Ekim 2024

INTERNATIONAL STUDIES AND EVALATIONS IN THE FIELD OF

ECONOMICS AND ADMINISTRATIVE SCIENCES

EDITORS

PROF. DR. GÜLSÜN İŞSEVEROĞLU

ASSOC. PROF. DR. SALIH BATAL

SERÜVEN YAYINEVİ

Genel Yayın Yönetmeni / Editor in Chief • C. Cansın Selin Temana

Kapak & İç Tasarım / Cover & Interior Design • Serüven Yayınevi

Birinci Basım / First Edition • © Ekim 2024

ISBN • 978-625-6172-40-1

Serüven Yayınevi / Serüven Publishing
Türkiye Adres / Turkey Address: Kızılay Mah. Fevzi Çakmak 1. Sokak
Ümit Apt No: 22/A Çankaya/ANKARA
Telefon / Phone: 05437675765
web: www.seruvenyayinevi.com
e-mail: seruvenyayinevi@gmail.com

Baskı & Cilt / Printing & Volume
Sertifika / Certificate No: 47083

INTERNATIONAL STUDIES AND EVALUATIONS IN THE FIELD OF ECONOMICS AND ADMINISTRATIVE SCIENCES

October 2024

Editors

PROF. DR. GÜLSÜN İŞSEVEROĞLU
ASSOC. PROF. DR. SALIH BATAL

CONTENTS

Chapter 1

THE USE OF ARTICIAL INTELLIGENCE IN MARKETING AND ACCOUNTING; BIBLIOMETRIC ANALYSIS WITH VISUAL MAPPING TECHNIQUES

Filiz ASLAN ÇETİN[1]

Seyhan ÖZTÜRK[2]

Osman Nuri AKARSU[3]

1 Doç. Dr., Kafkas University Faculty of Economics and Administrative Sciences, Department of Business Administration, Kars/Turkey, filizaslan79@gmail.com, 0000-0002-8210-799X.

2 Doç. Dr., Kafkas University Faculty of Economics and Administrative Sciences, Department of Business Administration, Kars/Turkey, seyhan87ozturk@gmail.com, 0000-0003-1458-840X.

3 Dr., Kafkas University Institute of Social Sciences, Department of Business Administration, Kars/Turkey, osmannuriakarsu@gmail.com, 0000-0002-5393-956X.

1. Introduction

Advances in technology are creating new opportunities for many sectors. On the one hand, these advances support the efficiency, quality, and cost-effectiveness of businesses, and on the other hand, they are disruptive to traditional technologies. Especially with Industry 4.0, technological elements such as cloud computing, the Internet of Things, big data and artificial intelligence, which have entered into daily life, are current concepts that have the potential to trigger development on the basis of businesses. Technological systems cause significant interactions between individual and corporate consumers and businesses with commercial concerns, which is why it becomes very important to closely follow technological developments, to be predisposed to the use of technology, to reduce human involvement and to use smart systems that can manage and monitor themselves.

Accordingly, artificial intelligence has a critical role in creating a strategy that has the ability to meet the wants, needs and demands of consumers in many different sectors and requires the least human element. In this way, consumers have the chance to fill the gap between their needs and the services provided by the business in the most optimal way and get the highest benefit. Artificial intelligence and its components in businesses are particularly evident in the fields of marketing and accounting. Modern business management is a concept that continues from the production of goods and services suitable for consumer needs to after-sales and includes the most up-to-date market conditions. Technological developments also give businesses a digital form, so many businesses can easily have global characteristics, and in general, the internet and many digital platforms support businesses in implementing global strategies.

Mainly due to scientific advances, businesses are trying to predict tomorrow based on today's data, and artificial intelligence is currently serving this purpose, albeit partially. Artificial intelligence is commonly defined as a technologically based analytical process created by computer systems, but it is also an intelligent system that makes sense of the complex and irregular data that businesses collect about people and "continuously learns" based on this data.

In this context, the study first elaborates on the concept of artificial intelligence and then explains the use of artificial intelligence in marketing and accounting. As a result of the bibliometric analysis conducted within the framework of the subject; it has come to the forefront in the findings that the theme in question is a field that has been widely studied academically in recent years, is open to development, and that joint studies between countries and authors are frequently carried out.

2. Concept Of Artificial Intelligence

In the current digital age, many cutting-edge technologies have emerged, and these technologies have had a significant impact on the working systems of businesses. In this sense, technological developments such as the Internet of Things, blockchain technologies, cloud computing, big data and artificial intelligence are transforming business processes. This technological situation, which is called disruptive innovation, focuses especially on artificial intelligence and is actively used in many areas, from education to health and from production to trade. Artificial intelligence, which is not limited to business areas, is also an indispensable part of people's daily lives. Especially in recent years, artificial intelligence-based products or services have become very visible (Özer Çizer, 2022).

In a paper originally published by Alan Turing in 1950, a question was asked about the possibility of machines being able to think. Although this question does not fully meet the concept of artificial intelligence, it has an important place in the history of technology. However, John McCarty, who first used artificial intelligence as a concept in 1955, uses the definition of "the engineering of making intelligent machines" for artificial intelligence. Accordingly, artificial intelligence is actually a branch of science that translates human abilities such as thinking, decision-making, or problem-solving into algorithms and makes machines intelligent. The main aim is to enable machines to show intelligent behavior. Based on many definitions made by scientists, it can be said that artificial intelligence is simply "the science of building intelligent machines" (Kuruca, Üstüner and Şimşek, 2022).

The development of artificial intelligence is happening at a very fast pace. The main goal is to make machines more intelligent and autonomous. So far, artificial intelligence has been given the ability to reason, learn, communicate, perceive, store or relocate. In a television interview, Edward Fredkin cited the emergence and development of artificial intelligence as one of the three major events in history. However, artificial intelligence with learning and interaction capabilities uses software, especially in the decision-making process. Today, many businesses carry out artificial intelligence studies through this software. As a result of all these, it is said that the feature that distinguishes artificial intelligence technology from human intelligence is only a lifeless imitation, and most of the studies focus on making artificial intelligence superior to human intelligence (Bayuk and Demir, 2019).

When we think of artificial intelligence as machine intelligence, we think of a system of intelligent machines that can perceive the environment in order to successfully complete a task. These machines are tools that can mimic the cognitive and emotional elements of the human mind and provide extraordinary progress. Research has led to significant innovations in countless sectors. In this system, data is collected according to the need and large piles of data are created. Working with huge amounts of data is one of the most important features of artificial intelligence, but it also draws heavily on psychology, linguistics, philosophy and mathematics when creating applications. Artificial intelligence, which is seen as a strong supporter, especially in the provision of financial services, also uses various analytical tools (Atlı, 2023).

Artificial intelligence is a simulation of human intelligence that is tuned to think and act like a human being. In fact, the ability of machines to learn is considered a function of artificial intelligence. However, although it seems to be related to artificial intelligence, the Internet of Things and big data are different concepts. While big data contains data collected in any way, the Internet of Things acquires external data that can be input for artificial intelligence. Artificial intelligence, defined as a set of intelligent systems, performs the reproduction of human behaviors based on emotional, social and cognition. The aim of AI is to provide intelligent products, services and experiences so that appropriate sustainable value can be created. Essentially, artificial intelligence is the performance intelligence of machines as they perform their functions in their working environments.

In this context, artificial intelligence is an advanced technology system that provides improved business performance and even increases performance as the process progresses. It consists of a set of algorithms involving deep learning and data processing. An intelligent and error-proof decision-making capability aims to minimize recurring problems and maximize accuracy. Here, the process is based on the absence of any emotional decision-making about the factors that create the problem and is based entirely on information and statistics (Şalvarlı and Kayışkan, 2022).

Essbinbirentially, artificial intelligence is a structure with a system that can make radical changes to existing technology. It is predicted that it will penetrate into daily life more rapidly over time and, together with globalization, will have a greater impact on humans than expected. Thanks to artificial intelligence, machines have the ability to speak, learn, or fly, unlike humans, along with five senses such as touch, sight, taste, and taste. With the use of these qualities in production processes, the quality and volume of products have increased significantly, and countries have become more competitive in the international arena. For this reason, countries or businesses that want to be strong in international markets increase their research and development expenditures and ensure the development of artificial intelligence. In this way, businesses can communicate faster and more effectively with their customers, increase their commercial performance, provide an automated shopping experience, and offer smart products and services (Yakubov and Konak, 2022).

In this context, businesses trying to meet consumer demands, which have increased significantly compared to the past, make full use of artificial intelligence technologies. In order to make their products and services effective in a fiercely competitive environment, they use artificial intelligence in a wide variety of units for innovation as well as research and development activities. However, how artificial intelligence will be used is shaped by business units and has a common benefit for each business unit. For example, increased productivity, superior speed, enhanced customer experience and improved quality of life are among the most important benefits. Artificial intelligence, which can easily perform tasks that seem especially complex and for which human solutions are inadequate, can offer personal suggestions, services, and products by predicting purchasing behaviors, habits, and tendencies from the data obtained from people's transactions on the internet. It also undertakes many tasks such as virtual assistant, purchasing consultancy, pricing and routing, as well as receiving and categorizing questions and requests and providing suggestions (Sarıoğlu and Develi, 2022).

In fact, artificial intelligence is a system that can effectively match consumer needs with business products and services. Thanks to data science, predictive models can be created and solutions developed, and the expectation that AI should be capable of reasoning, business forecasting, or planning has increased in recent years. Modern business demands an automated, data-driven, intelligent and error-free system, which has a direct impact on the results of business operations. Technological developments are very important for businesses to make a difference and become stronger in competition. Artificial intelligence in business has a critical role in developing and implementing recommendations to achieve the best results. Adapting to rapidly changing needs is at the forefront for innovative businesses and artificial intelligence not only provides this but also offers profitable solution packages to business stakeholders. In the digital transformation with artificial intelligence, the business becomes modern, state-of-the-art and fast in implementing its main operations.

Consumers, in particular, like to use exciting and up-to-date technologies, and they like businesses to leverage these technologies to leverage artificial intelligence capabilities such as image and voice recognition and semantic search. In this way, businesses have continuous and customized interactions with their customers and gain a sustainable competitive advantage. Businesses that can understand the importance of artificial intelligence in the real-time world and implement the right system are successful (Erdem, 2022).

As a result, many different professions, such as technologists or engineers, have been interested in artificial intelligence from the past to the present, but currently, artificial intelligence has spread to a wide range of fields, including social sciences. Especially in recent years, there have been many applications of artificial intelligence in the fields of medicine, education and business, which are becoming widespread in every aspect of daily life and making human life easier and easier. In fact, as a step forward, it is predicted that even many jobs that require manpower will be performed by artificial intelligence-supported tools, and human contribution will be minimized (Aktaş and Çavuşoğlu, 2023).

3. The Use Of Artificial Intelligence in Marketing

Artificial intelligence, which is a very different subject from the traditional one, comes to the forefront by making an extraordinary effort to respond to increasing consumer demands and expectations. In parallel with the developing technology, it is a fact that marketing science cannot stay away from artificial intelligence. Artificial intelligence and marketing have become a challenge, going far beyond the traditional ways of interacting with actors in the market. This challenging approach has triggered an innovation and technology shift in marketing that has been ongoing for the last 15 years. Marketing professionals see AI both as a time-saving element to achieve their goals and as a tool that threatens employment. When this process is viewed from a marketing perspective, it is striking how the changes brought about by AI fit into the bigger picture, how they affect business networks, and how the boundaries of knowledge are changing. In fact, from a macro perspective, the actors who are effective in routine business life and marketing are gradually shifting to an understanding based on the human-machine relationship (Ekinci and Bilginer Özsaatçi, 2023).

Essentially, marketers have to make their products, brands and services available wherever consumers are. In the 2020 report of companies conducting marketing research, it is stated that consumer behavior is influenced by artificial intelligence and robotic developments and that the use of artificial intelligence is becoming widespread in this direction. Competition in the digital world is also related to the extent to which the information produced is agile and innovative, as well as the extent to which it is used in marketing activities. However, it should not be forgotten that the digital world generates huge amounts of data. Generating, managing, analyzing and analyzing this huge mass of data and reflecting the results positively on marketing is possible with artificial intelligence technologies. In particular, the interaction between marketing and artificial intelligence extends from managerial and strategic issues with business and social life to the psychological behavior of consumers (Özaydın, 2021).

In this context, artificial intelligence in marketing has focused on identifying and managing customer needs and making offers accordingly. Existing research evaluates the effects of technological development on the marketing performance of the business and its application areas. However, when recent developments are observed, it is seen that there is an increase in studies investigating the intersection of artificial intelligence and marketing. In terms of marketing science, artificial intelligence is defined as "the development of artificial factors that recommend and/or perform marketing actions to achieve the best marketing result, given the information they have about consumers, competitors and the focal company" (Şalvarlı and Kayışkan, 2022).

Considering the intensive technology-oriented fourth industrial revolution, it is an indisputable fact that this situation also affects marketing processes and artificial intelligence, the most popular tool of this revolution, should be used in marketing. Today, artificial intelligence offers serious support to marketing, especially in areas such as business-customer relations, promotion tools, product development, pricing and target market control. With this support, it also brings time and cost advantages. In a 2016 report, 55% of senior marketing executives believe that artificial intelligence is more effective than communication or social media. Since artificial intelligence-supported technological developments allow customer information to be made more useful, businesses focus on developing more customer-centered strategies (Üstüner and Şimşek, 2022).

Within the scope of marketing, artificial intelligence is used, from algorithms developed for consumers to make the best purchases to virtual shopping assistants that analyze customer experience and offer suggestions. Essentially, it is possible to expand the customer portfolio, retain customers and ensure business sustainability with the support of artificial intelligence. Artificial intelligence algorithms created to provide this support focus on providing the most accurate product and service to the target audience. Business models based on artificial intelligence adopt an approach that focuses on the customer (Çizer, 2022).

The utilisation of artificial intelligence (AI) in marketing is becoming increasingly prevalent, with businesses leveraging its innovative capabilities, including speech and image recognition, and machine learning. Artificial intelligence (AI) provides marketers with up-to-date, knowledge-driven insights. Notable applications include Apple Siri, which employs natural language processing for voice commands, and Google DeepMind, which employs deep learning to analyse raw data and optimise operations, such as reducing cooling energy. Artificial intelligence (AI) has become a necessity for businesses of all sizes, as it enables enhanced efficiency and the delivery of personalised customer experiences (Okay, 2023).

In fact, it is important for businesses to adopt technological innovations for many reasons. These innovations provide businesses with sustainable competition in the new economy and make it easier for brands to grow and expand into new markets. Technology also manifests itself in the design, production and presentation of a new product. Shortening and automating processes, providing consumers with superior service and experience, making existing products attractive, and developing a new technology-enabled service concept make businesses superior. Many marketing professionals believe that digital technology will trigger radical developments that will affect consumer behavior and that this impact will be greater as more people connect to the internet.

Artificial intelligence has taken its place at the top of the agenda of innovative businesses. Rising costs, shrinking profit margins and intensifying competition require managers to come up with innovative solutions. In this context, artificial intelligence is not limited to improved customer experience or higher levels of customer satisfaction; it also creates opportunities for making more informed decisions, increasing revenue and productivity, and automating processes. With artificial intelligence technology, many elements that provide holistic solutions, such as mobile applications, virtual reality, augmented reality, blockchain, autonomous robots, smart sensors, and cyber security technologies, have been included in the business world (Gülşen, 2019).

As it is understood, artificial intelligence undertakes the task of matching the needs of potential consumers with what businesses offer in the most effective way. As of today, first-generation artificial intelligence applications are everywhere. For example, recognizing and tagging faces in any photo posted on Facebook, Apple Siri is acting by recognizing the user's voice, or Tesla producing self-driving cars. In addition, applications developed in the field of marketing have been transformed into modern services that every business can easily implement and access (Binbir, 2021).

The utilisation of intelligent systems in business marketing planning has the potential to enhance online resources and to strengthen business-consumer relationships. Artificial intelligence (AI) is a crucial component in the management of these relationships. As the generation of global data continues to expand, traditional methodologies are becoming increasingly inadequate to cope with the demands of the modern business environment. In contrast, AI is able to excel where traditional methods are unable to keep pace. Artificial intelligence (AI) facilitates the storage, modelling, and analysis of data derived from blogs, social media, and websites, thereby enabling the generation of crucial insights that inform the design of effective marketing campaigns (Sarıoğlu and Develi, 2022).

Artificial intelligence, which has a great impact on the marketing world, has a wide range of applications. Amazon automates transportation and delivery operations with the help of drones using its "prime air" service. Domino's Pizza delivers pizza with autonomous vehicles and delivery robots.

RedBalloon finds and reaches new customers through an artificial intelligence platform called Albert. Lexus creates the scenarios of the advertisements to be shown on television with IBM Watson, while Replika imitates many communication styles to provide emotional support to consumers (Aktaş and Çavuşoğlu, 2023).

In this context, marketing is now shifting from a standardized production-based process to a tailored customer-oriented process. Traditional marketing strategies have been replaced by digital tools, where the marketing mix is now determined by identifying technologies and online communities. The combination of AI and marketing is a growing understanding of functionality for successful businesses. Artificial intelligence has evolved from simple technological tools to a direction that determines and significantly affects the performance of the business (Gür, 2022).

As a result, the age of marketing with artificial intelligence foresees fundamental changes that need to be made, from the strategies used to achieve goals to the daily responsibilities in the workplace. The process that began with the advent of computers shows that AI has the potential to change the entire nature of marketing (Şahin, 2021).

4. Use Of Artificial Intelligence in Accounting

Artificial intelligence, which has become an integral part of today's studies, can replace human beings wherever there are human beings, so it can be used in every profession and every sector. In parallel with this situation, the field of accounting also takes its share of these developments (Gacar, 2019: 391). The new order in which artificial intelligence affects every profession and every activity involving human power actually proves how powerful the phenomenon of artificial intelligence is (Serçemeli, 2018: 377).

Artificial intelligence is fundamentally changing the functioning of financial institutions for reasons such as saving costs and increasing the efficiency of activities. In fact, during the past period, the accounting profession has transformed from a profession in which manual calculations are made using paper and pen to a profession that is intertwined with technology involving computers and software (Chuckwudi et al., 2018). The use of artificial intelligence in the accounting profession has brought about a transformative process for the future of the profession. This situation brings to the fore advantages such as more accurate presentation of financial statements and ease in detecting fraud (Bao et al., 2022). It also offers opportunities for operational improvement, cost efficiency, and transition to strategic roles for professionals (Li and Zheng, 2018).

Accounting is a profession where human labor is used intensively. Therefore, it is thought that artificial intelligence will be very efficient in this profession, as it will minimize the errors that may occur due to human error. The reason for the emphasis on minimizing errors rather than zero is that it is a human being who writes the algorithm. On the other hand, it is possible to alleviate the workload in accounting with algorithms such as analyzing, classifying and processing, which are the functions of accounting, with the use of artificial intelligence (Yardımcıoğlu Şıtak, 2020: 347).

However, the use of artificial intelligence to automate activities such as financial analysis and invoice management raises various concerns. The increase in the use of artificial intelligence also leads to the obsolescence and disappearance of some intermediate staff (Frey and Osborne, 2017). In other words, the use of artificial intelligence technologies exposes the accounting profession to the risk of machines performing tasks that were performed by humans in the past. The high accuracy and efficiency demonstrated by artificial intelligence in its work also shows that many accounting positions may become redundant (Autor and Dorn, 2013).

Another issue that artificial intelligence affects the field of accounting is taxation. Tax is explained as the part that expresses the right of society to the earnings of taxpayers; simultaneously, it is explained as the source of income used by the state in the realization of public activities (Turan, 2020). It is seen that artificial intelligence is widely used in tax applications. The use of artificial intelligence in this field helps to reduce human-induced accounting errors and reduce tax administrative costs (Zhou, 2019).

The impact of artificial intelligence (AI) on accounting is significant, particularly in the context of reporting. While AI can easily perform many accounting functions, reporting remains an exception due to the need for professional judgment. Professional judgment involves the knowledge and experience used for strategic decisions and interpreting accounting standards. Since judgment is a human interpretation process, it is unlikely that the reporting function will be significantly affected by AI in the near future. (Nalbantoğlu, 2017).

The most important step in the digital transformation is to bring people and machines together, enabling each to contribute in the areas they are best at. Machines can efficiently and accurately analyze large amounts of data, detect patterns in data, and easily learn how to handle various types of data. At this point, while machines will take care of monotonous tasks, accounting and finance professionals will find time to take on more critical tasks (Marr, 2018).

The digital transformation has many positive and negative consequences. Economically, increased unemployment can be diverse enough to affect overall economic growth through reduced consumer spending (Benanav, 2020). Socially, potential job losses can intensify mental health problems and change family dynamics (Brynjolfsson and McAfee, 2014). In particular, the idea that some professionals will no longer be needed raises concerns.

In this framework, despite the advantages and disadvantages of artificial intelligence, it is clearly seen that it has created a transformation in the accounting profession as a whole in the context of tax, audit and reporting areas and made it more technology-oriented. What needs to be considered here is to adapt to the changing and transforming process, to improve oneself as a member of the profession, and to try to gain the innovations required by the change.

5. Literature Review

In social sciences, bibliometric analyses have become a key approach for assessing research output, uncovering collaboration trends, and tracing the development of knowledge across various fields. These analyses use quantitative methods to evaluate the influence and spread of scientific work, often relying on citation data from databases like Web of Science and Scopus.

In the accounting field, bibliometric analysis has been applied as a tool for mapping the intellectual framework of the discipline. For instance, a detailed bibliometric review of accounting research, conducted using the Web of Science database, identified influential authors, journals, and institutions that have significantly impacted the field (Merigó and Yang, 2016). The results of this study showcase the utility of bibliometric methods in structuring knowledge and detecting trends in accounting research. Likewise, the study of social and environmental accounting in the public sector by Fusco and Ricci (2019) underlines the increasing importance of bibliometric approaches in management studies, highlighting how these analyses can guide future research directions.

In marketing, bibliometric methods have also gained significant momentum, especially in exploring themes like digital marketing and sustainability. For example, researchers applied co-word and co-citation analyses to study the progression of digital marketing research, revealing key trends and thematic clusters within the literature (Pham et al., 2022). Additionally, Tian and Kamran (2023) utilized co-citation analysis to trace intellectual connections in their work on sustainability in marketing, highlighting the interrelation of research themes and the collaborative nature of academic efforts in this field.

The use of bibliometric analysis also extends to understanding consumer behavior and brand relationships in marketing. A meta-analysis of consumer-brand relationships, employing bibliometric techniques, provided valuable insights into foundational literature and emerging trends in this area (Fetscherin and Heinrich, 2015).

Nurhayadi's (2023) mapping of environmental management accounting systems offers a prime example of how visualization techniques can enhance the understanding of connections between research contributions. Similarly, bibliometric mapping was used to examine smartphone online marketing, revealing patterns and influential works within the field (Suki et al., 2023).

In the area of sustainability, Altin and Yilmaz conducted a bibliometric analysis with a specific emphasis on sustainability accounting and reporting. Using clustering techniques, the researchers organized and examined the core elements of sustainable accounting, uncovering established research topics and emerging trends within the field. This study supports the findings of earlier research by demonstrating how bibliometric analysis can be effectively applied in both accounting and marketing, particularly in the context of sustainability (Altın & Yılmaz, 2023).

Further expanding the intersection of these fields, a bibliometric and visualization analysis of corporate social responsibility (CSR) and marketing literature was conducted. The authors highlighted the current state of CSR-related marketing research, stressing the need for more structured bibliometric studies in this domain (Quezado et al., 2022). This analysis not only clarifies the relationship between CSR and marketing but also points to increasing interest in how these concepts interact with accounting practices, especially regarding transparency and ethical considerations.

Moreover, the bibliometric analysis conducted on accounting in the blockchain era highlights how emerging technologies are transforming accounting practices and, consequently, marketing strategies. Their findings demonstrate that bibliometric methods can effectively uncover the relationship between technological advancements and traditional fields like accounting and marketing (Rahmawati and Subardjo, 2022).

The convergence of accounting and artificial intelligence (AI) has garnered significant attention in recent years, leading to an increasing number of bibliometric analyses exploring the trends, impacts, and research landscapes in this area. A bibliometric study by Khan et al. (2023) underscores the pivotal role AI plays in revolutionizing business management and accounting practices. It suggests that AI will not replace accountants but will shift their responsibilities towards more analytical tasks. This study utilizes bibliometric techniques to classify existing reviews and pinpoint research gaps, offering a detailed overview of the current state of AI in accounting.

An additional expansion of the bibliometric approach was carried out through a bibliometric analysis specifically targeting the applications of AI across various fields, including accounting. The study utilized data from the Scopus database, employing analytical tools like VOSviewer and RStudio to visualize publication trends and research outputs related to AI technologies in business management and accounting. This approach not only highlights the rise of AI-related publications but also helps identify key authors, leading journals, and emerging research themes within the accounting domain (Jrad, 2023).

In another relevant study, a bibliometric analysis was conducted on the role of information systems and technology in tax accounting. This research focused on articles published between 2013 and 2023, emphasizing the application of artificial intelligence and related technologies in tax accounting practices. The findings underscore the importance of integrating AI into accounting processes to enhance efficiency and accuracy in tax operations (Figueredo, 2023).

A key area of focus in the current literature is the transformative role of AI in marketing communication and strategy. Senyapar (2024) highlights how AI enhances personalization and efficiency in marketing communications, enabling real-time engagement and providing deeper insights into consumer behavior. This perspective is reinforced by Noranee and Othman (2023), who emphasize AI's ability to analyze market sentiments, allowing marketers to make data-driven, informed decisions. Furthermore, a systematic review by Chintalapati and Pandey (2021) categorizes various AI applications in marketing, identifying 170 use cases that demonstrate how AI can improve outcomes across different marketing functions.

Another important topic is the improvement of customer engagement through the application of artificial intelligence (AI). Purnawati (2024) examines the influence of AI technologies on market segmentation and marketing strategies, demonstrating how these tools enable more precise and personalized marketing efforts. Similarly, Mishra et al. (2022) show that AI integration leads to reduced advertising costs and the execution of more effective marketing campaigns, illustrating the efficiency benefits of AI adoption. Additionally, the framework proposed by Yau et al. (2021) highlights how AI can enhance customer relationships by leveraging big data to generate insights that shape marketing strategies.

The ethical implications of AI in marketing are becoming an increasingly relevant topic in academic discussions. Su (2023) identifies ten ethical challenges associated with AI in marketing and consumer behavior, stressing the importance of marketers addressing these issues responsibly. Likewise, Anjorin (2024) underscores the need to consider data privacy and ethical concerns when implementing AI in marketing strategies, advocating for a structured approach to effectively manage risks.

It is crucial for the accounting and marketing departments to collaborate in order to improve organizational performance and achieve strategic goals. This partnership becomes especially important in integrated marketing strategies, where aligning financial insights with marketing initiatives can lead to greater supply chain efficiency and overall business success. Clear communication between supply chain teams and marketing departments is key to ensuring that marketing campaigns are feasible and aligned with accurate inventory levels and product availability, thereby boosting the effectiveness of promotional activities (Mitchell, 2024).

Furthermore, the collaboration between these two functions can promote innovation and creativity within the organization. Combining the analytical strengths of accounting with the creative insights of marketing enables businesses to develop innovative solutions that meet customer demands while ensuring financial sustainability. This is particularly relevant in today's fast-paced business environment, where adaptability and responsiveness to market trends are essential for maintaining a competitive edge. The integration of diverse perspectives from both departments fosters more comprehensive decision-making, enhancing the organization's ability to navigate complex market environments (Elhelaly, 2024).

The integration of accounting and marketing with artificial intelligence (AI) holds the potential to create powerful synergies in the modern business landscape. Traditionally, accounting focuses on ensuring financial accuracy and guiding decision-makers, while marketing is centered on developing customer-oriented strategies. AI helps bridge these distinct functions, enabling businesses to operate more cohesively and efficiently. In accounting, AI enhances data analysis and forecasting, allowing for the optimization of marketing strategies based on real-time financial insights. For instance, AI-driven cost analysis ensures that marketing efforts remain financially sustainable, while personalized customer experiences in marketing can be informed by accounting data, improving resource allocation and targeting.

This integration enables businesses to make more informed, financially sound decisions and adopt a strategic approach to marketing, ultimately boosting productivity and securing a competitive edge through faster and more accurate decision-making.

To explore the significance of this integration, a bibliometric analysis was conducted to map the academic knowledge surrounding the convergence of accounting, marketing, and AI in business. The study provides valuable insights into AI's impact on these fields, highlights opportunities for cross-functional collaboration, and identifies future research directions.

6. Method

In this section, the methodology of the study is explained in terms of purpose, importance and data source.

6.1. Purpose and Importance

The main purpose of the study is to perform a statistical analysis of the publications in which the concepts of "artificial intelligence," "accounting," and "marketing" are used together. For this purpose, by reaching the number of publications in international databases, it aims to determine the contributions of academic research conducted by different groups of researchers from different universities and countries to the theme of "artificial intelligence, accounting, and marketing."

The study is important in terms of aiming for the progress and expansion of the studies on the same theme, as well as being a road map for researchers who will work on a similar theme. In addition, it is considered important in terms of contributing to the literature on the extent to which the concept of artificial intelligence, which is increasing in importance and usage area, is used in accounting and marketing academic publications.

6.2. Data Source

There are many databases that can be used as data sources for bibliometric research. Google Scholar, Scopus, WOS (web of Science), PubMed, and MEDLINE are some of the important databases. WOS has a very important place in the field of social sciences as it covers a large number of journals with high impact factors. This database is preferred in bibliometric studies because it provides researchers with great convenience in making analyses. (Demir and Erigüç, 2018). In this study, the WOS database was used as a data source.

6.3. Bibliometrics and Scientific Mapping

Bibliometrics is a tool used to map the state of the art in a given field of scientific knowledge. It is, therefore, a fundamental element used to determine the scientific performance of authors, articles, journals, institutions, and countries through the analysis of keywords and citations. (El Mohadab et al., 2020: 3).

Bibliometric analysis is a statistical technique used to evaluate the quality and quantity of published scientific literature, to examine research trends in a particular field, various citation analyses. Bibliometric analysis has many advantages. The main advantage is the ability to perform quantitative analysis based on measurable, objective, accessible data based on coded information. Therefore, the bibliometric analysis method is a useful and efficient tool for identifying research trends in different disciplinary fields. Literature statistics on the subject are analyzed using representative keywords or by selecting the best journals (Büber and Köseoğlu, 2022).

Bibliometrics involves the collection, processing and management of quantitative bibliographic data from scientific publications. Basically, its statistical indicators allow us to understand the quantity and characteristics of scientific publications (Villalobos et al., 2022).

A research area needs two qualities to be considered an established area. It needs to be "attractive" to the research community and have "sufficient scope" for future research. As the volume of scientific publications grows, searching for information becomes more difficult for researchers. This calls for the need for sense-making, which can help reduce uncertainty through a screening process, an "interpretive schema," or a "cognitive map." Bibliometric analysis helps to make sense of the research field. Bibliometric analysis lies on a continuum between systematic literature review and meta-analysis (Khare and Jain, 2022).

6.4. Data Analysis

During data analysis, the WOS analysis tool was used to conduct preliminary reviews, including the impact assessed by the h-index, which includes leading authors, universities, journals and other factors that define scientific production in this theme. In addition, "R" and "Python" programming languages were used for content analysis of the publications.

6.5. Findings

The document search framework planned before the data analysis is shown in Table 1. In the bibliometric analysis performed in the WOS database, the words artificial intelligence, accounting and marketing were searched using "R" and "Phyton" programming languages. The time period covers academic studies between 2002 and 2024. The use of artificial intelligence, accounting, and marketing themes together was evaluated according to the selected document types and WOS categories. At the same time, according to the selected document and category, it was seen that academic publications related to the theme in question were realized in the context of four languages. At this point, 144 published documents were reached.

Table 1. *Search framework for document*

Parameters	Election
Choice approach	Bibliometric analysis
Database used	WOS (Web of Science)
Tools used for analysis	Python, R
Search query	Artificial Intelligence, Accounting, Marketing
Nature of the document	Article / Book Chapter / Paper / Compilation
Time interval	2002-2024
Language	English/Turkish/Russian/Ukrainian
Total number of documents for analysis	144
Publication phase	The final stage is to publish

Table 2 shows the types of documents accessed, the sub-categories under which they were studied, the indices and sub-topic distributions.

Table 2. *Evaluation of document criteria*

Criteria	Numerical Value
Document Types	
Article	131
Proceedings Book	8
Compilation	4
Book Chapter	1
WoS Categories	
Business-Finance	77
Governance	34
Economy	28
Statistics Probability	3
Social Sciences Interdisciplinary	2
WOS Index	
Emerging Sources Citation Index (ESCI)	73
Social Sciences Citation Index (SSCI)	63
Conference Proceedings Citation Index-Social Sciences and Humanities (CPCI-SSH)	5
Conference Proceedings Citation Index-Science (CPCI-S)	3
Research Areas	
Business-Economics	139
Mathematics	3
Other topics in Social Sciences	2
Total	144

The distribution of documents was 131 articles, eight papers, four reviews and one book chapter in total. According to WOS categories, 77 studies were conducted in the field of business finance, 34 in management, 28 in economics, and 3 in statistical probability. In addition, two studies were conducted in the interdisciplinary social sciences category.

In the index categories, ESCI 73, SSCI 63, CPCI-SSH 5 and CPCI-S index three studies were listed. In the research areas category, 139 studies were found in the field of business economics, 3 in mathematics, and 2 in other social sciences. This table provides a statistical summary to analyze the trends and distribution of academic studies in the fields of artificial intelligence, accounting, and marketing.

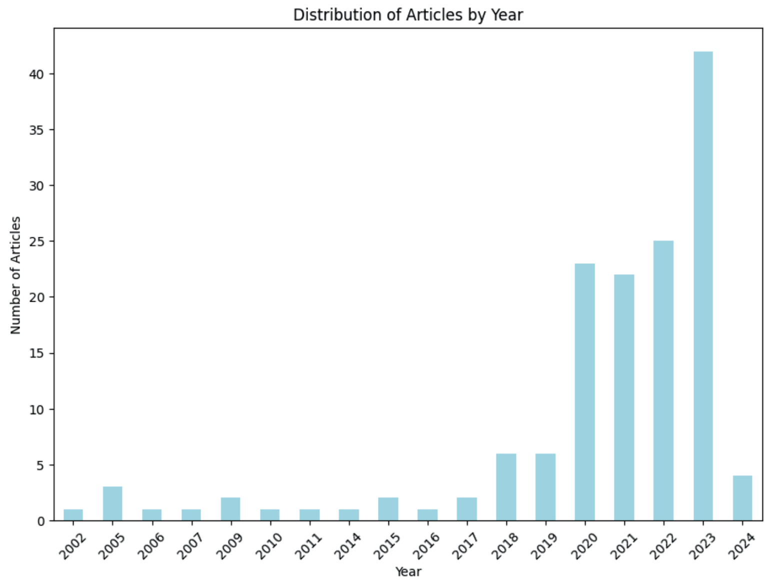


Figure 1. *Number of publications by year*

Figure 1 shows the distribution of academic studies by year from 2002 to the present. From 2002 to 2014, the annual number of studies remained at low levels and remained in single digits until 2016. In 2018, there was a noticeable increase in the number of publications, and approximately six studies were published annually. This number remained stable in 2019. However, a significant increase was observed in 2020 and 2021, with approximately 22 studies published annually. This trend continued with 25 studies published in 2022. In 2023, the number of studies peaked at 42. This shows that interest in the field is growing or research activities are expanding. In 2024, only four academic studies were recorded. This suggests that the data collection process may not yet be complete or that the number may increase during the year. The trends in this figure visually illustrate the increases and fluctuations in research and publication activity over time.

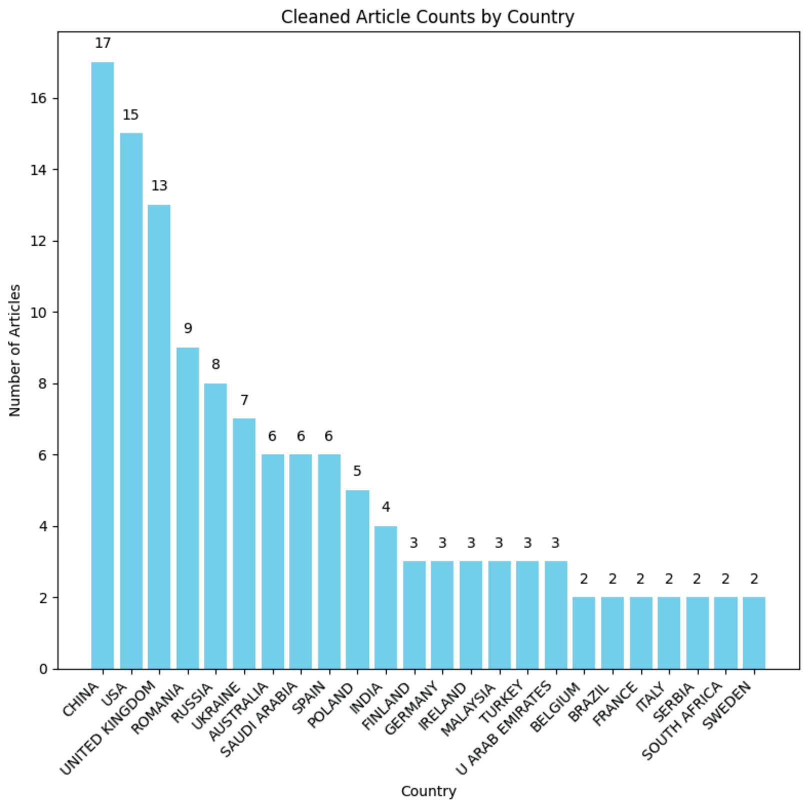


Figure 2. *NUMBER of articles by country (top 24 countries)*

Figure 2 shows the distribution of academic studies by country. China stands out as the country with the highest number of publications in the dataset, with 17 studies. This shows that China has made a significant contribution to the research field and has a leading position in this field. The USA ranked second with 15 studies. The United Kingdom ranked third with 13 studies. These three countries stand out as the most active countries in the research area analyzed.

Romania and Russia followed the first three countries with 9 and 8 studies, respectively. This shows that they are clearly trying to contribute to the field. Turkey and many other countries were included in this ranking with three publications. These data reveal the diversity and intensity of these countries' contributions to scientific research and publication activities. The leading positions of China, the USA and the UK reflect the importance these countries attach to scientific research and development. This distribution provides valuable insights into how scientific publication capacity and research focus may differ between countries around the world.

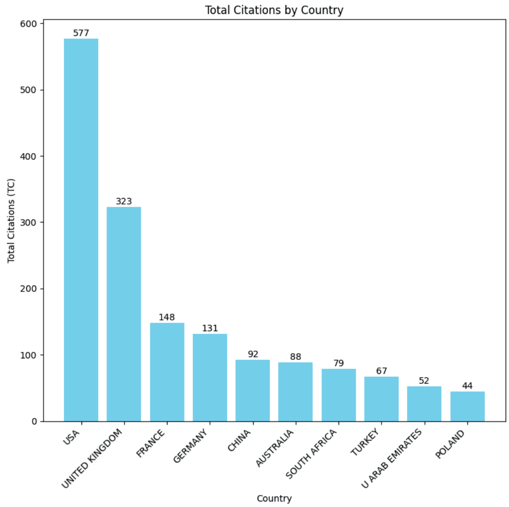


Figure 3. *Most cited countries (top 10 countries)*

Figure 3 illustrates the contribution of countries to scientific studies based on total citations. The USA leads with 577 citations, indicating its significant impact on research. The UK follows with 323 citations, marking it as a major player in science and technology. France and Germany contribute 148 and 131 citations, respectively. This graph highlights the leading countries in knowledge production and innovation, offering insights into the geographical distribution of research and development.

Table 3. *Most relevant authors*

Author	Publication Count	Numerical Value
1	Nwogugu, M	3
2	Guo, X	3
3	Duppati, G	2
4	Scrimgeour, F	2
5	Tiwari, AK	2
6	Potì, V	2
7	Kaczorowska-Spychalska, D	2
8	Buckley, P	2
9	Doyle, E	2
10	McCarthy, B	2

Table 3 presents authors who have focused on specific research themes and topics and have made significant contributions in these areas. The number of publications is an important indicator of an author's influence within the research community and contribution to the development of the field. The publications of the top 10 authors have significantly contributed to the development of new theories, methodologies and findings in their respective research areas. Their work provides a foundation for future research and plays an important role in shaping research directions.

When the data set is analyzed, it is seen that the top 10 authors have made significant contributions to the research field. In particular, Nwogugu, M; Guo, X has the highest number of publications, with three publications indicating a significant contribution to the knowledge and discourse of the field. The other nine authors have two publications each: Duppati, G; Scrimgeour, F; Tiwari, AK; Potì, V; Kaczorowska-Spychalska, D; Buckley, P; Doyle, E; and McCarthy, B. This demonstrates the authors' consistent and influential work in their respective research areas.

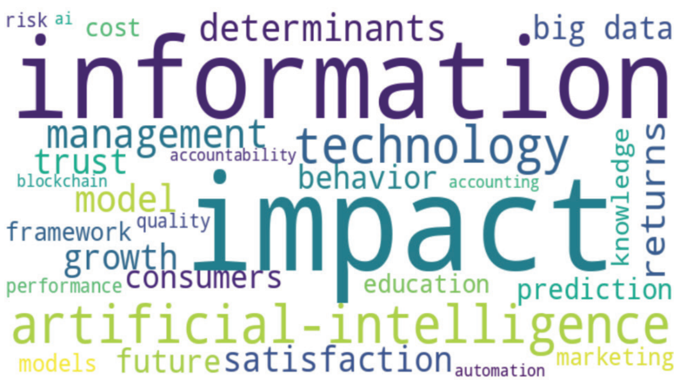


Figure 4. *Most frequently used words (top 30 words)*

Figure 4 shows a visualization of the most frequently used words in academic studies on artificial intelligence, accounting and marketing. This word cloud visually represents the focal points and important themes of the analyzed concepts. Larger and bolder words in the cloud indicate the most frequent terms and the main focus of the text. For example, the size of words such as 'impact,' 'knowledge,' 'artificial intelligence,' and 'technology' emphasize their importance and frequency in the text.

This visualization helps to quickly understand the main topics and technological or managerial concepts highlighted in the text. It provides an effective summary of the conceptual analysis, making it easy to see how certain terms are distributed and which topics are prominent. It can be seen in the details that the words 'accounting' and 'marketing' are also used with a certain frequency.

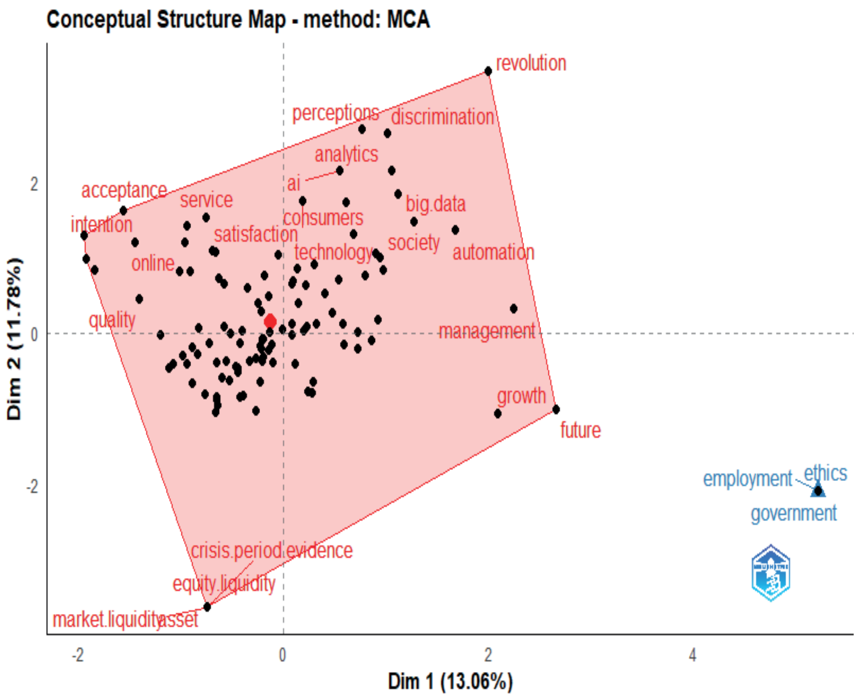


Figure 5. *Factorial analysis of the conceptual structure map method: multiple relevance analysis of high-frequency keywords*

Figure 5 shows the analysis output, called the conceptual structure map, which visualizes the relationships and patterns of the concepts in the categorical data. In the figure, the distribution in two-dimensional space gives an idea of how close the concepts are to each other and reveals their degree of relationship. The horizontal axis (Dim 1) represents 13.06% of the variation in the dataset and positions business ethics or public administration concepts such as "employment," "ethics," and "government" on the right side and financial risk concepts such as "crisis," "period," "evidence," "equity liquidity" on the left side. The vertical axis (Dim 2) explains 11.78% of the variation. Social and transformation-related concepts such as "revolution," "discrimination," "analytics," and "big data" are on the top, while finance and business-based concepts are on the bottom. The red area indicates a cluster of frequently related terms such as "big data," "automation," "management," and "growth," which are often centered on common themes such as technological innovation and business growth.

This structural map stands out as a useful tool for understanding the conceptual relationships and main themes in the research area.

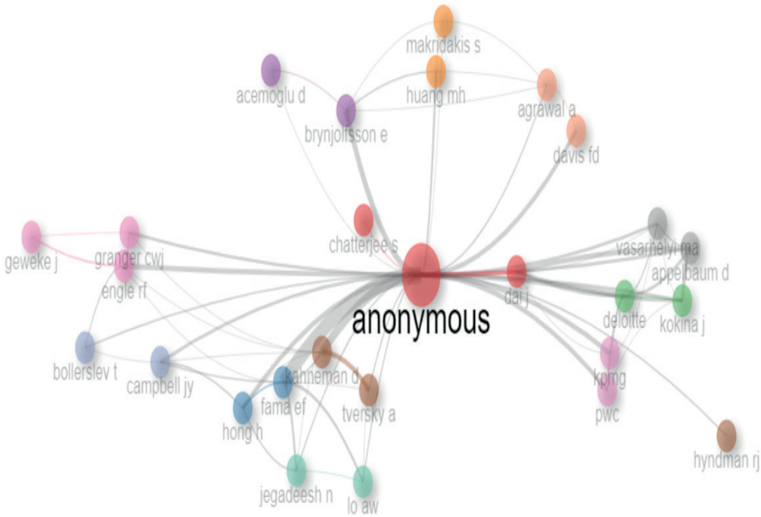


Figure 6. *Authors' collaborative citation network*

Figure 6 shows the citation network of co-authors in academic studies on this theme. Each node (dot) in the network represents an author or a work. The links between the nodes (edges) show the ties between these authors or studies through citation. The size of the nodes usually depends on the frequency of citation, with larger nodes indicating more cited authors or studies. Colors represent different disciplines, communities or citation types.

The "anonymous" node, shown large and in red in the center, represents an author or work that has a central position in the network and is likely to be frequently cited by many other authors or works. This indicates that this author or work has had a significant impact in the field. The links between other authors or works reflect their scholarly dialogues and interactions with each other. For example, links between "Chatterjee s" and "dai h" indicate that the works of these two authors are frequently cited together or that they work on the same topic.

In general, this co-citation network allows us to see which authors or works play a central role in a scientific field, which authors or works are frequently associated with each other, and how communities are structured. This is a valuable tool for analyzing the structural and relational context of scientific works, subjects or disciplines.

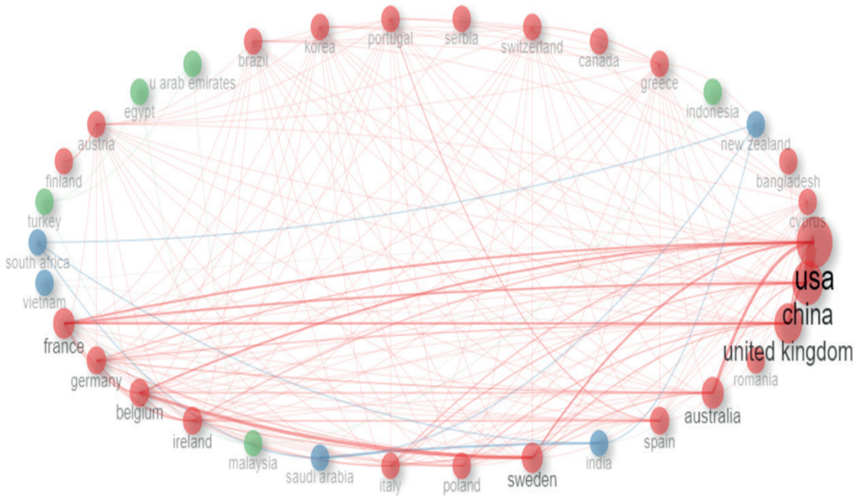


Figure 7. *Cooperation network of countries*

Figure 7 presents a network map showing the cross-country cooperation or interaction of academic studies on this theme. Each node in the network represents a country, while the links (edges) between nodes symbolize the relationships between these countries. The thickness and color of the links may vary depending on the intensity of the relationship or the type of collaboration.

In this image, large nodes such as "USA," "China," and "United Kingdom" stand out. These probably represent the most cooperative or influential countries in the global environment. The large number of links to these countries indicates their weight in international affairs and their extensive cooperation networks. Other countries are represented by smaller nodes and thinner links, indicating that they have less dense relationships in the network. The colors represent different regional groups or perhaps degrees of cooperation. For example, warm colors (reds) represent more dense relationships, while cool colors (blues) represent less dense relationships.

7. Conclusion

The widespread use of artificial intelligence in every field has brought about changes and transformations in the short, medium and long term. It is seen that these changes will have advantages and disadvantages both in the field of marketing and accounting. At this point, adapting to the process would be the best option to realize the renewal required by the change.

The main purpose of this study, which deals with artificial intelligence in the context of its use in marketing and accounting, is to statistically analyze academic studies in which the terms "artificial intelligence," "marketing," and "accounting" are discussed together in a certain period of time. According to the findings, the academic studies using these terms in the WOS database between 2002 and 2024 are mostly in English but also in Turkish, Russian, and Ukrainian. There were 144 documents of different types, such as articles, papers, book chapters, and reviews. These are generally interdisciplinary studies in the fields of business, finance, management, and economics. It has been observed that the related studies have increased, especially as of 2020, and interest in and studies on the theme have increased. China, the USA and the UK are the countries with the highest number of academic studies on the subject. The USA, the UK, France and Germany were the countries with the most cited studies. It was noteworthy that the terms impact, knowledge, artificial intelligence and technology were frequently used in the studies. In addition, the findings also show that joint studies between countries and authors were frequently conducted.

In the context of the analysis, it is clearly seen that the subject has an increasing importance. Therefore, similar analyses can be repeated in the future by considering different disciplines and different keywords. At the same time, the process of adaptation to artificial intelligence and the advantages and disadvantages it creates in professions can also be suggested for future studies.

Sources

Aktaş, M., & Çavuşoğlu, S. (2023). Artificial intelligence in marketing. In E. S. Yılmaz (Ed.), *Digitalization and marketing research* (pp. 61-73). Gaziantep: Özgür Publishing House.

Altın, M., & Yılmaz, R. (2023). Bibliometric Analysis of Sustainability Accounting and Reporting. *Journal of Accounting and Taxation Studies*, *16*(1), 1-15.

Anjorin, K. F., Raji, M. A., Olodo, H. B., & Oyeyemi, O. P. (2024). Harnessing artificial intelligence to develop strategic marketing goals. *International Journal of Management & Entrepreneurship Research*, *6*(5), 1625-1650.

Atlı, H. F. (2023). Customer experience with artificial intelligence (AI) in marketing research: Artificial intelligence solutions in the analysis of consumer behavior. In E. S. Yılmaz (Ed.), *Digitalization and marketing research* (pp. 75-104). Gaziantep: Özgür Publishing House.

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review, 103*(5), 1553-1597.

Bao, Y., Hilary, G., & Ke, B. (2022). Artificial intelligence and fraud detection. *Innovative Technology at the Interface of Finance and Operations, 1*, 223-247.

Bayuk, M. N., & Demir, B. N. (2019). Artificial intelligence and the future of marketing within the scope of Industry 4.0. *Journal of Social, Humanities and Administrative Sciences, 5*(19), 781-799.

Benanav, A. (2020). *Automation and the future of work*. Verso Books.

Binbir, S. (2021). A descriptive study on the use of artificial intelligence in marketing studies. *New Media Electronic Journal, 5*(3), 314-328.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton and Company.

Büber, M., & Köseoğlu, B. (2022). A bibliometric review and scientific mapping research on oil spill response. *Bulletin of Marine Science and Technology, 11*(1), 123-134.

Chintalapati, S., & Pandey, S. K. (2022). Artificial intelligence in marketing: A systematic literature review. *International Journal of Market Research*, *64*(1), 38-68.

Chukwudi, O. L., Echefu, S. C., Boniface, U. U., & Victoria, C. N. (2018). Effect of artificial intelligence on the performance of accounting operations among accounting firms in South East Nigeria. *Asian Journal of Economics, Business and Accounting, 7*(2), 1-11.

Demir, H., & Erigüç, G. (2018). Examining the management thinking system with a bibliometric analysis. *Journal of Business and Human, 5*(2), 91-114.

Ekinci, G., & Bilginer Özsaatçi, F. G. (2023). Bibliometric analysis of publications on artificial intelligence and marketing. *Socioeconomics, 31*(56), 369-388.

El Mohadab, M., Bouikhalene, B., & Safi, S. (2020). Bibliometric method for mapping the state of the art of scientific production in Covid-19. *Chaos, Solitons & Fractals, 139*, 110052.

Elhelaly, N., & Ray, S. (2023). Collaborating to Innovate: Balancing Strategy Dividend and Transactional Efficiencies. *Journal of Marketing*, 00222429231222269.

Fetscherin, M., & Heinrich, D. (2015). Consumer brand relationships research: A bibliometric citation meta-analysis. *Journal of Business Research*, *68*(2), 380-390.

Figueredo, K. (2023). Information systems and technology contributions applied to tax accounting: Bibliometric analysis.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerization? *Technological Forecasting and Social Change, 114*, 254-280.

Fusco, F., & Ricci, P. (2019). What is the stock of the situation? A bibliometric analysis on social and environmental accounting research in public sector. *International Journal of Public Sector Management*, *32*(1), 21-41.

Gacar, A. (2019). Artificial intelligence and its effects on the accounting profession: Opportunities and threats for Turkey. *Balkan Journal of Social Sciences, 8*(Eurefe'19), 389-394.

Gülşen, İ. (2019). Artificial intelligence applications and benefits in businesses: A review in the retail sector. *Journal of Consumer and Consumption Research, 11*(2), 407-436.

Gür, Y. E. (2022). Artificial intelligence and marketing relationship. *Fırat University IIBF International Journal of Economic and Administrative Sciences, 6*(2), 131-148.

Jrad, M. (2023). A role of artificial intelligence in the context of economy: Bibliometric analysis and systematic literature review. *International Journal of Membrane Science and Technology*, *10*(3), 1563-86.

Khan, H. M. R., Ahmad, S., Javed, R., & Nasir, N. (2023). The significance of artificial intelligence in business and accounting: A bibliometric analysis. *Pakistan Journal of Humanities and Social Sciences*, *11*(2), 1061-1082.

Khare, A., & Jain, R. (2022). Mapping the conceptual and intellectual structure of the consumer vulnerability field: A bibliometric analysis. *Journal of Business Research, 150*, 567-584.

Kuruca, Y., Üstüner, M., & Şimşek, I. (2022). The use of artificial intelligence in digital marketing: Chatbot. *Media and Culture, 2*(1), 88-113.

Li, Z., & Zheng, L. (2018). The impact of artificial intelligence on accounting. In *Proceedings of the 4th International Conference on Social Science and Higher Education (ICSSHE 2018).*

Marr, B. (2018, June 1). The digital transformation of accounting and finance - Artificial intelligence, robots and chatbots. *Forbes*. https://www.forbes.com/sites/bernardmarr/2018/06/01/the-digitaltransformation-of-accounting-and-finance-artificial-intelligence-robots-and-chatbots/#1dda9c464ad8

Merigó, J. M., & Yang, J. B. (2017). Accounting research: A bibliometric analysis. *Australian Accounting Review*, *27*(1), 71-100.

Mishra, S., Ewing, M. T., & Cooper, H. B. (2022). Artificial intelligence focus and firm performance. *Journal of the Academy of Marketing Science*, *50*(6), 1176-1197.

Mitchell, E. (2024). The Impact of Integrated Marketing Strategies on Supply Chain Efficiency in Retail Businesses.

Nalbantoğlu, R. (2017). Professional and technological developments with restructuring in financial reporting, auditing and tax regulations. In *Proceedings of the Association of Accounting Professionals of Turkey VII. Turkey Accounting Professionals Congress* (pp. 1-7).

Noranee, S., & bin Othman, A. K. (2023). Understanding consumer sentiments: Exploring the role of artificial intelligence in marketing. *JMM17: Jurnal Ilmu ekonomi dan manajemen*, *10*(1), 15-23.

Nurhayadi, W., Meutia, M., Hanifah, I., & Muchlish, M. (2023, September). Scopus Indexed and VOSviewer-Based Environmental Management Accounting System Mapping: Bibliometrics and Visualization. In *Proceedings of the International Conference on Sustainability in Technological, Environmental, Law, Management, Social and Economic Matters, ICOSTELM 2022, 4-5 November 2022, Bandar Lampung, Indonesia*.

Okay, S. (2023). The use of artificial intelligence and machine learning in digital marketing. *Electronic Journal of Social Sciences, 22*(85), 135-142.

Özaydın, E. (2021). The hidden hero of innovative digital marketing strategies: Artificial intelligence. In C. Tor Kadıoğlu (Ed.), *Current research in digital marketing* (pp. 71-80). Istanbul: Artikel Akademi.

Özer Çizer, E. (2022). Artificial intelligence applications in marketing. In *Proceedings of the Congress on Individual, Society, Politics in the Digitalizing World* (pp. 16-32), 26-27 May 2022, Istanbul-Turkey.

Pham, X. L., Nguyen, P. M. B., & Truong, G. N. T. (2022). A Co-Word and Co-Citation Analysis of Digital Marketing Research. *International Journal of Service Science, Management, Engineering, and Technology (IJSSMET)*, *13*(1), 1-20.

Purnawati, E. (2024). The Influence of Digital Technology on Marketing Strategy. *Management Studies and Business Journal (PRODUCTIVITY)*, *1*(3), 432-446.

Quezado, T. C. C., Cavalcante, W. Q. F., Fortes, N., & Ramos, R. F. (2022). Corporate social responsibility and marketing: a bibliometric and visualization analysis of the literature between the years 1994 and 2020. *Sustainability*, *14*(3), 1694.

Rahmawati, M. I., & Subardjo, A. (2022). A bibliometric analysis of accounting in the blockchain era. *Journal of Accounting and Investment*, *23*(1), 66-77.

Sarıoğlu, B., & Develi, İ. (2022). Campaign management and the use of artificial intelligence in marketing. *International Journal of Public Relations and Advertising Studies, 5*(2), 91-124.

Senyapar, H. N. D. (2024). Artificial Intelligence in Marketing Communication: A

Comprehensive Exploration of the Integration and Impact of AI. *Technium Social Sciences Journal*, *55*, 64-81.

Serçemeli, M. (2018). Artificial intelligence in the digital transformation of accounting and auditing professions. *Turkish Studies, 13*(30), 369-386.

Su, Y., Wang, E., & Berthon, P. (2023). Ethical marketing AI? A structured literature review of the ethical challenges posed by artificial intelligence in the domains of marketing and consumer behavior. In *Proceedings of the 56th Hawaii international conference on system sciences 2023*.

Suki, N. M., En, Y. J., Suki, N. M., Hanafi, M., & Rosmaini, S. (2023). Smartphones Online Marketing: A Bibliometric and Visualized Analysis. *International Journal of Interactive Mobile Technologies*, *17*(8).

Şahin, O. (2021). The effects of artificial intelligence and machine learning on marketing processes. In A. Özbebek Tunç, Y. Yurder, & M. Samioğlu (Eds.), *Rethinking business management* (pp. 241-258). Istanbul: Türkmen Kitabevi.

Şalvarlı, M. S., & Kayışkan, D. (2022). An overview of the evolving role of artificial intelligence in marketing. *Izmir Journal of Management, 2*(2), 106-115.

Tian, Y., & Kamran, Q. (2023). Mapping the intellectual linkage of sustainability in marketing. *Business and Society Review*, *128*(2), 251-274.

Turan, D. (2020). Artificial intelligence and its impact on tax practices. *Anadolu Academy Journal of Social Sciences, 2*(1), 55-70.

Villalobos, D., Povedano-Montero, J., Fernández, S., López-Muñoz, F., Pacios, J., & del Río, D. (2022). Scientific research on verbal fluency tests: A bibliometric analysis. *Journal of Neurolinguistics, 63*, 101082.

Virtue, B. (2022). The effect of artificial intelligence on marketing. In D. Terzioğlu & S. Soğukoğlu Korkmaz (Eds.), *Interdisciplinary academic studies in social sciences* (pp. 87-98). Istanbul: Eğitim Kitabevi.

Yakubov, R., & Konak, A. (2022). The importance of artificial intelligence in digital production and marketing process. In *Proceedings of the I. International Economic and Administrative Research Congress* (pp. 49-60), 21-23 May 2022, Karabük-Turkey.

Yardımcıoğlu, M., & Şıtak, B. (2020). Reflections of artificial intelligence technology on accounting: A literature review. *Bilecik Şeyh Edebali University Journal of Social Sciences, 5*(2), 342-353.

Yau, K. L. A., Saad, N. M., & Chong, Y. W. (2021). Artificial intelligence marketing (AIM) for enhancing customer relationships. *Applied Sciences*, *11*(18), 8562.

Zhou, L. (2019). Opportunities and challenges of artificial intelligence in the application of taxation system. *Advances in Economics, Business and Management Research, 109*, 201-206.

Chapter 2

FORECASTING DIRECTION OF STOCK MARKET USING DEEP LEARNING ALGORITHMS: AN APPLICATION ON ISTANBUL STOCK EXCHANGE

Ümit Hasan GÖZKONAN[1]

Umut Ali Koray KAYALIDERE[2]

Mahmut KARĞIN[3]

1 Öğr. Gör. Dr., Manisa Celal Bayar University, ORCID:0000-0002-7187-6304, umit.gozkonan@cbu.edu.tr
2 Prof. Dr., Manisa Celal Bayar University, ORCID:0000-0003-4073-1644, koray.kayalidere@cbu.edu.tr
3 Prof. Dr., Manisa Celal Bayar University, ORCID:0000-0002-8602-0453, mahmut.kargin@cbu.edu.tr

INTRODUCTION

Forecasting stock market trends has been a persistent challenge in the financial industry. The complexity, volatility, and non-linear characteristics of financial time series complicate the process of making precise forecasts. Conventional techniques, such as statistical methods and linear models, frequently fail to detect the intricate patterns and interconnections in stock market data. However, the latest developments in machine learning (ML) and deep learning (DL) have introduced new strategies for achieving more accurate and efficient market forecasts.

Machine learning techniques like Support Vector Machines (SVM), Decision Trees (DT), and Random Forests (RF) have been widely researched for their ability to improve market forecasts. These approaches utilize historical data alongside various technical indicators to forecast future stock prices and trends (Rath et al., 2024). Additionally, the combination of several machine learning algorithms, such as Classification Trees, SVM, RF, and Neural Networks, has been investigated to increase the precision of stock market forecasts. These models draw on daily stock, bond, and currency data from various nations, offering a comprehensive system for early warnings that aid central banks and financial institutions in adjusting monetary policies to maintain financial stability (Chatzis et al., 2018).

Recently, deep learning models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) and have showed considerable potential in this area. These models excel at identifying long term dependencies and complex patterns within data, making them especially suitable for forecasting stock index trends (Nabipour et al., 2020; Jiang, 2021).

Deep learning algorithms, particularly LSTM networks, have shown great potential in this field. These models can learn from technical indicators beside historical data to forecast future stock prices, helping investors and analysts make well-informed decisions. Deep learning techniques have been extensively researched, focusing on various elements such as forecast methods, trading strategies, profitability measures, and risk management (Li & Bastos, 2020). Additionally, hybrid models that integrate different ML and DL algorithms have been developed to enhance forecast accuracy and resilience (Zhong & Enke, 2019).

Recent progress in deep learning has led to the creation of innovative models like the Multi-Filters Neural Network, which combines recurrent and convolutional neurons for feature extraction and stock price movement forecast. This model has outperformed traditional machine learning models in both accuracy and stability (Long et al., 2019). Moreover, reinforcement learning techniques, such as the Multi-DQN ensemble, have been introduced to reduce overfitting and enhance the robustness of stock market forecasts by optimizing return functions during the training phase (Carta et al., 2021).

Despite the advancements, there are still several challenges and limitations in the application of deep learning to stock market forecasting. For example, the imbalanced nature of financial datasets and the need for extensive computational resources can pose significant hurdles. Moreover, while many studies focus on model accuracy, fewer address the practical aspects of profitability and risk management, which are crucial for real-world applications (Chatzis et al., 2018; Li & Bastos, 2020).

The use of deep neural networks in stock market forecasting marks a substantial advancement over traditional approaches. By harnessing the power of deep learning, researchers and analysts can generate more precise and dependable forecasts, leading to improved investment choices and greater financial stability. Nevertheless, continuous research and innovation are crucial to overcoming current limitations and unlocking the full potential of these sophisticated models.

In this study, LSTM and GRU deep learning models were used to forecast the direction of Borsa Istanbul 100 Index. LSTM and GRU algorithms are learning algorithms that contain changeable parameters. Unlike previous research, this study analyzes the forecast performance of these deep learning models by testing various parameters, ultimately identifying the model with the lowest error rate.

LITERATURE REVIEW

In the literature, various methods have been used, investigating various models and data sources to enhance stock market forecasting, particularly through the integration of technical indicators, news sentiment, and macroeconomic variables.

Leung et al. (2000) conducted a comparison between classification models and level estimation models for stock index forecasting. The techniques they employed included logit, probit, linear discriminant analysis, and probabilistic neural networks, as well as methods like vector autoregression with Kalman filters and, exponential smoothing using data from the FTSE100, S&P500, and Nikkei225. Their findings revealed that classification models, which focus on forecasting market direction, outperformed level forecast models in terms of boosting trading profits, emphasizing the significance of market direction forecast over merely reducing forecast errors.

Chen et al. (2003) utilized probabilistic neural networks (PNN) to forecast the Taiwan Stock Index and compared its performance to GMM with Kalman filters and random walk models. PNN-based strategies achieved higher returns, showing that forecasting market direction is more profitable. The study also found that PNN outperformed other methods, including buyand-hold strategies, in both forecast accuracy and trading returns.

Huang et al. (2005) evaluated SVM for forecasting the Nikkei225 stock index's weekly movement, comparing it to LDA, QDA, and EBNN. SVM outperformed these methods in accuracy, and a combined model further improved forecasting. The study concluded that SVM is an effective tool for forecasting stock market movement, with combined models offering even better results.

Kumar and Thenmozhi (2005) compared the effectiveness of SVM and Random Forest models in forecasting the direction of the S&P CNX NIFTY Index. Their study, using data from 2000 to 2005, showed that SVM outperformed Neural Networks, Random Forest, Logit, and Discriminant Analysis in forecasting stock index movements. SVM achieved the highest forecast accuracy (68.44%), followed by Random Forest (67.40%). The results demonstrated that SVM is a most powerful tool for forecasting stock market direction, offering better accuracy than traditional models.

Liao and Wang (2010) proposed a stochastic neural network model for forecasting global stock indices, including S&P500, IXIC, DJI, HSI, SAI, and SBI. The model integrates a stochastic time function and Brownian motion to weigh historical data based on recency, giving more influence to recent data. The study showed that this model improves forecast accuracy, especially in short-term forecasts, and is highly effective for volatile stock markets. Their analysis demonstrates that adding stochastic elements enhances the precision of forecasts, particularly for Chinese stock markets.

Kara, et al. (2011) conducted a comparison between ANN and SVM to forecast stock movements in the Istanbul Stock Exchange (ISE) 100 Index. Using ten technical indicators as input variables, they evaluated both models on data spanning from 1997 to 2007. ANN achieved an average forecast accuracy of 75.74%, outperforming SVM, which recorded 71.52%. The study concluded that while both models are effective for stock price forecast, ANN demonstrated superior performance in this instance.

Imandoust and Bolandraftar (2014) used three data mining techniques-Naïve Bayesian Classifier, Decision Tree, and Random Forest-to predict stock market index movements on the Tehran Stock Exchange (TSE). They employed ten technical indicators alongside three macroeconomic variables. The results showed that the Decision Tree model achieved the highest accuracy at 80.08%, followed by Random Forest at 78.81% and Naïve Bayesian Classifier at 73.84%. The research highlighted the effectiveness of machine learning methods in forecasting stock index trends, especially when technical indicators are included.

Qiu and Song (2016) developed a hybrid model that combines genetic algorithms (GA) with artificial neural networks (ANN) to forecast the direction of the Nikkei 225 stock market index. By using GA to optimize the ANN, the model achieved greater forecast accuracy. The study tested two groups of technical indicators, with the Type 2 indicators outperforming Type 1 and reaching a hit ratio of 81.27%. The research concluded that the GA-ANN hybrid model offers a highly effective method for forecasting stock market trends.

Oriani and Coelho (2016) analyzed the influence of technical indicators on stock price forecast using multilayer perceptron (MLP) neural networks. They evaluated twelve commonly used technical indicators, both separately and in combination, to forecast the closing prices of five companies listed on the Brazilian IBovespa index. The study revealed that lagging indicators like DEMA and TEMA enhanced forecast accuracy, and the use of multiple indicators together yielded even better results. The research emphasized the potential of technical indicators in improving the precision of stock price forecasts.

Malagrino, et al. (2018) used a Bayesian Network algorithm to forecast the daily movement direction of the iBOVESPA stock index, incorporating global market influences. The model was tested with two time windows (24 and 48 hours) and several stock indices from different continents. The study found that the 24-hour model, which included one stock index per continent, delivered higher accuracy, reaching up to 78%. The findings indicated that certain indices, such as the NYSE Composite, CAC 40, and Hang Seng, had the greatest impact on forecasting iBOVESPA's movement. Due to its simplicity, the model is well-suited for decision support systems in financial markets.

Ren et al. (2019) developed a stock market movement direction forecasting model by integrating sentiment analysis with a Support Vector Machine (SVM). Using investor sentiment data from news and forums, along with stock market data, the model was applied to forecast the SSE 50 Index. The study achieved an accuracy of 89.93% after including sentiment variables, demonstrating that investor sentiment analysis plays a crucial role in forecast stock index movements. The model also showed potential to improve trading strategies by reducing risks and increasing profitability.

Zhou et al. (2020) utilized various data sources, such as transaction data, technical indicators, social media, news, and Baidu search indices, to forecast stock price movements in China's A-share market. The study, which employed SVM, discovered that integrating non-traditional data sources enhanced forecast accuracy for highly active stocks, while a combination of traditional and non-traditional data performed best for less active stocks. The highest forecast accuracy was observed during periods of intense stock activity.

Manjunath et al. (2021) introduced a stock market forecast model that combines deep learning techniques with technical analysis to forecast the movements of the NIFTY 50 index. They evaluated Recurrent Neural Networks (RNN), LSTM, and three variations of the GRU using two different sets of technical indicators (TA1 and TA2). The findings revealed that GRU variant 1 (GRU1) paired with TA1 produced the most accurate forecasts, surpassing both RNN and LSTM. The research highlighted that incorporating technical data augmentation enhances the forecasting accuracy of deep learning algorithms in stock market forecasts.

Chandola et al. (2022) introduced a hybrid deep learning model that merges Word2Vec and LSTM to forecast stock price directional movements by incorporating financial time series data and news headlines. The model was applied to companies from different sectors, such as Apple, PepsiCo, and AT&T. The findings demonstrated that combining news data with stock prices enhanced forecast accuracy compared to conventional models. The study emphasizes the value of hybrid approaches in improving decision-making for stock market forecasting.

DATA AND METHODOLOGY

Within the scope of the research, the direction of Borsa Istanbul 100 index, which is the benchmark index of Turkey, was forecasted by deep learning algorithms. In this context, the index data of the following stock exchanges were used as variables.

- BIST (Borsa Istanbul-100 Index)
- NASDAQ (Nasdaq Composite Index)
- NYSE (New York Stock Exchange Index)
- FTSE (Financial Times Stock Exchange 100 Index)
- N225E (Nikkei 225 Stock Index)
- Euronext (Euronext/Pan-European 100 Index)
- DAX (German Stock Exchange Index)

Borsa Istanbul 100 Index (BIST100) was determined as the dependent (target) variable in the study. To forecast the dependent variable, 6 different international indices with high trading volume and market value[1] were included in the study as independent variables (forecasters). Those indices were included in the study by considering the short/long term integrated or cointegrated indices with Borsa Istanbul index in different studies in the literature. In the study, weekly data set of the indices between 26.09.2014 - 20.09.2024 was used. LSTM and GRU algorithms from deep learning

1 Market Statistics - Focus | The World Federation of Exchanges, 2024

algorithms were used in the study. In order to ensure the learning of the algorithms, 484 weeks of data between 2014-2023 were determined as training data and 38 weeks of data from the beginning of 2024 until 20 September 2024 were determined as test data.

Introduced by Sepp Hochreiter and Jürgen Schmidhuber in 1997, LSTM is a variant of Recurrent Neural Networks (RNN) that surpasses traditional RNNs in capturing long-term dependencies in sequential data. This ability stems from its use of a cell state, which functions as a memory unit, enabling the model to store and access information over longer durations (Shewalkar et al., 2019; Ergen & Kozat, 2020; Ahmadzadeh et al., 2022):

- Forget Gate: Identifies which portions of the previous cell state should be kept.
- Input Gate: Selects the new information that will be incorporated into the cell state.
- Output Gate: Regulates how much of the cell state will contribute to the final output.

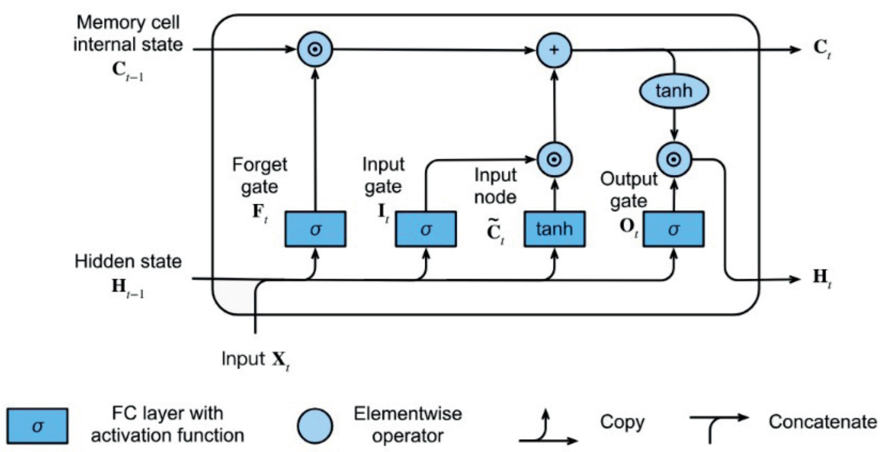


Figure 1. *Long Short-Term Memory Algorithm (Zhang et al., 2021)*

LSTM's gates enable it to selectively retain or discard information, making it particularly efficient at capturing long-term dependencies in sequential data, such as financial time series or speech recognition tasks.

GRU, proposed in 2014 by Kyunghyun Cho and his team, is another type of RNN. It is similar to LSTM in that it addresses the long-term dependency problem, but with a simpler structure, which makes GRUs faster and easier to train in some cases. GRU operates with two main gates (Mateus et al., 2021; Zarzycki & Ławryńczuk, 2021; Mahjoub et al., 2022; Cahuantzi et al., 2023):

- Update Gate: Regulates the amount of past information that should be carried forward. It determines how much of the hidden state will be refreshed with new data.

- Reset Gate: Decides how much of the past information should be "discarded" and how much should impact the current input.

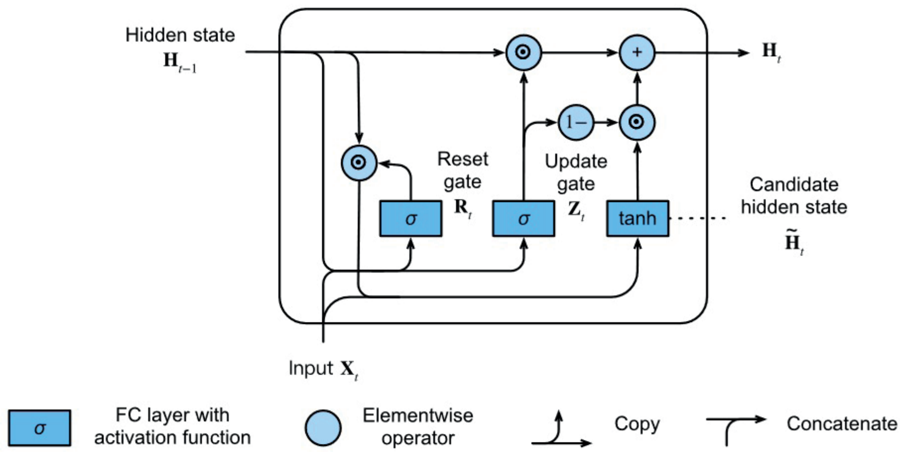


Figure 2. *Gated Recurrent Unit Algorithm (Zhang et al., 2021)*

GRU combines the hidden and cell states into a single state, which simplifies its architecture compared to LSTM. This makes GRU computationally more efficient while often yielding performance similar to LSTM, especially for shorter sequences.

FINDINGS

The results from both LSTM and GRU algorithms, applied with various parameter combinations, reveal important insights into forecasting the direction of the Borsa Istanbul 100 (BIST100) index. Overall, the LSTM algorithm consistently outperforms GRU, as indicated by its lower RMSE (Root Mean Squared Error) values, suggesting that LSTM provides more accurate forecasts for the BIST100 index. The lowest RMSE was achieved with the LSTM model using 128 neurons in the first hidden layer and 64 neurons in the second hidden layer, along with 50 epochs and a batch size of 32, resulting in an RMSE of 39.101. For the GRU algorithm, the lowest RMSE was obtained with 64 neurons in the first hidden layer and 32 in the second, combined with 100 epochs and a batch size of 16, yielding an RMSE of 46.179.

Table 1. *RMSE values of algorithms according to parameters*

1st Hidden Layer (Number of neurons)	2nd Hidden Layer (Number of neurons)	Number of Epoch	Number of Batch	LSTM	GRU
32	16	50	8	40,074*	68,660
		50	16	48,598*	69,227
		50	32	78,623	78,561*
		100	8	82,779	73,516*
		100	16	74,301	72,642*
		100	32	62,115	58,736*
		200	8	85,620*	85,879
		200	16	42,884*	65,577
		200	32	46,336*	87,636
64	32	50	8	69,119*	86,973
		50	16	61,067*	69,920
		50	32	70,563*	91,413
		100	8	82,286	76,033*
		100	16	74,941	46,179**
		100	32	44,342*	70,667
		200	8	55,510*	93,951
		200	16	74,262	50,648*
		200	32	78,590	70,633*
128	64	50	8	62,831*	63,767
		50	16	54,466*	61,690
		50	32	39,101**	75,156
		100	8	90,353	51,318*
		100	16	65,716	62,973*
		100	32	77,780*	86,278
		200	8	75,930*	79,020
		200	16	60,810*	91,687
		200	32	83,655*	93,722

**Lower error rate, **Lowest error rate*

When analyzing the effect of hidden layer neurons, it is seen that the RMSE values obtained in the LSTM model are lower on average in the 32-

16 neuron combination. The same pattern is observed on average in the 64-32 neuron combination in the GRU model. Therefore, it is not seen that the increase in neurons makes a positive contribution to the forecast performance in the analysis.

As for the number of epochs, the lowest RMSE values in all neuron combinations in the LSTM model were obtained at low epoch values. In other words, the lowest RMSE values in all neuron combinations were obtained in 50 epoch analyses. In the GRU model, the lowest RMSE values in all neuron combinations were generally obtained in 100 epoch analyses.

Batch size also affects model performance. For both algorithms, the lowest average RMSE values in terms of batch size were obtained with 16 batch sizes. Supporting this finding, the smallest RMSE value obtained in the GRU algorithm was obtained with 16 batch sizes. However, the lowest RMSE value in the LSTM algorithm was obtained with 32 batch sizes, which is the second batch size that gave the lowest RMSE values on average.

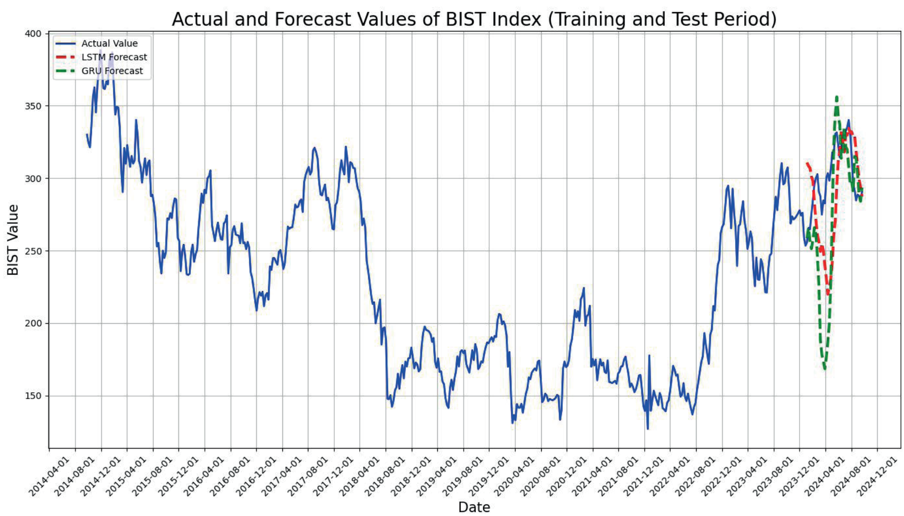


Figure 3. *Actual and Forecast Values of BIST Index (Training and Test Period)*

Figure 3 illustrates the actual and forecasted values of the BIST index during both the training and test periods. The blue line represents the actual BIST index values, while the red dashed line shows the forecast generated by the LSTM algorithm, and the green dashed line represents the GRU forecast. The actual values exhibit significant fluctuations over time, reflecting market volatility. During the test period, both the LSTM and GRU forecasts track the overall trend of the actual BIST index values, although the LSTM forecast (red line) aligns more closely with the real data, particularly in capturing the upward and downward movements. The GRU model (green line) shows more deviation from the actual values, especially in terms of overshooting certain peaks and valleys. This visual reinforces the findings that the LSTM model provides a more accurate forecast, as indicated by its closer fit to the actual BIST index during the test period.

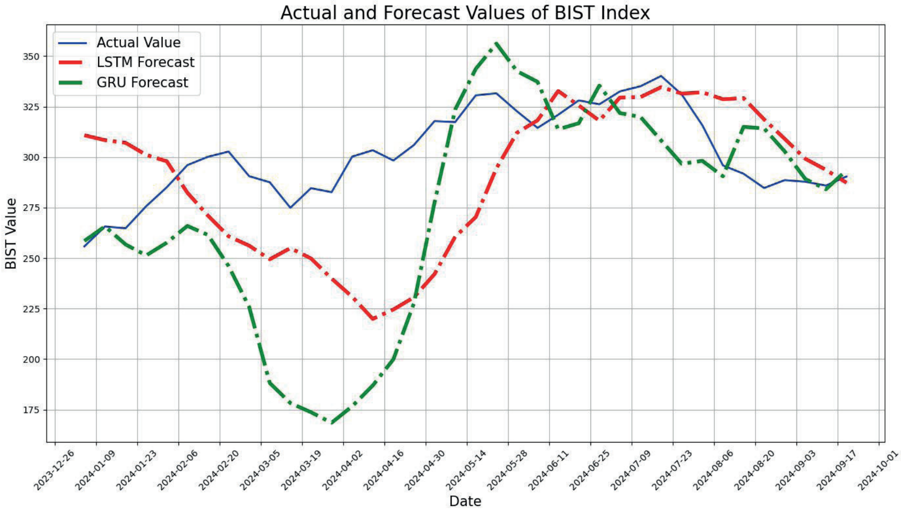


Figure 4. *Actual and Forecast Values of BIST Index (Test Period)*

Figure 4 provides a closer view of the actual and forecasted values of the BIST index over a shorter time span. The blue line represents the actual BIST index values, while the red dashed line shows the LSTM forecast and the green dashed line displays the GRU forecast. The actual values (blue line) show an overall fluctuating pattern with periods of both increase and decline. The LSTM forecast (red line) more closely follows the trend of the actual values, especially during the upward movements, though it slightly underestimates the peaks. The GRU forecast (green line), however, diverges more significantly from the actual values, with larger deviations both above and below the real trend, particularly during periods of more rapid change. This visualization reinforces the LSTM model's better performance in capturing the overall trend, while the GRU model struggles to maintain consistent accuracy, often overshooting the actual values during rapid movements.

DISCUSSION

In this study, the dependent variable, the Borsa Istanbul 100 Index (BIST100), was forecasted using six independent variables: NASDAQ, NYSE, FTSE, N225E, Euronext, and DAX. These indices represent international markets with high trading volumes and were chosen for their potential correlation with the BIST100. The results show that both LSTM and GRU models were capable of capturing these relationships, though the LSTM model outperformed GRU in forecasting the BIST100 movements. This can be attributed to LSTM's superior ability to retain long-term dependencies, which is crucial in financial time series data where market trends across different global indices can have delayed or extended impacts on the BIST100.

The results from this study demonstrate that deep learning algorithms, particularly LSTM and GRU, can forecast the direction of the Borsa Istanbul 100 (BIST100) index. However, the findings highlight a clear performance difference between the two models, with LSTM consistently outperforming GRU. The lower RMSE values achieved by LSTM indicate its superior ability to capture the complex, non-linear patterns inherent in stock market data, especially when compared to the simpler GRU architecture.

Several factors contribute to LSTM's better performance. The LSTM model's ability to retain and leverage long-term dependencies through its cell state and gating mechanisms appears crucial for financial time series forecasting, where past information is often key to forecasting future trends. In contrast, GRU estimates, which have a simpler structure and fewer gates, are thought to show greater deviations from the actual BIST100 index values due to the lack of long-term information.

The analysis also revealed the importance of tuning hyperparameters such as the number of epochs, batch size, and the number of neurons in the hidden layers. It was observed that the performance of LSTM achieved better results at lower numbers of neurons and epochs and was able to better capture the underlying trends in the dataset with lower numbers of neurons and epochs. On the other hand, the performance of GRU was better at the 64-32 neuron combination, but it was also observed that its performance changed depending on the parameters.

Moreover, the closer alignment of the LSTM model's forecasts with the actual BIST100 index values during the test periods demonstrates its performance in capturing market volatility and short-term fluctuations. In the GRU algorithm, it is observed that it has a low performance in capturing fluctuations, while moving in line with the general trends.

CONCLUSION AND RECOMMENDATIONS

In this study, which was conducted using two different algorithms to predict the direction of the BIST100 index, it can be said that the 6 global indices used as independent variables are usable indices in forecasting the direction of the BIST100 index and can capture the index movements. On the other hand, the study confirms that LSTM is a more reliable model for forecasting the BIST100 index compared to GRU. The results indicate that LSTM's architecture is better suited for financial time series data, where long-term dependencies play a significant role in shaping future movements. Given its superior performance, LSTM should be considered a strong candidate for stock market forecasting tasks, particularly in markets that are characterized by volatility and complexity.

The findings of this research also underscore the importance of selecting appropriate hyperparameters. Increasing the number of neurons and training epochs, along with choosing the optimal batch size, can significantly enhance the model's forecast accuracy. For practitioners, these results suggest that careful experimentation with these parameters is necessary to achieve the best forecasting performance.

Moreover, while LSTM has demonstrated its effectiveness in this study, future research could investigate the potential of hybrid models. By combining the strengths of LSTM with other machine learning techniques, such as reinforcement learning or convolutional neural networks (CNNs), it may be possible to further enhance forecast accuracy and robustness. Exploring different architectures or integrating additional data sources, such as economic indicators, news sentiment, or social media data, could also improve the model's ability to capture market dynamics.

Additionally, it is recommended that future studies focus on the practical application of these models in real-time trading environments. Beyond forecast accuracy, aspects such as profitability and risk management should be evaluated to determine the full utility of these models in decision-making processes. By developing strategies that integrate these forecasts with effective risk mitigation, LSTM-based models can be employed more effectively by financial institutions and individual investors alike. Exploring their impact in a broader array of financial markets would also help validate the robustness and adaptability of these models in various global contexts.

REFERENCES

Ahmadzadeh, E., Kim, H., Jeong, O., Kim, N., & Moon, I. (2022). A Deep Bidirectional LSTM-GRU Network Model for Automated Ciphertext Classification. *IEEE Access*, *10*, 3228–3237. https://doi.org/10.1109/ACCESS.2022.3140342

Cahuantzi, R., Chen, X., & Güttel, S. (2023). A Comparison of LSTM and GRU Networks for Learning Symbolic Sequences. In K. Arai (Ed.), *Intelligent Computing* (Vol. 739, pp. 771–785). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-37963-5_53

Carta, S., Ferreira, A., Podda, A. S., Reforgiato Recupero, D., & Sanna, A. (2021). Multi-DQN: An ensemble of Deep Q-learning agents for stock market forecasting. *Expert Systems with Applications*, *164*, 113820. https://doi.org/10.1016/j.eswa.2020.113820

Chandola, D., Mehta, A., Singh, S., Tikkiwal, V. A., & Agrawal, H. (2023). Forecasting Directional Movement of Stock Prices using Deep Learning. *Annals of Data Science*, *10*(5), 1361–1378. https://doi.org/10.1007/s40745-022-00432-6

Chatzis, S. P., Siakoulis, V., Petropoulos, A., Stavroulakis, E., & Vlachogiannakis, N. (2018). Forecasting stock market crisis events using deep and statistical machine learning techniques. *Expert Systems with Applications*, *112*, 353–371. https://doi.org/10.1016/j.eswa.2018.06.032

Chen, A.-S., Leung, M. T., & Daouk, H. (2003). Application of neural networks to an emerging financial market: Forecasting and trading the Taiwan Stock Index. *Computers & Operations Research*, *30*(6), 901–923. https://doi.org/10.1016/S0305-0548(02)00037-0

Ergen, T., & Kozat, S. S. (2020). Unsupervised Anomaly Detection With LSTM Neural Networks. *IEEE Transactions on Neural Networks and Learning Systems*, *31*(8), 3127–3141. https://doi.org/10.1109/TNNLS.2019.2935975

Huang, W., Nakamori, Y., & Wang, S.-Y. (2005). Forecasting stock market movement direction with support vector machine. *Computers & Operations Research*, *32*(10), 2513–2522. https://doi.org/10.1016/j.cor.2004.03.016

Imandoust, S. B., & Bolandraftar, M. (2014). *Forecasting the direction of stock market index movement using three data mining techniques: The case of Tehran Stock Exchange*. *4*(6).

Jiang, W. (2021). Applications of deep learning in stock market prediction: Recent progress. *Expert Systems with Applications*, *184*, 115537. https://doi.org/10.1016/j.eswa.2021.115537

Kara, Y., Acar Boyacioglu, M., & Baykan, Ö. K. (2011). Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul Stock Exchange. *Expert Systems with Applications*, *38*(5), 5311–5319. https://doi.org/10.1016/j.eswa.2010.10.027

Khoa, B. T., & Huynh, T. T. (2022). Forecasting stock price movement direction by machine learning algorithm. *International Journal of Electrical and Computer Engineering (IJECE)*, *12*(6), 6625. https://doi.org/10.11591/ijece.v12i6.pp6625-6634

Kumar, G., Jain, S., & Singh, U. P. (2021). Stock Market Forecasting Using Computational Intelligence: A Survey. *Archives of Computational Methods in Engineering*, *28*(3), 1069–1101. https://doi.org/10.1007/s11831-020-09413-5

Leung, M. T., Daouk, H., & Chen, A.-S. (2000). Forecasting stock indices: A comparison of classification and level estimation models. *International Journal of Forecasting*, *16*(2), 173–190. https://doi.org/10.1016/S0169-2070(99)00048-5

Li, A. W., & Bastos, G. S. (2020). Stock Market Forecasting Using Deep Learning and Technical Analysis: A Systematic Review. *IEEE Access*, *8*, 185232–185242. https://doi.org/10.1109/ACCESS.2020.3030226

Liao, Z., & Wang, J. (2010). Forecasting model of global stock index by stochastic time effective neural network. *Expert Systems with Applications*, *37*(1), 834–841. https://doi.org/10.1016/j.eswa.2009.05.086

Lin, Y., Yan, Y., Xu, J., Liao, Y., & Ma, F. (2021). Forecasting stock index price using the CEEMDAN-LSTM model. *The North American Journal of Economics and Finance*, *57*, 101421. https://doi.org/10.1016/j.najef.2021.101421

Liu, C., Wang, J., Xiao, D., & Liang, Q. (2016). Forecasting S&P 500 Stock Index Using Statistical Learning Models. *Open Journal of Statistics*, *06*(06), 1067–1075. https://doi.org/10.4236/ojs.2016.66086

Long, W., Lu, Z., & Cui, L. (2019). Deep learning-based feature engineering for stock price movement prediction. *Knowledge-Based Systems*, *164*, 163–173. https://doi.org/10.1016/j.knosys.2018.10.034

Mahjoub, S., Chrifi-Alaoui, L., Marhic, B., & Delahoche, L. (2022). Predicting Energy Consumption Using LSTM, Multi-Layer GRU and Drop-GRU Neural Networks. *Sensors*, *22*(11), 4062. https://doi.org/10.3390/s22114062

Malagrino, L. S., Roman, N. T., & Monteiro, A. M. (2018). Forecasting stock market index daily direction: A Bayesian Network approach. *Expert Systems with Applications*, *105*, 11–22. https://doi.org/10.1016/j.eswa.2018.03.039

Manjunath, C., Marimuthu, B., CHRIST (Deemed to be University), Ghosh, B., & RV Institute of Management. (2021). Deep Learning for Stock Market Index Price Movement Forecasting Using Improved Technical Analysis. *International Journal of Intelligent Engineering and Systems*, *14*(5), 129–141. https://doi.org/10.22266/ijies2021.1031.13

Market Statistics—Focus | The World Federation of Exchanges. (n.d.). Retrieved September 26, 2024, from https://focus.world-exchanges.org/issue/september-2024/market-statistics

Mateus, B. C., Mendes, M., Farinha, J. T., Assis, R., & Cardoso, A. M. (2021). Comparing LSTM and GRU Models to Predict the Condition of a Pulp Paper Press. *Energies*, *14*(21), 6958. https://doi.org/10.3390/en14216958

Nabipour, M., Nayyeri, P., Jabani, H., S., S., & Mosavi, A. (2020). Predicting Stock Market Trends Using Machine Learning and Deep Learning Algorithms Via Continuous and Binary Data; a Comparative Analysis. *IEEE Access*, *8*, 150199–150212. https://doi.org/10.1109/ACCESS.2020.3015966

Oriani, F. B., & Coelho, G. P. (2016). Evaluating the impact of technical indicators on stock forecasting. *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*, 1–8. https://doi.org/10.1109/SSCI.2016.7850017

Qiu, M., & Song, Y. (2016). Predicting the Direction of Stock Market Index Movement Using an Optimized Artificial Neural Network Model. *PLOS ONE*, *11*(5), e0155133. https://doi.org/10.1371/journal.pone.0155133

Rath, S., Das, N. R., & Pattanayak, B. K. (2024). An Analytic Review on Stock Market Price Prediction using MachineLearning and Deep Learning Techniques. *Recent Patents on Engineering*, *18*(2), e030323214351. https://doi.org/10.2174/1872212118666230303154251

Ren, R., Wu, D. D., & Liu, T. (2019). Forecasting Stock Market Movement Direction Using Sentiment Analysis and Support Vector Machine. *IEEE Systems Journal*, *13*(1), 760–770. IEEE Systems Journal. https://doi.org/10.1109/JSYST.2018.2794462

Shewalkar, A., Nyavanandi, D., & Ludwig, S. A. (2019). Performance Evaluation of Deep Neural Networks Applied to Speech Recognition: RNN, LSTM and GRU. *Journal of Artificial Intelligence and Soft Computing Research*, *9*(4), 235–245. https://doi.org/10.2478/jaiscr-2019-0006

Wang, J.-Z., Wang, J.-J., Zhang, Z.-G., & Guo, S.-P. (2011). Forecasting stock indices with back propagation neural network. *Expert Systems with Applications*, *38*(11), 14346–14355. https://doi.org/10.1016/j.eswa.2011.04.222

Wu, H., Long, H., Wang, Y., & Wang, Y. (2021). Stock index forecasting: A new fuzzy time series forecasting method. *Journal of Forecasting*, *40*(4), 653–666. https://doi.org/10.1002/for.2734

Zarzycki, K., & Ławryńczuk, M. (2021). LSTM and GRU Neural Networks as Models of Dynamical Processes Used in Predictive Control: A Comparison of Models Developed for Two Chemical Reactors. *Sensors*, *21*(16), 5625. https://doi.org/10.3390/s21165625

Zhang, A., Lipton, Z. C., Li, M., & Smola, A. J. (2021). *Dive into Deep Learning* (Version 5). arXiv. https://doi.org/10.48550/ARXIV.2106.11342

Zhong, X., & Enke, D. (2019). Predicting the daily return direction of the stock market using hybrid machine learning algorithms. *Financial Innovation*, *5*(1), 24. https://doi.org/10.1186/s40854-019-0138-0

Zhou, Z., Gao, M., Liu, Q., & Xiao, H. (2020). Forecasting stock price movements with multiple data sources: Evidence from stock market in China. *Physica A: Statistical Mechanics and Its Applications*, *542*, 123389. https://doi.org/10.1016/j.physa.2019.123389

Chapter 3

LEVERAGING BIG DATA ANALYTICS IN E-EXPORT MARKETING: KEY STRATEGIES AND APPLICATIONS

Zeynep DERELİ[1]

1 Zeynep DERELİ, PhD Research Assist., Burdur Mehmet Akif Ersoy University Bucak Zeliha Tolunay School of Applied Technology and Business Administration, Department of Customs Business Administration, zdereli@mehmetakif.edu.tr.

INTRODUCTION

In today's rapidly evolving global market, businesses are increasingly reliant on technology and data to drive their strategies and decision-making processes. The rise of digital technologies has revolutionized international trade, offering new avenues for businesses to expand into global markets through e-commerce and e-export. In particular, e-export, which involves cross-border electronic transactions, has become a critical channel for businesses looking to tap into international markets. The seamless flow of goods and services across borders, facilitated by digital platforms, has empowered companies to reach global audiences like never before.

E-export, or cross-border e-commerce, allows businesses to overcome geographical barriers, enabling them to offer products and services to international customers through online platforms. Unlike other forms of online trade, cross-border e-commerce involves global trade elements such as customs clearance, insurance, and shipping while enabling transactions to be conducted over the Internet without any country or time restrictions (Liu et al., 2021). The use of digital channels allows for real-time engagement with customers, and the convenience of online shopping has driven a surge in demand for e-export. With increasing internet penetration and mobile device usage, e-commerce platforms have become indispensable for global trade, enabling even small and medium-sized enterprises (SMEs) to compete in international markets. However, the global competition and the diversity of consumer preferences require businesses to adopt advanced tools to succeed in e-export.

One of the key enablers of success in e-export is the use of data-driven technologies. As businesses collect vast amounts of data from different markets, the challenge lies in analyzing and utilizing this information effectively. Big Data Analytics (BDA) has emerged as a powerful tool that enables companies to make informed decisions based on real-time data. In e-export, BDA helps businesses optimize market entry strategies, tailor marketing campaigns to different regions, and provide personalized customer experiences. By analyzing customer behavior, market trends, and competitor strategies, BDA provides deep insights that enable companies to be more agile and responsive in highly competitive international markets.

Big Data Analytics leverages a variety of methods to extract value from vast datasets. Among these methods are data mining, predictive analytics, and machine learning. Data mining is used to discover patterns and relationships in large datasets, allowing businesses to identify opportunities and risks. Predictive analytics enables companies to forecast future trends and customer behaviors based on historical data, helping them anticipate demand and tailor their offerings accordingly. Machine learning, on the other hand, automates decision-making by allowing systems to learn from data over time, improving the accuracy of recommendations and predictions. These methods are essential for e-export businesses that need to analyze diverse datasets from multiple regions, ensuring that they can adjust their strategies to meet local market demands.

This book chapter first explores the fundamentals of Big Data and BDA, providing a detailed overview of their key components and techniques. The second section focuses on how BDA is applied to various aspects of e-export marketing. The chapter delves into how BDA enhances market segmentation and improves targeting by analyzing customer behaviors across different regions. Following that, the role of BDA in creating personalized marketing campaigns is examined, showing how data-driven strategies can be tailored to individual customer preferences. Additionally, the importance of pricing optimization is discussed, illustrating how BDA helps businesses adjust prices based on real-time market conditions and customer insights. The final section of the chapter focuses on customer management and retention, emphasizing how BDA enables businesses to create enduring relationships with their clients in the cutthroat global economy.

1. BIG DATA ANALYTICS: AN OVERVIEW

As businesses increasingly rely on data to drive their operations and strategies, understanding the complexity and potential of big data has become vital. This section will first provide an introduction to the idea of big data and examine some of its key attributes, including volume, velocity, and variety. After that, the emphasis will move to big data analytics, outlining how companies use these enormous datasets to obtain knowledge, enhance decision-making procedures, and create data-driven strategies.

1.1. Understanding Big Data

Big data analytics has evolved into a vital tool for companies looking to obtain a competitive edge and deeper insights, revolutionizing the way they approach strategy development, operational effectiveness, and decision-making. The term "big data" describes the enormous and intricate datasets that are produced quickly and with a great deal of variation. Due to the size of these datasets, conventional data processing software is unable to handle, evaluate, or extract valuable insights from them (Russom, 2011). Laney (2001) proposed the 'Three Vs' (Volume, Variety, and Velocity) as core ideas to define big data (Ducange et al., 2018, p. 327).

- *Volume* is the primary characteristic of big data, which can be measured not only in terabytes (TB) or petabytes (PB) but also by the number of records, transactions, tables, or files. The main challenges associated with this aspect include the acquisition, storage, and efficient management of immense volumes of information, often measured in zettabytes, which must be organized, validated, and analyzed.

- *Velocity* describes both the rapid speed at which data is distributed across networks and the need for quick processing in real-time. This is a crucial feature distinguishing big data from simply large datasets. One of the potential challenges is identifying trends or opportunities within minutes, as even a short delay in data analysis can result in a lost competitive edge, particularly in fast-moving markets.

- *Variety* relates to the diverse types of data originating from various sources such as sensors, social networks, and other devices or applications. It also highlights the richness of data, which is not conveyed in traditional datasets. The challenge here lies in the ability of conventional technologies to handle structured, semi-structured, and unstructured data simultaneously, necessitating the development of new, specialized solutions (Figure 1).

Over time, Laney's original three Vs have been found insufficient to capture the complexity of big data fully. As a result, additional Vs have been introduced to better describe its characteristics. This evolution has led to a progression from the three Vs. model to a five Vs. framework (Brown and Harmon, 2014; Ducange et al., 2018; Elgendy and Elragal, 2014):

- *Veracity* refers to the inherent uncertainty and unreliability of certain data sources, which necessitates thorough analysis to ensure that accurate and trustworthy insights can be derived. It refers to the reliability and accuracy of data, assessing whether it is good, poor, or uncertain. This characteristic highlights the issues that can arise from data inconsistency, incompleteness, ambiguity, delays, deception, and approximations.

- *Value* highlights the potential of big data to generate meaningful benefits and actionable insights, provided that the data is properly processed and utilized (Sun & Liu, 2020; Kuo, 2024, p.367).

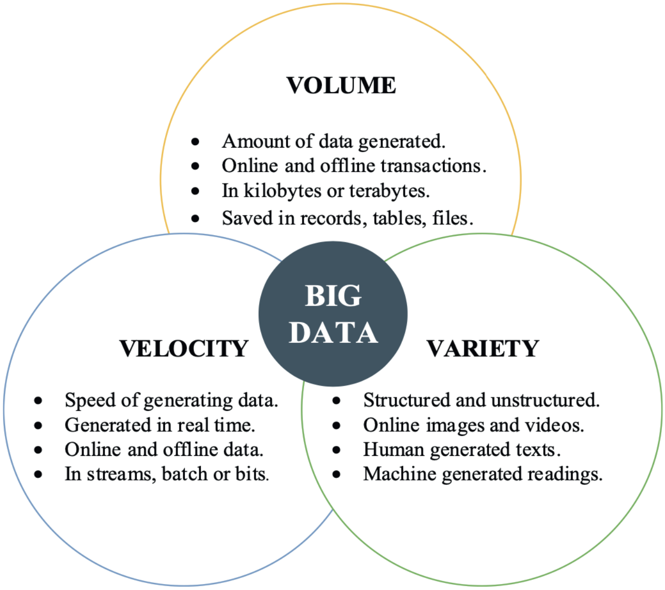


Figure-1. Three Vs of big data: volume, velocity, and variety
Source: Yu and Wang, 2020, p.5.

Big data is widely applied across multiple industries. In the IT sector, it is used for log storage and analysis, helping resolve rare system issues. Sensor data is analyzed to improve safety and efficiency in industries. In finance, big data enhances risk analysis by enabling more accurate risk modeling. Social media relies on big data to track customer sentiments, allowing businesses to adjust strategies based on feedback. Governments use big data for cybersecurity, while companies like Amazon and Walmart utilize it to optimize operations and improve customer transactions (Katal et al., 2013).

The McKinsey Global Institute outlined the potential of big data across five major sectors (Sağıroğlu and Sinanç, 2013, p.43): In healthcare, big data can enhance clinical decision support systems, enable personalized medicine, and improve public health by analyzing disease patterns and individual patient profiles. In the public sector, it increases transparency, improves decision-making through automated systems, and fosters innovation by identifying needs and customizing services. In retail, big data is used to analyze in-store behavior, optimize product variety and pricing, improve logistics, and enhance web-based markets. Manufacturing benefits from improved demand forecasting, supply chain planning, and production operations through big data applications. Finally, personal location data enables smart routing, geo-targeted advertising, emergency response improvements, urban planning, and the creation of new business models.

In essence, big data has altered how industries operate by introducing new ways to handle and analyze enormous, complicated datasets. Big data offers insightful information that was previously impossible to obtain using conventional techniques, improving decision-making in the public and healthcare sectors as well as streamlining operations in manufacturing, retail, and other industries. The relevance of data variety, velocity, and volume is being recognized by organizations in all sectors, and as a result, big data will play an increasingly important role in influencing industry practices going forward.

1.2. Big Data Analytics

Building on the foundational characteristics of big data, big data analytics emerges as a powerful tool, enabling businesses to extract actionable insights from vast datasets, optimize processes, and make data-driven decisions that drive competitive advantage and innovation. With the rapid evolution of technology and the growing influx of data into organizations, the need for faster and more efficient methods of analysis has become essential. Simply having large volumes of data is no longer enough to make timely and effective decisions (Elgendy and Elragal, 2014). Organizations, including businesses, research institutions, and governments, are now regularly producing data on an unprecedented scale and complexity. Extracting valuable insights and gaining a competitive edge from these vast datasets has become increasingly crucial for organizations worldwide (Zakir et al., 2015). The ability to efficiently analyze and interpret this data is now critical for businesses to make timely, informed decisions and sustain a competitive edge.

Big data analytics (BDA) involves the application of advanced analytical techniques to process and analyze large datasets (Russom, 2011). BDA combines big data and analytics to generate valuable business insights (Alsmadi et al., 2023). It refers to techniques used to analyze data from various sources and is regarded as a powerful technology applicable across different activities within the value chain, producing significant impacts (Veglio & Romanello, 2020; Chiarvesio & Romanello, 2018; Veglio & Romanello, 2019). By leveraging big data analytics, organizations can gain deeper insights into customer behavior, market trends, and operational inefficiencies. This enables them to not only react to current challenges but also to predict future outcomes and optimize their strategies accordingly. Ongsulee et al. (2018, p.2-3) outlined the key components of Big Data Analytics as follows:

- *Data mining* refers to the process of discovering patterns, correlations, and anomalies within large datasets. It is a crucial technique for extracting useful information from raw data and identifying relationships that may not be immediately visible. Through advanced algorithms, data mining uncovers hidden patterns that help organizations make more informed decisions and predictions.

- *Predictive analytics* involves analyzing historical data to predict future trends and outcomes. It uses statistical algorithms and machine learning techniques to identify patterns and forecast future events. Predictive analytics is applied in various fields, such as marketing, finance, and healthcare, to anticipate customer behavior, assess risks, and optimize strategies.

- *Machine learning*, a subset of artificial intelligence, enables computers to learn from data without explicit programming. It uses algorithms that learn from historical data to make predictions or decisions. Machine learning is essential in Big Data Analytics because it allows systems to improve their performance over time as they are exposed to more data. Examples include recommendation systems, fraud detection, and automated decision-making.

BDA offers a wide range of advantages, enabling organizations to enhance decision-making, optimize operations, and gain a competitive edge through the extraction of actionable insights from vast and complex datasets. First, the implementation of BDA, including data mining and predictive analytics, allows companies to lower production costs and boost productivity by optimizing production processes and using sensor data for predictive maintenance to prevent equipment failures and minimize downtime (Wagner, 2024). Second, BDA enables firms to monitor their customers' purchasing behaviors, allowing them to predict buying trends and offer personalized recommendations. This approach captures customer attention and enhances their shopping experience through tailored services provided by the company (Falahat et al., 2022). Third, managers are increasingly relying on big data analytics to guide their decision-making processes in real-time, allowing them to make more informed choices and shape future organizational strategies. By leveraging data-driven insights, they can better anticipate market trends, optimize operations, and effectively plan initiatives that align with their long-term goals (Mikalef et al., 2019; Constantiou & Kallinikos, 2015). In summary, firms can utilize BDA to integrate large datasets from various sources, uncovering patterns that would otherwise be unimaginable. Effectively leveraging these patterns can help companies mitigate threats or create new opportunities (Cheng & Shiu, 2023).

2. THE APPLICATION OF BIG DATA ANALYTICS IN E-EXPORT MARKETING

Big Data Analytics (BDA) is a crucial tool in e-export marketing, enabling businesses to analyze vast amounts of data from diverse markets and customer segments. Big Data can help firms become more customer-centric, entrepreneurial, and learning-oriented in their international market strategies, thereby indirectly enhancing their performance in international business (Gnizy, 2019). Businesses can improve market segmentation, adjust marketing campaigns based on the tastes of foreign consumers, and optimize market entry strategies by employing BDA. Furthermore, dynamic pricing models are supported by BDA, enabling businesses to modify their pricing strategy in response to real-time data. Businesses can build enduring relationships in international markets by tracking client satisfaction and retention with the aid of BDA.

2.1. Optimizing Market Entry Strategies

Big Data analytics is essential to optimizing market entry plans because it helps companies to determine high-potential regions, evaluate market preparedness, and create data-driven strategies that meet customer requests and local market realities. Businesses can use BDA to extract and analyze massive datasets from a variety of sources, including public databases, social media, and e-commerce sites. Through the identification of high-potential markets for entrance, this analysis assists businesses in identifying new trends and market demands in international regions.

Fundamental theoretical perspectives, such as the Uppsala internationalization model and the knowledge-based view, regard information and knowledge as the most critical resources necessary for successful internationalization (Chabowski et al., 2018). As information and knowledge are key to navigating foreign markets, the ability to process and utilize this data efficiently becomes essential. To address the challenges of internationalization and manage the uncertainties of foreign expansion more effectively, firms need to analyze growing volumes of real-time, semi-structured, and unstructured data. In this context, BDA can serve as a strategic tool to drive the international growth of enterprises (Bertello et al., 2021).

Businesses can use predictive analytics to estimate market trends by analyzing historical and real-time data. This gives them a better understanding of high-potential markets and helps them determine customer demand more precisely. Businesses may focus on markets with the best chance of success and allocate resources more effectively thanks to this data-driven approach. Furthermore, social media and online platform sentiment analysis provide insightful information about customer attitudes and preferences, which helps businesses assess public opinion and demand levels in new markets prior to entering the market.

Businesses can use BDA to collect and evaluate information on the pricing tactics, market share, and customer feedback of their rivals. This assists businesses in customizing their approach to entering new markets by pinpointing opportunities or niches in which they may provide a competitive edge. Businesses can utilize BDA to compare their performance to that of rivals in their intended markets. Businesses can set realistic entrance goals and modify their strategies by analyzing operational and financial key performance indicators.

Natural Language Processing (NLP) is a computer-assisted technique used to analyze and understand human language by interpreting text or speech in a way that allows machines to process, comprehend, and respond to it (Kang et al., 2020). NLP is widely used in marketing to analyze and interpret vast amounts of unstructured text data, such as customer reviews, social media posts, and search queries (Hartman & Netzer, 2023). NLP assists companies in comprehending the language, customs, and preferences of customers across many geographies. Better localization of goods, advertising, and customer support is made possible as a result, guaranteeing that the company's offers are appealing to regional consumers.

2.2. Enhanced Market Segmentation and Targeting

By offering comprehensive insights into customer behavior, preferences, and demographics across many areas, big data analytics helps organizations improve market segmentation and targeting. This leads to the development of more accurate and successful marketing strategies in foreign marketplaces. Market segmentation entails dividing a large, diverse market into smaller, homogeneous segments, each reflecting differing consumer preferences and needs, driven by the desire for more tailored and specific satisfaction within those segments (Cao &Manrai, 2014). Accurate market segmentation enables companies to enhance marketing efficiency by directing their limited financial, material, and human resources toward key markets identified through segmentation, ultimately boosting the company's market competitiveness (Jiang & Li, 2024).

Cross-border e-commerce companies can use BDA to obtain in-depth understanding of consumer preferences and behaviors in various geographic areas. This will enable them to create more specialized and targeted marketing campaigns that meet the particular needs of customers throughout the world. Businesses can anticipate future customer requirements and behaviors with the use of predictive analytics. Businesses can determine which client segments are likely to be more profitable and create customized marketing efforts in response by looking at prior purchasing trends and engagement history. Using trends in surfing history, online engagement, and purchase behaviors, behavioral data mining finds patterns in customer behavior. This enables businesses to target particular customer segments according to their distinct buying behavior or level of brand involvement. Big Data Analytics (BDA) makes it possible to segment clients in cross-border e-commerce according to their online habits, including the sites they visit, how long they spend on the site, and the particular products they look at. Businesses are able to create customized user experiences and focused marketing strategies that are suited to the unique inclinations and behaviors of every consumer category thanks to this in-depth behavioral analysis.

2.3. Personalized Marketing Campaigns

The importance of big data extends beyond customer-centric marketing. In today's digital and mobile-driven marketplace, real-time, personalized marketing has become more prominent than ever. Businesses are increasingly relying on digital media and mobile technologies to craft targeted and tailored customer experiences (Okorie et al., 2024). The emergence of machine-learning algorithms has transformed the landscape of personalization in marketing. These advanced algorithms allow businesses to predict consumer behavior with remarkable precision, enabling a move toward highly tailored, one-to-one marketing strategies at scale. This shift makes it possible for companies to deliver perfectly customized offers, products, and experiences to individual consumers, significantly enhancing the effectiveness of their marketing efforts (Kotras, 2020).

Based on the user's location, BDA can be used to dynamically modify website information, including language, currency, and product availability. An e-commerce site may, for instance, show country-specific promos or time-limited deals based on regional holidays and events, giving foreign buyers a more customized experience. Personalized email marketing can be designed in the context of e-export to take into account regional preferences, demand patterns, and customer behavior in other nations. For example, a foreign consumer who makes regular purchases during a particular season can be sent special offers or promotions during that time. Furthermore, BDA enables companies to apply machine learning for sentiment analysis on online interactions, social media posts, and customer reviews in a variety of languages and geographical areas. This aids e-export businesses in modifying their messaging to suit the attitudes and tastes of consumers in every area, guaranteeing that their marketing initiatives are well-received by a global audience.

2.4. Pricing Optimization

When making purchase decisions, customers consider more than just the price; they conduct a thorough evaluation of the benefits and costs associated with each available product. They compare these factors before selecting the option that offers the best overall value. Therefore, when setting prices, businesses must also assess the perceived value of their products by analyzing the benefits and costs from the customers' perspective. This ensures that pricing aligns with customer expectations and enhances competitiveness in the market (Guo, 2022). Businesses can examine the perceived value of products from the customer's point of view by using BDA to obtain greater insights into customer preferences. Businesses can optimize price points that are in line with customer satisfaction and market competitiveness by using BDA to customize their pricing strategies to meet client expectations.

BDA allows businesses to implement dynamic pricing strategies by analyzing market conditions and consumer demand in real-time. Through the analysis of factors including demand patterns, consumer income levels, and regional economic situations, predictive models assist businesses in making dynamic price adjustments. Additionally, BDA enables companies to monitor rivals' prices in real-time across several geographic areas. This information helps businesses stay competitive by giving them insight into the local competition and enabling them to modify their rates accordingly.

2.5. Customer Retention and Relationship Management

Customer retention and relationship management have become central to achieving long-term success in the e-commerce sector as businesses increasingly focus on fostering strong, personalized connections with their customers to enhance loyalty and drive repeat business. Relationship marketing refers to the set of marketing activities aimed at attracting, developing, maintaining, and strengthening customer relationships (Liang et al., 2008). E-commerce companies may successfully apply relationship marketing tactics through targeted loyalty programs, customized consumer experiences, and personalized communication by utilizing BDA. Businesses may create relevant offers and services that boost customer engagement and increase retention rates by using these data-driven insights to better understand client preferences.

Using patterns identified in previous customer interactions, businesses can forecast behaviors and create proactive strategies aimed at enhancing satisfaction and reducing churn. Predictive models can pinpoint customers who may stop engaging with offerings, supporting efforts to retain them with focused initiatives. For example, by analyzing purchase history, firms can anticipate which customers are likely to disengage and take proactive steps to re-engage them with personalized offers, thus enhancing customer loyalty and satisfaction (Wassouf et al., 2020). Organizations can leverage sentiment analysis to examine verbal and textual interactions with customers throughout their journey, from the negotiation phase to the post-purchase stages, including requests for support or after-sales assistance (Cheng & Shiu, 2023). When it comes to customer retention, these kinds of predictive insights, when combined with sentiment analysis, enable companies to recognize high-risk clients early on and take appropriate action by offering solutions that suit their tastes and guarantee a customized experience. This data-driven strategy improves lifetime value and sustains business growth by strengthening long-term relationships in addition to helping retain valuable clients.

CONCLUSION

The importance of Big Data Analytics (BDA) in the changing field of e-export marketing is examined in this book chapter. The goal is to give a comprehensive overview of how BDA, a potent data-driven technology, can optimize a range of e-export activities, from customer retention plans to market segmentation. Businesses can use business process optimization (BDA) to improve decision-making based on data, which gives them a competitive advantage in international marketplaces.

E-export, also known as cross-border e-commerce, is the process of using digital platforms to offer products and services to clients around the world. E-export, as opposed to traditional export techniques, allows companies to reach international customers without being limited by time zones or geographical restrictions. It entails overseeing crucial components of global trade, including shipping logistics, regulatory compliance, and customs clearance, all the while providing a flawless online shopping experience for clients throughout the globe. Through the use of digital channels, e-export has made it possible for small and medium-sized businesses (SMEs) to participate in international marketplaces. This has made it simpler for SMEs to interact with customers abroad and increase their market presence internationally.

The enormous amounts of organized and unstructured data that consumers and organizations produce on a daily basis are referred to as "big data." Contrarily, BDA deals with the methods and resources utilized to examine this vast amount of data and produce insights that can be put to use. It was noted that data-driven decision-making, trend identification, and behavior prediction are all made possible by employing techniques like data mining, predictive analytics, and machine learning. These insights assist businesses in better segmenting their markets, streamlining their international strategy, and customizing their marketing campaigns to serve their global clientele better.

Offering real-time insights into client behavior, market trends, and pricing plans is one of BDA's biggest benefits in e-export marketing. As a result, companies are better equipped to make decisions and react swiftly to shifts in global marketplaces. Additionally, BDA enables businesses to customize consumer experiences, which raises client happiness and loyalty and eventually propels long-term success in international marketplaces. The capacity to examine big information helps firms better understand their consumers and optimize tactics based on solid data.

When incorporating BDA into their e-export operations, small and medium-sized firms (SMEs), especially those with low financial means, may encounter significant challenges. For smaller businesses, the high implementation costs of advanced data analytics technologies and the requirement for qualified staff to handle and evaluate the data might be problematic. Moreover, the intricacy of data protection laws between nations presents an additional challenge, making it more difficult for companies to effectively utilize BDA without substantial investments.

Future developments in the way companies use BDA to enhance their global marketing initiatives have a great deal of room for expansion. Prospects to optimize procedures, cut expenses, and further customize the client experience will only increase with the development of data-driven technology. Better and more affordable BDA solutions could help SMEs overcome their present obstacles and take full advantage of the global e-commerce market. Thanks to ongoing improvements in BDA tools and infrastructure, it will be possible for even tiny businesses to leverage data to thrive in the global economy.

REFERENCES

Alsmadi, A. A., Shuhaiber, A., Al-Okaily, M., Al-Gasaymeh, A., & Alrawashdeh, N. (2023). Big data analytics and innovation in e-commerce: current insights and future directions. *Journal of Financial Services Marketing*, 1-18.

Bertello, A., Ferraris, A., Bresciani, S., & De Bernardi, P. (2021). Big data analytics (BDA) and degree of internationalization: the interplay between governance of BDA infrastructure and BDA capabilities. *Journal of Management and Governance*, *25*(4), 1035-1055.

Brown, R., & Harmon, R. (2014). Viral geofencing: An exploration of emerging big-data driven direct digital marketing services. In *2014 Portland International Conference on Management of Engineering and Technology* (pp. 3300-3308).

Chabowski, B., Kekec, P., Morgan, N. A., Hult, G. T. M., Walkowiak, T., & Runnalls, B. (2018). An assessment of the exporting literature: Using theory and data to identify future research directions. *Journal of International Marketing*, *26*(1), 118-143.

Cheng, C. C., & Shiu, E. C. (2023). The relative values of big data analytics versus traditional marketing analytics to firm innovation: An empirical study. *Information & Management*, *60*(7), 103839.

Cheng, C. C., & Shiu, E. C. (2023). The relative values of big data analytics versus traditional marketing analytics to firm innovation: An empirical study. *Information & Management*, *60*(7), 103839.

Chiarvesio, M., & Romanello, R. (2018). Industry 4.0 technologies and internationalization: Insights from Italian companies. In *International business in the information and digital age* (Vol. 13, pp. 357-378). Emerald Publishing Limited.

Constantiou, I. D., & Kallinikos, J. (2015). New games, new rules: big data and the changing context of strategy. *Journal of Information Technology*, *30*(1), 44-57.

Ducange, P., Pecori, R., & Mezzina, P. (2018). A glimpse on big data analytics in the framework of marketing strategies. *Soft Computing*, *22*(1), 325-342.

Elgendy, N., & Elragal, A. (2014). Big data analytics: a literature review paper. In *Advances in Data Mining. Applications and Theoretical Aspects: 14th Industrial Conference, ICDM 2014, St. Petersburg, Russia, July 16-20, 2014. Proceedings 14* (pp. 214-227). Springer International Publishing.

Falahat, M., Cheah, P. K., Jayabalan, J., Lee, C. M. J., & Kai, S. B. (2022). Big data analytics capability ecosystem model for SMEs. *Sustainability*, *15*(1), 360.

Gnizy, I. (2019). Big data and its strategic path to value in international firms. *International Marketing Review*, *36*(3), 318-341.

Gonzalez, M., & Rabbi, F. (2023). Evaluating the impact of Big Data Analytics on personalized E-commerce shopping experiences and customer retention strategies. *Journal of Computational Social Dynamics*, *8*(2), 13-25.

Guo, L. (2022). Cross-border e-commerce platform for commodity automatic pricing model based on deep learning. *Electronic Commerce Research*, *22*(1), 1-20.

Hartmann, J., & Netzer, O. (2023). Natural language processing in marketing. In *Artificial intelligence in marketing* (Vol. 20, pp. 191-215). Emerald Publishing Limited.

Jiang, Y., & Li, L. Research and optimization of cross-border e-commerce marketing mode based on big data technology. *Applied Mathematics and Nonlinear Sciences*, *9*(1).

Kang, Y., Cai, Z., Tan, C. W., Huang, Q., & Liu, H. (2020). Natural language processing (NLP) in management research: A literature review. *Journal of Management Analytics*, *7*(2), 139-172.

Katal, A., Wazid, M., & Goudar, R. H. (2013, August). Big data: issues, challenges, tools and good practices. In *2013 Sixth international conference on contemporary computing (IC3)* (pp. 404-409). IEEE.

Kotras, B. (2020). Mass personalization: Predictive marketing algorithms and the reshaping of consumer knowledge. *Big data & society*, *7*(2), 2053951720951581.

Kuo, S. Y. (2024). Improving innovation performance through learning capability and adaptive capability: The moderating role of big data analytics. *Knowledge Management Research & Practice*, *22*(4), 364-376.

Laney, D. (2001). 3D data management: Controlling data volume, velocity and variety. *META group research note*, *6*(70), 1.

Liang, C. J., Chen, H. J., & Wang, W. H. (2008). Does online relationship marketing enhance customer retention and cross-buying?. *The service industries journal*, *28*(6), 769-787.

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment. *British journal of management*, *30*(2), 272-298.

Okorie, G. N., Egieya, Z. E., Ikwue, U., Udeh, C. A., Adaga, E. M., DaraOjimba, O. D., & Oriekhoe, O. I. (2024). Leveraging big data for personalized marketing campaigns: a review. *International Journal of Management & Entrepreneurship Research*, *6*(1), 216-242.

Ongsulee, P., Chotchaung, V., Bamrungsi, E., & Rodcheewit, T. (2018, November). Big data, predictive analytics and machine learning. In *2018 16th international conference on ICT and knowledge engineering (ICT&KE)* (pp. 1-6). IEEE.

Russom, P. (2011). Big Data Analytic s. *TDWI Best Practices report, TDWI Reserarch, 4th Quarter*.

Sagiroglu, S., & Sinanc, D. (2013, May). Big data: A review. In *2013 international conference on collaboration technologies and systems (CTS)* (pp. 42-47). IEEE.

Sun, B., & Liu, Y. (2021). Business model designs, big data analytics capabilities and new product development performance: Evidence from China. *European Journal of Innovation Management*, *24*(4), 1162-1183.

Veglio, V., & Romanello, R. (2020). International new ventures in the digital age: the case of a big data and analytics provider. *Piccola Impresa/Small Business*, (2).

Veglio, V., & Rubina, R. (2019). What is the potential of Big Data Analytics? Insights for SMEs competing in the Digital Age. In *2nd Interactive Research Development Workshop and Conference. Internationalization of SMEs in the Digital Age.*

Wagner, J. (2024). Big Data Analytics and Exports—Evidence for Manufacturing Firms from 27 EU Countries. *Open Economies Review*, 1-10.

Wassouf, W. N., Alkhatib, R., Salloum, K., & Balloul, S. (2020). Predictive analytics using big data for increased customer loyalty: Syriatel Telecom Company case study. *Journal of Big Data*, *7*(1), 29.

Yu, T., & Wang, X. (2022). Real-time data analytics in internet of things systems. In *Handbook of real-time computing* (pp. 541-568). Singapore: Springer Nature Singapore.

Zakir, J., Seymour, T., & Berg, K. (2015). Big data analytics. *Issues in Information Systems*, *16*(2).

Chapter 4

THE ROLE OF FOREIGN DIRECT INVESTMENT IN SHAPING THE DIGITAL ECONOMY: OPPORTUNITIES, CHALLENGES, AND GLOBAL IMPLICATIONS

Ahmet Emre BİBER[1]

1 Prof. Dr., Bolu Abant İzzet Baysal University Faculty of Applied Sciences, Department of Finance and Banking, Bolu, Turkiye, ORCID: 0000-0001-5251-3156 biber_a@ibu.edu.tr, +905052500259

1. Introduction

Globalization is influenced by particular political and economic structures. Among these influences are structural changes such as the liberalization of trade and investment, which enhance the flow of international trade and investments. These shifts profoundly impact economic growth, alter the distribution and composition of economic activities, stimulate competition, and facilitate the global spread of technologies, thereby influencing sustainable development in both beneficial and adverse ways. Multinational enterprises (MNEs) play a crucial role in this globalized environment, with foreign direct investment (FDI) by MNEs becoming increasingly central to global economic activity. Economists characterize a multinational enterprise (MNE) as a corporation that "owns, controls, and manages income-generating assets across multiple countries." (Dunning, 1992, p. 34), distinguishing it from entities engaged solely in portfolio investment, which lacks managerial control. MNEs typically employ three primary strategies for foreign market entry: FDI, joint ventures (JV), and licensing. The advent of cyberspace has revolutionized governance and economic practices by connecting computers through high-speed networks and wireless systems, potentially transforming national politics. An e-MNE, described as a virtual enterprise functioning across various countries via cyberspace, oversees both tangible and intangible assets through digital networks and electronic agents. These electronic agents, programmed by humans, facilitate global transactions and management from a centralized location. As globalization progresses, the digital economy increasingly intersects with traditional economic models, utilizing e-commerce and technology. This analysis seeks to examine the impact of Foreign Direct Investment (FDI) on the evolution of the digital economy, focusing on how traditional economic activities and digital processes interconnect and influence one another.

2. What Is The Digital Economy

Currently, the theoretical framework for understanding the impact of the growing flow of information on the existing socio-economic system is defined by the concepts of post-industrial society and information society. Scholars of the digital society identify key characteristics of this new type of information society, such as the transformation of production processes, the shift from the creation of tangible goods to the provision of services, and the globalisation of the economy. When discussing the 'digitalisation' of the economy and society, it is crucial to establish clarity in terminology. Broadly speaking, 'digitalisation' refers to a socio-economic transformation driven by the extensive adoption and integration of digital technologies, including those used for creating, processing, exchanging, and transmitting data (Kluver, 2000; Borremans et al., 2018).

The digital economy is a relatively recent phenomenon, particularly in developing countries and rural regions (World Economic Forum, 2015), although its technological foundations were established in the 1990s with the introduction of enterprise computing and computerised production systems (Sturgeon, 2021). The advent of the Internet in the early 2000s marked a critical shift towards the digital economy in its current form. The broad adoption of the Internet at the corporate level facilitated the development and integration of various technologies and services that are central to the digital economy. Numerous definitions of the digital economy have been proposed over time. However, as Bukht and Heeks (2017) note, "definitions are always a reflection of the periods and trends from which they emerged," implying that they must evolve to reflect changes in the technological landscape and the increasing knowledge and sophistication of users.

Definitions of the digital economy differ significantly in terms of scope, and there is no clear consensus on what should be included or excluded from it. However, drawing on the definition provided by Bukht and Heeks (2017), the digital economy can be described as an economic model distinguished by the extensive and effective use of digital technologies to collect, store, process, transform, and transmit data across all domains of human activity.

Since the digital economic transformation began with the use of commercial mainframes in the 1960s, advancements in computerisation, alongside continuous developments in microelectronic hardware and software, have significantly enhanced the capabilities of information and communication technologies (ICT). These advancements have reduced hardware costs, energy consumption, and size requirements, facilitating the transformation of a diverse array of products and processes. The increased power and decreasing costs of digital ICT have enabled mass access to portable devices, global positioning systems, and the Internet. From the 1990s onwards, the Internet has supported, embodied, and accelerated many of these technological trends. Thus, the "third industrial revolution," characterized by autonomous automation and digital ICT, laid the groundwork for the emergence of the fourth industrial revolution (Sturgeon, 2021). Within this context, it can be argued that two primary domains—industrial applications and consumer applications (including platforms, products, and services)—and four key technological applications drive and integrate with the digital economy.

When discussing the new (digital) economy, it is crucial to differentiate between data and knowledge. Data refers to raw collections of information, while knowledge encompasses the frameworks—such as theories and hypotheses—that allow for the organization and interpretation of that data. The traditional economy was characterized by physical elements such as cash, cheques, invoices, shipping documents, face-to-face interactions, analog phone conversations, radio and television broadcasts, blueprints, maps, photographs, sheet music, and direct mail. In contrast, the new digital economy involves the digitisation of information in all its forms—transforming it into bits stored on computers and transmitted across networks at the speed of light. This paradigm shift, comparable in its significance to the invention of language, has created a new realm of possibilities that redefines all formerly physical interactions (Coulson, 1999).

While knowledge itself is not a new concept, what has changed is the way it is collected, manipulated, stored, and transmitted. The period between 1700 and 1850 saw a fundamental shift in economic activity, marked by the transformation of practical experience into systematic, codified knowledge. The era following 1950 is often referred to as the "management revolution," distinguished by the application of knowledge to information. In the current context, information has emerged as the only truly significant resource. Although traditional factors of production remain relevant, they have assumed a secondary role. Therefore, in this new paradigm, knowledge is understood as an asset and a means for achieving social and economic outcomes (Carlsson, 2004).

Consequently, activities involving complex problem definition, problem solving, or high-technology design—resulting in innovative new products or services or new methods of market exploitation—have rapidly emerged as central drivers of economic growth, as well as individual and organizational well-being. In the long term, knowledge-intensive industries, including financial services, entertainment, healthcare, education, and government, are expected to undergo the most significant transformation and derive the greatest benefits from digitalisation and the internet. In the medium term, sectors such as retail, manufacturing, and travel are likely to experience the most visible effects of this digital transformation (Carlsson, 2004).

3. Globalization and FDI: Shaping the Digital Economy

Globalization is a complex phenomenon influenced by particular political and economic systems, as well as techno-economic dynamics. It is marked by substantial structural reforms such as the liberalization of trade and investment, which drive economic growth, modify the allocation and nature of economic activities, and facilitate the global spread of technological advancements. These changes have profound positive and negative impacts on sustainable development (Dunning, 1992). Multinational enterprises (MNEs) play a central role in this globalized framework, with foreign direct investment (FDI) from MNEs becoming a progressively larger component of global economic activity. The expansion of international investment has amplified the influence of MNEs on the sustainable development of host countries. (Dunning, 1992).

MNEs are characterized as entities that “own, control, and manage income-generating assets across multiple countries” (Dunning, 1992). This definition underscores the difference between direct investment, which provides both managerial authority and financial interest in foreign operations, and portfolio investment, which offers only a financial stake without managerial oversight. MNEs generally adopt three main strategies for entering international markets: foreign direct investment (FDI), joint ventures (JVs), and licensing agreements. The emergence of cyberspace, driven by high-speed data connections and wireless technologies, has significantly reshaped both national and global governance frameworks. Cyberspace continues the historical trend of information technologies transforming political and economic environments. An electronic multinational corporation (e-MNC) can be characterized as a virtual enterprise that, while maintaining physical production facilities across multiple countries, leverages an advanced electronic network to manage intangible goods and services (Dussart, 2001). These firms leverage both tangible and intangible assets across global markets, employing electronic agents programmed by humans to manage transactions and operations. This allows e-MNCs to control and manage assets across multiple locations from a centralized electronic base.

The increasing internationalization of production and consumption raises questions about the digital economy’s emergence. The current digital economy operates alongside traditional economic forms, integrating elements of e-commerce and advanced technology (Blomström, 2014). The aim of analyzing FDI’s role in the digital economy is to explore how traditional and digital economic activities interact and influence each other. FDI’s impact on global economic integration includes various benefits and challenges. MNEs, by driving international investment flows, significantly influence global economic activity. These enterprises engage in activities that encompass technology transfer, managerial expertise, and human capital development, which are essential for competitive advantage and productivity enhancement in host countries (De Mello, 1999; Markusen and Venables, 1999). The benefits of FDI are most notable when foreign affiliates are fully integrated into the parent company’s global operations, facilitating advanced technology transfer and management practices to the host country, thus improving local competitiveness and creating employment opportunities (Dunning, 1994).

The influence of foreign direct investment (FDI) on the labor market in the home country can differ markedly. The extent to which activities in the home and host countries are complementary or substitutable affects the impact on employment and wages. When activities abroad complement those in the home country, both the firm and its workers may benefit. Conversely, when activities are highly substitutable, the home country may experience job losses and wage reductions (Zhao, 1998). The complex relationship between

FDI and labor market outcomes depends on various factors, including the level of substitutability and the strategic decisions of the firm. In the European context, the EU is a major player in global FDI, acting both as a significant source and destination for foreign investments (Barrell and Pain, 1997). The internal market reforms and economic integration within the European Union (EU) have significantly increased intra-regional foreign direct investment (FDI) flows and cross-border mergers and acquisitions. By removing trade and capital barriers among member states, these reforms have shifted the locational advantages across the EU, leading to a marked increase in FDI across major European economies (Barrell and Pain, 1999). These dynamics illustrate broader trends of regional integration and globalization.

The characteristics of neighboring countries and their policies also influence FDI dynamics. The interdependencies between foreign locations, whether they act as substitutes or complements, are shaped by initial transport costs and the investment climate. Industry-specific factors further influence these relationships, highlighting the need for a nuanced understanding of FDI's interaction with regional and global economic environments (Markusen and Venables, 2000).

Leadership and management in the digital age present new challenges and opportunities. Effective leadership requires adaptability and technical expertise to navigate global networks and electronic transactions. E-leaders must balance innovation and control while leveraging technological advancements to drive organizational success. The impact of financial crises on investment decisions underscores the need for strategic flexibility in managing global business operations (Goleman, 2000; Park and Campbell, 2001).

In summary, the role of foreign direct investment (FDI) in the development of the digital economy highlights the complex interactions between traditional economic practices and contemporary digital advancements. As globalization continues to evolve, understanding how FDI affects both traditional and digital economic activities is crucial for policymakers, businesses, and investors. The integration of digital technologies with traditional economic models presents both challenges and opportunities for advancing sustainable development and enhancing global economic connectivity (Saggi, 2002; Ahn and Hemmings, 2000).

4. ICT and Global Economic Asymmetries

It is argued that the way firms compete and succeed, their business models and value creation processes are changing as a result of the diffusion of information and communication technologies (ICTs). These changes both create new ventures and restructure existing ones, opening up new opportunities. This process of change is underpinned by ICT's ability to transmit, capture and manage large amounts of information and to break down spatial and temporal boundaries. As a result, the transaction costs of knowledge-intensive activities can be reduced through the use of ICTs. Small and medium-sized enterprises (SMEs), which often operate in a dense network of intra-firm relationships and thus have to manage large amounts of information, can benefit particularly from these opportunities (Carbonara, 2005).

ICT (Information and Communication Technology) emerges from the sequential introduction of new, complementary technologies along a shared technological path, characterized by similar output elasticity of production factors (Antonelli, 2001). This evolution raises essential questions about the trajectory of emerging technologies and the structural attributes of the economic systems they infiltrate. The impact of technological change is crucial in assessing its effects on total factor productivity growth. Information and Communication Technology (ICT) stands as a leading global technology with widespread applications across various product and factor markets. However, its impact on productivity growth varies markedly by region, shaped by local resources and relative pricing conditions.

The effects of ICT on productivity and profitability are not uniform across countries. In fact, the increase in total factor productivity varies widely due to specific national characteristics and resource endowments compared to those of innovating countries (Freeman and Louca, 2001). Companies operating in diverse product and factor markets can capitalize on ICT, resulting in significant asymmetries and increased variance in economic performance among global trading partners (Ruttan, 2001). As a result, the adoption of ICT can swiftly reduce technological diversity, influencing comparative advantages in nations where certain productive inputs are relatively costly. This dynamic creates new asymmetries not only in the rate of technology diffusion but also in each country's ability to derive economic benefits from adopting these technologies.

The emerging knowledge-intensive business-related services are global and rely heavily on advanced communication and information-processing services, which are key intermediary inputs. Valuable insights into the development of new technological systems are provided by the interplay between technological complementarities and convergences, and by firm strategies influenced by frequent cross-entries from related markets and technologies. These insights contribute to an understanding of rapid and systemic technological change, which is characterised by a high degree of interdependence in the production and use of new products and processes (Varian etc. 2004).

ICT has significantly contributed to the increased segmentation and asymmetries within labor markets in advanced economies that are at the forefront of technology adoption (Quah, 2001). Adopting them requires specific innovations involving developing new applications, using new intermediate inputs and new capital goods. Growth opportunities in the global economy are reduced by the widening of the digital divide, which exacerbates total factor productivity differentials and average production costs. In addition, this divide requires the introduction of contingent technologies, reinforcing the need for the integration of external and domestic technological knowledge in order to adapt globally available general knowledge to local resource structures (Mansell, 2001). The high fungibility of ICT serves as a key input for both corporate technology strategies and national technology policies. As highlighted by Antonelli (2003), ICT's flexible nature enables its application across various contexts, making it a critical tool for driving technological advancement and economic growth at multiple levels.

5. Transforming the Global Economy Through Digitalization

It is clear that digitalization—the use of digital technologies to transform business practices—has a profound impact on economies globally, leading many governments to launch initiatives to support the digital transformation of their industries and public sectors. As the pace of digitalization accelerates, it is essential for both global and national decision-makers to comprehend the factors driving digital development and to anticipate how these trends might shape the global economy and society. A deep understanding of the interrelationships among the driving forces of digitalization is vital for policymakers, enabling them to make informed, evidence-based decisions.

The transition to a digital economy is characterized by the increasing role of cyberspace, which both drives and results from the evolution of the global economy. Businesses must harness information technology and e-commerce to thrive in this new economic environment. The widespread adoption of digital tools and connectivity allows for a more level playing field among firms of varying sizes and contributes to increased productivity by reducing costs associated with transactions, communication, and inventory management (Sichel, 1999). Cyberspace's capacity to lower barriers to entry and improve market competition further enhances economic efficiency and encourages investment, especially in countries with well-established digital infrastructures.

In this context, digital and physical "dot-com" companies have emerged, each contributing to the growth of online commerce in distinct ways. Digital companies like Yahoo! and eBay offer digital products and services directly through cyberspace, while physical dot-coms sell tangible products but face challenges due to their reliance on traditional business models that include managing inventory and shipping (Ruttan, 2001). To remain competitive, physical dot-coms must increase their adoption of digital processes throughout their value chains.

The digital economy, representing a shift in how businesses operate and markets function, has led to unprecedented productivity gains and economic growth. This transformation is rooted in the rapid development and diffusion of new technologies, particularly information and communication technologies (ICT). These advancements, often driven by startups rather than established companies, highlight a paradigm shift in economic activities, where new digital tools offer innovative solutions across sectors (David, 1991). As a result, the digital economy has become more integrated globally, and businesses must adapt to the fast pace of technological change to maintain their competitive advantage.

ICT's role in economic transformation is evident in its ability to enhance communication, reduce costs, and increase efficiency in both production and distribution. The adoption of ICT is not only seen in developed economies but also presents opportunities for growth and development in emerging markets. However, this shift has also highlighted disparities between countries that effectively utilize digital tools and those that do not, creating a "digital divide" that poses challenges for global equity and development (Andrea, 2002).

Furthermore, the digital economy necessitates new business models and organizational strategies, with an emphasis on innovation, agility, and the ability to quickly respond to market changes. For instance, in industries such as logistics, the adoption of digital tools has facilitated new forms of e-commerce and collaborative business practices. Efficient logistics are now central to the digital economy, serving as both enablers of other businesses and pioneers of new economic models (Slack and Rowley, 2002).

Despite the volatility and challenges faced by companies in the digital economy, such as the dot-com bust, the continued growth of internet connectivity and e-commerce highlights the enduring impact of digital transformation on global markets. Companies that can effectively integrate digital tools into their operations and value chains are better positioned to capitalize on the opportunities presented by this new economic landscape. This transition also underscores the need for policies and regulations that address the complexities of a digital economy, such as intellectual property rights and market organization, to ensure sustainable and inclusive growth (Zekos, 2002).

In conclusion, the digital economy represents a fundamental shift in the global economic landscape, driven by rapid technological advancements and the pervasive use of ICT. As businesses and countries navigate this transformation, the ability to innovate, adapt, and leverage digital tools will be critical to sustaining growth and competitive advantage in an increasingly interconnected and digital world.

Today, the evolution of global and local markets creates a favourable environment for digital transformation in countries with high levels of education and integrated with digital technologies. Statistical analyses and scientific evaluations reveal that the level of development of the digital economy is closely related to the overall income level of the country. Analyses show that as of 2020, the top twenty countries in the Network Readiness Index (NRI) ranking consist of high-income countries, while low-income countries are at the lower rungs of the ranking (Shevchenko et al., 2023). This situation emphasises that digital economic development is closely linked not only to economic prosperity but also to education and technological infrastructure.

It states that the level of economic growth of a country is directly related to the effective and comprehensive use of information and communication technologies (ICT). Considering the effects of digitalisation on social and economic processes, it becomes clear that the economic sphere should support the digital transformation process. The integration of digital technologies into the economic structure requires reshaping traditional market dynamics, social interactions and public administration. This transformation aims to radically change value creation mechanisms and the overall economic structure through more efficient economic processes enabled by digital infrastructure (Amankwah-Amoah et al., 2021).

A systemic look at the conceptual approaches to defining and developing the digital economy shows that this new economic model cuts across all industries globally. This is an opportunity for promoting the worldwide expansion of capital, goods, services and labour markets. Reveals that digital transformation is effectively taking place today at all levels of the economic system - international, national, regional and local. The overall structure of the digital economy is based on consumer-oriented approaches and strategic use of information on a large scale, taking into account the characteristics of consumer segments in specific regions and the global use of digital transformation technologies of business processes (Ferracane & Marel, 2019; Qian, Liu & Pan, 2022).

The fourth industrial revolution has led to the emergence of an innovative digital environment that combines the physical and biological domains with the virtual world. Information and communication technologies (ICT) have emerged as the main pillars of this evolution. In today's world, the future of countries is more dependent than ever on the ability of national governments to manage and effectively integrate digital technologies. This political objective covers a wide range of issues, from the physical foundations of internet infrastructure, regulatory frameworks, business readiness and consumer skills. Policy makers need to develop comprehensive policy measures that support the development of the basic infrastructure, in co-operation with business, academia and individuals, so that they can rapidly implement modern technological advances and ensure that ICTs deliver the maximum benefits (Sepashvili, 2020).

The global economy has benefited greatly from digitalisation. However, it is not the reality of every national economy that digital development is seen as an ongoing process. To support the growth of the digital economy, national governments should step up their efforts to develop infrastructure. Infrastructure needs to be strengthened digitally as well as physically for the digital economy to thrive. The development of infrastructure requires more than the expansion of the economy through physical means. In this context, in order to support the spread of the best innovations on a global scale, building an effective ecosystem remains a critical policy objective (Sepashvili, 2020).

6. Conclusion

The analysis of Foreign Direct Investment (FDI) within the context of a rapidly evolving digital economy reveals significant insights into the complex interactions between traditional and digital economic activities. FDI plays a critical role in promoting global economic integration by facilitating technology transfer, managerial expertise, and human capital development, all of which are essential for enhancing the competitiveness and productivity of host countries. As globalization progresses, the increasing convergence of traditional economic models and digital processes underscores the need for a nuanced understanding of how these domains intersect and influence one another.

The digital economy, characterized by its reliance on Information and Communication Technologies (ICT) and data-driven processes, has reshaped the global economic landscape. Digital transformation has introduced new business models, enhanced productivity, and driven economic growth, particularly in knowledge-intensive sectors such as financial services, healthcare, and entertainment. The widespread adoption of ICT has also lowered barriers to entry, increased market competition, and created new opportunities for both multinational enterprises (MNEs) and small and medium-sized enterprises (SMEs). However, the benefits of digital transformation are not evenly distributed, with a notable "digital divide" between countries that effectively leverage digital tools and those that do not.

The integration of digital technologies into the economic structure has created a dynamic environment where FDI acts as a conduit for advancing digital development. MNEs, through their foreign investments, contribute to the diffusion of digital technologies and practices across borders. This diffusion promotes technological innovation, enhances productivity, and fosters economic growth in host countries. Nonetheless, the impact of FDI on the labor markets of both home and host countries varies depending on the level of complementarity or substitutability of economic activities. Policymakers must consider these dynamics when designing strategies to maximize the benefits of FDI while mitigating potential negative impacts on employment and wages.

The findings of this study highlight the importance of policy frameworks that support digital transformation and attract quality FDI. For host countries, particularly those in developing regions, it is crucial to create an enabling environment that facilitates the integration of digital technologies and the transfer of knowledge and skills. This requires investment in digital infrastructure, education, and regulatory reforms that promote innovation and entrepreneurship. In parallel, MNEs should adopt strategies that align with the digital transformation goals of host countries, ensuring that their investments contribute to sustainable development.

Moreover, the intersection of FDI and digital economy underscores the need for a more resilient global economic framework that can withstand external shocks such as financial crises, geopolitical tensions, and pandemics. The COVID-19 pandemic has demonstrated the critical role of digital readiness and FDI in maintaining economic continuity and fostering recovery. Countries with robust digital infrastructures and those that actively attract FDI have shown greater resilience in adapting to new economic realities. This highlights the importance of building flexible, adaptive economic systems that can leverage digital tools to respond swiftly to unforeseen global events.

Looking ahead, the continued evolution of the digital economy will likely introduce new forms of FDI, such as investments in artificial intelligence, blockchain technologies, and advanced digital infrastructures. These investments will not only redefine global supply chains but also shape the future contours of economic development. Policymakers and business leaders must remain agile, continuously updating their strategies to harness the potential of these emerging technologies while addressing the regulatory, ethical, and social implications that accompany them. As digitalization accelerates, fostering international cooperation and ensuring inclusive growth will be vital for creating a sustainable digital future for all.

Furthermore, the interplay between FDI and the digital economy suggests that a holistic approach is necessary to address the challenges and opportunities arising from globalization and digitalization. Collaborative efforts among governments, businesses, and international organizations are needed to bridge the digital divide, enhance global connectivity, and ensure that the benefits of digital transformation are widely shared. This includes addressing the regulatory challenges associated with digital trade, data privacy, and cybersecurity, which are increasingly relevant in a connected global economy.

In conclusion, FDI remains a vital driver of economic development in the digital age, enabling countries to harness the benefits of digital technologies while navigating the complexities of a globalized economy. As digital transformation continues to reshape economic activities, understanding the role of FDI in this process becomes ever more critical. By fostering an environment that supports innovation, investment, and collaboration, countries can better position themselves to thrive in a digital economy that is both inclusive and sustainable.

References

Ahn, S., & Hemmings, P. (2000). Policy influences on economic growth in OECD countries. OECD Economics Department Working Papers

Amankwah-Amoah, J., Khan, Z., Wood, G., & Knight, G. (2021). COVID-19 and digitalization: The great acceleration. Journal of business research, 136, 602-611.

Andrea, G. (Ed.). (2002). *Development Centre Studies Electronic Commerce for Development*. OECD Publishing.

Antonelli, C. (2001). The microeconomics of technological systems. Oxford University Press, USA.

Antonelli, C. (2003). The digital divide: understanding the economics of new information and communication technology in the global economy. Information Economics and Policy, 15(2), 173-199.

Barrell, R., & Pain, N. (1999). Domestic institutions, agglomerations and foreign direct investment in Europe. European Economic Review, 43(4-6), 925-934.

Blomstrom, M. (2014). Foreign Investment and Spillovers (Routledge Revivals). Routledge.

Borremans, A. D., Zaychenko, I. M., & Iliashenko, O. Y. (2018). Digital Economy. IT Strategy Of The Company Development. In MATEC Web Of Conferences. *EDP Sciences*, Vol. 170,10-34.

Bukht, R., & Heeks, R. (2017). Defining, Conceptualising And Measuring The Digital Economy. Development Informatics Working Paper (68).

Carbonara, N. (2005). Information and communication technology and geographical clusters: opportunities and spread. Technovation, 25(3), 213-222.

Carlsson, B. (2004). The Digital Economy: what is new and what is not?. Structural change and economic dynamics, 15(3), 245-264.

Coulson, J. (1999). The Digital Economy: Promise and Peril in the Age of Networked Intelligence. Information Management Journal, 33(2).

David, P. A. (1991). The modern productivity paradox in a not-too-distant mirror. Technology and Productivity: The Challenge for Economic Policy, The Technology Economy Programmer, OECD Publishing, Paris, France, 315-347.

De Mello Jr, L. R. (1999). Foreign direct investment-led growth: evidence from time series and panel data. Oxford economic papers, 51(1), 133-151.

Dunning, J. (1992), Multinational Enterprises and the Global Economy, Addison-Wesley, Wokingham, pp. 3-4.

Dunning, J. H. (1994). The prospects for foreign direct investment in Central and Eastern Europe. The economics of change in East and Central Europe, 15-47.

Dunning, J. (2013). International production and the multinational enterprise (RLE international business). Routledge.

Dussart, C. (2001). Transformative power of e-business over consumer brands. European Management Journal, 19(6), 629-637.

Ferracane, M., & Marel, E. V. D. (2019). Do data policy restrictions inhibit trade in services?. Robert Schuman Centre for Advanced Studies Research Paper No. RSCAS, 29.

Freeman, C., & Louçã, F. (2001). As time goes by: from the industrial revolutions to the information revolution. Oxford University Press.

Goleman, D. (2000), "Leadership that gets results", Harvard Business Review, Vol. 78 No. 2, pp. 78-90.

Kluver, R. (2000), Globalization, Informatization, and Intercultural Communication, *American Communication Journal*, 3 (3).

Mansell, R. (2001). Digital opportunities and the missing link for developing countries. Oxford Review of Economic Policy, 17(2), 282-295.

Markusen, J. R., & Venables, A. J. (2000). The theory of endowment, intra-industry and multi-national trade. Journal of international economics, 52(2), 209-234.

Park, R., & Campbell, A. (2001). E-commerce in financial services:: An e-agenda for the corporate parent. European Management Journal, 19(4), 417-423.

Qian, W., Liu, H., & Pan, F. (2022). Digital economy, industry heterogeneity, and service industry resource allocation. Sustainability, 14(13), 8020.

Quah, D. (1999). The weightless economy in economic development. London, UK.

Ruttan, V.W. (2001), Technology Growth and Development. An Induced Innovation Perspective, Oxford University Press, Oxford.

Saggi, K. (2002). Trade, foreign direct investment, and international technology transfer: A survey. The World Bank Research Observer, 17(2), 191-235.

Sepashvili, E. (2020). Supporting digitalization: Key goal for national competitiveness in digital global economy. Economia Aziendale Online-, 11(2), 191-198.

Shevchenko, I., Lysak, O., Shyshak, A. Z., Mazur, I., Korotun, M., & Nestor, V. (2023). Digital economy in a global context: world experience. International Journal of Professional Business Review: Int. J. Prof. Bus. Rev., 8(4), 11.

Sichel, D. E. (1999). Computers and aggregate economic growth: An update. Business economics, 34(2), 18-25.

Slack, F., & Rowley, J. (2002). Kiosks 21: a new role for information kiosks?. International journal of information management, 22(1), 67-83.

Sturgeon, T. J. (2021). Upgrading Strategies For The Digital Economy. *Global Strategy Journal*, 11(1), 34–57.

Varian, H. R., Farrell, J., & Shapiro, C. (2004). The economics of information technology: An introduction. Cambridge University Press.

Zekos, G. I. (2002). Issues of intellectual property in cyberspace. J. World Intell. Prop., 5, 233.

Zhao, L. (1998). The impact of foreign direct investment on wages and employment. Oxford economic papers, 50(2), 284-301.

World Economic Forum (WEF). (2015). Expanding Participation And Boosting Growth: The Infrastructure Needs Of The Digital Economy. http://www3.weforum. org/docs/WEFUSA_DigitalInfrastructure_Report2015.pdf

Chapter 5

DIGITALIZATION[1]

Alparslan OĞUZ[2]

1 This study is derived from the doctoral thesis titled " Tedarik Zinciri Entegrasyonu ve Dijitalleşmenin Performansa Etkisinde Alıcı-Tedarikçi Risk Yönetiminin Aracı Rolü" prepared under the supervision of Prof. Dr. Selçuk Perçin.

2 Asst. Prof., PhD., Erzincan Binali Yildırım University, Kemah Vocational School, Office Services and Secretarial Department, aoguz@erzincan.edu.tr, ORCID: 0000-0003-1920-5674

INTRODUCTION

The concept of digitalization was first introduced in 1971 by Robert Wachal through the phrase "societal digitalization" (Brennen & Kreiss, 2016: 5). Digitalization is defined as the use of digital technologies to transform a business model, creating new opportunities for revenue and value generation. It represents the process of transitioning to a digital business (Gartner, 2020a). Through digitalization, access to information becomes cost-effective, rapid, and user-friendly, enabling sharing and utilization of data (Castells, 1996). According to Brennen and Kreiss (2016: 1), digitalization is characterized as "the increased adoption or usage of digital or computer technologies by an organization, industry, country, etc." This has given rise to a common language and platform where individuals can freely share their thoughts, producing easily accessible information that enriches the global community (Bhutani & Paliwal, 2015: 12).

Digitalization involves the process of converting digitized resources into new revenue streams, growth, and operational efficiencies that create value for the organization. It can also be described as the integration of a company's physical and intellectual resources with technological capabilities to ensure efficient resource utilization. Ultimately, this results in the emergence of new business models and opportunities that provide a better customer experience (Şükranlı, 2020: 10). In this context, digitalization serves as a technological force that enriches globalization from both economic and cultural perspectives. The impact of digitalization on increasing globalization is evident in various domains, including digital products, enhanced cross-border communication, globally distributed teams, and optimized flows of goods and services through electronic platforms (Isaksson & Wennberg, 2016: 68).

A related term is digitization, which refers to the transition from analog to digital formats (Gartner, 2020b). Digitization involves the conversion of physical formats—such as images, sounds, and texts—into digital binary formats. Digitalization, however, goes a step further, representing the practical application of digital information. The data obtained through digitization are utilized in digital technologies. Examples of digital technologies that utilize data derived from digitization include big data, mobile applications, and the Internet of Things. While digitization encompasses the technical process of converting analog signals into digital formats, the broader processes of adopting and utilizing digital technologies in individual, organizational, and societal contexts are typically referred to as digitalization (Legner et al., 2017: 301). Thus, it can be argued that digitization is a sub-concept of digitalization.

The concepts of digitalization and technology have evolved in a mutually influential manner. According to Tapscott (2008), advancements in technology lead to digitalization. At the core of digitalization lies the widespread use of information technologies (Chen & Tsou, 2007: 2-5). The rapidly evolving nature of information technologies, the commodification of technology, and the phenomenon of ubiquitous computing have resulted in short digital innovation cycles that demand organizations to respond flexibly to continuously changing environments (Fichman et al., 2014: 330; Gimpel et al., 2018: 32). These digital innovations have triggered significant changes and various advancements across industries in recent years. Digital innovation is characterized by the new combination of digital and physical components to develop new products and services (Yoo et al., 2010: 725). Due to its specific focus on products and services, digital innovation can not only lead to new business models but also significantly impact the competitive strength of organizations (Nambisan et al., 2017: 223).

Digitalization brings forth extensive technologies that are accessible to everyone, resulting in changes from cultural, behavioral, demographic, and lifecycle perspectives. The emergence of terms such as e-commerce, e-banking, e-books, e-news, and e-learning has been a direct consequence of digitalization, which has also given rise to the concept of an information society. In this context, digital transformation is framed not only as business-oriented but also as a general trend in our daily lives (Kupiainen, 2006: 280-287). Digitalization reflects the adoption of digital technologies in both the business world and society, as well as related changes in the connections between individuals, organizations, and objects. From a business perspective, digital transformation represents an innovation concerning how a company creates value and generates revenue by implementing technological systems and structures (Gimpel et al., 2018: 33; Tiersky, 2017).

Digitalization and digital technologies lead to fundamental changes in all aspects of society and promote innovation at an extraordinary pace across various industries (Veit et al., 2014; Karimi & Walter, 2015; Legner et al., 2017). The increasing digitalization of organizations and ecosystems presents challenges that require these entities to adapt to change. Consequently, businesses must continuously monitor evolving digital technologies and assess their potential benefits and threats. Governments and manufacturing firms are heavily investing in innovative technologies to reduce production costs and maintain competitiveness in the market (Tilson et al., 2010: 754-756; Bharadwaj et al., 2013: 478; Bär et al., 2018: 747).

While digitalization offers numerous opportunities for individuals and organizations, it also brings certain challenges. Increased efficiency in business processes, accelerated access to information, and cost reductions are among the most prominent advantages of digitalization; however, its downsides, such as cybersecurity risks, privacy issues, and the transformation of the workforce due to automation, cannot be overlooked. Moreover, digitalization, in conjunction with Industry 4.0 technologies, has fundamentally redefined production processes and facilitated the integration of smart systems into the business world. This study examines the concept of digitalization in detail, analyzing both its benefits for businesses and the challenges it poses. Additionally, the innovative solutions offered by digital technologies and Industry 4.0 are explored, and their impacts on businesses are discussed. In this way, the significance of digitalization for modern enterprises and its potential future effects are comprehensively assessed.

Benefits and Drawbacks of Digitalization

Investments in digital technologies contribute significantly to business development. These investments enhance profitability through their impact on revenue growth and cost reduction. Digitalization can offer consumers a new value proposition. The new marketing techniques and sales channels created by digitalization facilitate revenue increases through improvements made for customers. These improvements lead to higher customer satisfaction, which in turn fosters greater loyalty and, consequently, increased revenue growth. All these steps can create a more profitable value chain. Digital technologies not only drive revenue growth but also assist firms in reducing overall administrative, marketing, and operational costs (Mithas, 2012: 205-224). By providing better supply chain coordination, digital technologies help lower costs. The use of digital technologies enables improved information sharing between relevant departments in the supply chain and the organization (Mithas, 2012; Banker, 2006, cited in Şükranlı, 2020: 13-14).

Digitalization offers potential benefits for internal efficiency. Certain processes traditionally performed by human labor can be executed through digital technologies, simplifying operations. With digitalization, more accurate data can be obtained, leading to higher operational efficiency, quality, and consistency. Additionally, by integrating structured and unstructured data, digitalization provides better visibility into organizational data. Moreover, integrating data from other sources can offer improved real-time visibility regarding operations and outcomes. Through the automation of routine tasks, digitalization can enhance job satisfaction for employees, allowing them more time to develop new skills. It also ensures data compliance through standardization of records, making data easier to back up and store. New digital technologies can present opportunities for new services or enhanced offers to customers.

While digitalization and the use of digital technologies provide benefits for businesses, they can also bring challenges. Companies must adapt their business models to meet the fast-paced changes required by new technological advancements. However, the rapid adoption of new digital technologies can pose a threat to traditional business models (Porter & Heppelman, 2014: 64-88; Bleicher & Stanley, 2016: 69).

Dedrick et al. (2003) noted that complementary investments made for digitalization could lead to low profitability figures in the short term due to high resource investments and capital depreciation rates. The combined effects of multiple digital innovations can also be disruptive. This impact can lead to digital transformation and cause profound changes (Hinings et al., 2018: 56). Through this transformation, existing business practices in organizations, ecosystems, or entire industries may be supplemented or modified with new roles, actors, values, and structures (Mangematin et al., 2014; Loebbecke & Picot, 2015; Hinings et al., 2018). Furthermore, the main disadvantages of fully digitizing customer services and internal processes can include the emergence of complex organizational structures, a lack of in-house expertise, vulnerabilities in security, and the occurrence of legal and compliance issues.

As a result of digitalization, companies may experience shifts within their industries. Two immediate concerns arise for these companies: the first is understanding how digitalization affects their business model, and the second is assessing how much performance can be improved through the advantages brought by new technologies. The adoption of digitalization processes can be challenging due to the desire to maintain existing structures and employees' reluctance to face risks and uncertainties (Doz & Kosonen, 2010: 379). For instance, Kodak lost its position in the industry due to its failure to prepare for the digital camera transition.

DIGITAL TECHNOLOGIES AND INDUSTRY 4.0

The control and operation of manufacturing facilities have undergone significant transformations compared to the old analog regulatory schemas. Computer-based control was first tested in the late 1950s. The digitization of industry began in the 1970s with the introduction of microprocessor controllers and distributed control systems. This initial phase is referred to as the first digital revolution. Subsequently, the increased computational power and the development of better optimization solutions have facilitated advancements in higher tiers of the automation hierarchy. Concurrently, the use of information technology, particularly the internet, has surged since the 1990s. Until recently, primary functions and information were segregated from the control room by a firewall, with data flow occurring in a unidirectional manner. Digitization is often referred to as the second digital revolution, as it has enabled the bidirectional flow of data (Isaksson et al., 2018: 122).

The utilization of digitalization and digital technologies within industries presents content closely related to Industry 4.0. Information technology has facilitated the use of automation in production systems since the last quarter of the 20th century, serving as a precursor to the digital technologies used today. The transition to the fourth phase of the industrial revolution (Industry 4.0) in the 2000s marked the beginning of a new process of digital transformation. Digital transformation occurs as a value chain comprised of the Internet of Things (IoT) and cyber-physical systems in today's world. The increasing automation process, along with artificial intelligence technologies and robots, allows for production to occur through diverse techniques. Current developments are generating new business models and professions. The personal computers, software, and internet that emerged during the third industrial revolution initiated the transition to the fourth industrial revolution (Karabulut, 2020: 4-5).

The concept of Industry 4.0 was first mentioned at the Hannover Fair in 2011. Industry 4.0 represents a digital chain that grants autonomy through the digitization of production and the complete integration of products with their environments. This chain signifies that machines, computers, sensors, and other integrated devices communicate with one another, enabling production to be largely coordinated independently of human intervention. Within the context of Industry 4.0 and digitization, various technological advancements are utilized in businesses. These include artificial intelligence, the Internet of Things, enterprise resource planning, digital payments, cloud computing, big data, 3D printing, mobile technologies, augmented reality, and social media.

Artificial Intelligence

Artificial Intelligence (AI) refers to intelligent activities that are programmed to perform specific tasks, encompassing systems that possess human-like qualities such as learning, speech, and other cognitive functions (Liu et al., 2020: 1367). Goralski & Tan (2019) assert that AI has the ability to think like humans. Additionally, they believe that AI can be employed to fulfill certain roles and tasks originally performed by people in public spaces and social life. AI encompasses a wide range of machine intelligence, from simple text-to-speech applications to autonomous vehicles and aircraft.

AI represents a cognitive approach that integrates technologies such as image processing, natural language processing, robotics, and machine learning. It can be combined with emerging technologies like the industrial Internet of Things, big data analytics, and cloud computing applied to industrial production. This integration helps generate flexible, efficient, and environmentally friendly operational methods while providing solutions within industrial applications. A primary advantage of this technology is its ability to analyze and make decisions within milliseconds, even in highly complex data analysis environments (Lee et al., 2018: 20; Iafrate, 2018: 5).

AI fundamentally has two aspects: computational intelligence and perceptual intelligence. Computational intelligence involves memory that contains data and algorithms, allowing for rapid calculation and storage capabilities. Perceptual intelligence refers to the sensory abilities of humans, such as seeing, hearing, and touching. AI can capture and analyze information from its environment, providing reasonable responses through various sensors (Liu et al., 2020: 2). AI is characterized by its capacity for continuous development due to technological advancements and its ability to adapt independently to new environments (Vocke et al., 2019: 811). This indicates that AI will become increasingly important across numerous sectors of the economy, industry, and society.

Internet of Things

IoT (Internet of Things) is defined as a network structure in which objects can connect to each other via smart sensors, allowing them to interact without human intervention (Li et al., 2015: 243). Here, the term "Internet" refers to a technology vision centered on virtual networks, while "objects" emphasizes items that can be integrated into a technological framework. Atzori et al. (2010: 2788) introduced IoT as a worldwide network composed of semantically interconnected objects. From an object-oriented perspective, IoT is considered a global network of machines and devices that can interact and communicate with each other (Jin et al., 2014: 114; Lee & Lee, 2015: 433).

The goal of IoT is to enable the efficient sharing of real-time information among autonomously connected actors (Yang et al., 2013: 1855). The realization of IoT and the digital network requires the use and integration of almost all information technologies in the process of acquiring, transmitting, and applying information (Jara et al., 2014: 999; Zhao et al., 2013: 197). IoT technologies can also be used to monitor any event or change in structural conditions that could compromise security and increase risk. Thus, it contributes to cost and time savings, improves quality, and positively impacts efficiency (Sestino et al., 2020: 2).

Today, billions of objects are equipped with advanced sensors, wireless networks, and innovative computing capabilities. This has led to the rise of wearable devices, smart home applications, advanced healthcare systems, smart cities, and industrial automation (Chen & Ji, 2016: 18; Marjani et al., 2017: 5248). The number of businesses adopting IoT technologies is increasing, and it is expected that the number of IoT-connected devices worldwide will reach 43 billion by 2023 (Gupta et al., 2017). The vision of IoT is to create a smart world equipped with sensing technologies and intelligent components.

Enterprise Resource Planning

Nofal and Yusof (2013: 659) define ERP (Enterprise Resource Planning) systems as a management toolset that uses proven business processes for decision-making, provides high degrees of cross-functional integration between sales, balances supply and demand, and includes the ability to connect customers and suppliers into a complete supply chain. ERP is considered one of the most powerful business information technologies that enable organizational adaptation to new business opportunities. ERP is software that can integrate the information needs of companies across various areas and functions, uniting organizational complexity. The core feature of ERP is to integrate all departments and business units within an organization, providing real operations, advanced databases, and a consistent user interface (Seethamraju and Sundar, 2013: 138; Chofreh et al., 2020: 4).

ERP systems integrate business processes such as production, distribution, accounting, finance, human resources, inventory management, project management, maintenance, and logistics through material requirements planning technology. This integration creates unity across the company, as well as accessibility and visibility. Effective ERP implementation can provide organizations with various benefits, including process efficiency, effective decision-making, improved business agility, and enhanced data security (Sadrzadehrafiei et al., 2013: 223). ERP is an integrated system designed to harmonize business processes and operations, thereby enabling organizations to operate in an environmentally conscious manner, particularly in supply chain management. The value of ERP software in terms of information processing and promoting competitive advantage is undeniable. Additionally, the implementation of ERP requires significant organizational effort. Many businesses fail to achieve the expected benefits or experience implementation failures (Chang et al., 2008: 929; Rodríguez et al., 2020: 230).

Digital Payment

The global spread and use of the Internet and mobile devices have contributed to the development of new forms of banking and financial payments. Digital payment and banking are considered new ways to conduct convenient and effective financial transactions (Alkhowaiter, 2020: 1). Digital payment systems refer to the execution of banking and payment transactions through digital platforms. Digital payment solutions function as digital platforms that facilitate direct interaction between various types of customers connected to them. Digital payment platforms have low marginal and high development costs (Yucha et al., 2020: 325).

The introduction of blockchain technology, the success of Bitcoin, the proliferation of various cryptocurrencies, and the increase in services supporting them have garnered interest, especially in developed countries where digital payment is regulated. Some widely used digital payment systems today include mobile payments, mobile wallets, mobile banking, electronic banking, internet banking, online banking, cryptocurrencies, and digital payment.

Cloud Computing

The emergence of the phenomenon commonly known as CC (Cloud Computing) represents a fundamental change in how information technology services are invented, developed, deployed, scaled, updated, maintained, and paid for. The National Institute of Standards and Technology defines CC as "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" (Mell & Grance, 2011: 2). CC is an information technology service model where computing services are provided to customers as a self-service over a network, independent of device and location. Resources required to maintain the necessary service quality levels are shared, dynamically scalable, quickly provisioned, virtualized, and released with minimal service provider interaction. Users pay for cloud services as an operating expense without making any significant capital investment, using a metering system that divides computing resources into appropriate portions (Marston et al., 2010: 177).

CC represents the convergence of two major trends in information technology. The first is the efficiency of information technology, where the power of modern computers is used more effectively through highly scalable hardware and software resources. The second is business agility, where information technology can be used as a tool to promote competitiveness through rapid deployment, parallel batch processing, computationally intensive business analytics, and mobile interactive applications that respond to user requirements in real-time (Kim, 2009: 65-68). Increasingly, more software and hardware solutions are being transferred to cloud-based technology. Companies producing systems such as artificial intelligence, enterprise resource planning, and the Internet of Things are now offering these technologies in a cloud-based environment. This not only represents a shift in how customers use computing resources but also a fundamental change in the value creation logic of vendors and partners' business models (Boillat and Legner, 2013: 40; Nieuwenhuis et al., 2018: 308).

Big Data

The term Big Data (BD) was first introduced in 1997 by two NASA researchers to describe the visualization challenges of computer systems with extremely large datasets (Cox & Ellsworth, 1997: 234). BD refers to data that exceeds the processing capacity of traditional database systems. Due to the sheer volume of the data and its rapid movement, it does not conform to the limitations of traditional database architectures. Numerous autonomous data sources, such as smartphones, web cameras, RFID readers, and sensor networks, constantly generate data streams without human intervention, thereby increasing the volume and speed of data collection. Most of the data collected is unstructured (Wang & Alexander, 2015: 60).

BD aids in optimizing supply chains, increasing sales, managing customer loyalty in marketing, optimizing real-time routing, reducing shipping costs, minimizing financial risks, and even improving the effectiveness of certain medical treatments. Insights derived from BD can help individuals within organizations make better decisions. Additionally, BD can assist with deepening customer engagement, optimizing operations, preventing threats and fraud, managing inventory more effectively, and capitalizing on new revenue streams (Ittmann, 2015: 4; Benabdellah et al., 2016: 1).

In the literature, six dimensions of BD are discussed: volume, velocity, variety, value, variability, and veracity (Bellini et al., 2013; Demchenko et al., 2013; Wang & Alexander, 2015). These dimensions are explained below:

- Volume: Refers to the large amounts of data generated, often measured in units like terabytes or petabytes.

- Velocity: Data is produced and collected in real-time and in a streaming manner, at high speeds.

- Variety: Indicates the diversity of data, which may include structured, semi-structured, unstructured data, text, audio, video, multimedia, etc.

- Value: While individual pieces of data may appear insignificant, valuable insights can be extracted from the collective data.

- Variability: Refers to changes in data during its processing and lifecycle. Increasing variety and variability enhance the data's attractiveness and its potential to provide unexpected, hidden, and valuable insights.

- Veracity: Has two aspects: data consistency and data reliability.

Three - Dimensional Printing

Three-dimensional printing (3DP), also known as additive manufacturing, was first proposed in the early 1980s by engineer Charles Hull (Ventola, 2014: 704). 3DP is a technology that creates three-dimensional objects from a digital model through additive processes. The printing process involves placing and joining successive thin layers in the x, y, and z directions to create geometries (Berman, 2012: 156; Wang et al., 2020: 3). Each layer can be seen as a thin, horizontal cross-section of the final product. 3DP utilizes wet or dry forms of polymers, minerals, or metals to create objects at micro-millimeter resolutions.

3DP offers extreme flexibility, allowing local control over material composition and microstructure. It provides various advantages, such as high flexibility, risk reduction for new product innovations, cost reduction, on-demand production, and waste minimization. 3DP focuses on technologies that facilitate digitization, increase industrial efficiency, enable on-demand and decentralized production, facilitate mass customization, change the role of consumers, and support sustainable development efforts (Holzmann et al., 2020: 2).

However, 3DP has some disadvantages related to production speed, accuracy, and the overall quality of printed objects, compared to traditional manufacturing processes (Holmström et al., 2010: 689; Petrovic et al., 2011: 1064). Material selection varies significantly between different 3DP technologies and is often severely limited (Berman, 2012: 156; Mellor et al., 2014: 194). Additionally, there are financial barriers to adopting 3DP, with high acquisition, operation, and maintenance costs depending on the printing technology and application area (Baumers et al., 2016: 194; Chekurov et al., 2018: 88). The technology is currently inefficient for producing large quantities of identical objects on an assembly line. For now, 3DP cannot compete with factory-based mass production systems in terms of cost, quality, or speed.

Mobile Technologies

With the development of information and communication technologies, mobile technologies are widely used in businesses. Mobile devices and applications provide businesses with more than just a new channel to reach customers. Mobile devices combine functionality and interaction, allowing users to shop or search for information while using a product (Ström et al., 2014: 1001). Tools enabling mobile communication include cell phones, smartphones, computers, personal digital assistants (PDAs), and global positioning systems (GPS). PDAs are handheld computers that allow users to store names and addresses, serve as notepads, and facilitate internet and email communication. GPS is a technological tool that allows precise location tracking on the Earth's surface by measuring the distance between satellites using a network that sends regularly encoded information (Sürücü & Bayram, 2016: 2025).

Mobile technology offers organizations opportunities to launch new or improved business processes that provide greater productivity, efficiency, and effectiveness. Mobile Customer Relationship Management (M-CRM) involves managing customer relationships through handheld devices like mobile or hybrid phones. M-CRM supports customer service and collaboration by providing access to important customer information, such as discussions, documents, workflows, notifications, and emails, anytime and anywhere (Coursaris et al., 2006: 20).

Electronic Data Interchange (EDI) was developed to leverage the advantages of modern information technologies by enabling computer applications to communicate with each other at lower costs and with greater efficiency. As one of the most important applications of e-commerce, EDI allows computers to automatically exchange structured messages in specific areas, as pre-programmed by users, and automatically evaluate the data received (İlhan & Ünsaçar, 2011: 249).

Radio Frequency Identification (RFID) has emerged as an evolving information and communication technology platform that transforms business processes. RFID replaces barcode scanners as the primary object tracking system. Barcodes are cheaper than RFID tags but have lower storage capacity, require a line of sight, and cannot be reprogrammed. RFID eliminates human errors by improving operational management and can be reprogrammed. These tags can operate in harsh environments (Singh, 2019: 19).

Social Media

The internet and social media have had significant impacts on business operations and success. The main reason is the ability of online communication, as evidenced by the popularity of websites like Facebook and LinkedIn, to replace physical proximity with virtual interaction and even closeness (Barnes et al., 2012: 688). Social media refers to content distributed through social interactions. It leverages various firms that offer services or tools to help consumers and businesses connect (Grewal & Levy, 2013: 82).

Social media is a crucial tool for all businesses as it enables them to communicate, listen, and learn from customers in ways previously impossible. The key advantage of having a website and social media presence is their direct impact on consumer attitudes and decision-making. Social media has a significant influence on consumer purchasing decisions (Jones et al., 2015: 614).

Augmented Reality

Augmented Reality (AR) is defined as the real-time view of the physical world, overlaid (augmented) with virtual, computer-generated information such as text, images, videos, or other interactive media (Azuma, 1997: 356). According to Faust et al. (2012: 1166), AR involves the overlay of virtual objects (computer-generated images, texts, sounds, etc.) onto the user's real environment. AR combines real and virtual world objects to extend the physical world, enabling the development of enriched environments. AR provides a rich and immersive experience for users by offering a high level of interactivity and vividness compared to traditional media (Yim & Park, 2019: 581).

AR's ability to overlay physical environments with virtual elements such as text-based information, rich media images, and video in real-time presents firms with new opportunities to provide consumers with unique experiences. The key benefit of AR is its ability to present products or experiences with computer-generated representations in the real world, eliminating the need for consumers to imagine them (McLean & Wilson, 2019: 212-214).

CONCLUSION

This study has examined the comprehensive impacts of digitalization on the business world and society. Digitalization is not merely a technological change but a transformation that fundamentally alters how organizations operate, interact with customers, and create value. The opportunities presented by digitalization include increased operational efficiency, reduced costs, improved customer experiences, and the creation of new revenue streams. However, this transformation process also brings challenges such as cybersecurity risks, data privacy issues, and the restructuring of the workforce.

The digital technologies explored in this study—artificial intelligence, the Internet of Things, enterprise resource planning, digital payments, cloud computing, big data, 3D printing, mobile technologies, augmented reality, and social media—play a critical role in enhancing the competitive advantage of businesses in the era of Industry 4.0. These technologies optimize production processes, strengthen customer relationships, and facilitate the emergence of new business models.

Digitalization enables businesses to gain flexibility and agility while also necessitating the continuous adoption of new technologies and the reassessment of existing business models. In this context, organizations must develop their digital transformation strategies by keeping up with technological innovations, enhancing their employees' digital skills, and adopting a customer-centric approach.

In conclusion, digitalization and Industry 4.0 technologies offer unprecedented opportunities for businesses but also pose significant challenges. For successful digital transformation, businesses must strategically adopt these technologies, manage potential risks, and foster a culture of continuous innovation. In the future, it is anticipated that the impact of digitalization on the business world and society will further increase, along with the emergence of new opportunities and challenges.

REFERENCES

Alkhowaiter, W. A. (2020). Digital payment and banking adoption research in Gulf countries: A systematic literature review. *International Journal of Information Management*, *53*, 1–17.

Atzori, L., Iera, A., & Morabito, G. (2010). The Internet of Things: A survey. *Computer Networks*, *54* (15), 2787-2805.

Azuma, R. T. (1997). *A survey of augmented reality*. Presence: Teleoperators and Virtual Environments/MIT Press .

Banker, R. D., Bardhan, I. R., & Chang, H. (2006). Understanding the impact of collaboration software on product design and development. *Information Systems Research*, *17* (4), 352-373.

Bär, K., Bruns, R., Sauer, J., & Schlick, C. M. (2018). Considering Industry 4.0 aspects in the supply chain for an SME. *Production Engineering*, *12* (6), 747-758.

Barnes, D., & Others. (2012). Web 2.0 and micro-businesses: An exploratory investigation. *Journal of Small Business and Enterprise Development, 19* (4), 687–711.

Baumers, M., & Others. (2016). The cost of additive manufacturing: Machine productivity, economies of scale and technology-push. *Technological Forecasting and Social Change*, *102*, 193–201.

Bellini, P., & Others. (2013). Tassonomy and review of big data solutions navigation. *Big Data Computing*, *57*, 1–30.

Benabdellah, A. C., & Others. (2016). Big data for supply chain management: Opportunities and challenges. *Proceedings of IEEE/ACS International Conference on Computer Systems and Applications*, AICCSA, Morocco , 1–16. https://doi.org/10.1109/AICCSA.2016.7945828

Berman, B. (2012). 3-D printing: The new industrial revolution. *Business Horizons*, *55* (2), 155–162.

Bharadwaj, A. O., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly*, *37* (2), 471-482.

Bhutani, S., & Paliwal, Y. (2015). Digitalization: A step towards sustainable development. *OIDA International Journal of Sustainable Development*, *8* (12), 11-24.

Bleicher, J., & Stanley, H. (2016). Digitization as a catalyst for business model innovation: A three-step approach to facilitating economic success. *Journal of Business Management*, *5* (12), 62-71.

Boillat, T., & Legner, C. (2013). From on-premise software to cloud services: The impact of cloud computing on enterprise software vendors' business models. *Journal of Theoretical and Applied Electronic Commerce Research*, 8 (3), 39–58.

Brennen, J. S., & Kreiss, D. (2016). Digitalization. In K. B. Jensen & R. Craig (Eds.), *The International Encyclopedia of Communication Theory and Philosophy,* (556-566). Chichester: Wiley-Blackwell.

Castells, M. (1996*). The rise of the network society* . United Kingdom: Blackwell Publishing.

Chang, M. K., & Others. (2008). Understanding ERP system adoption from the user's perspective. *International Journal of Production Economics*, *113* (2), 928–942.

Chekurov, S., & Others. (2018). The perceived value of additively manufactured digital spare parts in industry: An empirical investigation. *International Journal of Production Economics*, *205*, 87–97.

Chen, B. W., & Ji, W. (2016). Intelligent marketing in smart cities: Crowdsourced data for geo-conquesting. *IT Professional*, *18* (4), 18–24. https://doi.org/10.1109/MITP.2016.75

Chen, J.-S., & Tsou, H.-T. (2007). Information technology adoption for service innovation practices and competitive advantage. *In Proceedings - ICSSSM'06: 2006 International Conference on Service Systems and Service Management* , 12, 472-477).

Chofreh, A. G., Goni, F. A., Klemeš, J. J., & Ismail, M. Y. (2020). Development of guidelines for the implementation of sustainable enterprise resource planning systems. *Journal of Cleaner Production*, *244*, 116. https://doi.org/10.1016/j.jclepro.2019.118655

Coursaris, C., & Others. (2011). Mobile technology and the value chain: Participants, activities and value creation. *Operations Management: A Modern Approach, 3* (3), 1430.

Cox, M., & Ellsworth, D. (1997). *Application-controlled demand paging for out-of-core visualization*. Proceedings of the IEEE Visualization Conference, 2, 35–44.

Dedrick, J., Gurbaxani, V., & Kraemer, K. L. (2003). Information technology and economic performance: A critical review of the empirical evidence. *ACM Computing Surveys*, *35* (1), 1-28.

Demchenko, Y., & Others. (2014). *Big security for big data: Addressing security challenges for the big data infrastructure. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 8425 LNCS2014, 76–94.

Doz, Y. L., & Kosonen, M. (2010). Embedding strategic agility: A leadership agenda for accelerating business model renewal. *Long Range Planning*, *43* (2-3), 370-382.

Faust, F., Roepke, G., Catecati, T., Araujo, F., Ferreira, M. G. G., & Albertazzi, D. (2012). Use of augmented reality in the usability evaluation of products. *Work, 41* (1), 1164–1167.

Fichman, R. G., Dos Santos, B. L., & Zheng, Z. E. (2014). Digital innovation as a fundamental and powerful concept in the information systems curriculum. *MIS Quarterly*, *38* (2), 329-353.

Gartner. (2020a). Digitalization. Retrieved April 5, 2020, from https://www.gartner.com/en/informationtechnology/glossary/digitalization

Gartner. (2020b). Digitization. Retrieved July 30, 2020, from https://www.gartner.com/en/informationtechnology/glossary/digitization

Gimpel, H., Hosseini, S., Huber, R., Probst, L., Röglinger, M., & Faisst, U. (2018). Structuring digital transformation: A framework of action fields and its application at ZEISS. *Journal of Information Technology Theory and Application*, *19* (1), 31-54.

Goralski, M. A., & Tan, T. K. (2020). Artificial intelligence and sustainable development. *International Journal of Management Education*, *18* (1), 1-9.

Greengard, S. (2015). *The Internet of Things*. Cambridge, MA: MIT Press.

Grewal, D., & Levy, M. (2013). *Marketing* (4th ed.). McGraw-Hill Education.

Gupta, H., Dastjerdi, A. V., Ghosh, S. K., & Buyya, R. (2017). IFogSim: A toolkit for modeling and simulation of resource management techniques in the Internet of Things, edge and fog computing environments. *Software: Practice and Experience, 47* (9), 1275–1296.

Hinings, B., Gegenhuber, T., & Greenwood, R. (2018). Digital innovation and transformation: An institutional perspective. *Information and Organization*, *28* (1), 52-61.

Holmström, J., & Others. (2010). Rapid manufacturing in the spare parts supply chain: Alternative approaches to capacity deployment. *Journal of Manufacturing Technology Management*, *21* (6), 687–697.

Holzmann, P., & Others. (2020). Business model design for novel technologies in nascent industries: An investigation of 3D printing service providers. *Technological Forecasting and Social Change*, *159*, 1–13.

Iafrate, F. (2018). *Artificial intelligence and big data: The birth of a new intelligence.* John Wiley & Sons.

Ilhan, I., & Unsacar, F. (2010). Otomotiv yedek parça sektörüne elektronik veri değişimi (EDI) uygulanması için veritabanı ve formların oluşturulması. *Politeknik Dergisi, 14* (4), 249–256.

Isaksson, A. J., Harjunkoski, I., & Sand, G. (2018). The impact of digitalization on the future of control and operations. *Computers & Chemical Engineering*, *114*, 122-129.

Isaksson, D., & Wennberg, K. (2016). Digitalization and collective value creation. In A. Bergström & K. Wennberg (Eds.), *Machines, jobs and equality: Technological change and labor markets in Europe* (pp. 67-87). Brussels, Belgium: European Liberal Forum.

Ittmann, H. W. (2015). The impact of big data and business analytics on supply chain management. *Journal of Transport and Supply Chain Management*, *9* (1), 1–9.

Jara, A. J., Parra, M., & Skarmeta, A. (2014). Participative marketing: Extending social media marketing through the identification and interaction capabilities from the Internet of Things. *Personal and Ubiquitous Computing*, *18* (4), 997–1011.

Jin, J., Jiong, J., Gubbi, J., Marusic, S., & Palaniswami, M. (2014). An information framework for creating a smart city through Internet of Things. *IEEE Internet of Things Journal*, *1* (2), 112–121. https://doi.org/10.1109/JIOT.2014.2316503

Jones, N., & Others. (2015). Impact of social media on small businesses. *Journal of Small Business and Enterprise Development, 22* (4), 611–632.

Karabulut, C. (2020). *Digitalization and paperless process management in foreign trade* (Unpublished master's thesis). İstanbul Ticaret Üniversitesi, Dış Ticaret Enstitüsü, İstanbul.

Karimi, J., & Walter, Z. (2015). The role of dynamic capabilities in responding to digital disruption: A factor-based study of the newspaper industry. *Journal of Management Information Systems*, *32* (1), 39-81.

Kim, W. (2009). Cloud computing: Today and tomorrow. *Journal of Object Technology*, *8* (1), 65–72.

Kupiainen, J. (2006). Translocalisation over the net: Digitalisation, information technology and local cultures in Melanesia. *E-Learning and Digital Media*, *3* (3), 279-290.

Lee, I., & Lee, K. (2015). The Internet of Things (IoT): Applications, investments, and challenges for enterprises. *Business Horizons*, *58* (4), 431–440. https://doi.org/10.1016/j.bushor.2015.03.008

Lee, J., Lapira, E., Bagheri, B., & Kao, H. (2018). Industrial artificial intelligence for Industry 4.0-based manufacturing systems. *Manufacturing Letters*, *18*, 20-23.

Legner, C., Eymann, T., Hess, T., Matt, C., Böhmann, T., Drews, P., & Urbach, N. (2017). Digitalization: Opportunity and challenge for the business and information systems engineering community. Business & Information Systems Engineering, *59* (4), 301-308.

Li, S., Da Xu, L., & Zhao, S. (2015). The Internet of Things: A survey. *Information Systems Frontiers*, 17 (2), 243-259.

Liu, J., Zhang, J., & Jiang, J. (2020). Influence of artificial intelligence on technological innovation: Evidence from the panel data of China's manufacturing sectors. *Technological Forecasting and Social Change*, *158*, 1-11.

Liu, X., Wang, Q., Su, B., & Ma, T. (2020). When do 3PLs initiate low-carbon supply chain integration? *International Journal of Operations & Production Management*, *40* (9), 1367-1395.

Loebbecke, C., & Picot, A. (2015). Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda. *Journal of Strategic Information Systems*, *24* (3), 149-157.

Mangematin, V., & Baden-Fuller, C. (2014). Disassembly and reassembly: An introduction to the special issue on digital technology and creative industries. *Technological Forecasting and Social Change*, *83* (1), 1-9.

Marjani, M., Nasaruddin, F., Gani, A., Karim, A., Hashem, I., Siddiqa, A., & Yaqoob, I. (2017). Big IoT data analytics: Architecture, opportunities, and open research challenges. *IEEE Access*, *5*, 5247–5261. https://doi.org/10.1109/ACCESS.2017.2689040

Marston, S., & Others. (2011). Cloud computing - The business perspective. *Decision*

Support Systems, *51* (1), 176–189.

McLean, G., & Wilson, A. (2019). Shopping in the digital world: Examining customer engagement through augmented reality mobile applications. *Computers in Human Behavior, 101*, 210–224.

Mell, P., & Grance, T. (2011). The NIST definition of cloud computing. *NIST Special Publication*, *800* (145), 1–7.

Mellor, S., & Others. (2014). Additive manufacturing: A framework for implementation. *International Journal of Production Economics*, *149*, 194–201.

Mithas, S., Tafti, A., & Mitchell, W. (2012). Digital business strategies and the duality of IT. *IT Professional*, *14* (5), 2-4.

Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital innovation management: Reinventing innovation management research. *MIS Quarterly*, *41* (1), 223-238.

Nieuwenhuis, L. J. M., & Others. (2018). The shift to cloud computing: The impact of disruptive technology on the enterprise software business ecosystem. *Technological Forecasting and Social Change*, *129*, 308–313.

Nofal, M. I., & Yusof, Z. M. (2013). Integration of business intelligence and enterprise resource planning within organizations. *Procedia Technology*, *11*, 658–665.

Petrovic, V., & Others. (2011). Additive layered manufacturing: Sectors of industrial application shown through case studies. *International Journal of Production Research*, *49* (4), 1061–1079.

Porter, M. E., & Heppelmann, J. E. (2014). How smart, connected products are transforming competition. *Harvard Business Review*, *92* (11), 64-88.

Rodríguez, R., & Others. (2020). The mediating role of organizational complexity between enterprise resource planning and business model innovation. *Industrial Marketing Management*, *84*, 328–341.

Sadrzadehrafiei, S., & Others. (2013). The benefits of enterprise resource planning (ERP) system implementation in dry food packaging industry. *Procedia Technology*, *11* (Iceei), 220–226.

Seethamraju, R., & Sundar, D. K. (2013). Influence of ERP systems on business process agility. *IIMB Management Review*, *25* (3), 137–149. https://doi.org/10.1016/j.iimb.2013.05.007

Sestino, A., Prete, M. I., Piper, L., & Guido, G. (2020). Internet of Things and Big Data as enablers for business digitalization strategies. *Technovation*, *98*, 1–9.

Singh, H. P. (2019). Exploiting RFID for business transformation: A strategic analysis vis-à-vis Agricultural Bank of China. *International Education and Research Journal, 5* (1), 19–23.

Ström, R., & Others. (2014). Mobile marketing: A literature review on its value for consumers and retailers. *Journal of Retailing and Consumer Services*, *21* (6), 1001–1012.

Sürücü, Ö., & Bayram, A. T. (2016). MOBİL pazarlama ve turizmde mobil teknolojilerin kullanımı. *Uluslararası Sosyal Araştırmalar Dergisi*, *9* (42), 2025–2032.

Şükranlı, D. (2020). *The effect of company's level of digitalization on employee satisfaction and productivity* (Unpublished master's thesis). Bahçeşehir University, Institute of Social Sciences, İstanbul.

Tapscott, D. (2008). *Grown up digital: How the net generation is changing your world* . United States: McGraw-Hill Education.

Tiersky, H. (2017). *5 top challenges to digital transformation in the enterprise*. Retrieved September 12, 2020, from https://www.cio.com/article/3179607/e-commerce/5-top-challenges-to-digitaltransformation-in-the-enterprise.html

Tilson, D., Lyytinen, K., & Sørensen, C. (2010). Digital infrastructures: The missing IS research agenda. *Information Systems Research*, *21* (4), 748-759.

Veit, D., Clemons, E. K., Benlian, A., Buxmann, P., Hess, T., Kundisch, D., & Spann, M. (2014). Business models: An information systems research agenda. *Business & Information Systems Engineering*, *6* (1), 45-53.

Ventola, L. C. (2014). Medical applications for 3D printing: Current and projected uses. *P and T*, *39* (10), 704–711.

Vocke, C., Röglinger, M., & Faisst, U. (2019). Application potentials of artificial intelligence for the design of innovation processes. *Procedia CIRP*, *84*, 10-13.

Wang, L., & Alexander, C. A. (2015). Big data driven supply chain management and business administration. *American Journal of Economics and Business Administration*, *7* (2), 60–67.

Wang, M., & Others. (2020). Logistics innovation capability and its impacts on the supply chain risks in the Industry 4.0 era. *Modern Supply Chain Research and Applications*, *2* (2), 83–98.

Yang, L., Prasanna, R., King, M., & Gibb, J. (2013). How the Internet of Things technology enhances emergency response operations. *Technological Forecasting and Social Change*, *80* (9), 1854–1867. https://doi.org/10.1016/j.techfore.2013.03.011

Yim, M. Y. C., & Park, S. Y. (2019). "I am not satisfied with my body, so I like augmented reality (AR)": Consumer responses to AR-based product presentations. *Journal of Business Research, 100*, 581–589.

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research*, *21* (4), 724-735.

Yucha, N., & Others. (2020). Digital payment system analysis of buying decision in Indonesia. *The Journal of Asian Finance, Economics and Business*, *7* (10), 323–328.

Zhao, L., Huo, B., Flynn, B., & Yeung, J. (2013). The impact of supply chain risk on supply chain integration and company performance: A global investigation. *Supply Chain Management: An International Journal*, *18* (2), 115–131. https://doi.org/10.1108/13598541311318773

Chapter 6

TRADING WAVES: THE IMPACT OF INTERNATIONAL STOCK MARKET DYNAMICS ON DIRTY TANKER FREIGHT RATES

Volkan ETEMAN[1]

1 Araş. Gör. Dr. Volkan ETEMAN
Munzur Üniversitesi İİBF
Uluslararası Ticaret ve İşletmecilik Bölümü
Aktuluk Kampüsü Merkez /Tunceli

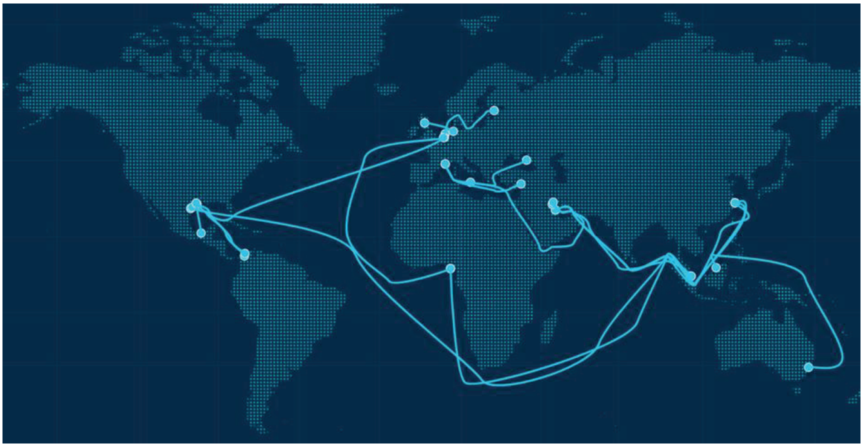
1. Introduction

The transportation of crude oil, a cornerstone of the global economy, via dirty tankers not only underpins international trade but also serves as a vital gauge of economic vitality and stability. In an era marked by the intricate intersection of global trade and financial markets, comprehending the nuanced relationship between dirty tanker freight rates and stock market dynamics is essential for investors, policymakers, and industry leaders alike. Central to this interplay are the transportation networks facilitating crude oil flow, notably through dirty tankers, acting as essential arteries of global commerce. Prominent among the key players in this intricate economic dance are nations such as Germany, the Netherlands, France, and China, heavily reliant on imported crude oil to drive industrial output and sustain economic expansion. Against the backdrop of global trade and energy interdependence, deciphering the relationship between dirty tanker freight rates and global stock markets emerges as a pivotal endeavor. Through an exhaustive examination of this relationship, our study aims to unveil the subtle dynamics shaping financial market performance and guide strategic decision-making amidst the ever-evolving landscape of international trade and finance.

As major players in the global economy, Germany, the Netherlands, France, and China heavily depend on crude oil imports to drive their industrial sectors and sustain economic growth. Crude oil serves as a fundamental resource for these nations, powering manufacturing processes, transportation networks, and energy production. In Germany, one of the world's largest economies, crude oil plays a central role in driving industrial output and supporting the country's export-oriented manufacturing sector. Similarly, the Netherlands, with its strategic location and extensive port infrastructure, serves as a key transit hub for crude oil shipments destined for Europe, underpinning the region's energy security and economic vitality. France, known for its diverse industrial base and advanced manufacturing capabilities, depends on imported crude oil to meet its energy needs and support its industrial activities. Meanwhile, China, the world's second-largest economy, relies on imported crude oil to fuel its rapid industrialization and urbanization, driving growth across various sectors of the economy. Given the critical importance of crude oil for these nations, fluctuations in crude oil prices and transportation costs via dirty tankers have significant implications for their economic performance and overall stability.

Compiled by the Baltic Exchange, a prominent provider of shipping market data and analytics, this index tracks freight rates for 16 specific routes utilized by dirty tankers worldwide, as shown in Figure 1. These routes, identified by codes such as TD2, TDC3, TD6, and so forth, cover transportation from major oil-producing regions to refineries and end markets across the globe. For instance, TD2 represents the route from Ras Tanura to Singapore, while TD8 encompasses Mena al Ahmadi to Singapore. Other routes include TD15 from Serpentina FPSO and Bonny Offshore Terminal to Ningbo, TD18 from Tallinn to Amsterdam, and TD25 from Houston to Rotterdam, among others (Baltic Exchange, 2024). The Baltic Dirty Tanker Index serves as a valuable tool for stakeholders in the energy, transportation, and finance sectors, offering critical insights into the costs associated with shipping crude oil and petroleum products. Fluctuations in the index mirror changes in global oil demand and supply dynamics, along with broader economic trends influencing the shipping industry. Consequently, the Baltic Dirty Tanker Index plays a pivotal role in facilitating transparent pricing and risk management for participants in the global crude oil and shipping markets. It also guides the participants with the help of graphs of investor indices made in certain periods, which you can see below.

Figure 1. Specific Routes Used by Dirty Tankers



Reference: https://www.balticexchange.com/en/data-services/routes.html, (10 May 2024)

In an increasingly interconnected global economy, the movement of goods, particularly commodities like crude oil, plays a pivotal role in shaping economic trends and financial markets. Dirty tanker freight rates, acting as a crucial indicator of this commercial activity, provide valuable insights into broader economic dynamics. Understanding the relationship between dirty tanker freight rates and global stock markets, especially the Dutch, German, French, and Chinese stock exchanges along the dirty tanker route, is essential for investors navigating volatile markets and policymakers crafting effective economic policies. Through a thorough examination of this relationship, our study aims to fill a significant gap in existing research and contribute to a deeper understanding of how fluctuations in freight rates are influenced by stock market movements. We seek to unravel the nuanced interplay between dirty tanker freight rates and global stock markets by exploring the intricate connections and dependencies that exist between these two domains. By conducting rigorous analysis and examination, we endeavor to elucidate how fluctuations in dirty tanker freight rates and the price movements of the Dutch, German, French, and Chinese stock markets along the dirty tanker route are influenced by and, in turn, reflect the dynamics of developed stock exchanges. These reflections within global stock markets have the potential to significantly impact investor sentiment, market volatility, and asset pricing, thus contributing to a deeper understanding of the intricate interplay between trade, finance, and economic stability. By addressing this critical gap in existing research, we aim to shed light on a previously understudied aspect of global trade, contributing to a deeper understanding of the complex relationship between trade, finance, and economic stability. This research aims to unveil the underlying mechanisms dictating the interplay between stock market movements along dirty tanker routes and the corresponding fluctuations in dirty tanker freight rates, thereby offering valuable insights to maritime transportation stakeholders, including shipowners, investors, policymakers, and industry participants, as they navigate the complexities of the modern global economy

The study's framework was structured as follows: the subsequent section discusses prior research that incorporated both dirty tanker freight and dry cargo freight rates. In Section 2, the methodology pertaining to the study's application model is delineated. Section 3 encompasses the variables utilized in the study along with their fundamental statistics. Empirical results are consolidated in Section 4, while Section 5 provides recommendations based on the findings. Finally, Shapter 6 offers concluding remarks for the study.

1.1. Literature Review

In this section, previous research including clean and dirty tanker freight rates and dry bulk freight rates will be discussed. When the studies in the literature are examined, it has been determined that the research on freight rates in maritime transportation, which minimizes transportation costs with the support of economies of scale compared to alternatives, is mostly on the Baltic dry cargo index (BDI). Although many studies have been conducted on the relationship between oil prices and sector indices; There are not many applications that try to explain the relationship between sector indices and clean and dirty tanker freight rates, which represent the freight prices used in the transportation of oil and oil by-products. With this study, we try to explain how the fluctuations in dirty tanker freight rates and the price movements in the Dutch, German, French and Chinese stock exchanges along the dirty tanker route are affected by the Dynamics. Since the lack of sufficient studies explaining the relationship between clean and dirty tanker freights and sector indices creates a gap in the literature, we want to fill this gap by applying the Johansen cointegration test and the error correction model with our study. We aim to contribute to the literature by explaining the relationship between dirty tanker freight rates and the stock markets of the countries on the dirty tanker route. Therefore, under this heading, past studies determined in parallel with the relationship of fluctuations in freight rates with sector indices were investigated.

To model the change in freight prices, Haijie and Xuying (2006) used the GARCH method and determined that the appropriate model was GARCH(1,2). Reporter et al. (2010) tried to explain the relationship between the US GDP and the BDI index by applying the MS VAR method and determined that the appropriate model was MSIH (3) VAR (4). In the research, a crisis regime lasting an average of 3.13 years, a growth regime lasting an average of 3.11 years, and a high growth regime lasting an average of 2.55 years were determined. Geman and Smith (2012), who analyzed the Baltic dry cargo index with the CEV (Constant Elasticity of Variance) model, determined that the breakdown in freight prices occurred before the crisis began in 2003. Lin and Sim (2012) determined freight prices by focusing on different trade cost criteria. Bakshi et al. (2012) found that the BDI index is a successful tool for forecasting commodity and stock prices. Apergis and Payne (2013) emphasized that tanker and dry bulk freight rates are a strong determinant of financial assets along with industrial production. The EMD (Empirical mode decomposition) model was applied to BDI by Zeng and Que (2014). In the analysis, they summarized the nonlinear structure of the series in three items: short-term fluctuations arising from market activities and freight prices, unexpected situations, and long-term expectations. The relationship between BDI and oil prices was investigated by Ruan et al. (2016) by applying the cross-correlation test and it was stated that the cross-correlation between the two variables was significant. Zeren and Kahramaner (2019) tried to explain the relationship between the Baltic dry cargo index and the Istanbul freight index with a unit root test, cointegration test, and Fourier Causality test. The relationship between oil prices and the Baltic dry index and the Baltic dirty tanker index was investigated separately by Choi and Yoon (2020) and by Michail and Melas (2020) in 2020 and the following year, the same relationship was analyzed by Khan et al. (2021) using a different method.

While Choi and Yoon (2020) conducted research using the decomposition method and the copula approach, Michail and Melas (2020) applied the Bayesian Vector Autoregressive method. Khan et al. (2021) used Beenstock's Homogeneous Model in their study. Baltic Capesize Index (BCI), Baltic Handysize Index (BHSI), Baltic Dirty Tanker Index (BDTI) and Baltic LNG Tanker Index (BLNG) over an eight-year period have been analyzed by Pourkermani (2023). It has been concluded that investing in different indices, which currently has a risk distribution system, is not a correct risk mitigation strategy. The long-term relationship between the Baltic dirty tanker and Baltic clean tanker index and the chemical, oil, and plastic index within Borsa Istanbul was examined by Tarkun (2023). Variables with similar degrees of integration according to the unit root test results were investigated with the Johansen cointegration test. Akdağ et al. (2023) tried to explain how to minimize economic risks by applying the Toda-Yamamoto approach to determine the macroeconomic variables affecting BDI. The volatility in the prices of the Baltic Dirty Tanker Index and the Baltic Clean Tanker Index, which are the sub-indexes of the Baltic Tanker Index, was analyzed by Ajith et al.(2023) with the GARCH model.

The relationship between oil and dirty tanker index returns was investigated by Pouliasis and Bentsos (2024). It was found that oil price uncertainty and the future correlation of oil and dirty tanker returns were negatively related. Sui et al. (2024) chose the Baltic dry cargo index and the Baltic dirty tanker index as the subject and interpreted the results of the VAR model and Granger causality test on shipping sensitivity. In another study on the Baltic stock market, Tarkun (2024) examined the bubble assets in the Baltic stock market indices with the Generalized Supremum Augmented Dickey-Fuller (GSADF) test. A bubble has been detected once in the Baltic Capesize Index, once in the Baltic Panamax Index, six times in the Baltic Supramax Index, and five times in the Baltic Handysize Index on the Baltic Stock Exchange. Chen and Liang (2024) investigated the complex transformation of the Baltic Clean and Dirty Tankers markets from 1998 to 2023. They commented on the multi-part structure of tanker markets and how global crises can affect the markets and stated that systemic risks should be taken into account in cargo market analysis. Nowruzi (2024) studied the Baltic dry cargo index, and Baltic dirty tanker and clean tanker indices with the VAR technique. He tried to explain the linearity of the relationships between freight rates by calculating the value at risk on the portfolios he created. A study investigating the dynamics and structural changes of world maritime trade for the period 2009-2023 and the vulnerability of this trade to recent external shocks such as the COVID-19 epidemic and the Ukrainian war was also conducted by Yakubovskiy and Zaidman (2024). Meng et al.(2024), Palaios et al. (2024), Sourmpi (2024), Anderl and Caporale (2024) have studied similar issues and made analyzes regarding tanker transportation, aiming to reduce risk and increase returns.

2. Methodology

This study examines the dynamic relationship between dirty tanker freight rates and the stock markets of the countries along the dirty tanker route. Two basic statistical techniques were used to examine this relationship: Johansen cointegration test and the error correction model. These methodological approaches provide robust analytical frameworks for assessing both the long-run equilibrium relationship and the short-run causal dynamics between dirty tanker freight rates and stock market movements. Using these methods, the study aims to reveal the subtle interactions and potential long-term co-movement trends between shipping costs and international stock market dynamics.

2.1. Johansen Cointegration Test

Cointegration, succinctly defined as the enduring joint movement among variables over the long term (Aktas, 2009), aims to mitigate spurious regression structures while discerning common trends among variables within a system. Although the concept of cointegration was first formally introduced by Engle and Granger in 1987, its evolution persisted through the development of various cointegration tests over time. Notably, in 1988, Johansen's cointegration test method revolutionized this field by centering on the relationship between the rank of a matrix and its characteristic roots. The Johansen cointegration test initiates with the estimation of a vector autoregressive (VAR) model, endeavoring to capture the dynamic interdependencies among variables across time. Hence, non-stationary time series are modeled within the VAR framework, as expressed by Equation 1:

$$\Delta x_t = \sum \prod \Delta x_{t-1} + \prod x_{t-1} + \varepsilon_t \tag{1}$$

Where x_t represents the vector of non-stationary level variables and

$$\prod = -I + A_i + \cdots + A_i \tag{2}$$

When expressing it, it is $i = (1, \dots, p)$. Equation 1 also includes the error correction system. In this equation, long-term information is included in $\prod x_{t-p}$. Therefore, focus on the matrix Π and the rank of this matrix, r. In other words, it is investigated by the rank of this matrix. If the rank of a Π matrix of size nxn is 0, all elements of x_t that complement the n variables in the model will contain the existence of a unit root. If the rank is equal to the number of variables (n) that make up the x_t vector in the model, then x_t is a stationary system. However, when $r < n$, the elements of x_t will express the existence of at most $n-1$ cointegrating vectors. In this situation,

$$\prod \alpha\beta' \tag{3}$$

It will happen. The β matrix is called the cointegrating matrix (Johansen, 1988). While x_t has a non-stationary feature, $\beta' x_t$ has a stationary structure through the cointegrating vector. For this reason, the main purpose of the analysis is to find the β' matrix and divide the variables in the x_t system into stationary and non-stationary parts. The α matrix is evaluated as the coefficients of the correction speed of the errors in the balance relationship of the relevant variables; therefore, it is defined as the correction matrix. In order for this process to take place, it is important to determine the rank. Research shows that rank can be determined by "trace" and "maximum eigenvalue" tests (Johansen & Juselius, 1990). The stage of this test, calculated with maximum likelihood, is as in Equation 4:

$$LR = -T \sum ln(1-\mu_i) \tag{4}$$

With this test, the hypothesis H_0: There are at most r cointegrating vectors, or $r = 0$, is tested.

2.2. Error Correction Models

After establishing the long-term relationship between the variables, determining the direction of causality becomes imperative. However, it has been noted that Granger causality tests are inappropriate when dealing with cointegrated variables. Instead, it is more suitable to conduct causality analysis using the Error Correction Model (ECM) (Granger, 1988). Consequently, the procedure for implementing the error correction model in this study is outlined as follows:

$$\Delta lnx_t = a_0 + \sum_{i=1}^{k} a_{1i}\Delta lnx_{t-i} + \sum_{i=1}^{m} a_{2i}\Delta lny_{t-i} + \gamma ECM_{t-1} + \varepsilon_t \quad (5)$$

$$\Delta lny_t = a_0 + \sum_{i=1}^{k} a_{1i}\Delta lny_{t-i} + \sum_{i=1}^{m} a_{2i}\Delta x_{t-i} + \gamma ECM_{t-1} + \varepsilon_t \quad (6)$$

It was calculated separately for each system created in the study. These equations show the one-lag value of the error terms obtained from the ECM_{t-1} cointegration equations and are called the error correction parameter. This parameter serves to keep the model dynamics in balance and forces the variables to converge towards the long-term equilibrium value. The fact that the error correction parameter is statistically significant indicates the presence of a deviation. The estimated coefficient is expected to be negative and statistically significant. The size of this coefficient is an indicator of the rate of convergence towards the long-term equilibrium value or tendency towards its average.

3. Sample Data and Descriptive Statistics

Our study, based on data spanning January 2016 through May 2024, uses a multifaceted analytical approach to uncover the intricacies of this relationship. Using the Johansen cointegration test and the error correction model, we investigate the long-term dynamics between Baltic dirty tankers. The Netherlands (AEX), France (CAC), Germany (DAX), Italy (FTSE Italia All Share), Singapore (STI), China (Shanghai), USA (Nasdaq), and ASX (Australia) stock market indices located on the delivery route of the Tanker Index are considered. taken. Given that the study comprises monthly observations, any seasonal effects were mitigated through the application of the Census_X12 method. Consequently, descriptive statistical characteristics pertaining to the variables under scrutiny are outlined in Table 1.

Table 1. Descriptive Statistics

	BDTI	AEX	CAC	DAX	NASDAQ	ITALY	SHANGAI	SINGAPUR	AXS
Mean	6.7425	6.4033	8.6510	9.4790	9.1337	10.1054	8.0453	8.0376	8.7644
Median	6.6744	6.3406	8.6172	9.4594	9.1073	10.0974	8.0506	8.0610	8.7811
Maximum	7.6172	6.8097	8.9884	9.8254	9.7406	10.5136	8.2037	8.1599	8.9697
Minimum	5.9476	6.0659	8.3674	9.1765	8.4282	9.8068	7.8105	7.7917	8.4961
Std. Dev.	0.3340	0.1959	0.1717	0.1549	0.3759	0.1654	0.0815	0.0843	0.1195
Skewness	0.3123	0.1478	0.2085	0.0964	-0.1737	0.2370	-0.3350	-1.1657	-0.2160
Kurtosis	2.9775	1.9230	1.9773	2.3804	1.7861	2.5577	3.0209	3.7076	1.9538
JB	1.6443	5.2490	5.1329	1.7718	6.7091	1.7688	1.8906	24.9804	5.3922
Prob	0.4395	0.0725	0.0768	0.4123	0.0349	0.4130	0.3886	0.0000	0.0675
Obs	101	101	101	101	101	101	101	101	101

Based on the data presented in Table 1, it is evident that the skewness values for all variables hover around zero. However, the kurtosis value slightly exceeds the corresponding values for the Shanghai and Singapore variables. Additionally, the Jarque-Bera statistics indicate negligible values, implying that the variables adhere to a normal distribution pattern. Given that the variables under examination pertain to financial time series, it is anticipated that certain variables may exhibit kurtosis values surpassing the conventional threshold of 3. The unit root analysis results for the variables investigated are delineated in Table 2.

Tablo 2. Unit Root Findings

	PP				ADF			
	I	I & T	I	I ve T	I	I & T	I	I & T
	Level		Δ		Level		Δ	
BDTI	-2.5253	-3.0317	-10.3184	-10.2702	-2.4279	-2.8846	-8.9173	-8.8856
AEX	-0.6700	-2.6944	-10.9709	-10.9250	-0.6700	-2.5806	-11.0035	-10.9558
CAC	-0.8537	-2.8059	-11.3015	-11.2533	-1.0051	-2.7647	-11.3057	-11.2567
DAX	-1.2376	-2.7908	-11.1347	-11.0790	-1.3289	-2.8230	-11.1201	-11.0647
ITALY	-0.7699	-2.5208	-11.4549	-11.4412	-0.9324	-2.4272	-11.4940	-11.4770
NASDAQ	-1.0000	-2.0442	-11.1994	-11.1662	-1.0112	-1.9925	-11.2657	-11.2297
SHANGAI	-2.8231	-2.7461	-11.0553	-11.0694	-2.8503	-2.7714	-11.0679	-11.0833
SINGAPUR	-2.7921	-2.7350	-11.6529	-11.6263	-2.7168	-2.6540	-11.7416	-11.7109
ASX	-1.8246	-3.9345	-10.5917	-10.5489	-1.9701	-3.8527	-8.6853	-8.6448

Note: The critical values for the model with a constant are 0.90 (-2.5823), 0.95 (-2.8906), and 0.99 (-3.4970), while for the model with both a constant and trend, they are 0.90 (-3.1534), 0.95 (-3.4554), and 0.99 (-4.0524). The Newey-West information criterion was applied for bandwidth selection in the Phillips-Perron (PP) test, whereas the Schwarz information criterion was utilized for bandwidth selection in the Augmented Dickey-Fuller (ADF) test. I, Intercept; I&T shows the Intercept and trend model.

The results displayed in Table 2 reveal that the test statistics calculated for the level values of the variables are lower than the critical values in absolute terms, implying the probable existence of a unit root in the variables. This indicates a comparable degree of integration among the variables. Furthermore, the test statistics obtained from the unit root analyses, employing first differences, exhibit significantly large absolute values for both the intercept and trend and intercept models. This finding suggests that the variables exhibit a stationary structure upon differencing at the first level.

4. Empirical Results

Our analysis reveals not only the existence of a significant long-term relationship between dirty tanker freight rates and stock market movements but also the varying equilibrium durations and causal paths between different indices. Through error correction model (ECM) coefficients, we illuminate the nuanced response of stock markets to shocks in dirty tanker freight rates and provide valuable insight into the underlying mechanisms driving these interactions. In this regard, Table 3 shows the cointegration findings.

Table 3. Cointegration Findings

Model	Dependent	Independent	$H_0: r = 0$	$Evigen$	λ_{Max_Evigen}	Prob	ECM_{t-1}	JB
Model 5 {2}	BDTI	AEX	$r \leq 1$	0.14734	15.62036	(0.0823)	-0.09075	7.7185
			$r = 0$	0.08757	8.981153	(0.0027)	[-3.6404]	(0.1025)
Model 5 {6}	BDTI	CAC	$r \leq 1$	0.12390	12.43404	(0.2132)	-0.22483	6.5085
			$r = 0$	0.04346	4.176741	(0.0410)	[-3.2646]	(0.1643)
Model 5 {4}	BDTI	DAX	$r \leq 1$	0.10983	11.16839	(0.2987)	-0.174460	7.9584
			$r = 0$	0.09201	9.266493	(0.0023)	[-3.2336]	(0.0931)
Model 5 {1}	BDTI	ITALY	$r \leq 1$	0.12438	13.1499	(0.1741)	-0.16808	34.388
			$r = 0$	0.03871	3.908698	(0.0480)	[-3.6375]	(0.0000)
Model 5 {3}	BDTI	SHANGAI	$r \leq 1$	0.12028	12.17447	(0.1042)	-0.15797	1.9592
			$r = 0$	0.04174	4.050318	(0.0442)	[-3.3052]	(0.7433)

Note: * indicates 0.05 significance, { } indicates lag lengths according to AIC, and [] indicates t-statistic.

In the context of stock markets, our analysis reveals a long-term relationship between them and the Baltic Dirty Tanker Index (BDTI). Specifically, the null hypothesis suggesting no cointegration relationship between the variables is rejected for the AEX, CAC, DAX, and Shanghai stock exchanges. However, it's worth noting that the models involving the Italian stock exchange did not exhibit a normal distribution. As a result, these models were excluded from subsequent parts of the study. Indeed, observing negative ECM coefficients with t-statistics exceeding 1.96 in absolute value across all models in the study, it becomes evident that deviations in the long-term balance of the Baltic Dirty Tanker Index (BDTI) are induced by shocks in AEX prices approximately 11 months later. Similarly, shocks in CAC prices lead to deviations in BDTI after 4.4 months, while DAX price shocks result in deviations after 5.7 months, and shocks in the Chinese stock market cause deviations after 6.3 months. These findings suggest that a shock in the Dutch stock market would cause BDTI to deviate from its average for a prolonged period of 11 months. Moreover, the statistically significant ECM coefficients in each model indicate a long-term causality from AEX, CAC, DAX, and Shanghai prices to dirty tanker freight rates.

The Netherlands has a significant relationship with oil due to its strategic location and extensive port infrastructure, which make it a key transit hub for crude oil shipments destined for Europe. The Port of Rotterdam, Europe's largest port and one of the busiest in the world, serves as a vital entry point for crude oil imports into the continent. The country's refining industry is also prominent, with several refineries located in Rotterdam and other ports along the Dutch coast.

Additionally, the Netherlands is heavily reliant on imported crude oil to meet its energy needs and support its industrial activities. Crude oil serves as a fundamental resource for various sectors of the Dutch economy, including transportation, manufacturing, and energy production. As such, fluctuations in crude oil prices and transportation costs via dirty tankers have significant implications for the Netherlands' economic performance and overall stability.

5. Recommendations and Implications

In line with these findings, some comprehensive inferences can be drawn. We can list these conclusions as follows:

Economic Sentiment: The AEX is a key indicator of economic sentiment and investor confidence in the Netherlands. A downturn in the AEX may signal broader concerns about the Dutch economy, including potential slowdowns in industrial production, decreased consumer spending, or uncertainties in the financial sector. Such negative economic sentiment can have ripple effects across various industries, including the maritime transportation sector.

Trade and Industrial Activity: The Netherlands is a major player in global trade, and disruptions in economic activity reflected by the AEX could impact trade volumes and patterns. Reduced industrial output or decreased demand for goods and commodities may lead to lower shipments of crude oil and other commodities, thereby affecting dirty tanker freight rates.

Global Market Dynamics: The Dutch economy is closely interconnected with global markets, and developments in the AEX may reflect broader trends and events impacting the global economy. Economic downturns or financial instability in other regions can influence investor behavior and market sentiment, leading to fluctuations in dirty tanker freight rates as market participants adjust their expectations and strategies. Germany is a major exporter and importer, and developments in the DAX may reflect broader trends in global trade dynamics. Negative situations in the DAX could be influenced by factors such as trade tensions, geopolitical risks, or shifts in consumer demand, which may impact trade flows and dirty tanker freight rates.

Manufacturing Output: Germany is known for its strong manufacturing sector, and changes in the DAX may reflect shifts in manufacturing output and export demand. Declines in the DAX could indicate slowdowns in manufacturing activity, reducing the need for crude oil imports and affecting dirty tanker freight rates.

Energy Consumption: Changes in the CAC may also reflect shifts in energy consumption patterns in France. Negative situations in the CAC could indicate reduced energy demand or slower economic growth, impacting the need for crude oil imports and, consequently, dirty tanker freight rates.

Economic Growth: The Shanghai Stock Exchange is a barometer of economic growth and investor sentiment in China. Negative situations in the exchange may signal concerns about economic slowdowns or financial instability, impacting trade volumes, industrial activity, and energy demand in China. This could affect crude oil imports and dirty tanker freight rates as trade patterns and market dynamics adjust.

Global Trade Relations: China is a major player in global trade, and developments in the Shanghai Stock Exchange may reflect shifts in trade relations, export demand, and supply chain dynamics. Negative situations in the exchange could be influenced by factors such as trade tensions, policy changes, or geopolitical risks, which may impact trade flows and dirty tanker freight rates globally.

Energy Demand: Changes in the Shanghai Stock Exchange may also reflect shifts in energy demand and consumption patterns in China. Negative situations in the exchange could indicate reduced industrial output or slower economic growth, affecting the need for crude oil imports and, consequently, dirty tanker freight rates as market conditions adjust.

Based on the findings of the study that demonstrate a significant relationship between stock market movements in the AEX, CAC, DAX, and Shanghai exchanges and deviations in the Baltic Dirty Tanker Index (BDTI), it is reasonable to consider these stock exchanges as potential leading indicators for changes in global trade activity within the dirty tanker market.

If the BDTI is indeed defined as a leading indicator, then shocks occurring in the AEX, CAC, DAX, and Shanghai stock markets that cause deviations in the BDTI from its average could signal broader trends in energy demand, global trade patterns, and economic conditions. Investors, policymakers, and industry stakeholders may therefore monitor these stock exchanges closely as indicators of potential shifts in energy consumption, trade flows, and economic activity that could impact the dirty tanker market.

Similar to the BDI, the BDTI can be considered a leading indicator of economic activity and trade volume, albeit within the context of the oil and energy markets. However, it's important to note that while the AEX, CAC, DAX, and Shanghai stock exchanges may serve as leading indicators for the dirty tanker market based on the study findings, the relationship may not be purely causal or deterministic. Other factors, such as geopolitical developments, supply and demand dynamics within the oil market, and regulatory changes, may also influence dirty tanker freight rates and the BDTI. Therefore, while these stock exchanges can provide valuable insights into potential trends in the dirty tanker market, it's essential to consider a holistic range of factors when making predictions or decisions related to maritime transportation and global trade.

Implications

Investment Decisions: Investors in the maritime transportation sector, particularly those involved in dirty tanker freight, can benefit from understanding the relationship between stock market movements and dirty tanker freight rates. The findings suggest that fluctuations in the AEX, CAC, DAX, and Shanghai stock exchanges can serve as leading indicators for changes in dirty tanker freight rates. Investors may incorporate this insight into their decision-making processes when assessing risks and opportunities in the shipping industry.

Risk Management: Understanding the factors that influence dirty tanker freight rates can help shipping companies and other industry participants better manage risk. By monitoring stock market movements and their potential impact on freight rates, companies can adjust their strategies, such as route planning, fleet management, and pricing decisions, to mitigate risks and optimize profitability.

Policy Development: Policymakers responsible for maritime trade and energy policies can use the study findings to inform policy development efforts. Recognizing the link between stock market dynamics and dirty tanker freight rates can help policymakers anticipate potential disruptions in trade flows and develop policies aimed at promoting stability and sustainability in the maritime transportation sector.

Global Trade Dynamics: The study sheds light on the interconnectedness of global financial markets and trade activity within the energy sector. Changes in stock market indices such as the AEX, CAC, DAX, and Shanghai exchanges can reflect broader trends in economic growth, energy demand, and trade patterns. Understanding these dynamics can contribute to a deeper understanding of global trade dynamics and facilitate more informed decision-making by governments, businesses, and international organizations

6. Conclusion

In conclusion, our study provides compelling evidence of the significant impact of stock market movements, particularly those of the AEX, DAX, CAC, and Shanghai stock exchanges, on dirty tanker freight rates. Through rigorous analysis, we have elucidated the nuanced interplay between these key financial indicators and the dynamics of maritime transportation. Negative situations in these stock exchanges have been shown to trigger deviations in dirty tanker freight rates, with varying time lags observed for each exchange. These findings underscore the interconnectedness of global financial markets and maritime trade, highlighting the importance of considering stock market dynamics in understanding fluctuations in dirty tanker freight rates. As such, our research offers valuable insights for investors, policymakers, and industry stakeholders seeking to navigate the complexities of the modern global economy and make informed decisions in the maritime transportation sector. Moving forward, further research in this area could explore additional factors influencing dirty tanker freight rates and refine predictive models to enhance risk management strategies and promote sustainable growth in the maritime industry.

References

Aktas, C. (2009). Türkiye'nin İhracat İthalat ve Ekonomik Büyüme Arasındaki Nedensellik Analizi. Kocaeli Üniversitesi Sosyal Bilimler Dergisi(18), 35-47.

Anderl, C., & Caporale, G. M. (2024). Shipping cost uncertainty, endogenous regime switching and the global drivers of inflation. International Economics, 178, 100500.

Apergis, N., & Payne, J. E. (2013). Renewable and Non-renewable Energy Consumption-Growth Nexus: Evidence from a Panel Error Correction Model. Energy Economics, 34(3), 733-738.

Ajith, P. J., Raju, T. B., Gupta, R., & Kulshrestha, N. (2023). Volatility in tanker freight markets. Case Studies on Transport Policy, 12, 100993.

Bakshi, G., Panayotov, G., & Skoulakis, G. (2012). The Baltic Dry Index as a Predictor of Global Stock Returns, Commodity Returns, and Global Economic Activity. SSNR,1-52.

Bildirici, M., Aykaç Alp, E., Ersin, Ö., & Bozoklu , Ü. (2010). İktisatta Kullanılan Doğrusal Olmayan Zaman Serisi Yöntemleri. İstanbul: Türkmen Kitapevi.

Chen, F., & Liang, X. (2024). Multifractal Dynamics and Complexity Transformation in the Tanker Freight Market.

Choi, K. H., & Yoon, S. M. (2020). Asymmetric dependence between oil prices and maritime freight rates: A time-varying copula approach. Sustainability, 12(24), 10687.

Geman, H. and Smith, W.O. (2012). Shipping markets and freight rates: an analysis of the Baltic Dry Index. Journal of Alternative Investments 15(1), 98-109.

Granger, C.W.J. (1988) "Some Recent Developments in a Concept of Causality", Journal of Econometrics, 39, ss. 199-211.

Haijie, Z., & Xuying, L. (2006). Volatility of Baltic Dry Index using GARCH type Models with Different Distributions. Journal of Shanghai Maritime University, 1-20.

Johansen, S. (1988). Statistical Analysis of Cointegration Vectors. Journal of Economic Dynamics and Control , 231-254.

Johansen, S., & Juselius, K. (1990). Maximum Likelihood Estimation and İnference on Cointegration—with Appucations to the Demand for Money. Oxford Bulletin of Economics and Statistics, 169-210.

Khan, K., Su, C. W., Tao, R., & Umar, M. (2021). How often do oil prices and tanker freight rates depend on global uncertainty?. Regional Studies in Marine Science, 48, 102043.

Lin, F., & Sim, N. (2012). Trade, İncome and Baltic Dry INDEX. European Economic Review,1-18.

Meng, B., Chen, S., Kuang, H., Haralambides, H., & Zhang, X. (2024). Advances in risk management: optimum investment portfolios in tanker shipping. Maritime Economics & Logistics, 1-20.

Michail, N. A., & Melas, K. D. (2020). Shipping markets in turmoil: An analysis of the Covid-19 outbreak and its implications. Transportation Research Interdisciplinary Perspectives, 7, 100178.

Nowruzi, M. (2024). Measuring the value at risk of portfolios in the shipping freight market by utilizing copula functions.

Özcan Akdağ, N., Kocabıyık, T., & Karaatlı, M. (2023). Determining The Causal Relationship Between Baltic Dry Index (BDI) And Macroeconomic Variables By Toda-Yamamoto Analysis. Journal of Management and Economics Research, 21(1), 59-80.

Palaios, P., Triantafyllou, A., & Zombanakis, G. (2024). Economic and geopolitical uncertainty vs energy variables: exploring connectedness in the LNG freight market. Maritime Policy & Management, 1-22.

Pouliasis, P. K., & Bentsos, C. (2024). Oil price uncertainty and the relation to tanker shipping. International Journal of Finance & Economics, 29(2), 2472-2494.

Pourkermani, K. (2023). Modeling the symmetric relation between Baltic Exchange indexes. Maritime Business Review, 8(3), 225-237.

Ruan, Q., Wang, Y., Lu, X., & Qin, J. (2016). Cross-Correlations Between Baltic Dry Index and Crude Oil Prices. Physica A: Statistical Mechanics and its

Applications, 278-289.

Robert F. Engle and C. W. J. Granger. (1987). Co-Integration and Error Correction: Representation, Estimation , and Testing. Econometrica, 55(2), 251–276.

Sourmpi, D. (2024). Freight rates forecasting in the dry handy sector (Master's thesis)

Sui, C., Wang, S., & Zheng, W. (2024). Sentiment as a shipping market predictor: Testing market-specific language models. Transportation Research Part E: Logistics and Transportation Review, 189, 103651.

Tarkun, S. (2023). Borsa İstanbul Petrol, Kimya ve Plastik Sektör Endeksi ile Baltık Kirli Tanker ve Baltık Temiz Tanker Endeksi Arasındaki Asimetrik İlişki: Saklı Eşbütünleşme Testinden Kanıtlar, Selçuk Üniversitesi Sosyal Bilimler Enstitüsü Dergisi 52, 51-62.

Tarkun, S. (2024). Baltık Borsası Endekslerindeki Balon Varlıkları, Erzurum Teknik Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 14-24.

Yakubovskiy, S., & Zaidman, G. (2024). Dynamics And Structure of World Seaborne Trade In 2009-2023: Impact Of Covid-19 Pandemic And Ukrainian War. Actual Problems of International Relations, 1(158), 70-84.

Zeng, Q., & Qu, C. (2014). An Approach for Baltic Dry Index Analysis Based on Empirical Mode Decomposition. Maritime Policy & Management The Flagship Journal of International Shipping and Port Research, 224-240.

Zeren, F., & Kahramaner, H. (2019). Baltik Kuru Yük Endeksi İle İstanbul Navlun Endeksi Arasindaki Etkileşimin İncelenmesi: Ekonometrik Bir Uygulama. Journal of International Management Educational and Economics Perspectives, 7(1), 68-79.

https://www.balticexchange.com/en/data-services/routes.html, (10 May 2024)