3 visualizes the change in the structure of employed Russians in the informal sector by type of economic activity.

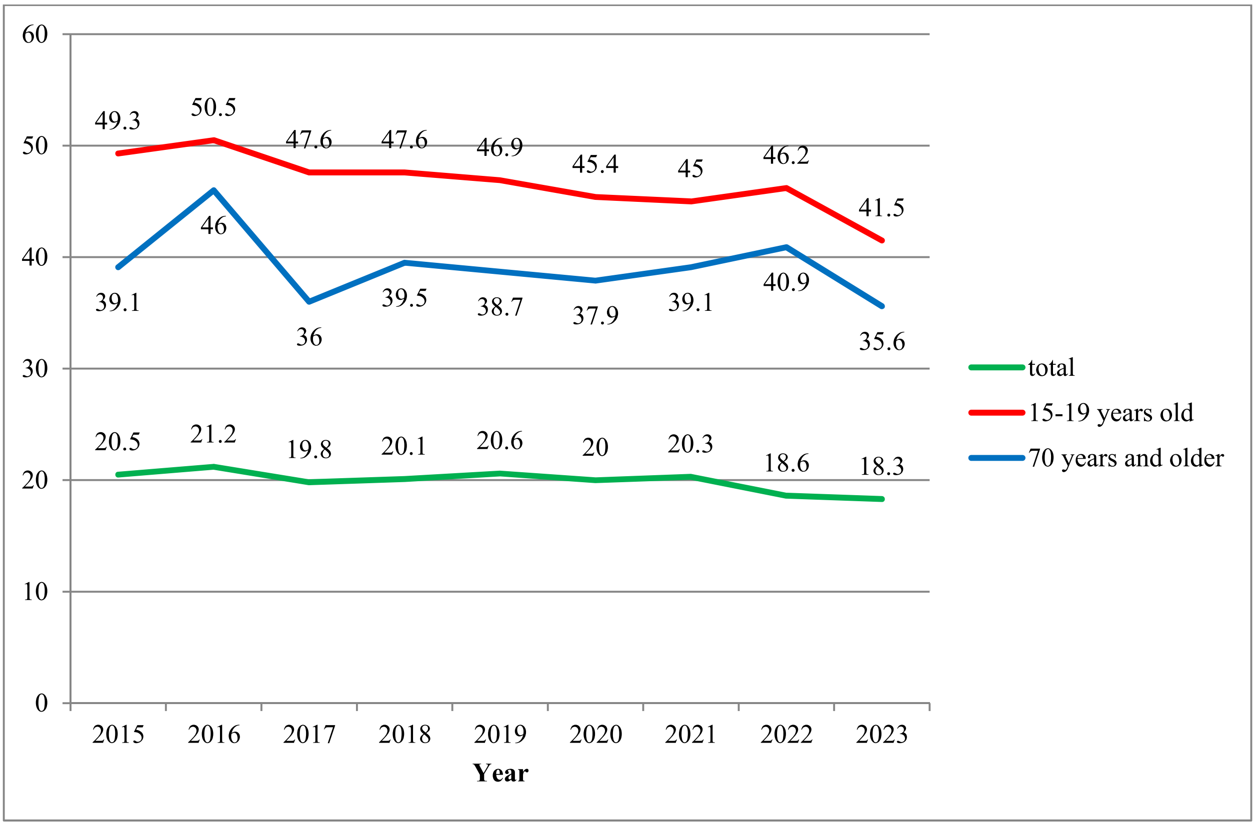

Fig. 2. **Change in the share of employees in the informal sector of the Russian economy (by age group) in 2015–2023,% (of total employment)**

Source: Compiled by the authors according to the data of the Labor Force, Employment and Unemployment in Russia (based on the results of sample labor force surveys). 2024 Stat.sb. Moscow: Rosstat; 2024.

As shown in *Fig. 3*, most of the employed Russians in the informal sector were distributed among five types of economic activity: agriculture, industry, construction, trade and transportation and warehousing logistics. The aggregate share of such workers was about 76–84% in different years of the analyzed period. At the same time, the most significant part of employed Russians in the informal sector of the economy (29–33%) in 2015–2023 worked in trade.

Summarizing the results of thematic analysis, we can conclude that informal employment for our country is a mass phenomenon. Thus, almost every 5th Russian works in the informal sector of the national economy. Moreover, for most of them, employment in the informal sector is the only place of work. At the same time, the composition of employed Russians in the informal sector of the economy, as a rule, includes young people and the elderly. Finally, their main place of work is in trade.

Literature review

In [4], it is rightly noted that the generally accepted approach to the study of the economy is to distinguish its two components (components): observed and unobserved. The second, in turn, includes underground, illegal, informal economies and the production of products by households for their own consumption. In this case, the informal sector of the national economy is understood as the legitimate market production of goods and services, but hidden from the state for monetary, regulatory or institutional reasons [5].

It should be noted that informal employment in economically developed and developing countries has fundamental differences. The main feature of informal employment for the first group of countries is relatively (compared to the second group of countries) good working conditions of the workers concerned [2, 6], which complicates the fight against such a phenomenon [7]. *Fig. 4* presents a number of important factors affecting the level of informal employment in different countries of the world. Along with the term “informal employment”, scientists often use the closely related definitions “vulnerable employment” and “precarious employment”. We adhere to the view that these terms have a close semantic meaning but are not synonyms.

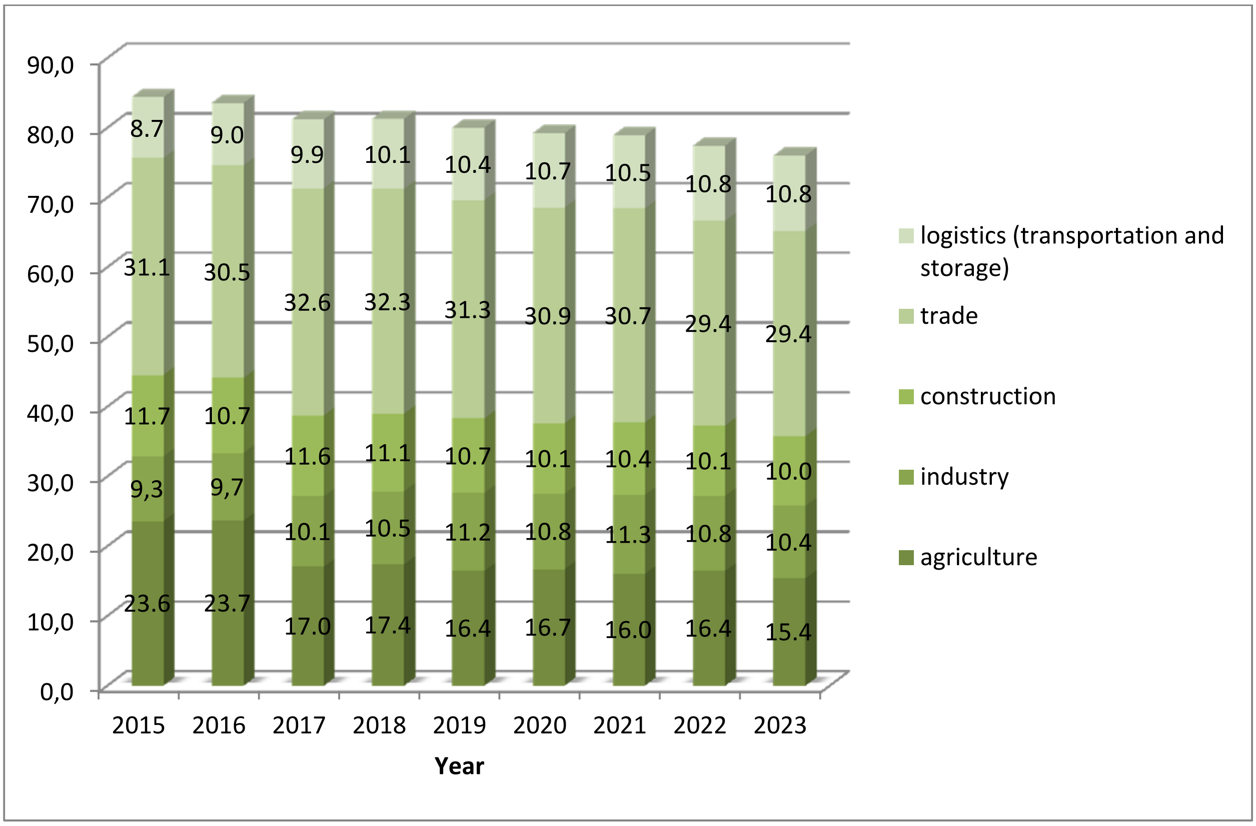

Fig. 3. **Change in the structure of employed Russians in the informal sector (by type of economic activity) for 2015–2023, %**

Source: Compiled by the authors according to the data of the Labor Force, Employment and Unemployment in Russia (based on the results of sample labor force surveys). 2024 Stat.sb. Moscow: Rosstat; 2024.

Sharing the opinion of the authors of [8], in the framework of this study we will consider informal employment as the main catalyst for the formation of precariat in our country.

In [18], it is rightly noted that, despite a significant number of thematic studies by foreign and Russian authors, the definition of "precarious employment" and the derivative term "precariat" still require clarification. Developing the thought, the scientist emphasizes the following: "...there is still no consensus even on the main issues related to it. There is no agreement neither on what criteria should be used to distinguish the precariat, nor on its social composition, nor even on its very existence as a class" [18, p. 105].

At the same time, most researchers have the main (sometimes the only) criterion for classifying the working population as precariat is the form of employment. Thus, for example, in [19], "workers who are employed under a temporary contract for less than a year or work without a labor contract at all" are referred to as the precariat. Another study by the previously mentioned author [20, p. 87] lists the main forms of informal employment: "temporary, casual, seasonal, secondary, part-time, as well as self-employment, platform employment and borrowed labor".

Also, there are works that present a multi-criteria procedure for categorizing a worker as precariat. For example, the article [21, p. 65] proposes a system of seven indicators or signs: "1) registration of labor without a contract or with a contract for no more than one year; 2) complete inconsistency of education with work; 3) overwork (more than 8 hours) permanent; 4) part-time work in their own or third-party organization (regular or irregular); 5) wages in an envelope (systematic or occasional); 6) change of job more than once in the last three years; 7) inability to influence important decisions in their work organization".

Corresponding member of the Russian Academy of Sciences J.T. Toshchenko [22] offers an almost identical system, including six main signs of precariat identification. Despite the existing discussion issues, most Russian researchers [19, 21, 23–28] adhere to the point of view about the

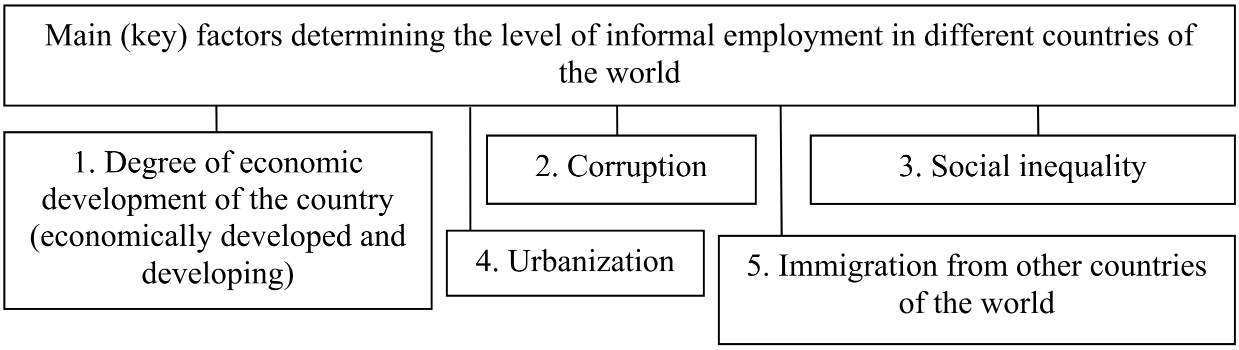

Fig. 4. **Key (main) factors affecting the level of informal employment in the world economy**

Source: Compiled by the authors on the basis of [2, 9–17].

negative impact of "precarious employment" on the quality of life of workers in the informal sector of the national economy. For example, in the work [28, p. 34] an important conclusion is made: "the public and private life of precarious workers vividly reveals social stratification in all the main characteristics of human life — in terms of labor employment guarantees, labor remuneration, the use of their intellectual and professional potential, and the sustainability of their daily life". Developing the idea [28, p. 34–35] focuses on the fact that "a constant feature of the life world of precarians is an isolationist position, manifested in anomie and loss of orientation, both in their future and the future of the country. The uncertainty of social and professional status, instability of well-being due to the lack of acceptable rules of labor remuneration, instability in the observance of social guarantees are complemented by the lack of a clearly articulated image of the future, which leads to the formation of indifference to political, economic and social life at all levels of social structure". It should be noted that the work of the Russian scientist largely agrees with the earlier results of a well-known foreign researcher [29, 30], who emphasized the infringement of various (civil, cultural and political) rights of the precariat.

Given the above, it is difficult to overestimate the importance of correct measurement of the quality of employment for modern Russia. In [31, p. 262] five most famous alternative approaches to measuring the quality of employment proposed by various international organizations are highlighted: "1) the global system of indicators for the UN Sustainable Development Goals; 2) Decent Work Indicators of the International Labor Organization; 3) guidelines for measuring the quality of the working environment of the Organization for Economic Cooperation and Development; 4) UN Economic Commission for Europe's initiative on measuring the quality of employment; 5) the quality of workplaces of the European Foundation for the Improvement of Living and Working Conditions together with the International Labor Organization".

The principal difference between the above approaches is the number of indicators used to assess the quality of employment. According to this criterion, all the variety of thematic methodologies developed by the scientific and expert community can also be grouped into three groups [31]: with one key (main) indicator, several private indicators and, finally, an integral (generalizing, summary) characteristic, which is the result of index construction ("convolution" of the values of a number of indicators according to a certain rule).

We believe that it is necessary to search for the optimal number of private indicators. An excessive number of indicators leads to "dilution" of results when decomposing the index. In addition, the labor intensity of thematic evaluation increases. In the reverse situation (minimum set of private indicators), the final result may be significantly distorted due to the fact that a number of significant factors are not taken into account.

Another equally important classification feature is the sources of information. Here, we can also distinguish three groups of thematic methodologies, which are based solely on statistical information or data from sociological surveys, and a mixed (hybrid) variant, when both of the above-mentioned sources of information are used simultaneously. Sample surveys (thematic surveys of the population) complement aggregated data of official statistics (formed on the basis of organizations' reports), but at the same time increase the subjectivity of the obtained estimates of employment quality.

Within the framework of this study, we will limit ourselves to measuring the quality of employment in our country with regard to the meso-level of management on the basis of one (main) indicator — the level of employment in the informal sector of the economy. Despite a significant number of case studies, there is virtually no research using genetic algorithm, artificial neural networks or modern machine learning techniques. One of the few such works is the article [32], where a not unsuccessful attempt to group Russian regions (their classification) depending on the level (calculated as a percent of the number of employed) of workers in the informal sector of Russian regions, more precisely, the key factors determining it using the random forest method (one of the methods of machine learning) was made.

Taking into account the above-mentioned, this study aims to develop an adequate modern toolkit for the realization of the predictive function in relation to the phenomenon under study. The hypothesis is put forward about the possibility of correct clustering and subsequent classification of RF subjects by the level of employment in the informal sector of the economy using a modern machine learning method.

Data and research methods

In the previously mentioned statistical compilation, the data on the number of employed in the informal sector of the national economy for the regions of Russia are given with a periodicity of once every two years. Therefore, the information base of this empirical study is the values of the studied indicators for 2017, 2019, 2021 and 2023. At the same time, the presence of lagged factor indicators in the initial system (with an offset of one year back in relation to the dependent variable) is explained by the "lagging" statistics in terms of the disclosure of data on gross regional product (GRP) by the subjects of the Russian Federation.

The dependent ("output") variable (result indicator) is the level of employment in the informal sector of the economy (expressed as a percentage of the total working population) in the Russian regions. Taking into account case studies by different authors [31–36], a system of twenty-five factor indicators ("input" or independent variables), including lag variables, was initially formed (*Fig. 5*). In *Fig. 5*, the 18th-21st indicators are lag-independent variables (with values shifted back one year) in relation to the 1st, 5th, 12th and 17th factors.

The decision on the expediency of including certain lag factor indicators was made taking into account the assessment of the strength of the influence of independent variables on the resultant indicator. Such strength was determined by calculating and analyzing pairwise Pearson's correlation coefficients (*Table 1*).

In order to ensure the comparability of the initial information in the spatial and temporal contexts, the cost indicators were preliminary adjusted. First, the influence of the price factor in dynamics was leveled out. Secondly, auxiliary calculations were made taking into account the purchasing power parity in the Russian regions. In this case, the cost of a fixed set of consumer goods and services in Moscow in 2017 was taken as a base of comparison (benchmark).

Table 1 does not show the factors that have a weak effect on the performance indicator (Pearson's pair correlation coefficient took values less than 0.4).

The strongest influence on the dependent variable (the value of the above coefficient was approximately 0.6–0.7), excluding lag factors (Z18–Z21), was exerted by a group of 6 "input" variables (Z1, Z5, Z9, Z10, Z12 and Z17). The final decision on the composition of factor indicators ("input" variables) for solving the classification problem is made during computational experiments. This task is solved within the framework of the study using one of the methods of modern machine learning — the LightGBM (Light Gradient-Boosting Machine) method. At the same time, it should be noted that the initial information for the classification of Russian regions in our case are the results of cluster analysis, i.e., the distribution of subjects of the Russian Federation into groups based on the level of employment in the informal sector of the economy. In turn, the clustering problem is solved using the k-means method in the Python programming language. Previously, the optimal number of clusters is determined using the Elbow method (*Fig. 6*).

As can be seen from the data in *Fig. 6*, based on the actual level of employment in the informal sector of the economy, it is reasonable to divide 82 Russian regions for 2017, 2019, 2021 and 2023 into five clusters. During a series of computational experiments, all observations were correctly recognized, i.e. the Russian regions were distributed

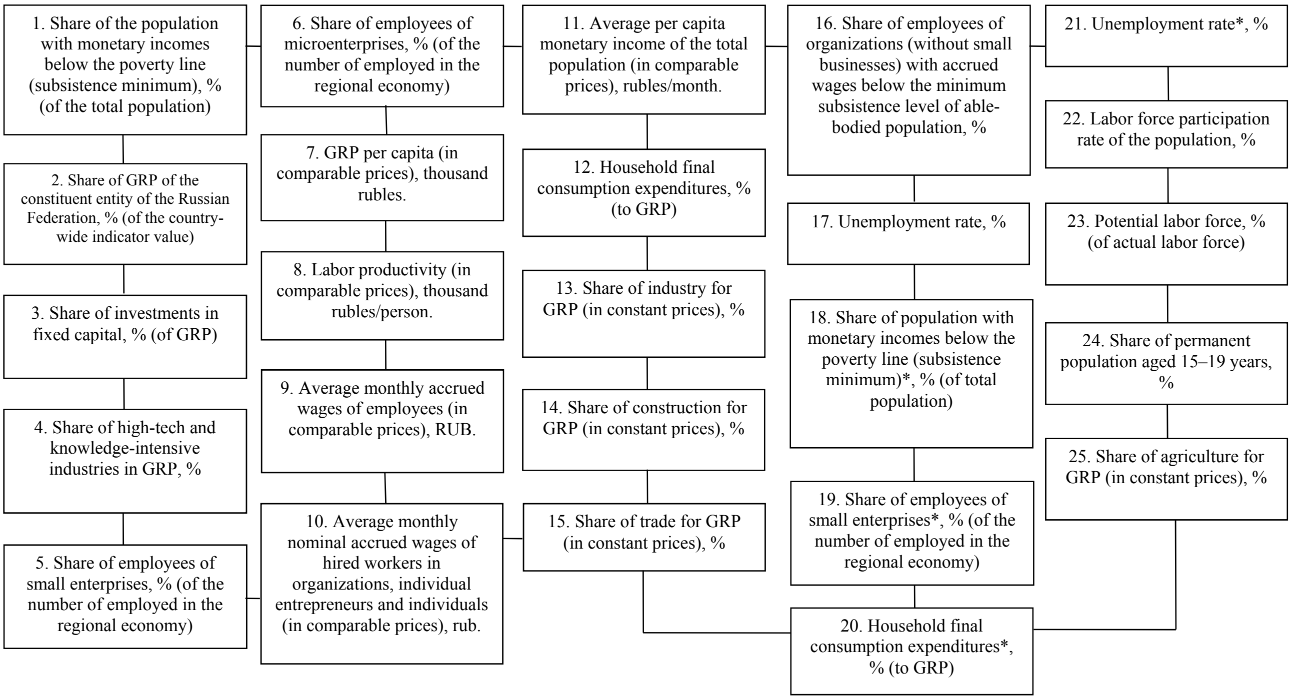

Fig. 5. **Initial system of factors affecting the level of employment in the informal sector of the economy of the constituent entities of the Russian Federation**

Source: compiled by the authors based on [31–36].

into five clusters according to the actual level of employment in the informal sector of the economy.

Returning to the solution of the classification problem, *Fig. 7* visualizes the results of the refined list of key factors affecting the level of employment in the informal sector of the economy of the Russian regions.

According to the data in *Fig. 7,* we can see that in our case, a system of 29 factors is used to solve the problem of classification of RF subjects. Initially, there were 100 factors (25 indicators presented in *Fig. 5* for 4 periods). Hence, most of the factors were eliminated due to their small significance in the formation of the resultant indicator.

In order to evaluate the accuracy of the procedure, a "Confusion Matrix in Multi-class Classification" is constructed (*Fig. 8*).

As shown in *Fig. 8*, in our case, the accuracy of recognizing the objects under study in the context of each class was 100%. This means that the applied modern method of machine learning allows us to correctly identify the cluster of any Russian region in the future, based on the expected level of employment in the informal sector of the economy.

Results

Table 2 presents the main results of clustering. *Fig. 9* visualizes the distribution of Russian regions by the level of employment in the informal sector of the economy.

At different "poles", a relatively small number of regions turned out to be in this distribution.

The most favorable employment situation (low level in the informal sector of the economy) was observed in five subjects of the Russian Federation: the Moscow Region, Moscow, Murmansk Region, St. Petersburg and the Chukotka Autonomous Okrug. According to the cluster profile, the average value of the indicator in the group was 8.3; 7.6; 7.5 and 6.5%, respectively, in 2017, 2019, 2021 and 2023. From the above data, it can be seen that there has been a positive downward trend in the average level of employment in the informal sector of the economy in this group of regions. The least favorable situation for the studied phenomenon has developed in four Russian regions from the North Caucasus Federal District: the Republic of Dagestan, the Republic of Ingushetia, the Kabardino-Balkarian Republic and the Chechen Republic. At the same time, the average level of employment in the informal sector of the economy for this group of regions was 53.3; 52; 50 and 46.1%, respectively, in 2017, 2019, 2021 and 2023. There is also a positive downward trend in the average value of the indicator. According to the results of the cluster analysis, it was found that the largest group of Russian re-

Table 1

Pearson's matrix of values of pairwise correlation coefficients (key fragment)

	Y	**Z_1**	**Z_5**	**Z_6**	**Z_7**	**Z_8**	**Z_9**	**Z_{10}**	**Z_{11}**	**Z_{12}**	**Z_{13}**	**Z_{16}**	**Z_{17}**	**Z_{18}**	**Z_{19}**	**Z_{20}**	**Z_{21}**	**Z_{24}**
Y	1																	
Z_1	0.58	1																
Z_5	−0.57	−0.48	1															
Z_6	−0.49	−0.52	0.69	1														
Z_7	−0.53	−0.49	0.26	0.31	1													
Z_8	−0.47	−0.43	0.22	0.27	0.99	1												
Z_9	−0.57	−0.44	0.08	0.25	0.85	0.82	1											
Z_{10}	−0.60	−0.41	0.14	0.27	0.87	0.84	0.98	1										
Z_{11}	−0.53	−0.70	0.27	0.41	0.80	0.74	0.80	0.79	1									
Z_{12}	0.64	0.33	−0.28	−0.28	−0.78	−0.76	−0.75	−0.78	−0.51	1								
Z_{13}	−0.47	−0.32	0.24	0.12	0.65	0.66	0.54	0.59	0.34	−0.72	1							
Z_{16}	0.51	0.47	−0.17	−0.31	−0.46	−0.46	−0.64	−0.61	−0.40	0.57	−0.42	1						
Z_{17}	0.68	0.73	−0.54	−0.47	−0.38	−0.33	−0.36	−0.35	−0.42	0.39	−0.36	0.49	1					
Z_{18}	0.55	0.99	−0.47	−0.51	−0.48	−0.43	−0.42	−0.40	−0.69	0.32	−0.31	0.45	0.72	1				
Z_{19}	−0.56	−0.49	0.92	0.66	0.28	0.24	0.14	0.18	0.27	−0.32	0.26	−0.27	−0.56	−0.49	1			
Z_{20}	0.64	0.35	−0.29	−0.29	−0.76	−0.75	−0.74	−0.76	−0.50	0.98	−0.71	0.59	0.39	0.33	−0.33	1		
Z_{21}	0.67	0.73	−0.57	−0.48	−0.39	−0.33	−0.33	−0.33	−0.43	0.37	−0.35	0.43	0.98	0.72	−0.59	0.37	1	
Z_{24}	0.54	0.46	−0.71	−0.48	−0.12	−0.07	0.07	0.04	−0.10	0.21	−0.20	0.15	0.63	0.45	−0.67	0.20	0.67	1

Source: Developed by the authors.

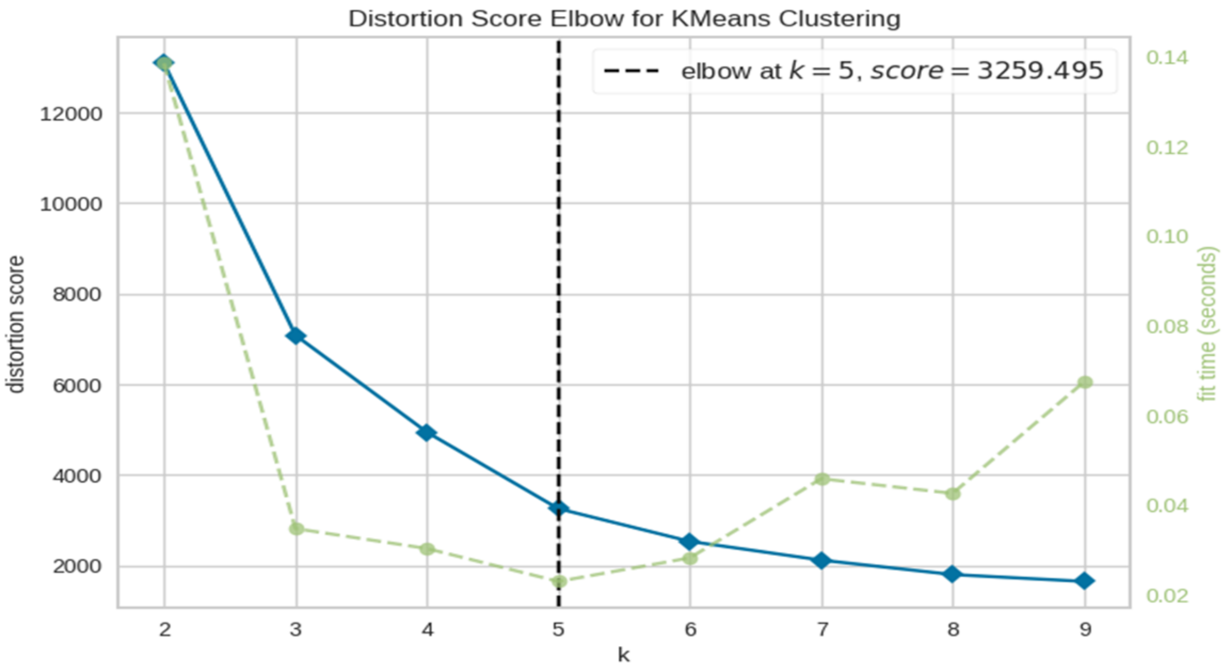

Fig. 6. **Visualization of the results of the elbow method in the Python programming language**

Source: Developed by the authors.

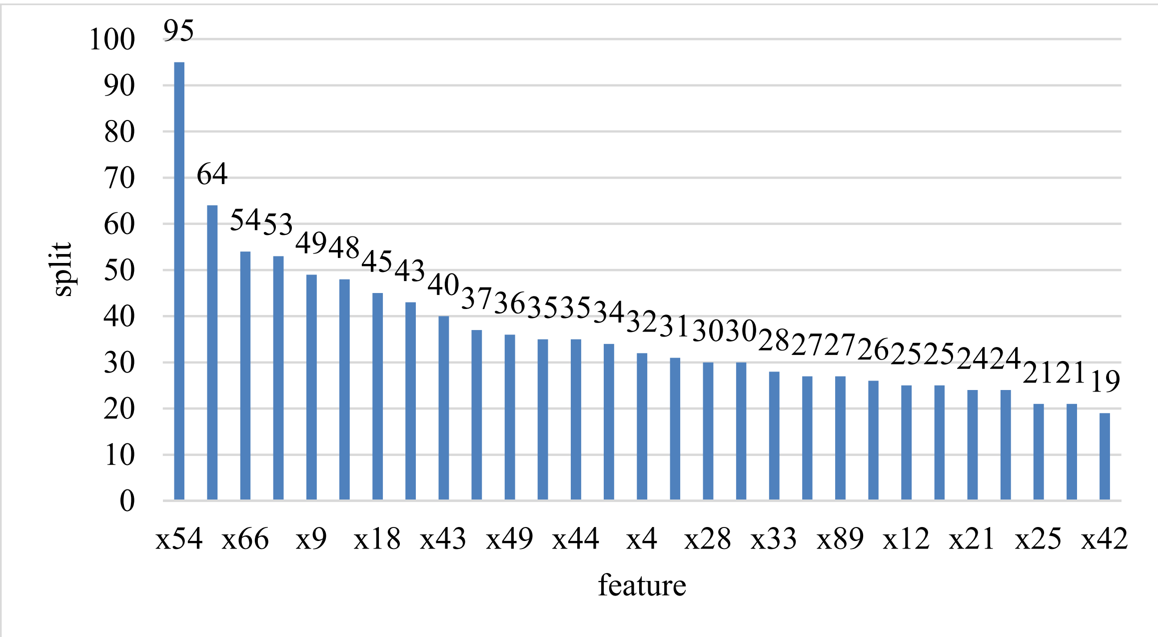

Fig. 7. **Ranked system of key factors determining the level of employment in the informal sector of the economy in Russian regions**

Source: Developed by the authors.

gions (40 or almost half of the total number) were formed by subjects of the Russian Federation with an employment level in the informal sector of the economy below average. In this group, the average value of the indicator was about 18.4–18.8% in 2017, 2019 and 2021. In 2023, there was a slight decrease in the indicator (to 16.6%).

The average level of employment in the informal sector of the economy was observed in 24 Russian regions, including the Republic of Bashkortostan. The average value of the indicator in this group of RF subjects was from the interval from 25.9% to 26.9% in 2017, 2019 and 2021. However, as in the previous cluster, it slightly (to 23.3%)

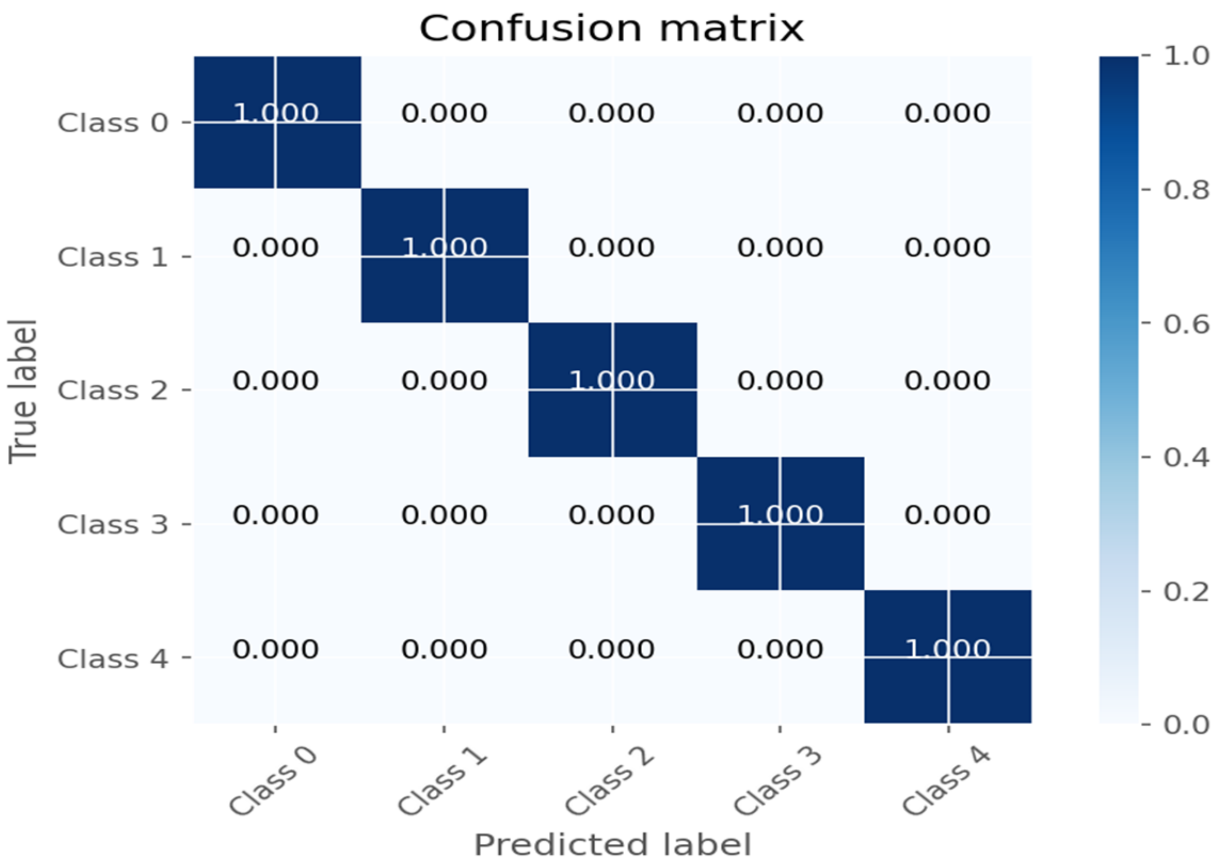

Fig. 8. **"Confusion matrix in multiclass classification" (LightGBM method, Python programming language)**

Source: Developed by the authors.

Fig. 9. **Distribution of Russian regions by level of employment in the informal sector of the economy**

Source: Developed by the authors.

Table 2
Main results of clustering of Russian regions by the level of employment in the informal sector of the economy

Cluster number	Average level of employment in the informal sector of the economy, %				Qualitative characterization of the level of employment in the informal sector of the economy	Cluster size	
	2017	2019	2021	2023		Number of regions. units.	Share of regions, %
The first one	8.3	7.6	7.5	6.5	Low level	5	6.1
Second	18.4	18.8	18.5	16.6	Below average	40	48.8
Third	25.9	26.9	26.2	23.3	Medium level	24	29.2
Fourth	32.2	35.4	35	32.8	Above average	9	11
Fifth	53.3	52	50	46.1	High level	4	4.9

Note: Clustering was carried out for 82 subjects of the Russian Federation. Arkhangelsk and Tyumen oblasts with autonomous okrugs in their composition. Without new regions of Russia (DNR, LNR, Zaporizhzhya and Kherson oblasts) due to the lack of necessary statistical information.

Source: Developed by the authors.

decreased in 2023, which is also characterized positively.

Finally, the group with the level of employment in the informal sector above the average economy included 9 Russian regions. Here, the average value of the indicator was about 35.4 (35)% in 2019 (2021), 32.2–32.8% in 2017 and 2023. As can be seen in 2019 and 2021, there was a slight increase in the level of employment in the informal economy for this group of Russian regions. However, in 2023 the average value of the indicator practically decreased to the level of 2017.

The city of Sevastopol and the Republic of Crimea, which are not represented on the map, were characterized by the average and above average level of employment in the informal sector of the economy, respectively.

Summarizing the results of cluster analysis, it is necessary to note the abnormally high value of employment in the informal sector of the economy in a number of subjects of the Russian Federation. For example, the highest level of employment in the informal sector of the economy among Russian regions in 2021 was recorded in the Republic of Ingushetia (52.7%). According to this indicator, the Russian region is comparable with Colombia (50.5%), Dominican Republic (51.2%), Armenia (51.5%), Iraq and Ethiopia (54.4%), and Mexico (55.2%), i.e. with a number of economically developing countries in Asia, Africa, North and South America [2]. It is necessary to emphasize the high degree of differentiation on the studied phenomenon in the regional context characteristic of modern Russia. Thus, the lowest value of the level of employment in the informal economy among the constituent entities of the Russian Federation in 2021 was recorded in Moscow (4.9%), which is comparable to the value of a similar indicator in such economically developed European countries as Austria, Spain and Finland.

Next, let us move on to the solution of the classification problem. Within the framework of the study we will limit ourselves to assigning two Russian regions from different groups by the level of employment in the informal sector of the economy to a certain cluster (class) in the future. Let us do this on the example of Moscow and the Republic of Bashkortostan for 2025. As previously noted, in 2023, the above two Russian regions were characterized, respectively, by low and medium level of employment in the informal sector of the economy.

The experts make a prospective assessment of key factors (including lag independent variables) based on their actual values for 2017, 2019, 2021, 2023 (taking into account the "lag" effect) (*Table 3*).

In case of development of events in the future according to the experts' scenario, it is expected that the city of Moscow and the Republic of Bashkortostan in 2025 will remain in the same groups (clusters) of Russian regions, i.e., they will

Table 3

Prospective assessment of values of key factor indicators for the city of Moscow and the Republic of Bashkortostan for the year 2025 (2024)

Indicator	Moscow	Republic of Bashkortostan
Population with incomes below the poverty line (subsistence minimum), % (of total population)	4	9
Share of investments in fixed capital*, % (of GRP)	23	25
Share of products of high-tech and knowledge-intensive industries in GRP*, %	25	23
Share of employees of small enterprises, % (of the number of employed)	11	5.5
Share of employees in microenterprises, % (of the number of employed)	15	5
GRP per capita (in comparable prices)*, thousand rubles.	1400	600
Average monthly accrued salary of employees (in comparable prices), rub.	90 000	60 000
Average per capita cash income of the total population (in comparable prices), rub.	95 000	45 000
Household final consumption expenditures*, % (to GRP)	45	80
Share of industry for GRP (in constant prices)*, %	15	31
Share of construction for GRP (in constant prices)*, %	5	7
Labor force participation rate of the population, %	67	59
Potential labor force, % (of actual labor force)	0.3	1

Note: * — prospective assessment of the indicator value is given for 2024.

Source: Developed by the authors.

be characterized, respectively, by a low and medium level of employment in the informal sector of the economy.

Conclusion

According to the results of cluster analysis, we can conclude that modern Russia is characterized by a high degree of differentiation of regions by the level of employment in the informal sector of the economy. In the group of the most favorable subjects of the Russian Federation, the situation with regard to the studied phenomenon is close to the economically developed countries of the West. For the group of Russian regions with the least favorable situation in terms of employment in the informal sector of the economy, the situation is almost identical to that in a number of economically developing countries of the world from Asia, Africa, North and South America. At the same time, for 40 subjects of the Russian Federation (almost half of their total number) the level of the studied phenomenon was below average (about 17–19%), comparable to that in a number of economically developing countries of Eastern Europe such as Bosnia and Herzegovina (18.8%), Serbia (16.9%), Czech Republic (15.3%), etc. [2].

The literature review emphasized the fundamental difference between informal employment in economically developed and developing countries of the world. Only the first group of countries is characterized by relatively good working conditions of informally employed. Given this and the results of the cluster analysis, we can conclude that in modern Russia most of the informally employed do not have good working conditions, and, therefore, need to increase the degree of social protection.

In order to prospectively assess the situation, the study solved the task of classifying Russian regions using a modern method of machine learning. This task is a logical continuation of cluster analysis. Under the influence of a number of key factors, it has specified to which group (class) of RF subjects a certain Russian region will belong in the future. The current situation, taking into account possible changes in the future, does not allow us to make an optimistic forecast about further significant reduction in the level of employment in the informal sector of the economy of the two subjects of the Russian Federation, so it is expected that the city of Moscow and the Republic of Bashkortostan in 2025 will remain in their respective clusters (as well as in 2023). Moscow and the Republic of Bashkortostan in 2025 will remain in the corresponding (as well as in 2023) clusters.

The results of the empirical study can be applied in the course of planning by the federal center of the volume of financial resources for social support of the working population in the informal sector of the economy of the constituent entities of the Russian Federation.

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The Use of Artificial Intelligence Technologies in Energy and Climate Security

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ABSTRACT

This study provides a theoretical analysis of the use and application of artificial intelligence (AI) in the energy sector as it relates to climate security. **The object** of the study is energy and climate security as types of economic activity and social activity. **The subject** of the research is artificial intelligence in relation to the object area of research. **The purpose** of the study is to create a sound scientific basis for the use of artificial intelligence in the energy sector, as well as to identify emerging problems in the formation of a science-based approach to climate policy development. The authors' research includes three interrelated research **methodologies:** topic modeling, text mining as part of qualitative analysis and object modeling as part of the systematization of results that are adequate to the subject area of the study and correspond to their reality; in addition, the authors supplemented the quantitative results with a theoretical and heuristic analysis of the scientific results of other researchers. The concept of parametric optimization (PO) is used as an effective method for solving the applied problem of testing the hypothesis of managing energy costs and energy efficiency based on AI in order to achieve optimal performance of the technical system and compliance with the Sustainable Development Goals (SDGs) in the field of climate security. The study's **findings** suggest that AI is becoming fundamental to the development of a modern energy sector based on data and complex relationships and provides tools to improve technical system performance and efficiency in the face of sanctions restrictions. The authors **conclude** that the truth of the hypothesis has been proven: the use of AI as a control feedback loop at a technical facility for purification and energy generation is a more cost-effective and technically optimal alternative to a "live" operator, which will eliminate the human error factor. In this regard, the energy industry, utilities, grid operators and independent power producers must pay special attention to the introduction of AI technologies into existing technical systems.

Keywords: artificial intelligence; energy efficiency; green economics; energy saving; feedback loop; intelligent algorithm; optimization; climate security; energy sector

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Использование технологий искусственного интеллекта в энергетике и климатической безопасности

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АННОТАЦИЯ

Настоящее исследование посвящено теоретическому анализу использования и прикладного применения искусственного интеллекта (ИИ) в энергетическом секторе в приложении к климатической безопасности. **Объектом исследования** выступает энергетика и климатическая безопасность как виды экономической деятельности и общественной активности. **Предметом исследования** является искусственный интеллект применительно к объектной области исследования. **Цель исследования** — создание обоснованных научных оснований для использования искусственного интеллекта в энергетике, а также выявления возникающих проблем в формировании научно обоснованного подхода к разработке климатической политики. Исследование авторов включает три взаимосвязанных **методологии** исследования: тематическое моделирование, интеллектуальный анализ текста в рамках качественного анализа и объектное моделирование в рамках систематизации результатов, адекватных предметной области исследования и соответствия их действительности. Кроме того, авторы дополнили количественные результаты теоретико-эвристическим анализом научных результатов других исследователей. Используется концепция параметрической оптимизации (ПО) в качестве эффективного метода для решения прикладной задачи проверки гипотезы управления энергозатратами и энергоэффективностью на основе ИИ с целью достижения оптимальных показателей работы технической системы и соответствия целям устойчивого развития (ЦУР) в области климатической безопасности. **Результаты исследования** свидетельствуют о том, что ИИ становится основополагающим фактором для развития современного энергетического сектора, основанного на данных и сложных взаимосвязях и предоставляет инструменты для повышения производительности технических систем и эффективности в условиях санкционных ограничений. **Доказана** истинность гипотезы, что использование ИИ в качестве управляющего контура обратной связи на техническом объекте очистки и генерации энергии является более экономически эффективной и технически оптимальной альтернативой «живому» оператору, что позволит исключить человеческий фактор ошибки. В связи с этим энергетическая отрасль, коммунальные предприятия, операторы энергосистем и независимые производители электроэнергии должны уделять особое внимание внедрению технологий ИИ в существующие технические системы.

Ключевые слова: искусственный интеллект; энергоэффективность; зеленая экономика; энергосбережение; контур обратной связи; интеллектуальный алгоритм; оптимизация; климатическая безопасность; энергетический сектор

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Introduction

The energy sector is undergoing fundamental changes due to the adoption of digital technologies, with artificial intelligence (AI) playing a pivotal role. The use of AI enables the integration of energy production, consumption, and renewable sources, allowing for autonomous energy system management through intelligent algorithms that optimize decision-making and operational processes. In the context of rapidly advancing information technologies, AI, and data analytics, regulatory authorities face the challenge of promptly and effectively approving new services and products. This requires informed and adaptive interaction while addressing issues of client safety, confidentiality, and information security. Climate change represents one of the most significant challenges for modern society, yet it often takes a backseat in political agendas, overshadowed by more immediate and pressing issues that align with current political priorities.

This research focuses on three main aspects of energy and climate security:

1. The use of AI in renewable electricity production.
2. The application of AI for managing circular processes in energy supply and energy savings.
3. Recent advancements in AI technologies for utilizing human-generated waste and byproducts to produce clean energy.

This paper presents an overview of the challenges associated with using AI in energy and climate change, emphasizing the applied nature of AI implementation in a technical facility. A scientific hypothesis is proposed: employing AI as a feedback control loop in a technical facility for energy purification and generation is a more cost-effective and technically optimal alternative to a "human" operator, eliminating the human factor.

Theoretical and practical significance of the research lies in the novel applied formulation of the problem of AI usage in the context of energy system design, the use of empirical performance evaluation strategies for parameter search algorithms, the development and assessment of new software implementation algorithms, and the demonstration of AI's application in solving specific design problems in technical and energy systems, contributing to the achievement of sustainable development goals in climate security.

Literature review

At present, extensive applied research on the impact of artificial intelligence (AI) and deep learning (DL) on the process and efficiency of achieving Sustainable Development Goals (SDGs) highlights the significant potential of these technologies across various fields of human activity. These include "environmental safety and sustainability" [1], "using AI to achieve carbon neutrality" [2], "the impact of AI on transformative changes in energy" [3], "quantum artificial intelligence for renewable and sustainable energy" [4], and "AI in the economic evaluation of energy efficiency technologies" [5]. Zhengcheng Fan and co-authors found that "AI can potentially contribute to achieving 134 out of 169 targets across all SDGs…" [6], emphasizing the need for a comprehensive exploration of the subject area.

In Industry 4.0, AI significantly influences various sectors of the economy, transforming activities and states in agriculture, education, and industry, with the emergence of new sectors and types of human activities. For example, "we view BCI (brain-computer interfaces) as a hardware-software communication system that enables humans or animals to interact with the environment without involving peripheral nerves and muscles, using control signals generated by brain activity" [7, p. 2].

The importance of interpretability in DL models is considered a key factor for the effective and optimal use of AI in daily and professional activities: "…due to their overly parameterized 'black-box' nature, it is often challenging to understand the predictive results of deep models. In recent years, numerous interpretability tools have been proposed to explain or uncover how deep models make decisions" [8, p. 3197].

S. Leonelli and H.F. Williamson compellingly argue that AI and DL also hold great promise for environmental sustainability, particularly in applying AI through plant biology systems, defining a new role for AI in achieving SDGs [9].

Research by Ahmad et al. convincingly shows that advancements in AI, such as machine learning, deep learning, the Internet of Things (IoT), and big data analytics, are significantly transforming the energy sector in terms of supply, production, demand, and electricity provision [10].

Numerous scientific studies are devoted to the broad application of AI in clean energy. For instance, researchers N.C. Ohalete et al. recognize the growing role of AI in promoting clean energy sources and its significant impact on improving the efficiency of renewable energy systems [11]. Asif Raihan found that AI and machine learning are actively being implemented in energy research domains, focusing particularly on renewable energy as a key future development direction for AI [12]. He also emphasizes that "future research using advanced sustainability assessment tools such as life cycle assessment, exergy analysis, etc., should further explore the sustainability of biomass-to-bioenergy conversion processes" [13, p. 10].

Researchers Kenji Masio, Mizuki Kasamatsu, and Eisuke Noda raise the critical issue of improving management and safety in nuclear energy. They propose the practical application of AI in disaster management information systems for nuclear power plants under the name DMP (Decision-Making Panel). This enhances the safety and resilience of the nuclear energy sector: "DMP was developed using a human-centered design approach based on international and Japanese human factor design guidelines… and validated through human factors verification (task support verification) to ensure DMP supports decision-making processes" [14, p. 346].

Barbara A. Han et al. explore future prospects for AI and ecology through synergy, emphasizing the need for guided, targeted synergy to expand the understanding of ecological sustainability while improving resilience. They highlight that current AI systems lack state certainty in terms of sustainability, leading to negative consequences in various human experience contexts [15].

Researchers Martin János Mayer, Arthur Silágyi, and Gyula Gróf address critical issues of optimization and efficiency in renewable energy systems, identifying significant differences between ecological and economic optima. At the same time, the proposed multi-objective optimization in applied use has proven effective as a compromise between two conflicting goals of optimization and efficiency [16].

Machelev R. et al. underscore the growing importance of AI in renewable energy and reveal its contribution to achieving sustainable development goals in the energy sector [17]. Researchers Jingze Li, Pei Liu, and Zheng Li examine the challenges of optimal design and management of renewable energy systems [18], while Abdalla et al. investigate the use of AI for optimizing the configuration of renewable energy systems, implementing energy management strategies, and employing energy storage technologies [19].

Connor Sweeney et al. highlight the critical issue of energy consumption forecasting and future energy development in their work [20], while T. Ahmad et al. emphasize and substantiate the fact that AI plays a crucial role in energy consumption prediction, creating a reliable benchmark for future energy initiatives [21].

Despite the extensive study of AI's technological impact on energy, empirical research on its influence on human energy development (HED) is expanding in the scientific field in search of more effective solutions [22]. The effectiveness of AI and DL applications in power systems is evident in the ability to predict optimal power flows by combining deep learning and Lagrangian methods. This improves the accuracy of AC power flow optimization, surpassing traditional power distribution systems [23].

The application of AI and DL in renewable energy, particularly in solar photovoltaic power plants, demonstrates significant success in fault detection and system management. For example, the integration of the solAIR system, which uses AI for automatic fault detection in photovoltaic plants, relies on thermal image analysis using drones and AI to promptly identify anomalies and provide maintenance recommendations [24].

The rapid development of artificial intelligence (AI) and deep learning (DL) in the field of renewable energy has driven numerous studies that foster the emergence of new methodologies and applications. These studies explore energy management systems and energy balance forecasting across various domains of human experience, demonstrating a wide range of approaches and technologies used in both everyday life and professional activities. For instance, the works of Sami Ben Slama and Marwan Mahmoud [25], as well as Zoltan Nagy et al. [26], highlight these advancements.

Vladimir Franki, Darin Majnaric, and Alfredo Viskovic conducted an analysis of the impact of AI on optimizing energy systems and expanding international business. Their findings emphasize the pivotal role of digitalization in unifying business processes and relationships, with a focus on leveraging AI to optimize energy consumption across various industries, including renewable energy [27].

Most of the studies reviewed underscore the importance of applying AI and DL to optimize renewable energy systems. The diversity of methodologies and application directions is notable, with some research focusing on real-time energy trading while others address challenges through comparative analysis of different AI algorithm performances.

In Russia, the applied use of AI in energy has also gained momentum in the scientific domain, expanding as a subject of interest and exploration. For example, Russian researcher L.V. Massel examines critical ethical risks associated with AI use and its prospects in various areas of human experience: "Three types of risks are highlighted: job shortages as machines replace humans; implications for human independence, freedom, and security; and concerns that smarter machines may dominate humans and cause humanity's demise" [28, p. 13]. Domestic researchers E.P. Grabchak and E.L. Loginov explore the implementation of AI-based digital platforms to enhance decision-making efficiency in technologically complex energy systems. They propose the development of an integrated digital platform to address these challenges [29]. Similarly, K.H. Zoido and E.L. Loginov tackle the crucial issue of ensuring reliability and standardization in management decisions within the energy sector using AI [30].

Despite the extensive body of academic research, a significant gap persists between academic studies and industry needs. While the authors have attempted to review applied research, the issue of empirical and practical studies remains relevant. It is crucial to continue research efforts aimed at the practical implementation and scaling of innovative solutions in real-world conditions. Moreover, additional studies addressing the socio-economic and environmental implications of integrating AI and DL into the renewable energy sector have become an urgent necessity.

Materials and methods

Different researchers have varying opinions regarding the advantages and disadvantages of quantitative and qualitative scientific research methods in the context of scientific inquiry and problem-solving. This study incorporates three interconnected research methodologies: thematic modeling, text mining as part of qualitative analysis, and object modeling for the systematization of results relevant to the research subject and their practical applicability. Additionally, the quantitative findings are supplemented with theoretical-heuristic analyses of other researchers' results.

The concept of parametric optimization (PO) is employed as an effective method to address the applied challenge of testing the hypothesis on energy cost management and efficiency using AI to achieve optimal performance of technical systems and alignment with Sustainable Development Goals (SDGs) in climate security. In this research, PO is defined as the process of finding the optimal solution dependent on one or more parameters influencing this solution through feedback loops. AI uses this infinite cycle for continuous regulation, effectively replacing the "human" operator, thereby eliminating the human error factor and improving the efficiency and optimization of the technical energy system.

To test the hypothesis, PID controllers (Proportional-Integral-Derivative controllers) are used as regulation tools. These controllers employ feedback loops and are widely applied in industrial systems for regulation and control, especially where continuous modulated control of an object is required. The PID controller continuously computes the error as the difference between the desired setpoint value (SPSP) and the measured process variable (PVPV). It then applies corrections based on proportional (PP), integral (II), and derivative (DD) components, which are reflected in its name. PID systems provide precise and timely adjustments to control functions.

The initial theoretical and practical application of PID controllers was found in automatic ship steering in the 1920s. Over time, their evolution has seen widespread use in process automation across manufacturing industries, starting with pneumatic controllers and later transitioning to electronic controllers [31]. Today, the PID concept is extensively applied in systems requiring precise and optimized automatic control.

The distinctive feature of PID controllers is their ability to implement three control conditions (proportional, integral, and derivative effects) on the controller's output signal for precise and optimal control. The proportional component (PP) is proportional to the current error between the setpoint and the process variable. Applying a gain coefficient results in a corresponding change in the control output based on the magnitude of the error. However, using proportional control alone may lead to a residual error under steady-state conditions [32].

The integral component considers past error values and integrates them over time to eliminate residual errors resulting from proportional control. The derivative component predicts future error trends and directs the controller to reduce their effect based on the rate of change. Balancing these components is achieved by tuning control loop parameters for optimal performance. The tuning constants must be adapted for each application, depending on the loop and process characteristics.

The direct control action of the controller ensures that a positive error change leads to a corresponding positive change in the control output signal. In some cases, reverse action may be required to apply corrective negative adjustments. AI-driven tuning and training of the control loop optimize the PID controller's operation, ensuring the necessary efficiency and stability in managing technical energy systems.

Application in water treatment and energy systems

The operation of wastewater treatment systems is associated with high energy consumption for technical systems such as pumping equipment, automated management systems, lighting, heating, and ventilation [33]. Special attention is given to sewage treatment facilities (STFs), which use various technical means to move water with specific flow rates and pressures. A critical aspect of STF operations is the backflow of treated water into a water body to ensure environmental safety [34]. Sewer pumping stations (SPS) with pressure dampening wells at the ends of pressurized collectors are often employed to maintain ecological balance in aquatic environments.

This study proposes using the volume of wastewater in the discharge collector to generate energy for STFs through renewable energy sources. The method involves producing clean and renewable electricity for STF needs using specialized installations for generating electricity in pressure-dampening wells, leveraging treated wastewater.

For these purposes, small-scale hydropower plants (HPPs), designed for small rivers or artificial reservoirs, are considered. Continuous water supply is essential for HPPs to avoid downtime. In turn, STFs must operate consistently to ensure a steady wastewater flow to sustain microorganisms in the treatment process. The PowerPal electricity generation unit meets these requirements, ensuring HPP operability [35]. When parameters exceed standard conditions, the unit generates additional power. Under standard conditions, the HPP generates 1250 watts, and the generator weighs 90 kg. PowerPal is easy to operate and maintain, providing long-term, fault-free operation when adhering to the manufacturer's instructions.

HPPs are chosen as a practical example of a technical energy system, prioritizing ecological and climate sustainability. As noted by international researchers, "One strategy is to increase the share of hydropower as a renewable energy source to reduce greenhouse gas emissions. The second strategy is to optimize the operation and management of hydropower to adapt to various climatic conditions" [36]. A subsequent significant study examined energy and climate sustainability and security based on 140 parameters across four categories: "...many researchers have realized the importance of sustainable hydropower development and explained the concept of sustainability from different perspectives" [37].

Results

Preparation stage

1. Selection of a technical device considering the specified parameters.
2. Installation of the technical device in the pressure-dampening well.
3. Development of AI algorithm principles.
4. Assessment of the techno-economic effect of using an alternative electricity source with AI integration.

To test the research hypothesis, a pressure-dampening well located at one of the enterprises in Russia, positioned on the discharge collector to a water body, was selected as the study object.

When designing the sewer pumping station (SPS), located at the highest point of the pressurized collector, the system was divided into two main sections:

1. Pressurized section

This section extends from the starting point to the highest point, where the direction of water movement changes.

2. Gravity-flow section

This section runs from the highest point to the endpoint, where water flows naturally without the use of additional devices.

This design was employed during the planning and operation of the sewer pumping station for discharging wastewater from sewage treatment facilities into a water body at the "N" site. The schematic diagram of this system is presented in *Fig*.

This staged approach allowed for the systematic implementation of AI-driven solutions, optimizing the energy efficiency of the wastewater treatment process while ensuring compliance with environmental safety standards. The results validate the feasibility of integrating renewable energy sources into such systems.

Operational features of the sewer pumping station (SPS)

During the operation of the sewer pumping station (SPS), specific characteristics are observed related to the functionality of submersible sewage pumps. These pumps can transfer wastewater through the centrifugal impeller while the pressurized pipeline operates as a siphon. This behavior is due to the steady-state movement of the liquid, where the product of the average velocity and cross-sectional area remains constant. This characteristic enables energy-saving measures during the transfer of wastewater from sewage treatment facilities to a water body.

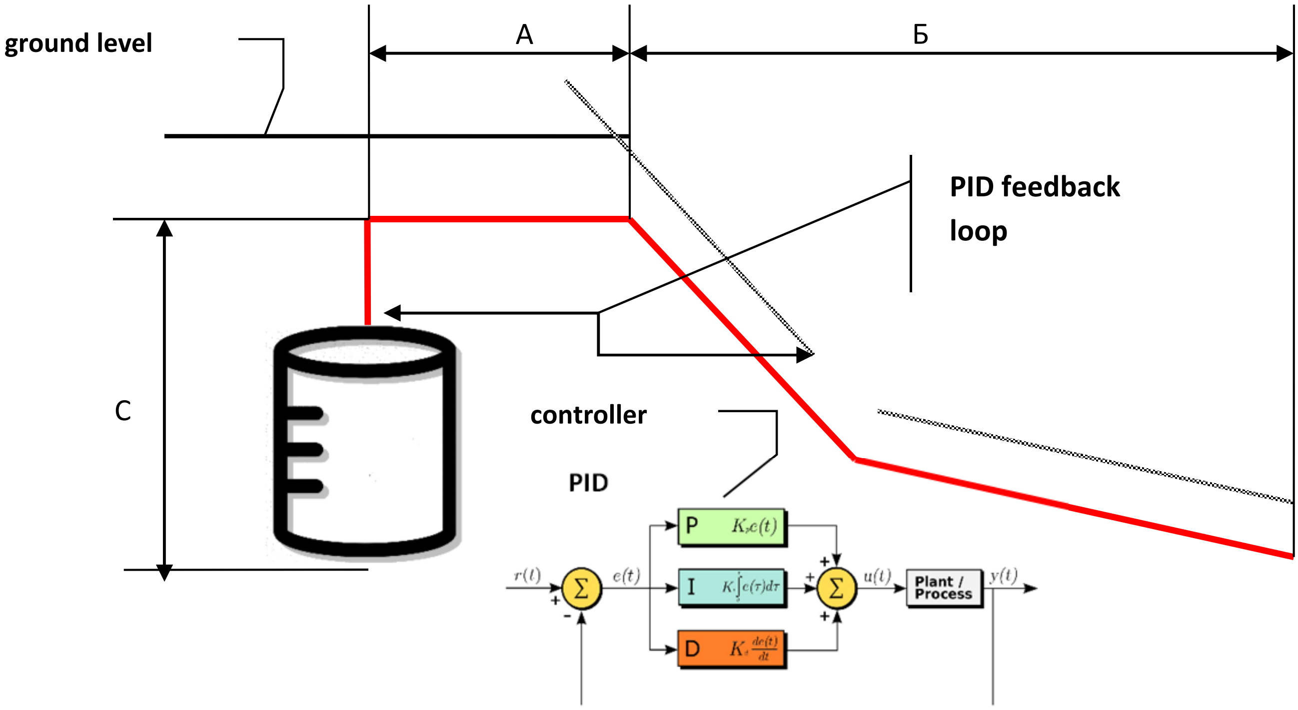

Fig. **Schematic diagram of the SPS device and pipeline system**

Source: Developed by the author.

Using the SIP program to calculate pipeline filling by pumps, it was determined that filling the pipes with water using two pumps takes 44 seconds. Once the pipeline is filled with water, it begins to function as a siphon, while the impeller of the submersible pump continues to pass water through itself.

Field study

A field study was conducted to evaluate the proposed SPS operation method, which included the following steps:

1. Pumping water with active pumps until the reservoir in the SPS reached its minimum level.
2. Employing the siphon method, where the pumps were switched off after the pressurized pipelines were filled with water, and measuring the time taken to empty the SPS reservoir.

Results of the Field study:

• Time for two pumps to operate: 32 minutes.

• Time to fill the pipelines using two pumps: 1 minute.

• Time to drain the water after pump shutdown: 38 minutes.

• Total drainage time: 42 minutes.

PID controller program algorithm and optimization

Steps:

1. Measure wastewater levels and energy consumption.
2. Determine the optimal pump speed using a PID controller (Proportional-Integral-Derivative controller).
3. Adjust the pump speed through an AI feedback loop.

Code for regulating energy generation by submersible sewage pumps

python

```
Copy code
import time
import math
# Parameter setup
setpoint = 50 # Optimal wastewater level (in percentage)
Kp = 0.5 # Proportional coefficient
Ki = 0.01 # Integral coefficient
Kd = 0.001 # Derivative coefficient
# Initialize variables
error_prev = 0
integral = 0
# Infinite loop for constant regulation
while True:
```

```
# Measure wastewater level and energy consumption
level = measure_wastewater_level()
power = measure_energy_consumption()
# Calculate error
error = setpoint — level
# Calculate integral
integral += error * 0.1 # Integral step (0.1 seconds)
# Calculate derivative
derivative = (error — error_prev) / 0.1 # Derivative step (0.1 seconds)
# Update previous error
error_prev = error
# Compute PID controller output
output = Kp * error + Ki * integral + Kd * derivative
# Limit output signal (0–100%)
output = min(100, max(0, output))
# Adjust pump speed
set_pump_speed(output)
# Pause for 0.1 seconds to refresh data
time.sleep(0.1)
```

Explanation of the code step-by-step

1. Define the optimal wastewater level and PID coefficients.
2. Initialize variables for error, integral, and derivative.
3. Measure the wastewater level and energy consumption.
4. Calculate the error between the setpoint and the measured level.
5. Compute the integral of the error.
6. Calculate the derivative of the error.
7. Update the previous error value.
8. Compute the PID controller output.
9. Limit the output within a range of 0–100%.
10. Adjust the pump speed based on the output signal.
11. Pause for 0.1 seconds to refresh the data.

AI logic for pump control

```
python
Copy code
import RPi.GPIO as GPIO # Import GPIO library
import time # Import time library
# Set GPIO numbering mode
GPIO.setmode(GPIO.BCM)
# Configure GPIO pin 18 as output for relay control
GPIO.setup(18, GPIO.OUT)
# Set initial relay state (off)
GPIO.output(18, GPIO.LOW)
# Define regulation interval (e.g., 1 minute)
interval = 60 # seconds
# Infinite loop for continuous regulation
while True:
# Get current time
current_time = time.time()
# Check if the regulation interval has elapsed
if (current_time — start_time) >= interval:
# Toggle relay state (turn pump on/off)
GPIO.output(18, not GPIO.input(18))
# Update last regulation time
start_time = current_time
# Clean up GPIO pins on program exit
GPIO.cleanup()
```

AI operational workflow

1. Import required libraries.
2. Configure GPIO numbering mode (BCM).
3. Set GPIO pin 18 as output for relay control.
4. Initialize the relay to the off state.
5. Define the regulation interval (e.g., 1 minute).
6. Enter an infinite loop for continuous regulation.
7. Retrieve the current time.
8. Check if the regulation interval has elapsed.
9. Toggle the relay state to control the pump.
10. Update the timestamp for the last regulation.
11. Clean up GPIO pins upon program exit.

Testing the scientific hypothesis

The proposed method of energy saving and energy supply primarily allows for the utilization of self-generated energy as a resource. This approach significantly reduces electricity costs and labor expenses, which can be viewed by the owner as income.

To begin, let us determine the difference in automation costs for the sewer pumping station (SPS) before and after implementing the energy-saving method:

1. The power of a single pump transferring wastewater is 7 kW/hour.
2. The daily throughput of the SPS is 530 m^3/day. The monthly throughput of the SPS is calculated as follows: $Q_{monthly} = Q_{daily} \times 30 = 530$ m^3/day × 30 = 15,900 m^3/month

Table 1
Using AI for energy generation: the reduction in operational costs and energy consumption

Parameters	Option with AI	Cost for Pressure Maintenance
Kilowatts per month	14*150.9 = 21,12.6 kW	14*11.04 = 154.6 kW
Monthly electricity cost (rubles)	2,112.6*11 = 23,238.6 rub	154.6*11 = 1,700.2 rub
Annual electricity cost (rubles)	23,238.6*12 = 278,863.2 rub	256.12*12 = 20,402 rub

Source: Developed by the authors.

Qmonthly = Qdaily × 30 = 530 m³/day × 30 = = 15,900m³/month.

3. Based on the experimental results, the approximate capacity of two pumps operating together is 105.4 m³/hour.

4. Calculate the monthly operating time of two pumps transferring wastewater under the first scenario: Toperating time = QmonthlyQcapacity = 15,900 m³/month105.4 m³/hour = = 150.9 hours/month. Toperating time = QcapacityQmonthly = 105.4m³/hour15,900m³/month = = 150.9hours/month.

5. For the pipeline filling scenario, calculate the time required to fill the pipelines: Tfilling = QfillingQpump rate = 22.08 m³2 × 0.5 m³/hour = 11.04 hours. Tfilling = Qpump rate Qfilling = 2 × 0.5m³/hour22.08m³ = 11.04hours.

6. The electricity tariff at this facility is 11 RUB/kW.

Table 1 presents the results of using AI for energy generation, demonstrating the reduction in operational costs and energy consumption through automation and self-sustained energy production.

Thus, the economic effect is evident: 278,863.2 RUB — 20,402 RUB = 258,461.2 RUB, solely from energy generation and savings, excluding labor costs (as AI eliminates the human factor).

The computational power required to support the growth of AI approximately doubles every 100 days. Consequently, achieving a tenfold increase in AI model efficiency may require a 10,000-fold increase in computational power. The energy consumption needed to execute AI tasks is already exhibiting an accelerated growth rate, increasing annually by 26% to 36%.

The economic impact of AI on the environment manifests at two key stages of its lifecycle: the training phase and the inference phase. During the training phase, models are developed by processing vast volumes of data, after which they move to the inference phase, where they are applied to solve real-world problems. Currently, the environmental footprint is distributed as follows: training accounts for approximately 20%, while inference constitutes the majority — 80%. As AI models are increasingly deployed across various sectors, the demand for inference, along with economies of scale and its environmental impact, will grow. Aligning AI's rapid progress with the need for environmental sustainability requires a carefully designed strategy encompassing immediate and short-term measures while laying the foundation for long-term sustainability.

AI contributes to efforts for transitioning to a climate-neutral and energy-efficient economy in numerous ways. It aids in the development of new materials for clean energy technologies, optimizes the performance of solar and wind power plants, advances energy storage technologies, enhances carbon capture processes, improves the accuracy of climate and weather forecasts for better energy planning, and catalyzes breakthroughs in green energy sources, such as nuclear fusion. Through the strategic application of AI to enhance renewable energy infrastructure, the future of AI promises not only the growth of the green economy but also the creation of more sustainable socio-economic systems for future generations.

In the long term, fostering synergy between AI and emerging quantum technologies is a critical strategy for ensuring sustainable societal development. Unlike traditional computing, where energy consumption grows proportionally to computational power, quantum computing demonstrates a linear relationship between computational power and energy consumption. This potential transformation allows AI to create more compact models, improve training efficiency, and enhance overall functionality, undoubtedly optimizing costs and expenditures for achieving sustainable development goals.

Realizing this potential requires collective efforts, including government support, industry investments, academic research, and public engagement. By uniting these elements, we can ensure a future where progress in AI harmonizes with the preservation of the planet's health.

Discussion

Concerns over data security, ethical dilemmas, and potential technological dependency are key challenges associated with artificial intelligence (AI). It is well known that AI is trained on data provided by owners or regular users, meaning its objectivity directly depends on the quality and objectivity of this data. This raises serious ethical issues related to morality, law, and other aspects of social life. For instance, in the absence of legislation protecting personal data, what would prevent AI from disclosing confidential information? Bias is also inherent in AI algorithms, as their responses are based on the limited datasets used during training. Additionally, AI can generate false information, facilitating propaganda and flooding media spaces with unreliable data.

Generative AI models such as Chat, DALLE-2, Stable Diffusion, and Midjourney rely on vast amounts of data but may still produce incorrect or unethical results. Furthermore, there is no clearly defined entity responsible for the content generated by AI.

The issue of securing data used to train AI is also highly relevant: who will ensure the protection of ordinary users from data breaches? Beyond the risks of data misuse and leaks from AI applications, the technology poses dangers to other services. Generative AI could be used to create fake data capable of bypassing cloud security systems. These generated datasets might launch attacks on systems, manipulate stolen data, or cause other damage, forcing energy companies targeted by AI-powered attacks to improve their security measures. The most effective tool to counter such attacks will likely be another machine learning-based system.

The emergence of modern AI systems has intensified longstanding moral concerns related to artificial intelligence, amplifying issues that have existed for centuries.

Potential long-term negative impacts of AI on environmental and social sustainability:

- **Energy consumption**: Data centers and other infrastructures supporting AI operations consume significant amounts of energy. According to the International Energy Agency (IEA), data centers consumed up to 2% of global electricity in 2023 (excluding cryptocurrency mining).[1] However, advancements in energy efficiency may mean that the computational power required for AI growth will not necessarily result in proportional energy consumption increases. Global data center energy use is expected to grow by only 6% through 2026.
- **Water usage**: Data centers using water-based cooling systems consume less electricity but require large amounts of water. By early 2022, Google's data centers used 16.3 billion liters (4.3 billion gallons) of water. By 2023, this figure rose by 30%, reaching 21.1 billion liters (5.6 billion gallons). Over the same period, Microsoft's water usage increased by 34%, from 4.7 billion liters (1.2 billion gallons) to 6.3 billion liters (1.6 billion gallons) annually.
- **Local utility impact**: AI-based data centers, regardless of their energy generation methods, place significant strain on local utility networks. A typical 100-megawatt data center requires enough electricity to power 80,000 homes.
- **Social bias**: AI systems can exacerbate existing social prejudices, hinder efforts to combat discrimination, and worsen public relations.
- **Fraud**: AI may serve as a tool for creating sophisticated phishing schemes and various forms of forgery used for fraud and deception.
- **Disinformation campaigns**: AI capabilities can be leveraged for targeted disinformation campaigns and public opinion manipulation.

Geopolitical and economic pressures

Rising geopolitical tensions and economic sanctions against Russia hinder technological development, especially in the high-tech sector. Sanctions target areas requiring complex problem-solving, including algorithm design

[1] How Much Energy Is Really Being Consumed by Data Centers? URL: https://thenewstack.io/how-much-energy-is-really-being-consumed-by-data-centers/

Table 2
The Role of AI in ensuring climate security

AI Application	Advantages	Challenges
Climate Condition Forecasting	Improved forecasting accuracy	Requires large, high-quality datasets
Environmental Climate Policy	Data-driven decision-making	Balancing interests of multiple stakeholders
Risk Assessment and Climate Modeling	Comprehensive variable analysis	Integration of diverse data sources

Source: Compiled by the authors.

and the creation of sophisticated software systems. However, AI can partially offset the negative effects of Western sanctions by automating repetitive operations and optimizing complex technological processes. AI is capable of generating innovative solutions based on existing templates and data. It already demonstrates the ability to understand context and adapt to changing conditions and requirements.

Climate risk assessment

Identifying climate risks is fundamental to planning adaptation measures for climate change. The use of machine learning methods significantly enhances this process by simultaneously accounting for numerous variables, leading to a deeper understanding of climate change consequences. *Table 2* provides a detailed analysis of climate risk assessment using AI-based models.

As machine learning technologies advance, their role in analyzing the state of the environment grows. Machine learning aids in predicting climate models and making informed policy decisions. Such AI tools are critically important in efforts to combat climate change.

Conclusion

Further regulation and prospects for AI use in technical and energy systems highlight the effectiveness of parametric optimization methods through AI in addressing complex challenges, especially those related to data instability in renewable energy [38]. Existing developed methods, such as patents for "parametric model generation for high-performance computing systems" [39] and the "universal algorithm for solving parametric optimization problems" [40], form a substantial domestic software foundation.

The authors foresee significant potential for developing software in the renewable energy sector based on artificial intelligence and deep learning, leveraging improvements in training methods and resource management. However, further research and updates to existing approaches are clearly needed to optimize renewable energy sources using advanced machine learning methods.

The study results indicate that AI is becoming a fundamental factor in the development of the modern energy sector, which is increasingly data-driven and characterized by complex interconnections. AI provides tools to enhance the performance of technical systems and improve efficiency under sanction constraints.

The hypothesis has been confirmed: using AI as a feedback control loop in technical facilities for energy purification and generation is a more economically efficient and technically optimal alternative to a "human" operator, eliminating human error. Consequently, the energy industry, utility enterprises, energy system operators, and independent power producers should prioritize the integration of AI technologies into existing technical systems.

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The Impact of Digital Transformation on Risk-Taking: An Empirical Study of Japanese Companies

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ABSTRACT

Goal: This paper examines the effect of digital transformation on corporate risk-taking in Japanese firms and, more importantly, identifies links between digital technology integration and risk appetite. This study inspects how digital transformation impacts internal control quality, investment efficiency, and general financial soundness, with special emphasis on the differences between state-owned versus non-state-owned enterprises. **Methods:** The empirical analysis uses the data of Nikkei Index firms from 2010 through 2023. Out of the total, excluding the financial and insurance sectors as well as aberrant statuses in trading, 225 firms resulted in 14,567 observations. The regression models controlled for a number of different factors, such as enterprise size, profitability, and industry type of firm. **Results:** The empirical evidence based on the pooled sample implies that enhanced digital transformation significantly boosts the capability of corporate risk-taking. Specifically, a comparison of the estimated coefficients obtained across the state-owned enterprises versus their non-state-owned counterparts shows a large difference in the magnitude for the latter. The increasing adoption of digital technologies heightens the propensity of those firms to invest in high-risk investments, hence improving their value at large. **Conclusions:** The study contributes to an understanding of how digital transformation affects corporate behavior in terms of risk-taking. It underlines the need to develop digital initiatives that contribute to investment efficiency and financial stability. The findings imply that policymakers and business leaders should encourage strategies of digital transformation, especially for non-state-owned enterprises, to achieve economic growth through increased risk-taking ability.

Keywords: enterprise risk-taking; digital transformation; property rights; investment efficiency; corporate governance; technological integration; economic growth

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Влияние цифровой трансформации на принятие рисков: эмпирическое исследование японских компаний

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АННОТАЦИЯ

Цель: в данной статье рассматривается влияние цифровой трансформации на корпоративное принятие рисков в японских фирмах и, что еще более важно, выявляются связи между интеграцией цифровых технологий и склонностью компаний к риску. В исследовании рассматривается влияние цифровой трансформации на качество внутреннего контроля, эффективность инвестиций и общую финансовую устойчивость, с особым акцентом на различия между государственными и негосударственными предприятиями. **Методы:** в эмпирическом анализе используются данные компаний, входящих в индекс Nikkei с 2010 по 2023 г. Из общего числа, за исключением финансового и страхового секторов, а также предприятий с аберрантными статусами в торговле, по 225 фирмах было проведено 14 567 наблюдений. Регрессионные модели включали различные факторы, такие как размер предприятия, прибыльность и отраслевой тип фирмы. **Результаты:** эмпирические данные, основанные на объединенной выборке, свидетельствуют о том, что расширенная цифровая трансформация значительно повышает способность корпоративного принятия риска. В частности, сравнение оценочных коэффициентов, полученных по государственным предприятиям и их негосударственным аналогам, показывает большую разницу в величине для последних. Широкое внедрение цифровых технологий повышает склонность этих фирм к инвестициям с высоким уровнем риска, что в целом увеличивает их стоимость. **Выводы:** исследование способствует пониманию того, как цифровая трансформация влияет на корпоративное поведение с точки зрения принятия риска. Оно подчеркивает необходимость разработки цифровых инициатив, которые способствуют эффективности инвестиций и финансовой стабильности. Результаты свидетельствуют, что политики и руководители бизнеса должны поощрять стратегии цифровой трансформации, особенно для негосударственных предприятий, для достижения экономического роста за счет повышения способности принимать риски.

Ключевые слова: принятие риска предприятием; цифровая трансформация; права собственности; эффективность инвестиций; корпоративное управление; технологическая интеграция; экономический рост

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Introduction

The fourth plenary session of the 19th government of Japan in October 2019 incorporated "data" into the distribution of production factors. It explicitly advocated for the use of digital transformation as the primary catalyst to advance the modernization of government governance and enhance the efficiency of enterprises in the capital market. In Japan's present economic development, digital transformation has emerged as a crucial strategic approach for firms to attain high-quality growth and gain essential competitive advantage. This transformation is a result of the integration of digital technology with the real economy. The ability of firms to effectively accomplish digital transformation and upgrading is crucial for economic development [1]. Digital transformation is a significant catalyst for stabilizing Japan's economic growth since it has a profound influence on all aspects of business operations and development [2]. It contributes to better economic growth by enhancing corporate growth. Furthermore, for smaller financial institutions, the tendency to take higher risks tends to increase investment in research and development (R&D) programs. This also has a significant impact on the value of the firm as it leads to socio-technical development and ultimately to economic growth [3]. By combining the aforementioned factors, the convergence of digital transformation and business risk management can significantly facilitate economic expansion. Digital transformation refers to the integration of digital technologies in the operations of a firm, leading to significant changes in its internal processes [4]. These changes have a significant impact on the company's ability to acquire resources. Organizational risk taking, which is considered a type of resource management behavior [5], can be affected by digital transformation, and the two are linked to some extent [6]. It is important to understand the the relationship between two. It provides valuable input and policy guidance to the government to guide economic growth [7].

Digital transformation significantly affects firms' risk appetite by increasing their investment efficiency, information processing capabilities, and internal process efficiency. Using big data analytics, firms can gain insights into customer demand, which can increase knowledge of capital markets and increase their risk tolerance [8, 9]. Digital transformation also improves information processing capabilities, allows direct access to business functions and processes, makes it easier to identify inefficiencies, and optimizes internal processes [10, 11]. This reduces inadequate information, enables companies to assess their growth status and improves financial stability. Digital transformation definition is a well-planned integration of digital technologies into all organization processes, which completely changes how it performs and delivers value for its customers [12]. It is more than just the adoption of big data, artificial intelligence, or the Internet of Things but represents the cultural shift that enables innovation and agility within the enterprise [13]. Risk tolerance definition is the degree of uncertainty that an investor is willing and able to withstand in the value of their investment portfolio [14]. The amount of risk that an investor is willing and able to take to meet their financial goals or objectives.

This study aims to investigate the relationship between digital transformation and business risk-taking in property opportunities, with the hypothesis that digital transformation can improve firm value through a higher willingness to risk by encouraging the development [15]. The research seeks the impact of digital transformation on investment in particular, total factor productivity and corporate performance [16]. The paper contributes to existing research on the economic consequences of digital transformation and introduces contextual variables related to the nature of property rights to enhance understanding of these relationships.

Literature review

Digital transformation refers to the strategic use of digital technology by organizations to gain a competitive advantage in the market [17]. Japan's digital economy is rapidly advancing, leading to an increasing number of enterprises adopting digital technologies such as big data, the Internet of Things, and artificial intelligence to revolutionize their business processes and models [18]. Factors that impact digital transformation include the macroeconomic environment and microenterprises peculiarities [19]. At the macroeconomic level, companies have a higher likelihood of acquiring financial resources due to interest rate marketization. The advancement of digital finance offers technological assistance for the process of digital transformation [20]. Existing research primarily examines microenterprise features through the lens of political linkages and institutional investors. Political ties may be a powerful catalyst for the digital transformation of small and medium-sized firms, while diverse institutional investors have varying impacts on digital transformation [21].

Financial repercussions of digital transformation include enhanced productivity and efficiency, bolstered internal control capabilities, innovation drive, reduced audit expenses, decreased information asymmetry, conveyed favorable messages to external stakeholders, enhanced corporate social responsibility, raised market expectations, and improved performance in the capital market [22]. Both the theoretical and practical communities have shown a great deal of interest in the factors that influence risk-taking, which is essential to the establishment and operation of businesses [23]. Differences in equity ratios have a significant impact on risk-taking within a company's internal governance. State-owned shares have a significant inhibiting effect on risk-taking, while foreign shares have a significant increasing effect [24]. Executives' aversion to risk can decrease their willingness to take risks when dealing with agency problems. Offering incentives to executives can effectively decrease agency problems in companies, thus enhancing the level of risk-taking [25].

External governance levels and industrial policy can enhance government subsidies and loan support for enterprises, increasing their risk appetite [26]. Regional economic policy uncertainty can significantly impact business decision-making and create development opportunities for enterprises, leading to increased risk-taking [27]. Tax increases have a fantastic effect in decreasing danger-taking conduct, at the same time as tax reductions do not have a considerable effect on the danger urge for food. Institutional fragility amplifies the uncertainty surrounding managers' destiny projections and heightens the chance of danger aversion, diminishing the propensity of companies to take dangers [28]. This paper conducts an empirical evaluation to observe the effect of virtual transformation on corporate risk-taking, exploring contextual traits and action mechanisms involved [29].

While setting up the causality between digital transformation and corporate risk-taking, other ways of analysis have to be taken into consideration in order to show the possible complicating variables. This can be done with the non-causal method of the two-step approach: establishing the relationship of digital transformation to the risk appetite, one examines how other variables affect this relationship. The proposed methodology enables researchers to account for a number of alternative confounding variables, organizational size, industry type, and external economic conditions that might also affect a firm's risk appetite. Indeed, factors other than digital transformation, such as managerial risk preferences, market competition, and regulatory environments, could separately influence a company's attitude toward taking risks. In a nutshell, although digital transformation has an essential role in shaping corporate risk appetite through improvement in information processing and efficiency of investment, the relationship is also crucially affected by other factors such as managerial preferences and market dynamics.

Theoretical analysis and research hypothesis

Risk-taking is a key driver of collaboration, and digital transformation is the process of integrating digital technology into various parts of an organization [30]. This transformation can improve resource management, reduce information duplication and increased economic stability. Digital transformation has increased distribution, improve internal control quality, and increase risk-taking [31]. By integrating real-time market data, businesses can make informed investment decisions based on market demand, leading to increased investment efficiency and risk-taking. Moreover, digital transformation can strengthen information management and internal controls, leading to increased risk-taking [32]. Furthermore, digital transformation has increased financial efficiency, enhanced financial stability, and increased risk-taking [33]. In situations of limited financial stability, favorable economic conditions can improve profitability and encourage managers to invest in equity, thereby increasing risk-taking [34]. Overall, digital transformation can increas corporate risk-taking through increased financial leverage, improved internal controls and financial stability. Therefore, this paper proposes hypothesis 1:

H1: Digital transformation can increase the level of corporate risk-taking.

Digital transformation can improve investment efficiency and increase risk-taking in organizations. However, property rights play a significant role in this process. State-owned firms, with limited market competition, may not be motivated to adopt digital transformation [35]. Private firms, on the other hand, face intense competition and digital transformation, which has enhanced their investment effectiveness and financial resilience. State-owned firms may prioritize stable projects over risk-taking, while privately-owned companies may allocate resources toward high-risk projects. Therefore, digital transformation's impact on risk-taking capacity is less significant in state-owned enterprises. State-owned enterprises (SOEs) in Japan are those businesses where the government has a significant share that enables it to direct operations, decisions, and strategies of the company. These companies, in general, serve public interests or play a very important economic, infrastructural, or strategic role. The Japanese government controls the company's stock through direct investments or designated entities. Most Japanese SOEs aim to stabilize vital services (such as electricity, transportation), and others contribute to promoting innovation or maintaining national security. Some of the privatized Japanese SOEs include Japan Post, Japan Railways, and Nippon Telegraph and Telephone. In certain strategic sectors, partial governmental ownership is maintained either for purposes of governance or public benefit. Because of their quasi-governmental character, SOEs may receive subsidies or special rules. This may lower the pressure to innovate or take risks via market forces. The study found that SOEs are less risk-taking and slower to implement digital transformation compared to non-state-owned firms because of their emphasis on stability and lesser competitive pressure. Based on this, this paper proposes hypothesis 2:

H2: Compared with state-owned enterprises, the digital transformation of non-state-owned enterprises has a stronger effect on improving the level of corporate risk-taking.

Research design

Sample selection and data sources

This study utilizes data from the Nikkei Index businesses in Japan's capital market between 2010 and 2023 as the research sample. The data is organized as follows: (1) Exclude data from the financial and insurance sectors; (2) Exclude data from aberrant trading statuses; (3) Exclude data with missing values, resulting in a final sample size of 14,567 observations of 225 companies listed on Japan's Nikkei Index. The internal control quality index is derived from the Internal Control Quality Index (ICQI) database, while additional data is sourced from the Bloomberg database. This work applies Winsorize shrinkage processing to all continuous variables, namely at the 1% and 99% quantiles, in order to mitigate the negative impact of extreme sample values on the data.

Variable definition

Explained variable. RISK denotes the degree of risk that a corporation is willing to undertake. This research examines the methodology used by [6] and utilizes the earnings volatility indicator as a measure of business risk-taking. More precisely, the industry-adjusted total asset return rate is analyzed over a three-year period to determine its standard deviation and range. These values are then referred to as RISK1 and RISK2, respectively.

Explanatory variables. DDT is a metric that quantifies the extent to which an organization has undergone digital transformation. This article discusses the study conducted by [36] and provides a definition of digital transformation as the fundamental concept used in the process of digitalization. The logarithm of word frequency in the deployment of digital technology inside a business is utilized to provide a precise measure of digital transformation. The indicator is derived using a dataset obtained from the textual content of the annual reports of publicly traded corporations, using the programming language Python.

Situational variables. NONSOE symbolizes the essence of possession. If the firm is controlled by a non-state entity, the value is 1; otherwise, it is 0.

Control variables. This article discusses the methodology used by Wu Fei et al. (2021) [36] and identifies the specific variables that were chosen for control. These variables include enterprise size (SIZE), cash holding level (CASH), debt-to-asset ratio (LEV), profitability (ROA), growth ability (GROWTH), equity concentration (FIRST), enterprise age (AGE), board size (BOARD), proportion of independent directors (RATIO), dual-position director combination (DUAL), loss status (LOSS), annual dummy variable (YEAR), and industry dummy variable (INDUS). *Table 1* displays the variables and their corresponding meanings in this study.

Model Setting

To examine the influence of digital transformation on corporate risk-taking as stated in Hypothesis 1, this study adopts the methodology proposed by Wu Fei [36] and develops model (1) to assess the extent to which digital transformation enhances corporate risk-taking.

$$\begin{gathered} RISK = \beta_0 + \beta_1 ADT + \beta_2 SIZE + \beta_3 CASH + \beta_4 LEV + \beta_5 ROA + \beta_6 GROWTH + \beta_7 FIRST + \\ + \beta_8 AGE + \beta_9 BOARD + \beta_{10} RATIO + \beta_{11} DUAL + \beta_{12} LOSS + YEAR + INDUS + \in . \end{gathered} \tag{1}$$

Based on the theoretical study presented in the previous article, the coefficient of the DDT item of anticipated digital transformation, β_1, is shown to be much bigger than 0. This suggests that digital transformation has a strong positive impact on the risk-taking capacity of organizations.

Table 1
Variable definition and description

Variable type	Variable name	Variable symbol	Variable definition
Interpreted variable	Corporate risk-taking level	RISK1	Rolling calculation of the standard deviation of the three-year industry-adjusted total return on assets
		RISK2	Rolling calculation of the extremely poor three-year industry-adjusted total return on assets
Explanatory variables	Degree of digital transformation	DDT	See the previous article for the specific calculation method
Situational variables	Nature of property rights	NONE	When the nature of the enterprise is non-state-owned, the value is assigned to 1, otherwise, it is 0

Control variable	Enterprise scale	SIZE	Natural logarithmic value of total assets
	Cash holding level	CASH	The ratio of cash flow to total assets at the end of the year
	Asset-liability ratio	LEV	The ratio of total liabilities to total assets
	Profitability	ROA	The ratio of net profit to average total assets
	Growth ability	GROWTH	(Current year's operating income-previous year's operating income)/Previous year's operating income
	Equity concentration	FIRST	The proportion of shares held by the largest shareholder
	Business age	AGE	LN (Research year-listing year +1)
	Size of the board of directors	BOARD	The natural logarithm of the number of directors
	Proportion of independent directors	RATIO	The ratio of the number of independent directors to the number of directors
	Two jobs in one	DUAL	If the chairman is also the CEO, the value is assigned to 1, otherwise it is 0
	Loss status	LOSS	Take 1 when the net profit is negative, otherwise take 0
	Year	YEAR	Covers 11 years and sets 10 virtual variables
	Industry	INDUS	Set industry virtual variables according to the 2012 SFC industry classification standards
RISK	Risk-taking level measured by earnings volatility	Standard Deviation (%)	Bloomberg
DDT	Degree of digital transformation	Logarithm of Word Frequency	Annual Reports Dataset

Source: Developed by the authors.

This study aims to analyze the function of property rights in different situations. To do this, the paper presents the cross-product DDT×NONSOE and property rights NONSOE of digital transformation, based on model (1), to develop a model (2).

$$\begin{gathered} RISK = \beta_0 + \beta_1 ADT + \beta_2 DDT \times NONSOE + \beta_3 NONSOE + \beta_4 SIZE + \beta_5 CASH + \beta_6 LEV + \beta_7 ROA + \\ + \beta_8 GROWTH + \beta_7 FIRST + \beta_{10} AGE + \beta_{11} BOARD + \beta_{12} RATIO + \beta_{13} DUAL + \\ + \beta_{14} LOSS + YEAR + INDUS + \in . \end{gathered} \tag{2}$$

Empirical results and analysis

Descriptive statistics and analysis

Table 2 presents the statistical summary of the primary variables. The average values for RISK1 and RISK2 are 0.0456 and 0.0598, with standard deviations of 0.0612 and 0.0875, and 3/4 quantiles of 0.0480 and 0.0628, respectively. This suggests that the majority of organizations have similar degrees of risk-taking. The average value of DDT is 1.3981, with a maximum value of 4.4438 and a minimum value of zero. This suggests significant variations in the extent of digital transformation

Table 2
Descriptive statistics of the main variables

variable	Observed value	Mean	Standard deviation	Minimum value	1/4 quantile	median	3/4 quantile	Maximum value
RISK1	14567	0.0456	0.0612	0.0016	0.0123	0.0185	0.048	0.3457
RISK2	14567	0.0598	0.0875	0	0.0177	0.0468	0.0628	0.4785
DDT	14567	1.3981	1.0657	0	0.6842	1.3843	2.1672	4.4438
NONSOE	14567	0.7532	0.5327	0	0	1	1	1
SIZE	14567	21.8721	1.3658	19.8622	20.4305	22.1832	22.8727	25.2325
CASH	14567	0.0487	0.0678	−0.3421	0.0085	0.0573	0.095	0.3313
LEV	14567	0.5054	0.2113	0.0485	0.1797	0.5136	0.5547	0.7862
ROA	14567	0.0487	0.0713	−0.413	0.0195	0.0426	0.0934	0.2359
GROWTH	14567	0.2075	0.4386	−0.4579	−0.0273	0.1282	0.3596	2.7573
FIRST	14567	0.2889	0.236	0.0317	0.2113	0.3108	0.4294	0.7465
AGE	14567	1.8957	0.8326	0	1.3843	2.0794	2.7726	3.2581
BOARD	14567	2.0246	0.1796	1.6183	1.7348	2.1672	2.1672	2.6391
RATI	14567	0.4093	0.0635	0.2537	0.2537	0.3545	0.4286	0.5714
DUAL	14567	0.4024	0.4347	0	0	0	1	1
LOSs	14567	0.0892	0.2847	0	0	0	0	1

Source: Developed by the authors.

among Japanese companies. This presents an opportunity for this paper to examine the correlation between digital transformation and levels of corporate risk-taking. The average value of NONSOE is 0.7532, suggesting that 68.41% of the firms in the study sample own property rights that are not controlled by the state. Therefore, it is very significant to include property rights as a contextual variable in further research. The average value of SIZE is 21.8721, with a high of 25.2325 and a low of 19.8622, suggesting a significant variation in the size of the sample firms. The average value of CASH is 0.0487, and the 3/4 quantile is 0.0950, suggesting that the majority of the sampled enterprises exhibit favorable cash flow. The average value of Return on Assets (ROA) is 0.0487, with a standard deviation of 0.0713. This suggests that the profitability of the enterprises in the sample is generally consistent. The average value of GROWTH is 0.2075, with a maximum value of 2.7573 and a lowest value of –0.4579. This suggests significant variations in the growth potential across the firms in the sample. The average value of DUAL is 0.4024, which signifies that 38.15% of the organizations in the survey had both the chairman and general manager positions held by the same person.

Correlation analysis

Table 3 reports the results of the correlation analysis of the main variables. The coefficients of RISK1, RISK2, and DDT are all significantly positive at the 10% level, and the Spearman correlation coefficients are similar, so they will not be repeated. This preliminary shows that the higher the degree of digital transformation, the higher the level of corporate risk-taking, and Hypothesis 1 is verified. However, the relationship between digital transformation and corporate risk-taking needs to be further tested in the following multivariate regression analysis.

Analysis of multiple regression results

Table 4 lists the results of the multivariate regression analysis of the relationship between digital transformation and corporate risk-taking. From the regression results, it can be found that

Table 3
Correlation analysis of main variables

Variable	RISK1	RISK2	DDT	NONSOE
RISKI	1	0.9841*	0.0468*	0.0378*
RISK2	0.9861*	1	0.0526*	0.0736*
DDT	0.0531*	0.0538*	1	0.0883*
NONSOE	0.0651*	0.0657*	0.0876*	1

Source: Developed by the authors.

Note: * — indicate that they are significant at the levels of 10%.

DDT is significantly positively correlated with RISK1 and RISK2 at the 1% level. This result shows that digital transformation can significantly improve the level of corporate risk-taking; that is, the higher the degree of digital transformation, the higher the level of corporate risk-taking, and hypothesis 1 is verified. The possible reason is that the higher the degree of digital transformation, the wider the scope of application of digital technology in the enterprise, the higher the information transparency of the enterprise, the lower the degree of information asymmetry, and it can improve the internal governance level and resource allocation efficiency of the enterprise, enhance financial stability, lay a stable development foundation for the enterprise, and enhance the confidence of the enterprise in venture capital, thereby improving the level of corporate risk-taking.

In terms of control variables: the coefficient of the SIZE item is significantly negative, indicating that the expansion of enterprise scale may reduce the enterprise's risk-taking level; the coefficient of the CASH item is significantly positive, indicating that the enterprise's cash holdings can improve the enterprise's risk-taking level to a certain extent; the coefficient of the AGE item is significantly positive, indicating that the longer the enterprise operates, the stronger its risk resistance ability and the higher its risk-taking level; the coefficient of the GROWTH item is significantly positive, indicating that the stronger the enterprise's growth ability, the higher its risk-taking level.

Digital transformation affects corporate risk-taking greatly because it improves the efficiency of investments, enhances internal controls, and contributes to better financial stability. When organizations become more digital, their capacity to process information about the market is heightened; therefore, decisions become better. The enhanced capability would then enable firms to spot more opportunities for growth and thereby optimally allocate their resources, culminating in the desire and will to undertake more ventures with a high level of risk. Research shows that those companies that are at high levels or have undergone digital transformation have significantly higher risk appetites, exemplified by investments in innovative projects and ventures that would have been viewed as too risky in the past. The digital transformation effects on risk-taking are noticeably different between SOEs and non-SOEs. Normally, SOEs focus on stability and public service but not on aggressive growth strategy, and thus the propensity of risk is relatively low compared with that of non-SOEs. Non-SOEs are, however, under the whip of competitive power and innovative impulse and are thus more likely to adopt digital transformation so as to enhance their operational efficiency and financial resilience. Therefore, the effect of digital transformation on risk appetite is more salient in the case of non-SOEs, where the integration of advanced digital technologies can lead to drastic improvements in investment effectiveness and an overall rise in corporate risk appetite.

The study reveals that digital transformation has a stronger effect on improving the risk-taking level of non-state-owned enterprises compared to state-owned enterprises. This is due to two reasons: first, state-owned enterprises have special policy attributes and natural advantages in resource acquisition and market recognition, while non-state-owned enterprises face fierce market competition and weaker competitive pressure. They lack motivation to carry out digital transformation, making it difficult to form positive feedback of resources. Second, state-owned en-

Table 4
Digital transformation and corporate risk-taking level

Variable	(1) RISK1	(2) RISK2
DDT	0.0031***(5.3276)	0.0048***(5.3236)
SIZE	−0.0054***(−11.7536)	−0.0120***(−12.1216)
CASH	0.0538***(6.1625)	0.0976***(5.7648)
LEV	0.0092**(2.2152)	0.0246**(2.1764)
N	−0.1743***(−11.2234)	−0.3321***(−11.1477)
ROA	0.0123***(5.4235)	0.0182***(6.5573)
GROWTH	−0.0127***(−4.5533)	−0.0176***(−4.5377)
FIRST	0.0064***(10.7438)	0.0114***(12.4367)
AGE	−0.0065**(−2.3833)	−0.0105**(−2.3456)
BOARD	0.0074(1.1324)	0.0183(1.1555)
RATI	0.0001(0.1148)	0.0004(0.2157)
DUAL	0.0347***(13.8915)	0.0546***(15.5374)
LOSS	0.1873***(16.3854)	0.2835***(14.1283)
Constant	Yes	Yes
YEAR/INDUS	15 258	14 659
Adj-R 2	0.3517	0.3535

Source: Developed by the authors.

Note: ***, ** — indicate that they are significant at the levels of 1% and 5%, respectively, and the t value is in parentheses. Same below.

terprises' managers are more inclined to invest in low-risk projects, limiting the room for digital transformation to improve risk-taking levels. However, non-state-owned enterprises are more concerned about their own profit-making goals, and investment returns are often closely related to performance evaluation. Therefore, compared to state-owned enterprises, the digital transformation of non-state-owned enterprises has a stronger effect on improving their own risk-taking level. This supports Hypothesis 2.

Sensitivity test

Instrumental variable method

This paper uses the regional mean of the degree of digital transformation as an instrumental variable. The rationality of this instrumental variable is as follows: first, the degree of digital transformation is closely related to the level of digital transformation in each region, which meets the correlation of the instrumental variable; second, the regional level of digital transformation is less correlated with the risk-taking level of individual enterprises, which meets the exogeneity requirement of the instrumental variable. The specific regression results are shown in *Table 6:* DDT and RISK1 and RISK2 are all significantly positive at the 5% level, indicating that after controlling for endogeneity, digital transformation can significantly improve the risk-taking level of enterprises, and the research conclusions are still robust.

Propensity score matching

This paper uses the 1:1 nearest neighbor matching method to address potential endogeneity issues in a model. The median of digital transformation is used as the dividing line, with values greater than the median set to 1 and values less than the median set to 0. The experimental group and control group showed significant differences before and after propensity score matching. The regression results show that DDT in Panel A is significantly positively correlated

Table 5
Digital transformation and enterprise risk-taking level: Situational analysis of the nature of property rights

Variable	_(1) RISK1	(2) RISK2
DDT	−0.0010***(−2.6353)	−0.0020***(−2.7496)
DDT×NONSOE	0.0030***(5.4754)	0.0055***(5.6017)
NONSOE	0.0036***(2.7581)	0.0068***(2.9144)
Constant	0.1770***(14.7478)	0.2574***(12.3306)
Control variable	Yes	Yes
YEAR/INDUS	Yes	Yes
N	14 567	14 567
Adj-R2	0.2644	0.2751

Source: Developed by the authors.

Note: *** — indicate that they are significant at the levels of 1%.

Table 6
Digital Transformation and Enterprise risk-taking level: Tool Variable Method

Variable	(1) RISK1	(2) RISK2
DDT	0.0063**(2.4144)	0.0058**(2.3419)
Constant	0.2085***(20.3713)	0.2965***(15.6935)
Control variable	Yes	Yes
YEAR/INDUS	Yes	Yes
N	14 567	14 567
Adj-R2	0.2540	0.2655

Source: Developed by the authors.

Note: ***, ** — indicate that they are significant at the levels of 1% and 5%, respectively.

with RISK1 and RISK2 at the 1% level, and the coefficients of the DDT×NONSOE items in Panel B are also positively correlated at the 1% level. The research concludes that after propensity score matching, the research conclusions remain robust.

Replace the explanatory variables

This paper focuses on the robustness of digital transformation research by dividing it into five aspects: artificial intelligence, big data, computing, blockchain, and digital technology applications. The indicators are derived from annual reports of listed companies using Python and classified into specific technical directions. The total indicators of digital transformation are obtained by summing up the five classified indicators, resulting in the Digital Transformation Group (DCG). The data is then re-substituted into regression models, and the results are shown in *Table 8*. The DCG is found to be significantly positively correlated with RISK1 and RISK2 at the 10% level, and the coefficients of the DCG×NONSOE items in Panel B are also positive at the 1% level. In conclusion, the research conclusions remain robust even after changing the measurement method of digital transformation.

Replace the explained variable

This paper refers to the practice of [7] and respectively calculates the standard deviation of the ratio of operating profit to total assets and the ratio of EBIT to total assets adjusted by the industry average for three years as alternative variables for corporate risk-taking level, denoted

Table 7
Digital transformation and enterprise risk-taking level: Tendency score matching method

Variable	Panel A: Digital Transformation and Risk-taking level		Panel B: Situational analysis of the nature of property rights	
	(1) RISK1	(2) RISK2	(3) RISK1	(4) RISK2
DDT	0.0025***(5.0286)	0.0024***(4.9724)	-0.0012**(−2.2362)	-0.0009*(−1.8735)
DDT×NONSOE			0.0033***(3.6634)	0.0028***(4.3245)
NONSOE			0.0038(1.5684)	0.0035(1.5467)
Constant	0.1532***(10.6452)	0.1604***(11.0435)	0.1664***(9.4514)	0.1457***(9.7655)
Control variable	Yes	Yes	Yes	Yes
YEAR/INDUS	Yes	Yes	Yes	Yes
N	7119	7119	7119	7119
Adj-R2	0.2629	0.2858	0.3768	0.2975

Source: Developed by the authors.

Note: ***, ** and * indicate that they are significant at the levels of 1%, 5% and 10%, respectively.

as RISK3 and RISK4. The re-measured corporate risk-taking level indicators are substituted into Model (1) and Model (2) for regression, and the results are shown in *Table 9.* It can be seen that DDT in Panel A of *Table 9* is significantly positively correlated with RISK3 and RISK4 at the 1% level, and the coefficients of the DDT×NONSOE items in Panel B are significantly positive at the 1% level. The above results show that after changing the measurement method of corporate risk-taking level, the research conclusions remain robust.

Path Analysis

In the theoretical analysis and research hypothesis part, this paper believes that digital transformation can improve investment efficiency, optimize internal control quality, and improve financial stability, thereby increasing the level of corporate risk-taking. Therefore, this paper adopts a mediation effect model to test the mediating role of investment efficiency, internal control quality, and financial stability in the relationship between digital transformation and corporate risk-taking, as follows:

Test of mediating effect based on investment efficiency

In order to test whether investment efficiency plays a mediating role in the relationship between digital transformation and corporate risk-taking, this paper constructs Model (3) and Model (4), as follows:

$$INVEFF = \beta_0 + \beta_1 DDT + \beta_2 SIZE + \beta_3 CASH + \beta_4 LEV + \beta_5 ROA + \beta_6 GROWTH + \beta_7 FIRST + \beta_8 AGE + \\ + \beta_9 BOARD + \beta_{10} RATIO + \beta_{11} DUAL + \beta_{12} LOSS + YEAR + INDUS + \in . \quad (3)$$

$$RISK = \beta_0 + \beta_1 DDT + \beta_2 INVEFF + \beta_3 SIZE + \beta_4 CASH + \beta_5 LEV + \beta_6 ROA + \beta_7 GROWTH + \\ + \beta_8 FIRST + \beta_9 AGE + \beta_{10} BOARD + \beta_{11} RATIO + \beta_{12} DUAL + \beta_{13} LOSS + YEAR + INDUS + \in . \quad (4)$$

Among them, INVEFF represents the investment efficiency of enterprises. This article refers to the practices of [8–12] and uses the absolute value of the residual in the investment efficiency model as a proxy variable for enterprise investment efficiency. The higher the absolute value, the lower the enterprise investment efficiency.

Table 10 reports the results of the mediation effect test based on investment efficiency. In Panel A, DDT and INVEFF are significantly negative at the 1% level, indicating that digital transformation can

Table 8
Digital transformation and enterprise risk-taking level: Changing the measurement method of digital transformation

Variable	Panel A: Digital Transformation and Risk-taking level		Panel B: Situational analysis of the nature of property rights	
	(1) RISK1	(2) RISK2	(3) RISK1	(4) RISK2
DCG	0.0005*(1.6325)	0.0011*(1.5872)	−0.0011***(−2.5454)	−0.0021***(−2.6587)
DCG×NONSOE			0.0031***(5.3646)	0.0054***(4.7236)
NONSOE			0.0035***(2.6472)	0.0057***(2.8132)
Constant	0.1944***(16.3335)	0.2812***(13.9548)	0.1762***(13.6569)	0.2463***(11.4515)
Control variable	Yes	Yes	Yes	Yes
YEAR/INDUS	Yes	Yes	Yes	Yes
N	13202	13202	13202	13202
Adj-R2	0.2484	0.2588	0.2755	0.2662

Source: Developed by the authors.

Note: *** and * indicate that they are significant at the levels of 1%, and 10%, respectively.

Table 9
Digital transformation and enterprise risk-taking level: Change the measurement method of enterprise risk-taking level

Variable	Panel A: Digital Transformation and Risk-taking level		Panel B: Situational analysis of the nature of property rights	
	(1) RISK3	(2) RISK4	_(3) RISK3	(4) RISK4
DDT	0.0022***(5.4513)	0.0022***(5.4956)	−0.0008**(−3.1784)	−0.0007*(−1.7258)
DDT×NONSOE			0.0035***(4.7257)	0.0019***(4.5472)
NONSOE			0.0024***(3.5114)	0.0026***(1.8539)
Constant	0.1725***(16.3372)	0.1627***(15.6125)	0.1541***(14.5924)	0.1547***(14.1713)
Control variable	Yes	Yes	Yes	Yes
YEAR/INDUS	Yes	Yes	Yes	Yes
N	13 202	13 202	13 202	13 202
Adj-R2	0.3746	0.1937	0.3765	0.2742

Source: Developed by the authors.

Note: ***, ** and * indicate that they are significant at the levels of 1%, 5% and 10%, respectively.

significantly improve the investment efficiency of enterprises. On the basis of model (1), the investment efficiency is further controlled, and the results are shown in column (3): DDT and RISK1 are significantly positive at the 1% level, and INVEFF and RISK1 are significantly negative at the 5% level; the results in Panel B are similar and will not be repeated. The above data show that investment efficiency plays a mediating role in the impact of digital transformation on the level of corporate risk-taking; that is, there is a mediation effect transmission path of "digital transformation-investment efficiency-enterprise risk-taking level". Therefore, digital transformation can improve the investment efficiency of enterprises, enhance the confidence of enterprises in venture capital, and thus improve the level of corporate risk-taking.

Test of the mediating effect based on internal control quality

In order to test whether internal control quality plays a mediating role in the relationship between digital transformation and corporate risk-taking level, this paper constructs Model (5) and Model (6), as follows:

$$IC = \beta_0 + \beta_1 DDT + \beta_2 SIZE + \beta_3 CASH + \beta_4 LEV + \beta_5 ROA + \beta_6 GROWTH + \beta_7 FIRST + \beta_8 AGE + \\ + \beta_9 BOARD + \beta_{10} RATIO + \beta_{11} DUAL + \beta_{12} LOSS + YEAR + INDUS + \in . \quad (5)$$

$$RISK = \beta_0 + \beta_1 DDT + \beta_2 IC + \beta_3 SIZE + \beta_4 CASH + \beta_5 LEV + \beta_6 ROA + \beta_7 GROWTH + \beta_8 FIRST + \\ + \beta_9 AGE + \beta_{10} BOARD + \beta_{11} RATIO + \beta_{12} DUAL + \beta_{13} LOSS + YEAR + INDUS + \in . \quad (6)$$

The article uses the Internal Control Quality Index (ICQI) to measure internal control quality, which is a key factor in determining an enterprise's internal governance level. The results of a mediation effect test show that digital transformation can significantly improve internal control quality, with DDT and IC showing significant positive results at the 1% level. This indicates that digital transformation can also enhance risk-taking levels in enterprises. The mediation effect transmission path is "digital transformation-internal control quality-enterprise risk-taking level". This suggests that digital transformation can enhance risk warning, prevention, and control capabilities, ultimately improving the risk-taking level of enterprises. The data suggests that digital transformation can play a mediating role in the impact of digital transformation on enterprise risk-taking levels.

Table 10
Digital transformation and enterprise risk-taking level: Intermediary effect test based on investment efficiency

Variable	**Panel A: RISK1**			**Panel B: RISK2**		
	(1) RISK1	(2) INVEFF	(3) RISK1	(4) RISK2	(5) INVEFF	(6) RISK2
DDT	0.0022*** (5.5634)	−0.0023* (−5.5367)	0.0021*** (5.5682)	0.0046*** (4.9558)	−0.0022* (−5.5684)	0.0028*** (4.4487)
INVEFF			−0.0265** (−2.3717)			−0.0578** (−3.3563)
Constant	0.1723*** (14.7244)	−0.0233*** (−5.1486)	0.1825*** (14.9348)	0.3824*** (14.8693)	−0.034* (−5.1255)	0.2765*** (12.7653)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
YEAR/ INDUS	Yes	Yes	Yes	Yes	Yes	Yes
N	13 191	13 191	13 191	13 191	13 191	13 191
Adj−R2	0.2674	0.3551	0.2677	0.2583	0.3552	0.2746

Source: Developed by the authors.
Note: ***, ** and * indicate that they are significant at the levels of 1%, 5% and 10%, respectively.

Table 11
Digital transformation and enterprise risk-taking level: Intermediary effect Inspection based on Internal control quality

Variable	Panel A: RISK1			Panel B: RISK2		
	(1) RISK1	(2) IC	(3) RISK1	(4) RISK2	(5) IC	(6) RISK2
DDT	0.0021*** (4.6951)	0.0064*** (6.1154)	0.0027*** (5.3651)	0.0027*** (5.7311)	0.0076*** (6.1174)	0.0044*** (3.2214)
IC			0.0333*** 6.8426)			0.0312*** (7.6553)
Constant	0.14782*** (13.3127)	0.4259*** (6.2352)	0.2417*** (13.4475)	0.2174*** (12.1556)	0.2456*** (7.2142)	0.1874*** (10.6755)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
YEAR/ INDUS	Yes	Yes	Yes	Yes	Yes	Yes
N	11 960	11 960	11 960	11 960	11 960	11 960
Adj-R2	0.2785	0.1357	0.2733	0.3752	0.2136	0.1817

Source: Developed by the authors.

Note: *** — indicate that they are significant at the levels of 1%.

Test of the mediating effect based on financial stability

In order to test whether financial stability plays a mediating role in the relationship between digital transformation and corporate risk-taking, this paper constructs Model (7) and Model (8), as follows:

$$Z-score=\beta_0+\beta_1 DDT+\beta_2 SIZE+\beta_3 CASH+\beta_4 LEV+\beta_5 ROA+\beta_6 GROWTH+\beta_7 FIRST+\beta_8 AGE+ \\ +\beta_9 BOARD+\beta_{10} RATIO+\beta_{11} DUAL+\beta_{12} LOSS+YEAR+INDUS+\in . \quad (7)$$

$$RISK=\beta_0+\beta_1 DDT+\beta_2 Zscore+\beta_3 SIZE+\beta_4 CASH+\beta_5 LEV+\beta_6 ROA+\beta_7 GROWTH+\beta_8 FIRST+ \\ +\beta_9 AGE+\beta_{10} BOARD+\beta_{11} RATIO+\beta_{12} DUAL+\beta_{13} LOSS+YEAR+INDUS+\in . \quad (8)$$

Among them, Z-score represents the financial stability of the enterprise. This article refers to the approach of [13] and uses Z-score to measure the financial stability of the enterprise. The higher the Z-score value, the lower the financial risk and the higher the financial stability.

Table 12 reports the results of the mediation effect test based on financial stability. The coefficients of DDT and Zscore in column (2) of Panel A are significantly positive at the 1% level, indicating that digital transformation can significantly improve the financial stability of enterprises. On the basis of model (1), the financial stability of enterprises is further controlled, and the results are shown in column (3): DDT and RISK1 are significantly positive at the 1% level, and Z-score and RISK1 are significantly positive at the 1% level; the results in Panel B are similar and will not be repeated. The above data show that financial stability plays a mediating role in the impact of digital transformation on the level of corporate risk-taking, that is, there is a mediation effect transmission path of «digital transformation-financial stability-enterprise risk-taking level». Therefore, digital transformation can improve financial stability and capital utilization efficiency, thereby improving the level of corporate risk-taking.

Expansion analysis

Digital transformation improves the internal environment such as internal control quality and financial stability, and enhances the willingness of enterprises to take risks by improving investment efficiency, thereby improving the level of corporate risk-taking. The economic consequences related to it deserve in-depth study. Risk, as the essence of business, is crucial to the operation and development of enterprises. Existing studies have found that the risk-taking activities undertaken by managers in pursuit of profit maximization are conducive to enhancing corporate value [15–16].

Table 12

Digital transformation and enterprise risk-taking level: An intermediary effect test based on financial stability

Variable	Panel A: RISK1			Panel B: RISK2		
	(1) RISK1	(2) Z_score	(3) RISK1	(4) RISK2	(5) Z_score	(6) RISK2
DDT	0.0034*** (5.7241)	0.2354*** (3.4566)	0.0034*** (5.7526)	0.0032*** (5.9736)	0.1242*** (3.1477)	0.0041*** (6.7962)
Z_score			0.0004*** (2.1358)			0.0003*** (1.8844)
Constant	0.1483*** (13.396)	25.4764*** (26.5138)	0.1224*** (14.6763)	0.2164*** (13.114)	25.2564*** (24.7258)	0.1877*** (12.5637)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
YEAR/ INDUS	Yes	Yes	Yes	Yes	Yes	Yes
N	12 848	12 848	12 848	12 848	12 848	12 848
Adj-R2	2816	0.5332	0.3624	0.471	0.3442	0.3734

Source: Developed by the authors.

Note: *** — indicate that they are significant at the levels of 1%.

The main reason is that a high level of risk-taking can increase managers' willingness to invest in projects with positive net present value but higher risks, fully tap and utilize favorable investment opportunities, promote the long-term development of enterprises, and promote corporate value creation. Therefore, this paper proposes the following hypothesis: Digital transformation enhances corporate value by increasing the level of corporate risk-taking.

In order to verify the above hypothesis, this paper uses TobinQ value to measure enterprise value and examines the mediating effect of digital transformation on improving enterprise value by increasing enterprise risk-taking level. The specific regression results are shown in *Table 13*. In the first column of Panel A, DDT and TobinQ are significantly positive at the 1% level, and in the second column, DDT and RISK1 are significantly positive at the 1% level, indicating that digital transformation can significantly improve the level of enterprise risk-taking. On the basis of model (1), digital transformation is further controlled, and the results are shown in column (3): RISK1 and TobinQ are significantly positive at the 1% level; the results in Panel B are similar and will not be repeated. The above data show that the level of enterprise risk-taking plays a mediating role in the impact of digital transformation on enterprise value, and digital transformation improves enterprise value by increasing the level of enterprise risk-taking.

Discussion

Considering the effect of digitization on risk-taking propensity among Japanese companies, this research has not given substantial discussion to the results; conclusions drawn here require further specification. This paper presents an empirical investigation of the impact of digital transformation on corporate risk-taking behavior by taking a sample of firms listed in Nikkei Index firms from 2010 to 2023. Digital Transformation Increases Risk-Taking: It was indicated that with an increased level of digital transformation, the corporations would engage in more and more risk-taking. Firms' ability to increase their willingness for riskier ventures rises with their enhanced digital capabilities. State-owned enterprises are less influenced in digital transformation for risk-taking, whereas the non-state-owned ones are impacted to a significant extent. This may be attributed to the fact that the latter focuses more on stability with low competitive pressure and thus has lower motivation to pursue the adoption of transformative technologies aggressively.

Mechanisms of digital transformation increase investment efficiency, improve the quality of internal control, and promote financial stability — the critical factors influencing risk-taking behavior within firms. Big data and advanced analytics can give a company a better notion of market demands and a better optimization of investment strategy, leading to its increased risk tolerance. Yet, while

Table 13
Digital transformation and enterprise value: Intermediary effect test based on risk-taking level

Variable	Panel A: RISK1			Panel B: RISK2		
	(1) Tobin	(2) RISK1	(3) TobinQ	(4) Tobin	(5) RISK2	(6) Tobin
DDT	0.0432*** (2.4355)	0.0020*** (5.1552)	0.0175*** (2.5743)	0.0462*** (3.4354)	0.0042*** (4.1122)	0.0379*** (2.9930)
RISK			2.7425*** (7.9925)			1.4426*** (8.6342)
Constant	10.3276*** (34.924)	0.1966*** (15.3873)	9.7663*** (30.6692)	10.4561*** (34.7841)	0.2716*** (14.8464)	11.5146*** (34.1516)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
YEAR/ INDUS	Yes	Yes	Yes	Yes	Yes	Yes
N	13 107	13 107	13 107	13 107	13 107	13 107
Adj-R2	0.2515	0.1545	0.2558	0.4513	0.3647	0.2564

Source: Developed by the authors.

Note: ***, ** and* indicate that they are significant at the levels of 1%, 5% and 10%, respectively.

the study gives good insights into the relationship between digital transformation and corporate risk-taking, it cautions that further discussion should be made on implications and recommendations at specific levels for businesses to leverage digital technologies for enhanced performances and risk management.

Conclusions and policy recommendations

Implementing digital transformation is a vital strategy for organizations to modernize and enhance their operations, and it plays a critical role in ensuring the long-term growth and success of these enterprises. Conceptually, the process of digital transformation will have an impact on the extent to which enterprises engage in risk-taking. This study utilizes the pertinent data of Japan's Nikkei Index businesses from 2010 to 2023 as the research sample to empirically examine the influence of digital transformation on the extent of enterprise risk-taking. The study findings indicate that digital transformation may significantly enhance the extent to which firms are willing to take risks.

Furthermore, digital transformation has a more pronounced impact on the risk-taking behavior of non-state-owned enterprises compared to state-owned enterprises. Despite conducting a number of sensitivity tests, including the instrumental variable approach, the propensity score matching method, and altering the measuring methods for digital transformation and corporate risk-taking, the study findings of this work remain consistent. Additional mechanism tests indicate that digital transformation mostly enhances company risk-taking by boosting investment efficiency, raising the quality of internal control, and bolstering financial stability. Furthermore, this study explores the economic implications of digital transformation on organizational risk-taking and concludes that digital transformation enhances company value by elevating the degree of risk-taking inside the organization. The objective of the study was to identify the consequences of digital transformation on risk-taking behavior at a firm level for Japanese firms. Increased digital transformation leads to a greater propensity of taking risks. Moreover, state-owned enterprises have less inclination towards digital transformation than the non-state-owned ones, which in turn are being significantly affected. Digital transformation improves internal control quality and investment efficiency, besides financial stability, which factors into risk-taking behavior. However, the implications and recommendations for businesses to utilize digital technologies to perform better and minimize risk require further discussion.

The study findings of this article are valuable for conducting a thorough analysis of the influence of digital transformation on the extent of corporate risk-taking. Additionally, they provide guidance to the government in promoting digital transformation and enhancing the degree of enterprise risk-taking. Based on the aforementioned study findings, this report proposes the following two recommendations. Firstly, it is crucial for organizations to prioritize digital transformation. Implementing digital transformation may promote resource allocation efficiency, optimize internal governance, improve financial stability, and ultimately increase the risk-taking capacity of organizations. Hence, it is imperative for organizations to capitalize on this growth prospect and use digital technologies such as big data, cloud computing, and the Internet of Things across all facets of their corporate operations. To enhance the enterprise's business development, it is necessary to establish a digital platform that creates a distinct digital ecosystem. This will enhance the enterprise's ability to integrate resources, minimize the costs associated with gathering information and acquiring resources, and improve the efficiency of resource allocation. Additionally, it will enhance the enterprise's ability to anticipate and prevent risks, thereby elevating its risk-taking capacity. Ultimately, this will establish a strong technological foundation for the enterprise's high-quality development. Furthermore, the government should provide diverse policy assistance for digital transformation based on the distinct characteristics of firms. Firstly, the government should actively encourage the adoption of digital transformation in state-owned enterprises. This can be achieved by raising awareness and setting an example for other enterprises to follow. Secondly, the government should provide stronger policy support for digital transformation in non-state-owned enterprises. This includes increasing subsidies and fostering confidence and determination among these enterprises. The ultimate goal is to facilitate the seamless integration of digital technology into enterprise development, enabling them to upgrade and achieve high-quality growth.

The study finds that with the increase in digital transformation efforts of the firms, the propensity of firms to risk-taking increases. This indicates that the organizations should strategically implement the digital technologies in order to enhance their risk appetite, particularly in highly competitive sectors. The management of risk should include developing frameworks that encourage innovation yet ensure oversight to mitigate any downsides. Non-SOEs have a better correlation between digital transformation and risk-taking compared to SOEs. Risk management for SOEs should aim to strike a balance in creating an environment that will support reasoned risk-taking but without threatening stability. It also shows the need to identify the inherent risks related to the digital transformation process, which include system failure or cybersecurity risks. Furthermore, investments in internal controls and efficiency lead to an enabling environment where resources are well utilized to make informed decisions. The findings provide valuable insights for policymakers in their pursuit of promoting digital transformation while managing the associated risks.

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Portfolio Management in International Syndicated Lending

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ABSTRACT

This article is **aimed** at presenting a wholesome approach to the management of a syndicated loan portfolio. **Methods** utilized include the following: (*i*) *portfolio analysis* — calculating the parameters of a syndicated loan portfolio (main, liquidity, diversification, and commercial parameters); (*ii*) *measuring completion of the Key Performance Indicators (KPIs)* — comparing the actual values of the parameters of the syndicated loan portfolio to the target values of the KPIs and making the required managerial decisions; (*iii*) *portfolio management* — using the various syndicated loan market techniques with which a portfolio can be managed to achieve the completion of the KPIs (actively, passively, and via restructurings). Active syndicated loan portfolio management includes the execution of transactions in both primary and secondary syndicated loan markets. Cases of passive syndicated loans management relate to repayments of the syndicated loans in the portfolio: voluntary full or partial repayments based on the decisions of the borrowers; mandatory repayments when the borrowers have to fully or partially repay the syndicated loans based on the decisions of the lenders; scheduled repayment in accordance with the repayment schedules of the syndicated loans. The portfolio can also be affected by restructurings, when the lenders agree to change a number of major terms and conditions of the syndicated loans due to the circumstances of the borrowers. In order to assess the **results** of the syndicated loan portfolio management, a managerial dashboard is built, an important accounting tool allowing for decision-making based on the comparison of the actual values of the parameters of the syndicated loan portfolio to the target values of the KPIs. An important issue in syndicated loan portfolio management is the monitoring of compliance of the borrowers with financial covenants: (*i*) the ratio of the Net Debt to EBITDA (earnings before interest, taxes, depreciation and amortization); (*ii*) the ratio of Net Interest Payments to EBITDA. In cases when the financial covenants or other terms and conditions of syndicated loans are violated, the borrowers can request the lenders with either waiver requests (for "one-off" issues) or amendment requests (for permanent changes). The process of handling waiver and amendment requests, including the involved parties, documents and timelines is reviewed. The **main conclusion** involves combining of syndicated loan portfolio management results, financial covenant monitoring, and working on waiver and amendment requests in order to create the executive report, as well as the formalization of the general scheme for managing a portfolio of syndicated loans.

Keywords: syndicated loans; portfolio management; investment banking; international capital markets; key performance indicators; managerial accounting; financial covenants

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Портфельный менеджмент в международном синдицированном кредитовании

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АННОТАЦИЯ

Целью данного исследования является разработка и представление целостного подхода к управлению портфелем синдицированных кредитов. **Методы:** (*i*) *портфельный анализ* — расчет параметров портфеля синдицированных кредитов (основные параметры, параметры ликвидности и диверсификации, коммерческие параметры); (*ii*) *измерение достижения ключевых показателей эффективности («КПЭ»)* — сравнение текущих параметров портфеля синдицированных кредитов с целевыми КПЭ для принятия управленческих решений; (*iii*) *управление портфелем* — использование инструментария рынка синдицированного кредитования для достижения КПЭ (активные и пассивные инструменты, реструктуризация). К активным инструментам рынка относятся сделки на первичном и вторичном рынках синдицированного кредитования. Пассивные инструменты включают случаи полного или частичного погашения задолженности по синдицированным кредитам: добровольное погашение по решению заемщика; обязательное погашение по решению кредиторов; плановое погашение в соответствии с графиком амортизации синдицированного кредита. На портфель также оказывают влияние реструктуризации входящих в него кредитов, когда с согласия кредиторов меняются основные условия сделки. **Результаты** исследования заключаются в построении управленческого дашборда (визуальной информационной панели), важного инструмента управленческого учета для оценки текущего состояния портфеля и принятия соответствующих решений для достижения КПЭ. Также в статье рассматриваются вопросы мониторинга выполнения финансовых ковенант по входящим в портфель синдицированным кредитам: (*i*) отношение чистого долга к показателю EBITD (аналитический показатель, равный объему прибыли до вычета расходов по выплате процентов, налогов, износа и начисленной амортизации); (*ii*) отношение чистых процентных платежей к показателю EBITDA. При нарушении пороговых значений финансовых ковенант или других условий синдицированного кредита заемщики обращаются к кредиторам с запросами либо на разовое согласие с данными нарушениями (*waiver requests*), либо на постоянное изменение соответствующих условий сделки (*amendment requests*). В статье описаны процессы работы над данными запросами, а также роли и функции вовлеченных сторон. В **заключение** представлены итоговый отчет по портфелю синдицированных кредитов, который интегрирует результаты анализа и управления портфелем, мониторинга финансовых ковенант и работы над запросами заемщика, а также общая схема портфельного менеджмента в синдицированном кредитовании.

Ключевые слова: синдицированные кредиты; портфельный менеджмент; инвестиционная деятельность банков; международные рынки капитала; ключевые показатели эффективности; управленческий учет; финансовые ковенанты

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Introduction

This article continues a series of papers by the author dedicated to the syndicated loan market (Tarasov [1–3]). A syndicated loan is provided to the borrower by a syndicate of benders. It is structured and arranged by a number of coordinating banks and is syndicated in the *primary* loan market to financial institutions, which include commercial and investment banks as well as institutional investors. lenders can also trade participation in the *secondary* syndicated loan, sharing the risks and rewards of syndicated loans among a wide investor base, including asset managers, hedge funds and insurance companies. The set of legal documents for syndicated loan transactions are prepared by reputable legal firms based on templates developed by market associations (such as the Loan Market Association and the Loan Syndications and Trading Association[1]). The main document of a syndicated loan is the facility agreement, which includes all terms and conditions of the transaction. The flows of funds and information between the borrower and lenders are channeled via the facility agent (a bank that executes its duties in accordance with the facility agreement.

The aim of this article is to develop a framework for banks and investors to work with a portfolio of syndicated loans. The objectives include the development of methods for: (*i*) analyzing the portfolio (by calculating the parameters of the portfolio and building a managerial dashboard where these parameters are compared to the Key Performance Indicators ("KPIs"); (*ii*) managing the portfolio (by executing transactions in the primary and secondary syndicated loan markets, dealing with repayments and restructurings); (*iii*) monitoring the portfolio (by calculating the financial covenants and working on waiver and amendment requests).

The article is arranged in three sections. In Section 1, we present a framework for analyzing

[1] For additional information regarding the LMA and the LSTA, please refer to: lma.eu.com, lsta.org.

a portfolio of syndicated loans, including the calculation of key parameters to build a managerial dashboard. In Section 2, we consider the various techniques of managing a portfolio: active, passive, and via restructurings. Active management includes the execution of transactions in both the primary and secondary syndicated loan markets. Cases of passive management relate to prepayments: voluntary prepayments based on the decisions of the borrowers and mandatory prepayments when the borrowers have to prepay the loans based on the decisions of the lenders, both scenarios being described in the relevant clauses of the facility agreements. The portfolio can also be affected by restructurings, when the lenders agree to change a number of major terms and conditions due to the circumstances of the borrower. Following these activities, the "new" portfolio can be analyzed at the end of the reporting period. In Section 3, we present an algorithm for monitoring a syndicated loan portfolio based on compliance with the financial covenants; this is done for each loan as per the process set out in each facility agreement, as well as for the portfolio as a whole. In conclusion, we combine portfolio management results and financial covenant monitoring to create the portfolio report, as well as the formalization of the general scheme for managing a portfolio of syndicated loans.

Literature overview

There are a number of major treatments of the global syndicated loan market: Dennis, Mullineaux [4], Fight [5], Altunbas et al. [6], Shutter [7], Shaiman, Marsh [8]. Since the syndicated loan market is a part of the broader capital markets, it is also considered in more general studies, including those relating to debt and structured finance (Altunbas et al. [9], Rhodes [10], Caselli, Gatti [11]), leveraged markets (Maxwell, Shenkman [12], Strumeyer, Swammy [13]), and investment banking (Davis [14], Iannotta [15], Liaw [16], Stowell [17]). Due to the importance of legal aspects, we must note the following specialized works: Ellinger et al. [18], Ryan [19], Wright [20], Bellucci, McCluskey [21], Campbell, Weaver [22]. Special attention should be granted to the books of the Loan Market Association ("LMA") that duly reflect the current topics of fundamental importance to the syndicated loan market Slocombe, Voisey [23–26]. The various issues relating to the management of a loan portfolio have been the subject of research by Amenc, Le Sourd [27], Gregoriou, Hoppe [28], Marston [29], Francis, Kim [30]. The latest impacts on the syndicated loan market of the COVID-19 pandemic and the trends dominating the market are assessed in Hasan [31] and Saharti [32].

The Russian syndicated loan market in recent years can be characterized as being in the phase of developing the local infrastructure and instruments [3]. It can be said that some of the most notable market events were related to legislation. The Federal Law dated 31.12.2017 "On Syndicated Credit (Loan)..."[2] has provided an important impetus for the Russian loan market, including defining loan market terms and streamlining legal processes, expanding the availability of funding for borrowers, providing for the participation in the market of institutional investors. The Federal Law dated 22.12.2020 "On amendments..."[3] changed and further expanded this law by covering such important issues as funded sub-participation deals, optimization of procedures relating to loan security, and the actions of the lenders and the facility agent in cases involving syndicated loans in bankruptcy proceedings. An important feature of the market is the availability of Russian-law documentation templates developed by the Association of Banks of Russia[4] ("ABR"). These documents are used for "local" deals, mainly bridge loans and project finance facilities, denominated in RUB and provided by Russian banks and development institutions. The methods presented in this article for working with the syndicated loan portfolio will have an important application with the Russian syndicated loan market having further developed, and lenders and investors will be focused not only

[2] Federal Law dated 31.12.2017 No. 486-FZ "On Syndicated Credit (Loan) and Amendments to the Legislative Acts of the Russian Federation".

[3] Federal Law dated 22.12.2020 No. 447-FZ "On Amendments to the Federal Law "On Syndicated Credit (Loan) and Amendments to the Legislative Acts of the Russian Federation" and to Certain Legislative Acts of the Russian Federation".

[4] The English language website of the Association of Banks of Russia can be found following the link: https://asros.ru/en/. The documentation for the syndicated loan market is developed by the Committee for Investment Banking Products (link to Russian language website is: https://asros.ru/committee/iproduct/).

Table 1
The syndicated loan portfolio, beginning of the reporting period

SL	Currency, USD exchange rate	Amount in SL currency, mln	Amount in USD mln	Base rate	Margin, % per annum (p.a.)	Tenor, years	Market price, % of notional	Credit rating of the Borrower	Industry of the Borrower
SL No. 1	USD	50.00	50.00	SOFR	3.50	1.20	97.50	BBB	Transport
SL No. 2	EUR, 0.90	60.75	67.50	EURIBOR	4.25	0.90	92.00	BB+	Manufacturing
SL No. 3	GPB, 0.75	56.25	75.00	SONIA	2.50	0.50	95.00	BB-	Trading
SL No. 4	USD	125.00	125.00	SOFR	3.75	3.50	99.00	BB	Chemicals
SL No. 5	EUR, 0.90	121.50	135.00	EURIBOR	2.75	2.30	100.00	BBB-	Metals and mining

Source: Author-generated data for illustrative purposes.

on the primary market (which will demonstrate sufficient deal volumes), but also on the secondary market and the efficiency of managing their syndicated loan portfolios.

Analyzing the syndicated loan portfolio

The syndicated loan portfolio that will be considered in this section is presented in *Table 1*. To note, this is a hypothetical portfolio that will only be used as an example. It is a "global" portfolio composed of syndicated loans governed by international law from the international capital markets, denominated in international currencies: US Dollars ("USD"), Euros ("EUR"), Pound Sterling ("GBP"). The reporting period can be set to equal a month, a quarter, or a year.

We can calculate the following parameters of the syndicated loan portfolio:

- *The main parameters* include the total nominal volume of the portfolio and the total market value of the portfolio.
- *Liquidity parameters* include the weighted average of the tenors of the loans in the portfolio (i.e., the synthetic tenor of the portfolio itself) and the breakdown of the loans in the portfolio into the following three term groups: (*i*) short-term loans (with a tenor of less than 1 year); (*ii*) medium-term loans (with a tenor between 1 year and 3 years); (*iii*) long-term loans (with a tenor of more than 3 years).
- *Diversification parameters* include the breakdown of the loans in the portfolio based on the following criteria: (*i*) industry of the borrowers; (*ii*) credit rating of the borrowers.
- *Commercial parameters* include the weighted average margin of the loans in the portfolio (i.e., the synthetic margin of the portfolio itself) and the weighted average market price of the loans in the portfolio (i.e., the synthetic market price of the portfolio itself).

The above parameters can be incorporated into a managerial dashboard that will compare the current values of the parameters to "KPIs" that have been set for the portfolio. A managerial dashboard for the portfolio at the beginning of the reporting period from *Table 1* is presented in *Table 2*.

The following conclusions can be made by the portfolio manager based on the analysis of the managerial dashboard:

- *Main parameters:* the actual total nominal volume of the portfolio and the total market value of the portfolio are less than the target KPIs by USD 77.50 mln and USD 84.15 mln.
- *Liquidity parameters:* the synthetic tenor of the portfolio is 0.3 years less than required; the share of short-term and long-terms exceeds the target share by 6.49% and 7.62% at the expense of medium-term loans (−14.12%).
- *Diversification parameters:* the share of borrowers from three industries exceeds the target (metals and mining, +4.83%; chemicals, 7.62%; trading, 6.57%); the share of borrowers from manufacturing (−15.08%) and transport (−3.95%) is less than required; the share of borrowers with non-investment grade rating is exceeded (+14.12%).
- *Commercial parameters:* the synthetic margin of the portfolio and the synthetic market price of the portfolio are less than the

Table 2
Managerial dashboard of the syndicated loan portfolio, beginning of the reporting period

Parameter	KPI value	Actual value	Difference	Parameter	KPI value	Actual value	Difference
Main parameters				Liquidity parameters			
Total nominal volume, USD mln	530.00	452.50	−77.50	Tenor of the portfolio, years	2.30	2.00	−0.30
Total market value, USD mln	525.00	440.85	−84.15	Breakdown of SLs by tenor (short-, medium-, long-term), %	25.00 55.00 20.00	31.49 40.88 27.6	+6.49 −14.12 +7.62
Diversification parameters				Commercial parameters			
Breakdown of SLs by industry of the Borrowers (manufacturing, metals and mining, chemicals, transport, trading), %	30.00 25.00 20.00 15.00 10.00	14.92 29.83 27.62 11.05 16.57	−15.08 +4.83 +7.62 −3.95 +6.57	Margin of the portfolio, % p.a.	3.75	3.29	−0.46
Breakdown of SLs by credit rating of the Borrowers (investment, non-investment grade), %	55.00 45.00	40.88 59.12	−14.12 14.12	Market price of the portfolio, % of notional	99.00	97.43	−1.57

Source: Author-generated data for illustrative purposes.

target KPIs by 0.46% per annum (p.a.) and 1.57% p.a.

From this analysis, it can be concluded that the following actions are required to be executed regarding the portfolio: (i) increasing both the total nominal volume and total market value of the portfolio; (ii) increasing the synthetic tenor of the portfolio and the share of medium-term loans; (iii) increasing the share of Borrowers from the manufacturing and transport industries, as well as the share of Borrowers with an investment-grade rating; (iv) increasing the synthetic margin of the portfolio and the synthetic market price of the portfolio. In order to achieve these aims, we will consider in the next section the following methods of managing the syndicated loan portfolio: active, passive, and restructurings.

Methods of managing the syndicated loan portfolio

Banks and investors in the syndicated loan market utilize a number of methods for managing the syndicated loan portfolio. These can be classified as active, passive, and restructurings. Active portfolio management methods include the execution of transactions in the primary and secondary syndicated loan markets. The result is the addition of new syndicated loans to the portfolio from both primary and secondary markets, as well as the sale of deals from the portfolio (fully or partially) in the secondary market.

We assume that in the current reporting period, three such transactions have been executed by the portfolio manager:

Table 3
Terms and conditions of syndicated loans No. 6 and No. 7

SL	Currency, USD exchange rate	Amount in SL currency, mln	Amount in USD mln	Base rate,% p.a.	Margin, % p.a.	Tenor, years	Market price, % of notional	Credit rating of the Borrower	Industry of the Borrower
SL No. 6	USD	180.00	180.00	SOFR	4.00	2.95	100.00	BBB	Manufacturing
SL No. 7	EUR, 0,90	40.50	45.00	EURIBOR	4.50	0.80	96.00	BB+	Transport

Source: Author-generated data for illustrative purposes.

• *Transaction 1:* participating in syndicated loan deal No. 6 (primary market).

• *Transaction 2:* buying the participation in syndicated loan deal No. 7 (secondary market).

The terms and conditions of these transactions are presented in *Table 3*.

• *Transaction 3:* selling the full amount of USD 50 mln in syndicated loan deal No. 1 (secondary market).

Passive portfolio management techniques relate to prepayments: voluntary prepayments based on the decisions of the borrowers and mandatory prepayments based on the decisions of the lenders, both scenarios being described in the relevant clauses of the facility agreements for each syndicated loan. It should also be noted that during the reporting period the scheduled repayments of syndicated loans as per the repayment schedule of the facility agreements occur.

We assume that in the current reporting period, three such events have taken place:

• *Repayment 1:* full mandatory prepayment in the amount of EUR 75.00 mln of syndicated loan No. 2 (based on the decision of the lenders).

• *Repayment 2:* partial voluntary prepayment in the amount of USD 25.00 mln of syndicated loan No. 4 (based on the decision of the lenders).

• *Repayment 3:* scheduled repayment in the amount of EUR 2.00 mln of syndicated loan No. 5 (based on the repayment schedule of the facility agreement).

Another event that can affect the portfolio is restructurings, when the lenders agree to change a number of major terms and conditions of the syndicated loans (according to the procedure set out in the relevant facility agreement).

We assume that in the current reporting period, the following restructuring has taken place:

• *Restructuring:* based on the decision of the lenders the terms and conditions of syndicated loan No. 3 have been restructured as set-out in *Table 4*.

Results of managing the syndicated loan portfolio

As a result of applying the above methods of portfolio management, at the end of the reporting period, the new syndicated loan portfolio has the composition presented in *Table 5*.

The portfolio of syndicated loans can also be analyzed between two time periods. In the considered case, we can calculate the changes in the parameters of the portfolio between the beginning of the reporting period and the end of the reporting period (*Table 6*).

As follows from the above table, the major changes in the syndicated loan portfolio during the reporting period that occurred were the following:

• *Main parameters:* increases in both total nominal volume and total market value of the portfolio (by USD 82.50 mln and USD 87.45 mln).

• *Liquidity parameters:* increase of the synthetic tenor of the portfolio by 0.31 years and increase of the share of medium-term loans (by 13.79%) at the expense of short- and long-term loans (−4.86% and −8.93%).

• *Diversification parameters:* significant increase in the share of borrowers from the manufacturing industry (+18.73%) and a mild increase in the share of borrowers from the transport industry (+5.77%), with decreases for the metals and mining (−8.81%), chemicals (−8.93%) and trading (−6.76%) industries; the share of borrowers with investment grade ratings increased by 13.79%.

Table 4

Terms and conditions of the restructuring of syndicated loan No. 3

SL	Currency	Amount in SL currency, mln	Amount in USD mln	Base rate	Margin, % p.a.	Tenor, years	Market price, % of notional	Credit rating of the Borrower	Industry of the Borrower
SL No. 3	GPB, 0.75	56.25	75.00	SONIA	2.50	0.50	95.00	BB-	Trading
Restructured SL No. 3		39.38	52.50		2.75	0.90	96.00	BB	

Source: Author-generated data for illustrative purposes.

Table 5

The new syndicated loan portfolio, end of the reporting period

SL	Currency	Amount in SL currency, mln	Amount in USD mln	Base rate	Margin, % p.a.	Tenor, years	Market price, % of notional	Credit rating of the Borrower	Industry of the Borrower
Restructured SL No. 3	GPB, 0.75	39.38	52.50	SONIA	2.75	0.90	96.00	BB	Trading
SL No. 4	USD	100.00	100.00	SOFR	3.75	3.40	99.00	BBB	Chemicals
SL No. 5	EUR, 0.90	101.25	112.50	EURIBOR	2.75	2.20	100.00	BBB-	Metals and mining
SL No. 6	USD	180.00	180.00	SOFR	4.00	2.95	100.00	BBB	Manufacturing
SL No. 7	EUR, 0.75	81.00	90.00	EURIBOR	4.5	0.80	96.00	BB+	Transport

Source: Author-generated data for illustrative purposes.

• *Commercial parameters:* increases in both the synthetic margin of the portfolio and the synthetic market price of the portfolio (by 0.36% p.a. and 1.32% p.a.).

Discussion of the results of portfolio management

The portfolio manager can now build the managerial dashboard for the new portfolio at the end of the reporting period based on *Table 5*. The updated managerial dashboard is presented in *Table 7*.

The following conclusions can be made based on the analysis of the updated managerial dashboard:

• *Main parameters:* the actual total nominal volume of the portfolio and the total market value of the portfolio now close to the target KPIs (exceeding by only USD 5.00 mln and USD 3.30 mln).

• *Liquidity parameters:* the synthetic tenor of the portfolio matches the required KPI; the breakdown of short-, medium- and long-terms closely follows the target (with a difference of less than 2.00%).

• *Diversification parameters:* the share of borrowers from all five industries is close to the KPI levels, with no significant mismatches; the share of borrowers with non-investment and investment grade ratings is very close to target (with a difference of less than 0.50%).

• *Commercial parameters:* the synthetic margin of the portfolio and the synthetic market price of the portfolio are less than the target KPIs, but only by 0.10% p.a. and 0.25% p.a. (both amounts being less than the differences at the beginning of the reporting period).

From this analysis, it can be concluded that at the end of the reporting period, the syndicated loan portfolio is demonstrating improved KPIs.

Table 6

Comparison of the parameters of the syndicated loan portfolio, beginning and end of the reporting period

Parameter	Actual value, beginning of reporting period	Actual value, end of reporting period	Difference	Parameter	Actual value at beginning of reporting period	Actual value at end of reporting period	Difference
Main parameters				**Liquidity parameters**			
Total nominal volume, USD mln	452.50	535.00	+82.50	Tenor of the portfolio, years	2.00	2.31	+0.31
Total market value, USD mln	440.85	528.30	+87.45	Breakdown of SLs by tenor (short-, medium-, long-term), %	31.49 40.88 27.62	26.64 54.67 18.69	−4.86 +13.79 −8.93
Diversification parameters				**Commercial parameters**			
Breakdown of SLs by industry of the Borrowers (manufacturing, metals and mining, chemicals, transport, trading), %	14.92 29.83 27.62 11.05 16.57	33.64 21.03 18.69 16.82 9.81	+18.73 −8.81 −8.93 +5.77 −6.76	Margin of the portfolio, % p.a.	3.29	3.65	+0.36
Breakdown of SLs by credit rating of the Borrowers (investment, non-investment grade), %	40.88 59.12	54.67 45.33	+13.79 −13.79	Market price of the portfolio,% of notional	97.43	98.75	+1.32

Source: Author-generated data for illustrative purposes.

Monitoring the syndicated loan portfolio

One of the major structural parameters of syndicated loans are financial covenants. Financial covenants are set out in the facility agreement of the syndicated loan, including the threshold levels and the mechanics of calculation for each covenant. During the tenor of the syndicated loan, the borrowers send to the lenders at the end of each reporting period the compliance certificate. This document includes all the relevant details regarding the calculations of the financial covenants and their compliance with the required levels.

The two main covenants used in syndicated loans facility agreement are the following:

Net Debt/EBITDA (earnings before interest, taxes, depreciation and amortization): the ratio of the borrower's net debt as of the end of the reporting period (calculated as total debt minus cash and cash equivalents) to the borrower's EBITDA on a rolling 12-month basis ending with the current reporting period. This covenant reflects the indebtedness of the borrower relative to its cash flow and is a key credit metric for lenders in the syndicated loan market.

Net Interest Expenses/EBITDA: the ratio of the borrower's net interest payments (calculated as interest paid minus interest received) to the

Table 7
Updated Managerial Dashboard of the new syndicated loan portfolio, end of the reporting period

Parameter	KPI value	Actual value	Difference	Parameter	KPI value	Actual value	Difference
Main parameters				**Liquidity parameters**			
Total nominal volume, USD mln	530.00	535.00	+5.00	Tenor of the portfolio, years	2.30	2.31	+0.01
Total market value, USD mln	525.00	528.30	+3.30	Breakdown of SLs by tenor (short-, medium-, long-term), %	25.00% 55.00% 20.00%	26.64% 54.67% 18.69%	1.64% −0.33% −1.31%
Diversification parameters				**Commercial parameters**			
Breakdown of SLs by industry of the Borrowers (manufacturing, metals and mining, chemicals, transport, trading), %	30.00 25.00 20.00 15.00 10.00	33.64 21.03 18.69 16.82 9.81	+3.64 −3.97 −1.31 +1.82 −0.19	Margin of the portfolio, % p.a.	3.75	3.65	−0.10
Breakdown of SLs by credit rating of the Borrowers (investment, non-investment grade), %	55.00 45.00	54.67 45.33	−0.33 +0.33	Market price of the portfolio, % of notional	99.00	98.75	−0.25

Source: Author-generated data for illustrative purposes.

borrower's EBITDA, both values calculated on a rolling 12-month basis ending with the current reporting period. This covenant reflects the debt service capacity of the borrower relative to its cash flow.

Consolidating the data from the compliance certificates for each syndicated loan in the portfolio, the compliance with financial covenants for the syndicated loan portfolio can be analyzed (*Table 8*).

As follows from the table above, all borrowers are in full compliance with the financial covenants. Therefore, the syndicated loan portfolio as a whole is also in full compliance. We can also calculate the synthetic financial covenants headroom for the portfolio as the weighted average of the headrooms for each loan: (*i*) the Net Debt/EBITDA headroom is 0.20x; (*ii*) the Net Interest Expenses/EBITDA headroom is 0.12x.

The facility agreement for each syndicated loan includes a number of clauses the violation of which require the obtaining of waivers from the lenders. The procedure of working on waiver requests is set out in detail in the facility agreement. This process involves the facility agent, the borrower, and the lenders. To note, cases of waivers deal with one-off violations of the facility agreement clauses.

As an example, we will assume that during the reporting period the borrower under Syndicated Loan No. 4 has violated the clause in the facility agreement that refers to restrictions on Mergers and Acquisitions (M&A). This clause is formulated as follows: "*Restriction on M&A transactions:* the total value of M&A transactions during the reporting period shall not exceed 10% of the borrower's total assets". The borrower under Syndicated Loan No. 4 has informed the facility agent that during the reporting period the total value of executed M&A transactions has totaled 12% of the borrower's total assets. The borrower then sends to the facility agent for further distribu-

Table 8
Financial covenants compliance of the new syndicated loan portfolio, end of the reporting period

SL	Financial covenant	Threshold value per Facility Agreement	Actual value	Headroom
Restructured SL No. 3	Net Debt / EBITDA	⩽ 2.75x	2.52x	+0.23x
	Net Interest Expenses / EBITDA	⩽ 0.40x	0.32x	+0.08x
SL No. 4	Net Debt / EBITDA	⩽ 4.00x	3.75x	+0.25x
	Net Interest Expenses / EBITDA	⩽ 0.80x	0.64x	+0.16x
SL No. 5	Net Debt / EBITDA	⩽ 3.25x	3.10x	+0.15x
	Net Interest Expenses / EBITDA	⩽ 0.75x	0.58x	+0.17x
SL No. 6	Net Debt / EBITDA	⩽ 3.00x	2.80x	+0.20x
	Net Interest Expenses / EBITDA	⩽ 0.45x	0.36x	+0.09x
SL No. 7	Net Debt / EBITDA	⩽ 3.50x	3.35x	+0.15x
	Net Interest Expenses / EBITDA	⩽ 0.50x	0.42x	+0.08x

Source: Author-generated data for illustrative purposes.

tion to the lenders a waiver request, describing the details of the executed M&A transactions and asking the lenders to waive the violation of the relevant covenant of the facility agreement. together with the waiver request, the borrower also prepares for the lenders a package of supplementary materials, including the Information Memorandum with the details of the M&A transactions and the updated financial model of the borrower with the impact of these transactions.

Following receipt of the waiver request, the facility agent checks that is in compliance with the template set out in the faculty agreement and then sends it to the lenders. The waiver request includes the timeframe for the lenders to provide their response (usually, 1–2 months) and the fee that the lenders will receive for agreeing to the request (usually includes an "early-bird" fee). After receiving the request, each lender launches the approval processes and obtains the decision of the credit committee. The lender then informs the facility agent of the decision. For the waiver to be granted, usually a positive response from Lenders with total participation amounts of more than 66.6% of the total syndicated loan amount is required. If this threshold is reached, the facility agent informs the borrower that the waiver request has been granted. If this threshold if not obtained, then the waiver request is not granted, and the borrower will be in a situation of technical default (leading either to a mandatary repayment of the syndicated loan or to a restructuring). The process of handling waiver requests is presented in *Fig. 1*.

The difference between amendment and waiver requests is that in cases of the former the relevant

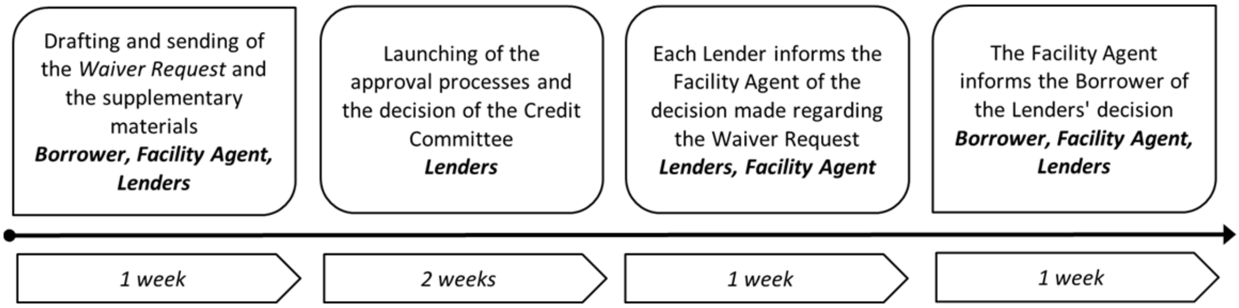

Fig. 1. **The process of handling waiver requests for syndicated loans**

Source: Prepared by the author.

Table 9

Comparison of the waiver and amendment requests of syndicated loans

Parameters	Waiver Request	Amendment Request
Legal nature	Request of the Borrower to the Lenders asking for a one-off agreement to a violation of one or a number of clauses of the Facility Agreement	Request of the Borrower to the Lenders asking for an agreement to permanently alter one or a number of clauses of the Facility Agreement
Facility Agreement clauses impacted	General covenants, Financial covenants, Information Covenants	General covenants, Financial covenants, Information Covenants, Facility Amount, Interest Rate, Facility Tenor, Repayment Schedule
Documents overview	The Waiver Request, package of supplementary materials (including the Information Memorandum and the updated Financial Model of the Borrower)	The Amendment Request, package of supplementary materials (including the Information Memorandum and the updated Financial Model of the Borrower), the Amendment Agreement, the Re-stated Facility Agreement
Involved parties	Borrower, Lenders, Facility Agent	Borrower, Lenders, Facility Agent, Legal Counsel
Fees payable	Waiver fee payable by the Borrower to the Lenders (including early bird fee)	Amendment fee payable by the Borrower to the Lenders. Legal fee payable by the Borrower to the Legal Counsel.
Time-frame for considering the request	1–2 months	3–4 months (depending on the complexity of the request)

Source: Prepared by the author.

clause (or clauses) of the facility agreement have to be changed (thereby representing not a one-off acceptance by the lenders of a covenant violation, but a new covenant threshold until the maturity of the syndicated loan). The procedure of working on amendment requests is set out in detail in the facility agreement. This process is more complex than for waiver requests since it also requires the work of the legal counsel, in addition to the facility agent, the borrower, and the lenders. The comparison of waiver and amendment requests for syndicated loans is presented in *Table 9*.

As an example of an amendment request, we will assume that during the reporting period the borrower under syndicated loan No. 5 has not only violated the clause in the facility agreement that refers to the restriction on total financial indebtedness (TFI). This clause is formulated as follows: "*Restriction on TFI level:* the level of TFI at the end of each reporting period shall not exceed

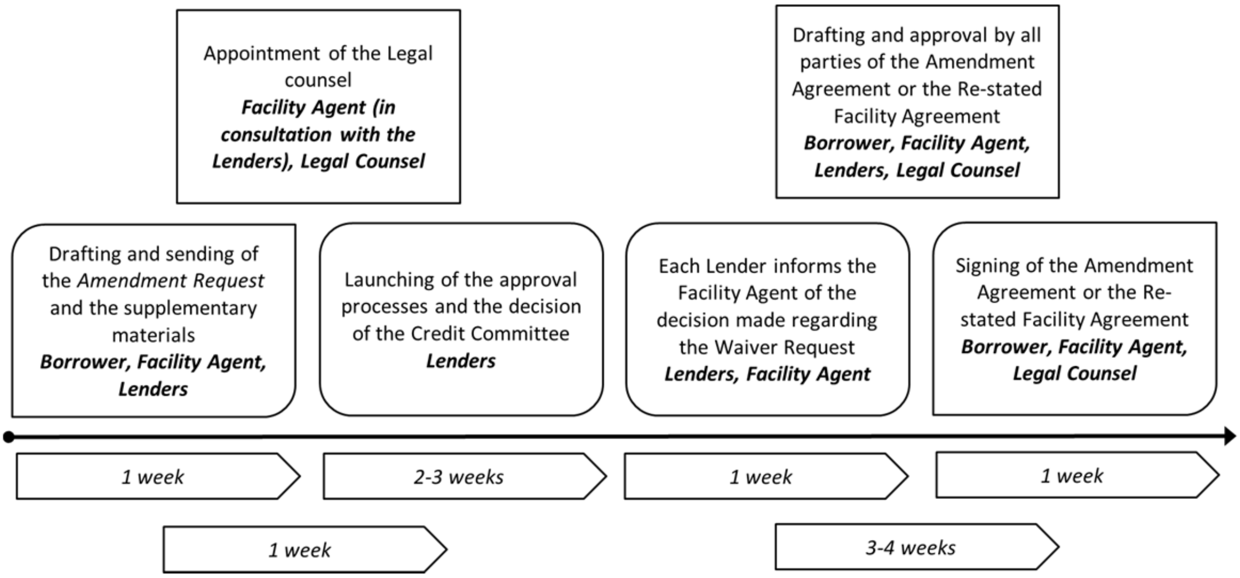

Fig. 2. **The process of working on amendment requests for syndicated loans**

Source: Prepared by the author.

25% of the borrower's total assets". The borrower under Syndicated Loan No. 5 has informed the facility agent that as of the end of the reporting period the level of TFI has totaled 32% of the borrower's total assets and will exceed the level of 25% of total assets until the final maturity of the syndicated loan. The borrower then sends to the facility agent for further distribution to the lenders an amendment request, describing the details of the TFI and asking the Lenders to agree to an amendment of the clause in the facility agreement to state: "*Restriction on TFI level:* the level of TFI at the end of each reporting period shall not exceed 35% of the borrower's total assets". The borrower also prepares for the lenders a package of supplementary materials, including the details of the TFI and the updated financial model. Following receipt of the amendment request, the facility agent checks that is in compliance with the template set out in the faculty agreement and then sends it to the lenders. The amendment request includes the timeframe for the lenders to provide their response (usually, 2–3 months) and the fee that the lenders will receive for agreeing to the request (higher than for waiver requests). For the amendment of the facility agreement and the preparation of the legal opinion regarding the amendment, the lenders will appoint a legal counsel. After receiving the request, each lender launches the approval processes and obtains the decision of the credit committee. The lender then informs the facility agent of the decision. For the amendment to be agreed, usually a positive response from lenders with total participation amounts of more than 66.6% of the total syndicated loan amount is required. If this threshold is reached, the facility agent informs the borrower that the amendment request has been granted. In this case the legal counsel prepares either an amendment agreement (regarding the changes to the amended clauses of the facility agreement) or a re-stated facility agreement (when the number of amended clauses is significant. If the required approval threshold if not obtained, then the amendment request is not granted, and the borrower will be in a situation of a technical default (leading either to a mandatary repayment of the syndicated loan or to a restructuring). The process of working on amendment requests is presented in *Fig. 2.*

Conclusion

Integrating all of the data regarding the syndicated loan portfolio during the reporting period, including the results of Transactions 1–3, Repayment events 1–3, the Restructuring event, as well as the results of *Tables 6–8,* at the end of each reporting period the portfolio manager prepares executive report (presented in *Table 10*).

In *Fig. 3* the general scheme for managing a portfolio of syndicated loans is presented.

We have considered three major aspects of managing a portfolio of syndicated loans. Firstly, it is the analysis of the portfolio and the building

Table 10
Executive Report of the new syndicated loan portfolio, end of the reporting period

Operational information					
Parameter	**Details**	**Parameter**	**Details**	**Parameter**	**Details**
Composition of the syndicated loans portfolio	Restructured SL No. 3; SL No. 4; SL No. 5; SL No. 6; SL No. 7	Executed transactions	1 primary market deal (SL No. 6); 2 secondary market deals (SL No. 1 and No. 7)	Repayments and restructurings	3 repayments: (mandatory SL No. 2; voluntary SL No. 4; scheduled SL No. 5); 1 restructuring (SL No. 3)
KPI information					
Parameter	KPI value	Actual value, beginning of reporting period	Actual value, end of reporting period	Difference between KPI value and value at beginning of period	Difference between value at end and beginning of period
Total nominal volume, USD mln	530.00	452.50	535.00	+5.00	+82.50
Total market value, USD mln	525.00	440.85	528.30	+3.30	+87.45
Tenor of the portfolio, years	2.30	2.00	2.31	+0.01	+0.31
Margin of the portfolio, % p.a.	3.75	3.29	3.65	−0.10	+0.36
Monitoring information					
Financial covenants	Compliance	Waiver requests	Details	Amendment requests	Details
Net Debt / EBITDA; Net Interest Payments / EBITDA	Yes, (headroom: +0.20x); Yes (headroom: +0.12x)	SL No. 4	Restriction on Mergers and Acquisitions transactions, granted	SL No. 5	Restriction on Total Financial Indebtedness, granted

Source: Author-generated data for illustrative purposes.

of the managerial dashboard in order to assess the status of the KPIs achievement. Secondly, based on this analysis, the portfolio manager can use various syndicated loans portfolio management methods in order to change the portfolio composition in order to achieve the KPIs. Thirdly, the monitoring procedure to assess the compliance with the financial covenants by the borrowers of the syndicated loans under each separate facility agreement, as well as for the portfolio as a whole.

What has been achieved in terms of new results is the combined application of established portfolio management techniques (KPIs, dashboard, financial ratios analysis) to the specifics of syndicated loans. The new theoretical approach takes account of the nature of the primary syndicated loan market (with various types of transactions for borrowers from various industries), the secondary syndicated loan market (with the opportunity to trade in participations and obtain a market price for the loans), as well as specialized financial covenants of international deals (Net Debt/EBITDA, Net Interest Expenses/EBITDA). In practice, the developed

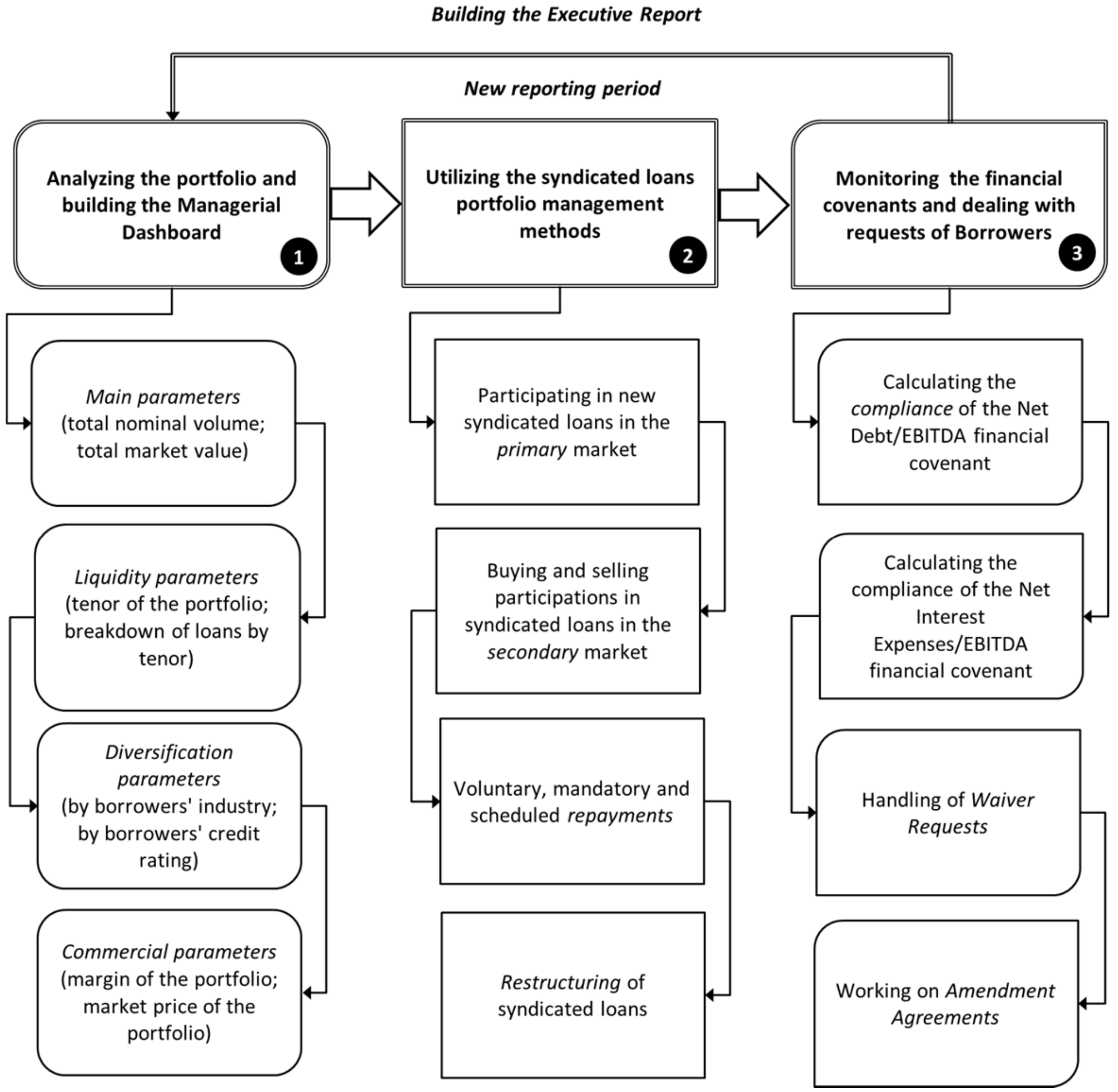

Fig. 3. **The general scheme for managing a portfolio of syndicated loans**

Source: Prepared by the author.

methods can be used by Portfolio Managers from various financial institutions (banks, insurance companies, asset managers and hedge funds) to analyze, manage and monitor their own syndicated loan portfolios. With certain adjustments that are the subject of future research, the presented approach can be applied not only to "global" portfolios composed of syndicated loans governed by international law and originated from international capital markets but also to "local" portfolios that include country-specific deals in various jurisdictions.

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Time-Varying Connectedness Between Global Uncertainties and Economic Activity in a Developing Economy Using a Dynamic Conditional Correlation — GARCH Model

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ABSTRACT

As economies become increasingly interconnected, individual economies are at risk of shocks from external uncertainties ranging from fluctuations in climate regulations to geopolitical conflicts and international economic policies. **The purpose** of the study is to investigate the time-varying correlation between global uncertainties (e.g., global economic policy uncertainty, climate policy uncertainty and geopolitical risk) and economic activity in a developing economy using a dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (GARCH) model. **The relevance** of the research lies in the increasing interconnectedness of global economies and the subsequent exposure of individual economies to external shocks. The scientific **novelty** is hinged on the study being among the first to study the relationship in Ghana. Using monthly data for the 2002–2022 period for Ghana, we estimate a multivariate GARCH model. **The results** of the study indicate that climate policy uncertainty and global economic policy uncertainty are mean reverting, implying that the volatility of the variables decay slowly and persists for a longer time such that the conditional variance will eventually return to its long-term average level after being disturbed by shocks. Global uncertainties over time are strongly negatively correlated with economic activity and produce significant spikes, especially during periods of major world events. **The study recommends** that policymakers need to consider the prolonged impact of global uncertainties on economic performance when designing economic policies and interventions. The significant spikes during major global events highlight the importance of crisis management and preparedness in maintaining economic stability during periods of heightened uncertainty.

Keywords: global uncertainties; economic activity; GARCH; dynamic correlations; vector autoregressive models; Ghana; Africa

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Исследование изменяющейся во времени связи между глобальной неопределенностью и экономической активностью в развивающейся экономике с использованием модели динамической условной корреляции — GARCH

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АННОТАЦИЯ

По мере того как глобальная экономика становится все более взаимосвязанной, отдельные страны подвергаются риску потрясений, связанных с внешней неопределенностью, обусловленной различными факторами, начиная от изменений климатических регламентов и заканчивая геополитическими конфликтами и международной экономической политикой. **Целью исследования** является изучение изменяющейся во времени корреляции между глобальными неопределенностями (например, неопределенностью глобальной экономической политики, неопределенностью климатической политики и геополитическим риском) и экономической активностью в развивающейся экономике с использованием динамической корреляционной модели с обобщенной авторегрессионной условной гетероскедастичностью (GARCH). **Актуальность** исследования обусловлена растущей взаимосвязанностью мировой экономики и, как следствие, подверженностью отдельных экономик внешним шокам. **Научная новизна** заключается в том, что данное исследование является одним из первых, изучающих указанную взаимосвязь на примере Ганы. Используя ежемесячные данные за период 2002–2022 гг. для Ганы, мы применили многомерную GARCH-модель. **Результаты** исследования показывают, что неопределенность в области климатической политики и неопределенность глобальной экономической политики являются среднереверсивными, что означает, что волатильность переменных медленно снижается и сохраняется в течение длительного времени, так что условная дисперсия в конечном итоге возвращается к своему долгосрочному среднему уровню после того, как будет нарушена потрясениями. Глобальная неопределенность с течением времени имеет сильную отрицательную корреляцию с экономической активностью и вызывает значительные всплески, особенно в периоды крупных мировых событий. Исследование **рекомендует** политикам учитывать длительное влияние глобальной неопределенности на экономические показатели при разработке экономической политики. Значительные всплески во время крупных мировых событий подчеркивают важность управления кризисами и готовности к поддержанию экономической стабильности в периоды повышенной неопределенности.

Ключевые слова: глобальная неопределенность; экономическая активность; GARCH; динамическая корреляция; векторные авторегрессионные модели; Гана; Африка

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Introduction

The world is becoming increasingly interconnected. As economies become more linked globally, individual countries face various external uncertainties. These uncertainties, such as fluctuations in international economic policies, changing climate regulations, and geopolitical conflicts, can significantly impact domestic economic activity over time. Following the work of Bloom [1], the effect of uncertainty on macroeconomic conditions has been extensively studied. Researchers have primarily used vector autoregressive models to study the effect of uncertainty at the macroeconomic level [2–5]. Since the end of the financial crisis of 2008, several geopolitical occurrences have emphasized in policy debates the potential threats that increased economic unpredictability could present to worldwide economic outlooks. These occurrences encompass the unforeseen United Kingdom (UK) referendum, known as BREXIT; the political landscape in Italy following the Constitutional referendum of 2016; the uncertainties surrounding recent trade protectionist policies and developments; the conflict in Ukraine; the Israel-Palestine conflict; and the impact of COVID-19.

It has been highlighted in both the theoretical and empirical literature that economic activity could be affected by heightened uncertainty in global economic policy [2, 6, 7]. This phenomenon could manifest across diverse channels, especially impacting household consumption and saving behaviors (precautionary savings), as well as firms' investment and employment choices. Geopolitical uncertainties and instabilities have been identified as significant factors influencing economic decision-making processes, as indicated by Lo Duca et al [8]. Consequently, it is plausible that geopolitical uncertainties and unfavorable geopolitical occurrences will exert a substantial impact on the economic growth rates of nations.

At both the corporate and individual levels, uncertainty slows down and negatively impacts most financial decisions, as indicated by Bloom [9]. The presence of uncertainty compels both individuals and corporations to adopt a more cautious approach, potentially resulting in reduced overall economic consumption and growth, a decrease in debt issuances, and a rise in unemployment [3, 10]. In addition, heightened uncertainty has implications for inflation rates [11] and currency exchange markets [12], with the housing market also being negatively impacted [13]. Furthermore, the consequences of governmental instability stretch to commodity markets, with studies indicating its adverse effects on oil [14], gasoline [15], and futures markets. Additionally, elevated economic policy uncertainty (EPU) can potentially have detrimental effects on the cryptocurrency market [16]. The author of [17] highlights the sensitivity of African economies to external shocks, emphasizing the need for robust policy frameworks to manage uncertainty.

Against the backdrop of empirical evidence of the impact of global uncertainties on output growth, predominantly presented at the collective level of individual countries or a group of nations, our objective is to contribute further to the literature in the following ways. For the first time, we analyse the time-varying effect of global uncertainties on economic activities using a unique index of economic activities for Ghana. The theoretical rationale for this study is grounded in subsequent lines of logic: Initially, it was well established that heightened levels of uncertainty can detrimentally impact the overall demand within the economy via the conventional mechanism linked to exchange rates. The study [1] posits that uncertainty influences decision-making by elevating the value associated with waiting. Moreover, uncertainty is also anticipated to adversely influence the productive aspect of the economy through efficiency, stemming from the improper allocation of resources among different enterprises [6]. According to [6], unproductive businesses contract, while productive businesses expand under normal circumstances, thereby contributing to elevated levels of overall productivity. However, in times of heightened uncertainty, firms curtail both expansion and contraction, thus impeding much of the productivity-enhancing reallocation, leading to a decline in the quantifiable aggregate total factor productivity.

The literature on how global uncertainties affect economic activity in developing economies in the global south is rare and still expanding. Our study is among the earliest to examine the relationship in Ghana. We use the dynamic conditional correlation Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model, which is well suited for analysing the volatility of economic variables over time and captures the episodic nature of global uncertainties. Second, it allows for the modelling of asymmetric effects, where positive and negative shocks to uncertainty can have different impacts on economic activity.

The remainder of the paper is organized as follows: an empirical literature section, a data and methodology section, and results, discussion and conclusions sections.

Literature review

Economic activity has been found in the literature to be influenced by global uncertainties (including global economic policy uncertainty, climate policy uncertainty and geopolitical risk). This review of the literature looks at empirical studies that investigate these correlations, stressing methods, conclusions, and areas of unmet research need. The influence of economic policy uncertainty (EPU) on a range of economic activities has been extensively researched. Using an EPU index, a study [2] discovered that higher levels of uncertainty result in lower levels of hiring, output, and investment. Using vector autoregressions (VARs), their study demonstrated that policy uncertainty shocks significantly impair economic performance. Research [1] used a model that takes adjustment costs and real options into account to investigate how uncertainty shocks affect the economy. According to his research, businesses may postpone hiring and investment due to uncertainty, which would reduce overall economic activity. The processes through which EPU influences macroeconomic variables were further established in this study. This topic has been further explored in other research by examining various nations and situations. Research [7], for example, used a time-varying parameter VAR model to demonstrate that macroeconomic variables in the UK are significantly impacted by EPU shocks in the US. Similarly, a study [18] demonstrated how EPU has a detrimental effect on investment and consumption in emerging nations using a structural VAR method.

Vaswani and Padmaja [19] conducted an analysis of the derivatives market, indicating that economic policy uncertainty (EPU) exerts a positive influence on the aggregate turnover of derivatives by shaping financial decision-making through innovative practices and market trends. Khurana et al. [20] investigated the impact of EPU on entrepreneurship in 26 countries spanning a period of 19 years and discovered that higher levels of EPU lead to an increase in necessity-driven entrepreneurship but do not significantly affect opportunity-driven entrepreneurship. This study underscores the significance of economic safety nets in advanced economies. Ashena and Shahpari [21] utilized a nonlinear autoregressive distributed lag methodology to explore the relationship between EPU and carbon emissions in Iran, revealing that EPU contributes to an increase in CO_2 emissions, with notable asymmetric effects of economic production on emissions. Study [22] delves into the correlation between EPU and corporate financialization in China, revealing that EPU has a dampening effect on financialization, especially within state-owned enterprises, and that this effect is moderated by CSR. Research [23] scrutinizes the impact of firm-level EPU on corporate innovation, demonstrating that heightened EPU has a negative effect on innovation activities, particularly in nonstate-owned enterprises and those facing financial constraints.

A relatively recent field of study, climate policy uncertainty (CPU), reflects growing concerns about climate change and policy responses. By building a CPU index, Fried [24] discovered that uncertainty around climate policy has a detrimental impact on firm-level investment decisions, especially in sectors of the economy that are heavily subject to climate regulation. Andersson [25] conducted an empirical analysis using panel data from OECD countries to show that CPU decreases investments in renewable energy. The analysis demonstrated strong negative implications of CPU for green investment, underscoring the importance of a stable climate policy in promoting economic activity. Fixed-effects models were employed to account for variation among nations. Bolton and Kacperczyk [26] investigated how financial markets were affected by the uncertainty surrounding climate policy. They discovered that CPU increases the cost of capital for businesses in carbon-intensive industries, which discourages investment and slows growth in these areas. They arrived at this conclusion using a panel regression technique. Uncertainty resulting from geopolitical events, such as conflicts, terrorism, and diplomatic difficulties, is referred to as geopolitical risk (GPR). Using a GPR index, study [27] discovered that decreases in trade, employment, and industrial production follow increases in geopolitical risk.

Recent research has started to investigate how various uncertainties work together to affect economic activity. For instance, Phan [28] used a dynamic connectivity technique to analyse the interaction between EPU, CPU, and GPR. The interdependence between these uncertainties was measured using a spillover index, and it was discovered that the sum of these uncertainties had a greater impact on economic activity than the sum of their individual uncertainties. Another study by Antonakakis [29] examined the relationships among oil prices, EPU, and GPR using a time-varying parameter VAR model. They discovered that changes in geopolitical risk have a major impact on oil prices, which in turn have an impact on economic activity, illustrating the intricate relationship between these concerns. Financial market factors were added to this research by Wang and Li [30]. They investigated the dynamic connections between stock market returns in major economies and global uncertainties using a DCC-GARCH model. According to their research, EPU, CPU, and GPR all work together to lower investor confidence and increase market volatility, which has an impact on economic growth.

Methodology

Data sources and analysis

We use monthly data on the index of economic activity from the Bank of Ghana for our study. Our data span the period from January 2002 to December 2022. The beginning of the data are motivated by the availability of data for the index of economic activity for Ghana. To capture global uncertainties, we use the global economic policy uncertainty index, climate policy uncertainty index and geopolitical risk index. In our study, we use the real exchange rate, which is used to control for spillovers to the economy.

To aid in the estimation of the data, we use OxMetrics, an econometric software suite that is particularly well-suited for time-series analysis and volatility modeling, including GARCH-based models like DCC-GARCH. OxMetrics provides a comprehensive set of tools for estimating, testing, and forecasting models in a user-friendly environment, which allowed us to efficiently implement the DCC-GARCH model with a multivariate t-distribution, as discussed in our study. The OxMetrics platform uses the Ox programming language for high-performance econometric computations.

Variable definitions

Economic activity index: The study uses a composite index of economic activity by the Bank of Ghana that is derived from a combination of 10 different components of economic time series data that contain the outputs and activities of key sectors of the economy, including all kinds of electricity consumption, imports, exports, patterns of employment growth, sale of key national assets, port/harbour activities, tourism, sale of companies involved in manufacturing, VAT collection domestically, and domestic credit to the private sector [31]. Further details about the index of economic activity can be found in [31].

Economic policy uncertainty: We use the global economic policy uncertainty index developed by [2].[1] A composite mean of three unique elements is utilized to construct the index. The principal and predominant aspect is ascertained by tallying print media publications containing pivotal phrases linked to policy uncertainty. The second element examines uncertainty relating to forthcoming changes in tax regulations by assessing the financial repercussions of expiring tax provisions. The ultimate element utilizes the dispersion of economic predictions of the Consumer Price Index and government spending as an alternative gauge to evaluate the degree of uncertainty regarding fiscal and monetary policies.

Climate policy uncertainty: To measure climate policy uncertainty, we use the index developed by [32] following the study of Baker et al. [2]. Further information on the computation of the index is found in [32].

Geopolitical risk: We use the index of geopolitical risk developed by Caldara and Iacoviello [33]. They constructed an index for geopolitical risk by counting the number of times words related to geopolitical tensions appear in leading international newspapers. The Caldara and Iacoviello Geopolitical Risk (GPR) index is based on automated text searches of 10 major newspapers, tracking articles related to adverse geopolitical events. The index is calculated monthly by counting the share of articles on topics such as war threats, military buildups, nuclear threats, and terror threats. It is divided into eight categories, with two subindexes: the Geopolitical Threats (GPRT) index, covering categories 1 to 5, and the Geopolitical Acts (GPRA) index, covering categories 6 to 8.

Model specification

To measure the time-varying volatilities and connectedness of global uncertainties and economic activities, we use the dynamic conditional correlation (DCC) GARCH model developed by Engle [34]. The key advantage of the DCC-GARCH model lies in its ability to capture time-varying correlations between multiple variables, which is essential when analyzing the dynamic and evolving relationships between uncertainties and economic activities over time. Unlike static models, which assume constant correlations, DCC-GARCH allows the correlations to change as new information becomes available, reflecting the reality of global uncertainties that are influenced by external shocks and policy changes.

Although the standard DCC-GARCH model assumes a Gaussian distribution, which may not be appropriate for heavy-tailed distributions (as seen in extreme events like geopolitical shocks or economic crises), we address this limitation by adopting a multivariate t-distribution, as recommended by Pesaran and Pesaran [35]. The t-distribution is well-

[1] The data is hosted at https://www.policyuncertainty.com/

suited for capturing the heavier tails often observed in real-world financial and economic data, thereby making the model more robust to extreme events and sudden spikes in volatility, which are frequently discussed in the literature on global uncertainties. This modification allows us to retain the strengths of DCC-GARCH — its capacity to model time-varying correlations and conditional volatilities — while also ensuring that the model accounts for the fat tails and extreme events that are characteristic of the uncertainties being studied. By doing so, the model provides more accurate estimates of both volatility and correlation dynamics, enabling a better understanding of the interconnectedness of global uncertainties. Moreover, the model offers enhanced precision in estimating conditional variances [34]. Thus, we specify the general DCC-GARCH model as follows:

$$H_t = D_t R_t D_t. \tag{1}$$

The definitions of the variables in equation (1) are as follows. The matrix conditional variance is denoted as H_t. D_t is denoted as a diagonal matrix of dimensions kxk with a conditional variance, which is denoted as $\sqrt{h_{it}}$ on the principal diagonals, while the matrix of time-varying correlations (values off the diagonal elements) is denoted by R_t. Thus, the conditional variance for the variables could be estimated using a univariate GARCH model as indicated;

$$h_t = \omega_i + \sum_{x=1}^{X_i} \alpha_{ix} r_{t-x}^2 + \sum_{y=1}^{Y_i} \beta_{iy} h_{t-y}^2. \tag{2}$$

From equation 2, ω_i, α_{ix} and β_{iy} are expected to be nonnegative values and must meet the conditions that $\sum_{x=1}^{X_i}\alpha_{ix} + \sum_{y=1}^{Y_i}\beta_{iy} < 1$ at which we indicate the model

to be mean reverting and where

$\sum_{x=1}^{X_i}\alpha_{ix} + \sum_{y=1}^{Y_i}\beta_{iy} = 1$, the model is said to be integrated.

α_{ix} measures the short-term persistence of shocks to economic activity variable to long-term persistence (denoted as GARCH effects). Furthermore, from the equation, we are able to estimate and obtain the conditional standard deviations and the residuals. The conditional standard deviation is expressed by a diagonal matrix D_t with $\sqrt{h_{it}}$ on the principal diagonal. This is shown in equation 3.

$$D_t = \begin{bmatrix} \sqrt{h_{11,}t} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{22,}t} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & \sqrt{h_{kk},t} \end{bmatrix}. \tag{3}$$

In equation 4, the standardized residuals de noted as $\left(\sigma_t = \frac{\varepsilon_t}{\sqrt{h_t}}\right)$ are used for estimating the dynamic or time varying correlation matrix R_t (Lim and Masih, 2017).

$$R_t = Q_t^{*-1} Q_t^* Q_t^{*-1}. \tag{4}$$

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11,}t} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22,}t} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & \sqrt{q_{kk},t} \end{bmatrix}. \tag{5}$$

In equation 5, Q_t^* shows the diagonal matrix of its diagonal elements. Q_t is a positive definitive conditional covariance matrix and is symmetrical such that $Q_t = (q_{ij,t})$ and $\bar{Q}$ are the unconditional covariances of the standardized residuals of the univariate model.

$$Q_t = (1-a-b)\bar{Q} + \alpha\varepsilon_{t-1} - 1\varepsilon_{t-1}^{'} + bQ_{t-1.} \tag{6}$$

In a typical correlation form, $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ij,t} q_{ij,t}}}$ (the conditional correlation) can be expressed by setting $Q_t = (q_{ij,t})$ from equation (6), as indicated in equation (7).

$$\rho_{ij,t} = \frac{(1-a-b)\bar{Q} + \alpha\varepsilon_{t-1} - 1\varepsilon_{t-1}^{'} + bQ_{t-1}}{\sqrt{(1-a-b)\bar{Q} + \alpha\varepsilon_{t-1} - 1\varepsilon_{t-1}^{'} + bQ_{t-1}}\sqrt{(1-a-b)\bar{Q} + \alpha\varepsilon_{t-1} - 1\varepsilon_{t-1}^{'} + bQ_{t-1}}}. \tag{7}$$

Additionally, as suggested by [34], the DCC-GARCH model based on t-distribution uses devola tised values $r_{i,t-1} = \frac{r_{it}}{\sigma_{i,t-1}^{realised}}$ and, as such, estimates the correlation model against the DCC-GARCH model that utilizes standardized values $r_{i,t-1} = \frac{r_{it}}{\sigma_{i,t-1}}$

and uses two steps in the model estimation. The parameters of the conditional covariance model can be estimated. Using GARCH(1,1) for conditional volatility $\sigma^2_{i,t-1}$ is presented in equation (8), which can then be used as a matrix to determine conditional correlation.

$$V\left(r_{it} \mid \Omega_{t-1}\right) = \sigma^2_{i,t-1} =$$
$$= \overline{\overline{\sigma}}^2_t \left(1 - \lambda_{1i} - \lambda_{2i}\right) + \lambda_{1i}\sigma^2_{i,t-2} + \lambda_{2i} r^2_{i,t-1}. \qquad (8)$$

In equation (8), $\overline{\sigma}^2_t$ denotes the unconditional variance of the economic activity index. λ_{1i} *and* λ_{2i} are volatility parameters for the global uncertainty variables. $\left(1 - \lambda_{1i} - \lambda_{2i}\right)$ represents the restriction to test whether the volatility is mean reverting. If the term $\left(1 - \lambda_{1i} - \lambda_{2i}\right)$ is equal to zero in this case, the model shows an integrated GARCH (IGARCH) process.

Results and discussion

Table 1 shows the summarized descriptive statistics of the variables used in the study. The return series are also presented in *Table 1*. The average value of the economic activity index for the study period is approximately 17.09, with minimum and maximum values of –1.71 and 44.07, respectively, per month. The mean values of global economic policy uncertainty (147.5062), climate policy uncertainty (120.2249), geopolitical risk (103.9464) and the exchange rate (82.9173) per month. For all the variables, the wide differences between the minimum and maximum values indicate significant fluctuations in the various series over the period of the data used for the study. Similarly, large values of the level series indicate high volatility in the variables. With the exception of the level series of the economics activity index, all other variables show the presence of nonnormality in the distribution of the data.

In *Fig. 1 and 2*, we show the graphical evolution of the variables on global uncertainties, the index of economic activity and the exchange rate. We also show the graphical evolution of their return series. The level series indicates the presence of a trend in the series and fluctuates over time. In particular, the trend of the level series of the economic activity index reflects major events in the Ghanaian economic landscape. We observe significant upwards spikes in 2004, 2008, and 2012, which reflect election periods. This could be explained by the fact that during election periods, government expenditures increase and introduce inflationary pressures to the economy.

Unit root test results

Time series frequently exhibit nonstationarity and trends. In light of this, regression estimates of one nonstationary variable on one or more additional nonstationary variables are erroneous and lead to a false conclusion. As a result, before estimating the regression models, it is essential to look at the variables' stationarity property. Furthermore, a fundamental tenet of GARCH models is the stationarity of the variables. Therefore, we ran the Phillips-Perron (PP) and enhanced Dickey-Fuller (ADF) unit root tests. The results of the unit root tests are presented in *Table 2*. The results of the augmented Dickey fuller test indicate that at levels, only the index of economic policy uncertainty and exchange rate are non-static. However, at the first difference for both methods, all the variables are stationary. Thus, to estimate our models, the return series are used for all the variables.

Univariate GARCH results

To estimate the DCC-GARCH model, we first estimate a symmetric GARCH (1, 1) model to determine the volatility characteristics of variables and subsequently identify the most efficient technique to employ in the estimation of the multivariate GARCH model. The GARCH (1, 1) model is a very efficient model for the estimation of series that exhibit volatile characteristics, as indicated by Engel [34]. The results of the univariate models, as shown in *Table 3*, indicate that the ARCH terms for all the models are significant, indicating the presence of both ARCH and effects in the variables used. The GARCH terms for all variables except geopolitical risk and exchange rate are significant, indicating the presence of a GARCH effect for all variables except geopolitical risk and exchange rate. Furthermore, we find that the indices of economic activity, climate policy uncertainty and geopolitical risk are all mean reverting since the sum of the alpha and beta terms are less than one; as such, their effects are persistent. The implication of the results is that volatility for the variables decays slowly and persists for a longer time such that the conditional variance will eventually return to its long-term average level after being disturbed by shocks. However, the sums for economic policy uncertainty and exchange rate are greater than one signifying

Table 1
Descriptive statistics

	ECONIN-DEX	EPU	CPU	GPR	EX-CHANGE	DECONIN-DEX	DEPU	DCPU	DGPR
Mean	17.59	147.5062	120.2249	103.9464	82.9173	−0.0462	0.6124	0.5321	−0.244
Median	17.03	126.8340	102.6259	92.5978	82.8911	0.03000	−0.7445	−0.0097	−0.744
Maximum	44.07	428.1531	411.2888	358.7111	105.5654	12	137.155	231.084	119.100
Minimum	−1.71	48.95131	28.1619	58.4207	51.2927	−20.1	−101.66	−149.267	−127.811
Std. Dev.	7.82	75.40141	64.4506	36.8125	12.4070	4.8752	30.62	47.54	24.763
Skewness	0.32	1.06542	1.42547	3.00529	0.14063	−0.27817	0.692	0.5017	0.029
Kurtosis	3.11	3.6033	5.1988	17.04030	1.9700	4.12779	6.843	6.4912	10.413
Jarque–Bera	4.57	51.49720	136.1093	2449.2027	11.9692	16.539	174.520	138.005	574.818
Probability	0.10	0.0000	0.0000	0.0000	0.0025	0.0003	0.0000	0.0000	0.0000
Observations	252	252	252	252	252	251	251	251	251

Note: ECONINDEX represents Index of Economic Activity, EPU represent Economic Policy Uncertainty, CPU represents Climate Policy Uncertainty, GPR represents Geopolitical Risk.

Source: Developed by the authors.

Table 2
Unit root test

Variable	ADF		PP	
	Level	First Difference	Level	First Difference
Index	−3.065**		−4.406***	
Epu	−2.261	−12.665***	−2.755*	
Cpu	−4.034***		−6.097***	
Gpr	−5.817***		−5.656***	
Exchange	−1.355	−12.492***	−1.393	−11.777***

Note: ***, ** and* indicate that they are significant at the levels of 1%, 5% and 10%, respectively.

Source: Developed by the authors.

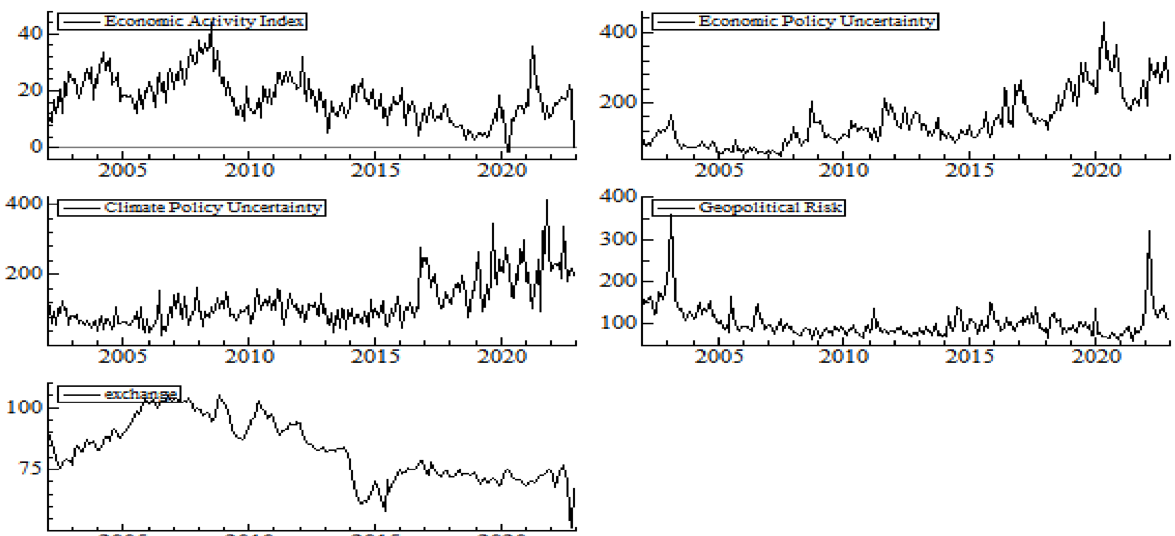

Fig. 1. **Dynamics of the economic activity index, global uncertainties and exchange rate at various levels**
Source: Developed by the authors.

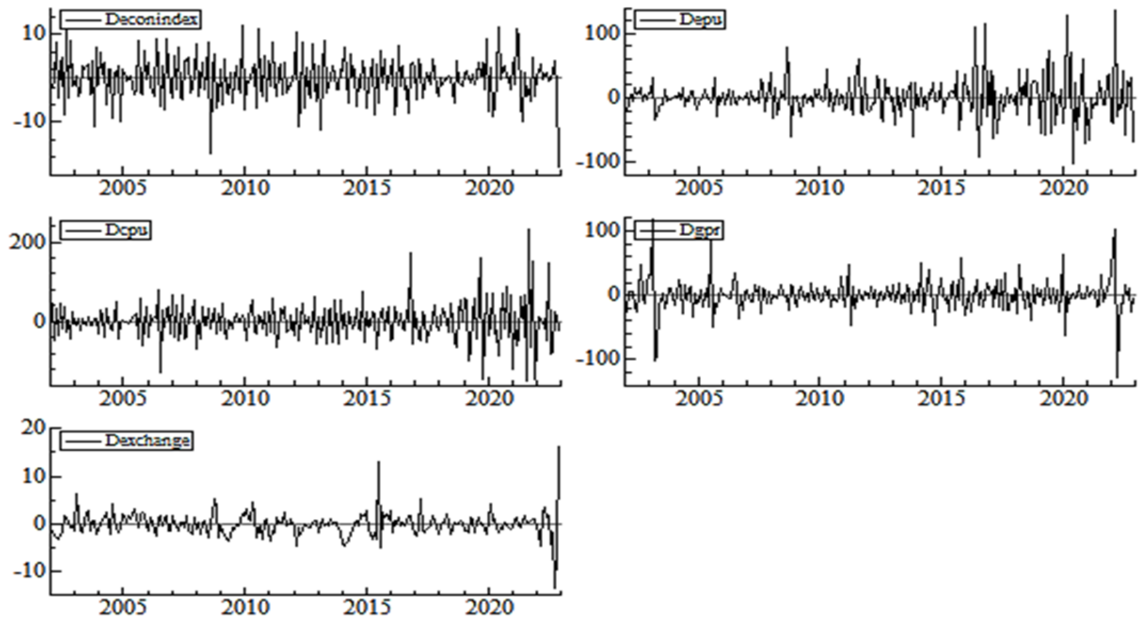

Fig. 2. **Dynamics of the economic activity index, global uncertainties and exchange rate at first difference**

Source: Developed by the authors.

a nonpersistence in their effects. This implies that the volatility of the model could increase without bounds over time. Importantly, for the index of economic growth, we find that since volatilities are mean reverting, shocks to the economy will eventually return the economy slowly to its long-term average level. However, the exchange rate is not mean reverting, suggesting that shocks could increase the conditional variance over time without bounds.

Multivariate model

Table 4 presents the results of the DCC-GARCH model. The results indicate the existence of a dynamic conditional correlation between the indices of economic activity, global economic policy uncertainty, climate policy uncertainty, geopolitical risk and exchange rate (for purposes of spillover) since the values of the alpha and beta are statistically significant. The constant conditional correlation hypothesis is rejected, suggesting that assuming independence or neutrality between the variables may be misleading. Additionally, we find that the sum of the alpha and beta parameters is less than 1, indicating that the conditional variance will eventually return to its long-term average level after being disturbed by shocks or that the conditional correlations between the variables are mean reverting. As a result, it can be argued that the DCC-GARCH model captures the time-varying conditional correlations between variables.

Fig. 3 presents the dynamic conditional correlation between the economic activity index, global economic policy uncertainty, climate policy uncertainty, geopolitical risk and exchange rate. We already find a time-varying correlation in the relationships between the variables, as shown in *Table 4.* This variability results in occasional sharp declines and increases in the conditional correlation, with oscillations observed between high and low values. The top-left graph shows the dynamic conditional correlation between the economic activity index and climate policy uncertainty (cpu). The correlation varies significantly over time, oscillating between positive and negative values. From approximately 2002 to 2010, the correlation fluctuates but remains mostly negative, indicating an inverse relationship. Post-2010, there are periods where the correlation turns positive, suggesting a direct relationship at times. Notably, significant negative correlations are observed approximately 2008 (coinciding with the global financial crisis) and 2015. In approximately 2020, the correlation became positive, potentially indicating a change in the impact of climate policy uncertainty on economic activity. This corresponds to the results of [17].

The top-right graph displays the dynamic conditional correlation between the economic activity index and global economic policy uncertainty (epu).

Table 3
Univariate GARCH estimates

Variable	Econindex	Cpu	Epu	Gpr	Exchange
Cst (Mean)	15.9938*** (0.7663)	93.4907*** (4.4301)	111.7467*** (3.7738)	91.4877*** (2.5101)	74.2019*** (0.3915)
Cst (Variance)	12.1378*** (3.5087)	158.5632 (130.20)	114.2265*** (42.412)	225.413*** (75.041)	1.7371** (0.6952)
ARCH (1)	0.6275*** (0.0937)	0.2005** (0.0911)	0.6506*** (0.1183)	0.8194*** (0.1474)	1.1025*** (0.1338)
GARCH (1)	0.1929** (0.0855)	0.7591*** (0.1205)	0.4160*** (0.0959)	−0.0405 (0.0639)	0.0241 (0.0534)
$\alpha+\beta$	0.82052	0.9596	1.0667	0.7789	1.12666
Log L	−833.092	−1337.346	−1339.090	−1140.850	−892.604
	Persistent	Persistent	Not Persistent	Persistent	Not Persistent

Source: Developed by the authors.

Note: *** and ** indicate that they are significant at the levels of 1% and 5%, respectively.

Table 4
Estimates of the DCC-GARCH model

Variable	DCC estimates	Standard Errors
Econindex vs cpu	−0.0822***	0.0134
Econindex vs epu	−0.1369***	0.0137
Econindex vs gpr	0.01504***	0.0013
Econindex vs exchange	0.2135***	0.0144
Alpha (α)	0.2198***	0.0318
Beta (β)	0.7108***	0.0452
$\alpha+\beta$	0.9306	
Log L	−5285.96	

Source: Developed by the authors.

Note: *** indicate that they are significant at the levels of 1%.

This correlation also oscillates but with more pronounced peaks and troughs. There was a notable negative correlation around the 2008 financial crisis, which indicates that global economic policy uncertainty had a significant adverse impact on Ghana's economic activity. The correlation becomes positive during 2010–2012 and again approximately 2020, suggesting that during these periods, global eco-

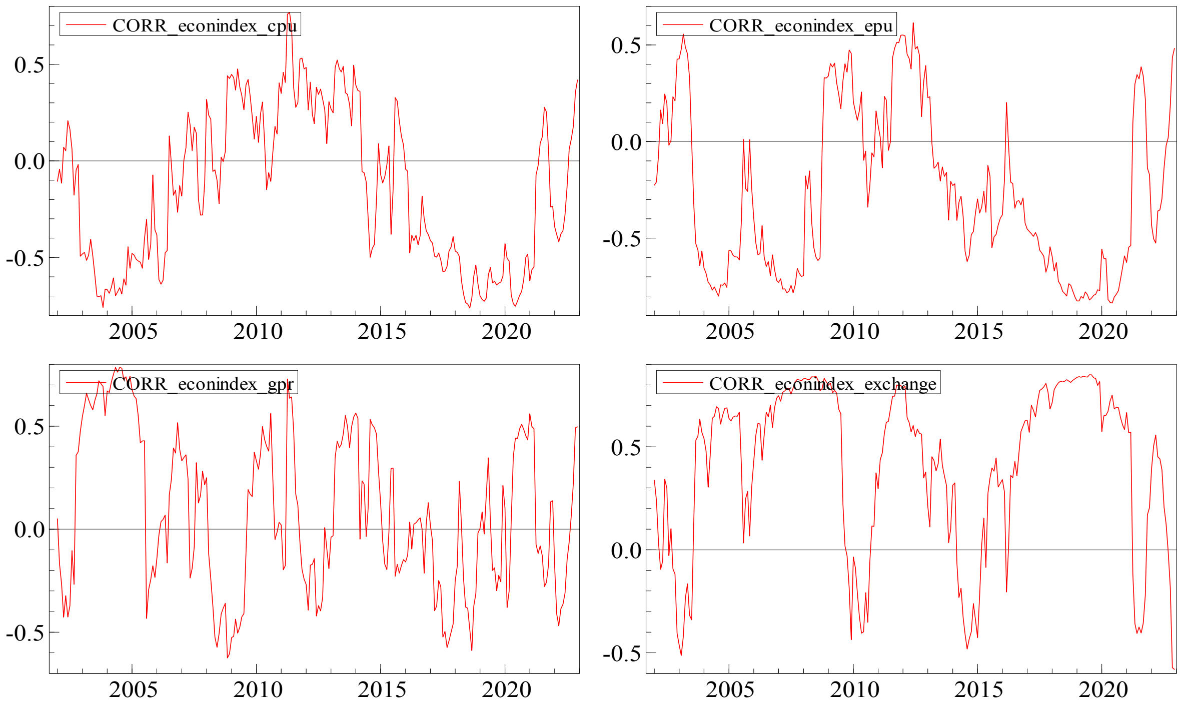

Fig. 3. **Dynamic conditional correlations between the economic activity index, global uncertainties and exchange rate**

Source: Developed by the authors.

nomic policy uncertainty may have had a different, possibly stabilizing, impact on economic activity. Antonakakis [29], on the relationship between global economic policy uncertainty and stock market returns in various countries, show similar fluctuating correlations, emphasizing the importance of policy uncertainty in economic dynamics. Similarly, [1] highlights how economic policy uncertainty can affect firm-level investment and economic activity, which aligns with the observed correlation patterns in the graphs.

In the bottom-left graph, the dynamic conditional correlation between the economic activity index and geopolitical risk (gpr) is depicted. The correlation here also fluctuates, with a more volatile pattern than in the previous two graphs. The early period (2003–2007) shows a strong positive correlation, suggesting that geopolitical risk is positively correlated with economic activity. However, after 2007, the correlation fluctuated more widely. At approximately 2008–2015, the correlation decreases significantly, showing negative values, which implies that geopolitical risk had a negative impact during these periods. Caldara and Iacoviello [27] indicated that geopolitical events can have substantial impacts on financial markets and economic conditions, which is consistent with the volatile correlations observed between economic activity and geopolitical risk in Ghana. This suggests that geopolitical tensions and conflicts could significantly disrupt economic stability. The bottom-right graph shows the dynamic conditional correlation between the economic activity index and exchange rates. The correlation is highly volatile with sharp oscillations. From 2003 to 2007, there was a predominantly positive correlation. After 2007, the correlation became more volatile, with periods of strong positive and negative correlations. The correlation is notably negative approximately between 2008 and 2015, suggesting that exchange rate fluctuations adversely impacted economic activity during these times.

Fig. 4 shows the time-varying covariance between the economic activity index, climate policy uncertainty, global economic policy uncertainty and geopolitical risk in Ghana. The covariance between economic activity and climate policy uncertainty fluctuates significantly over time, with notable negative spikes in approximately 2008 and again in 2020. These periods correspond to the global financial crisis and the COVID-19 pandemic, respectively, suggesting that climate policy uncertainty had a substantial negative impact on economic activity during these crises. Prior to 2008, the covariance hovered around zero, indicating minimal impact. Post-2008, there

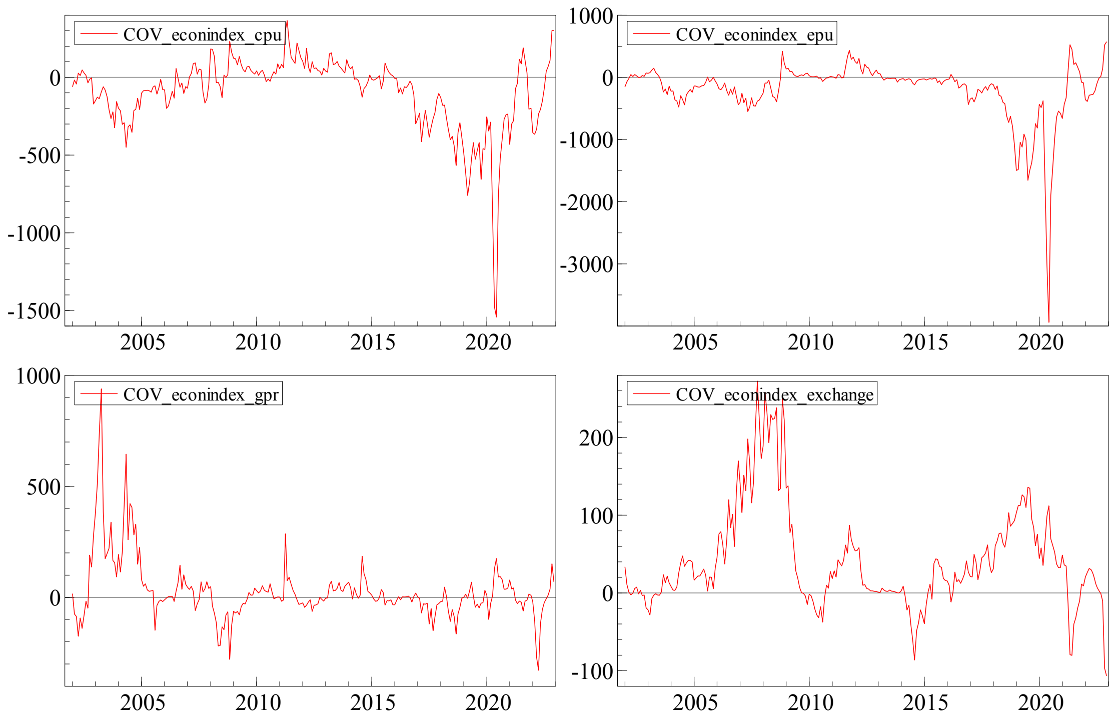

Fig. 4. **Dynamic conditional covariance between the economic activity index, global uncertainties and exchange rate**

Source: Developed by the authors.

are periods of both positive and negative covariance, reflecting changing dynamics and possibly varying policy responses and economic conditions.

The conditional covariance between the economic activity index and global economic policy uncertainty (epu) also fluctuates, with a marked negative spike approximately in 2020. The period from 2003 to 2010 shows relatively stable, slightly negative covariance, suggesting a mild inverse relationship. After 2010, the covariance fluctuates more, with significant decreases, particularly around global economic events. The strong negative covariance approximately 2020 aligns with the onset of the COVID-19 pandemic, indicating that global economic policy uncertainty significantly adversely impacted Ghana's economic activity. The covariance between the economic activity index and geopolitical risk is more volatile in the early period (2003–2005), with high positive spikes, suggesting that geopolitical risk had a positive impact on economic activity during these times. However, after 2005, the covariance became relatively stable at approximately zero, indicating a neutral impact of geopolitical risk on economic activity. In approximately 2020, there was a significant negative spike, again reflecting the adverse impact of the global pandemic and heightened geopolitical tensions.

Conclusions and recommendations

This study investigates the time-varying correlation between global uncertainties (e.g., global economic policy uncertainty, climate policy uncertainty and geopolitical risk). The dynamic conditional correlation GARCH model is used in the estimation using monthly data from January 2002 to December 2022. The DCC-GARCH model is adept at capturing time-varying correlations between variables, which is crucial for understanding the dynamic relationships in economic and financial time series. The univariate GARCH models for each of the variables indicate that the series were mean reverting. For the economic activity index, climate policy uncertainty and global economic policy uncertainty, the implication of the results is that the volatility of the variables decays slowly and persists for a longer time, such that the conditional variance will eventually return to its long-term average level after being disturbed by shocks. From the multivariate GARCH model, we find that over time, the correlation between economic activity and variables measuring global uncertainties oscillated and were predominantly negative for climate policy uncertainty and global economic policy uncertainty. We also find major spikes in the correlation, especially during periods of major world events, notably the 2008 global financial crisis and the COVID-19. These periods witnessed significant negative spikes. The results demonstrate the significant impact of global uncertainties.

The findings have significant implications for policymakers, investors, and economic analysts. The persistent and mean-reverting nature of volatility in economic activity, climate policy uncertainty, and global economic policy uncertainty suggests that shocks to these variables can have long-lasting effects. Policymakers need to consider the prolonged impact of global uncertainties on economic performance when designing economic policies and interventions. The predominantly negative correlations indicate that heightened global uncertainties can dampen economic activity, emphasizing the need for robust policy measures to mitigate these adverse effects. The significant spikes during major global events highlight the importance of crisis management and preparedness in maintaining economic stability during periods of heightened uncertainty.

Therefore, from the findings of the study, several policy recommendations can be drawn. It is crucial that policymakers develop strategies to manage and minimize the impacts of climate policy uncertainty and global economic policy uncertainties on economic activity. This can be done through the creation of more stable and predictable policy environments that streamline and improve transparency in communication around policy changes and, finally, through the implementation of measures that reduce related volatility to both of these uncertainties. Second, from the policy-making perspective, it is important to apply crisis management, especially for large global events, and to be better prepared to minimize negative impacts on economic activity. To strengthen monetary-fiscal coordination and the proactiveness of public communication during the crisis, more targeted support should be offered to affected sectors, financial safety networks that bind major economies should be reconstructed, and an international response to global crises should be coordinated as they emerge. The time-varying relationships of economic activity with global uncertainties can also be exploited for better-informed risk management and investment strategies for investors. Therefore, investor portfolios should be considered for potential impacts of global uncertainties, thus diversifying investors' investments. Finally, this research further recommends determining the channel-specific impacts of global uncertainties on economic activity and other factors that may alter these relationships.

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