AI RENAISSANCE

Transforming Industries and Decision-Making in the 21st Century

Editor
Mustafa Kenan Ustahaliloğlu

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PREFACE

In the dawn of the 21st century, we stand witness to an era of unprecedented transformation, where the confluence of technology and innovation has ushered in what we now refer to as the "AI Renaissance." This profound revolution is meticulously chronicled in our editorial book, "AI Renaissance: Transforming Industries and Decision-Making in the 21st Century." Within its pages, readers will embark on a journey through the labyrinthine landscape of artificial intelligence (AI) and explore the profound implications it holds for our world.

Each chapter of this book serves as a gateway to a realm where AI is the guiding light, illuminating the myriad sectors it touches with its transformative brilliance. From the heart of financial centers to the corridors of strategic management, and from the realms of employment to the very bedrock of healthcare, the impact of AI is nothing short of remarkable.

In "AI Renaissance," we delve into the nuanced and ever-evolving relationship between artificial intelligence and the infrastructure of financial centers. "Impact of Artificial Intelligence on the Infrastructure of Financial Centers: Transforming Financial Operations with Advanced Technologies" explores how AI has revolutionized the very foundations of global finance, redefining efficiency, security, and innovation.

Moving beyond finance, we venture into the intricate terrain of decisionmaking behavior in strategic management. "The Effect of Human-Centered Artificial Intelligence on Decision-Making Behavior in Strategic Management" uncovers how AI is reshaping the cognitive landscape of leaders, offering novel insights into adaptive decision-making processes.

AI's impact extends even into the realm of employment, a facet of our lives that has been profoundly influenced by technological advancement. "Artificial Intelligence and Employment" unravels the complexities of the AI-driven workplace, examining both its potential for job displacement and its capacity to enhance productivity and creativity.

As we continue our exploration, we take a closer look at the strategic implications of AI in recruitment. "Artificial Intelligence Assisted Recruitment

From a Strategic Management Perspective" offers a fresh perspective on talent acquisition, shedding light on how organizations can harness AI to build dynamic and diverse teams.

Our journey then leads us into the sacred precincts of healthcare, where AI is saving lives and revolutionizing patient care. "Artificial Intelligence Applications in Healthcare" illuminates the path to a future where diagnostic accuracy, treatment recommendations, and patient outcomes are elevated to unprecedented heights.

Finally, we gaze into the crystal ball to contemplate the technologies that will shape the future of AI. "Technologies and Future of Artificial Intelligence" paints a vivid picture of the innovations on the horizon, from quantum computing to neural interfaces, that will propel AI into new realms of possibility.

As the pages of "AI Renaissance" unfold, readers will gain a profound understanding of how artificial intelligence is reshaping our world, transforming industries, and guiding decision-making in this remarkable era. Join us on this intellectual odyssey, where the past, present, and future of AI converge to paint a portrait of unprecedented innovation and limitless potential.

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Chapter I

IMPACT OF ARTIFICIAL INTELLIGENCE ON THE INFRASTRUCTURE OF FINANCIAL CENTRES: TRANSFORMING FINANCIAL OPERATIONS WITH ADVANCED TECHNOLOGIES

Güneş Topçu

INTRODUCTION

Technology has become an inevitable component of our daily lives, and it is of particular significance in the financial sector. Efficiency, service quality, and speed are paramount in this era, making technology an absolute necessity in the financial industry. The evolution of finance and technology has together given birth to the term "Fintech" (Arner et al., 2015). Beginning with COVID-19, digitalization accelerated and became a part of our lives, even for ordinary individuals. It increased digital financial inclusion, along with the expansion of capabilities of mobile phones, such as mobile payment apps, and cryptocurrency wallet apps. Technological advancement has given rise to new terms such as blockchain technology, and artificial intelligence (AI), which are particularly used in the financial sector.

AI is of great importance in the financial sector because it enhances efficiency, and can perform tasks more quickly and accurately than human beings, especially those related to the statistical analysis of big data. Financial firms possess vast amounts of customer data, and determining the best products for these customers necessitates analysing their past behaviour, which is achievable through advanced data analysis techniques such as machine learning (ML) and artificial neural networks.

Risk management is another issue that should be considered. While it is challenging for individuals to consider every type of risk, AI-developed models can calculate risk exposure by incorporating in each risk component. Utilizing AI in the financial sector is not a luxury but a necessity, given the benefits it provides to firms in this industry.

Traditionally, financial centres have been established in regions with strong physical infrastructure. For instance, London has "An ancient banking tradition, a major port, the capital seat, the hub of the railroad network built after 1830…" (Kindleberger, 1973). In such cases, trade often preceded the growth of financial activities, as seen in Venice as another example. Over time, physical infrastructure has been replaced by technology-based infrastructure with globalization, technological advancements, and the advancement of capitalism.

The application of AI becomes significantly important when implemented in financial centres. These centres consist of conglomerates of various financial institutions, each with distinct roles. Nevertheless, their coexistence creates economies of scale, where costs can be minimized through AI implementation within the infrastructure of these centres. In this context, infrastructure encompasses not only physical aspects but also legal and technological elements. When financial centres are developed within the framework of a smart city concept, the efficiency gains from interconnected networks and cost-sharing become substantial. Moreover, the utilization of AI for big data analysis within these centres enhances operational efficiency. The aim of this chapter is to examine the application of AI to the infrastructure of financial centres. Examining this issue is important because the application of AI in financial centres increases efficiency, competitiveness, and customer satisfaction, creates better risk management, and reduces cost.

This chapter consists of four sections aimed at comprehending the concepts and subsequently examining the implementation of AI in the infrastructure of financial centres. Section 1 provides concise information about AI and its subcomponents. Section 2 provides a general overview of financial centres. Section 3 focuses on the implementation of AI in the infrastructure components of financial centres, and finally, Conclusion summarizes the main points discussed thus far and explores the future prospects of implementing AI in financial centres.

1. Artificial Intelligence

In order to understand AI, we should first understand the concept of intelligence, as human intelligence constitutes a foundation for the theory of machine intelligence (Cohen & Feigenbaum, 1982). Intelligence is defined as an individual's cognitive capacity to acquire knowledge from experience, engage in effective reasoning, retain crucial information, and effectively manage the challenges of daily life (Sternberg, 1995). The human brain collects huge amount of data, processes them, and utilizes its cognitive skills to make decisions. Information processing system has the following sequence: input, processing, storage, and output. While computers process information explicitly, humans and animals process information implicitly (Gershenson, 2021). Algorithms are used in information processing to perform many tasks ranging from data analysis to decision making. An algorithm is any well-defined computational procedure that takes input values or information, processes it, and generates output (Cormen et al., 2010). An algorithm is a real mathematical object, and an equivalence class of programs (Yanofsky, 2011).

There is a high association between AI and information processing. When we consider the meaning of AI refers to the science and engineering of creating smart machines, particularly intelligent computer programs (McCarthy, 2007). The term AI is used when a machine mimics human-like mental functions like “learning” and “problem solving” (Ongsulee, 2017), which involves processing information and generating output. Following World War II, a number of individuals began working independently on intelligent machines, including Alan Turing, the English mathematician (McCarthy, 2007). His well-known Turing Test (Turing, 1950) aimed to determine whether a conversation was with a computer or a human being, with the objective of assessing a machine's ability to exhibit human-like intelligence.

Subfields of AI include ML, Deep Learning (DL), Natural Language Processing (NLP), Reinforcement Learning (RL), and Deep Reinforcement Learning (DRL) (Campesato, 2023). In this chapter, my emphasis will be on ML and DL.

ML is “the technique that improves system performance by learning from experience via computational methods” (Zhou, 2021). This statement demonstrates that computers learn automatically from its faults and corrects them like human beings with the help of new or improved algorithms such as

linear regression, decision trees, and random forests (Campesato, 2023). ML is also defined as *"...* the ability to continuously 'statistically learn' from data without explicit programming" ("What is Artificial Intelligence in Networking?", nd). As the machine uses data to solve the problems, data gains a crucial importance. Learning methods using data include supervised learning, which uses abundant labelled data; semi-supervised learning, which employs partially labelled data; unsupervised learning, which involves clustered data; and reinforcement learning, where the machine learns from experience (Campesato, 2023). ML has been initially developed in 1952 by Arthur Samuel, who developed a checkers program at IBM (Zhou, 2021). The program was able to learn from analysing past games so that it can detect "good moves" and "bad moves" in the current game; finally, it outperformed Arthur Samuel (Zhou, 2021).

DL is "the subfield of artificial intelligence that focuses on creating large neural network models that are capable of making accurate data-driven decisions" (Kelleher, 2019). To understand what DL is, we first need to know the definition of an artificial neural network (ANN). An artificial network receives input from other networks, processes it, and produces output (Singh, 2021). Inputs are multiplied by weights, and these weights are computed using mathematical functions (Gupta, 2013). The output of an artificial neuron may serve as input for another neuron. A neural network consists of vertically stacked components called layers (Singh, 2021). ANNs are inspired by real neurons in the brain. Like in the brain, these artificial neurons are interconnected; however, they have a threshold value. If the output of any individual layer exceeds this value, that node can send data to the next layer of the network. Neural networks can learn through algorithm training. Once they do this accurately, it means they can help us quickly organize and group data (IBM, nd).

DL is closely linked with ANNs. ANNs consist of layers of nodes, including an input layer, one or more hidden layers, and an output layer (IBM, nd). The deeper the network with more hidden layers, the deeper it is (Singh, 2021). DL derives its name from this connection. These deep artificial neural networks utilize multiple processing layers to reveal patterns and structures within large datasets (Rusk, 2016). Each layer learns from the data in the previous layers, leading to an accumulation of knowledge (Rusk, 2016).

In the field of finance, AI was initially adopted by hedge funds to create algorithms for stock selection and making short-term bets on asset prices

("Lessons from finance's experience," 2023). Nowadays, AI is being used by banks and other financial institutions in developing countries for their operational processes (Kshetri, 2021) and in asset management. Additionally, AI is employed by numerous financial technology (fintech) firms. Table 1 provides examples of how AI is utilized in financial institutions (Kshetri, 2021).

Table 1. Some Fin-Tech Companies Employing AI, Utilization of AI in These Companies, and The Resulting Outcomes

Company	Country	Use of AI	Outcome
Ant Group's AI-based customer service chatbot	China	Handles 2 to 3 million queries per day. It uses deep-learning technology to detect fraud (Kshetri, 2020).	Losses related to fraud: one in 1 million. Outperformed human agents in customer satisfaction.
UBA	Nigeria	A banking chatbot Leo helps customers to transfer money, pay bills, buy airtime, check account balance and other functions.	Available 24 hours a day and faster than human agents
Safaricom Chatbot assistant Zuri	Kenya	Provides services such as managing subscription, canceling SMS services, reversal of money sent to a wrong recipient, airtime top up and checking M-PESA and airtime balances.	To reverse pay, a M-PESA user no longer needs to contact a customer service team, which takes a long time.
TymeBank	South Africa	Interacts with customers online and via kiosks. The bank has only 250 employees, compared to about 50,000 in an average South African bank.	Serve consumers at a low-cost (e.g., card replacement charge is R40, much lower than competitors).

2. Overview of Financial Centres

"A financial centre is a location, usually a city or district, where intermediaries involved in the provision of financial services are concentrated" (Pogliani et al., 2022). This definition is linked to agglomeration, which is the clustering of firms in a specific geographic area (Bolter & Robey, 2020). Agglomeration economies arise when firms that produce similar or complementary goods or services cluster in proximity, resulting in positive externalities for these firms (Porter, 1998).

Costs of production and services decrease in these locations due to advanced technology and infrastructure. Firms can share infrastructure, as well as resources, knowledge, and expertise. Regardless of the number of users, financial centres incur some fixed costs by sharing infrastructure. In the case of transport and telecommunications infrastructure, initial costs are higher, which incentivizes sharing. The value of this infrastructure increases as the network becomes denser (Bolter & Robey, 2020). Similarly, if these financial centres are located in large cities, they can draw upon a pool of skilled labour (Bolter & Robey, 2020).

Kindleberger (1973) outlines the benefits of financial centres as follows:

- Financial centres play a crucial role in balancing the savings and investments of individual entrepreneurs, acting as intermediaries between savers and investors. They also facilitate the transfer of savings overseas and facilitate international payments.
- Financial centres play a crucial role in balancing the savings and investments of individual entrepreneurs, acting as intermediaries between savers and investors. They also facilitate the transfer of savings overseas and facilitate international payments.
- Financial centres excel in balancing both seasonal and long-term surpluses and deficits of financial savings.
- For international payments and overseas loans or borrowing, a single central location, often serving as a specialized hub for domestic interregional payments, is the preferred choice.

To attract business, a financial centre must meet certain essential conditions, including having a stable currency, a consistent demand for and supply of that currency, a stable balance of payments account to withstand shocks, specialized institutions for foreign financial transactions, advanced financial expertise, extensive financial infrastructure, a trusted legal system, and connections with a broad network of global investors (Nadler, 1955, as cited in Reed, 1980; Elliott, 2011).

Z/Yen, the City of London's one of the leading commercial think-tank institutions, created an index that evaluates the competitiveness of the financial centres based on criteria such as business environment, human capital, infrastructure, financial sector development, and reputation (Z/Yen, 2023). Figure 1 gives the detailed components of each subcategory.

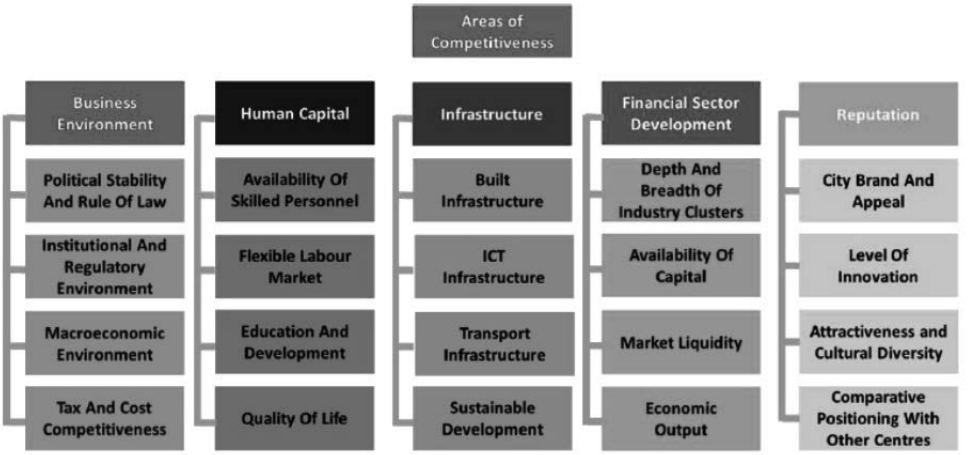


Figure 1. Global Financial Centres Index: Areas of Competitiveness

According to the Global Financial Centers Index prepared by the same think-tank institution, Z/Yen, New York, London, Singapore, Hong Kong, Chicago, Boston, and Seoul are the leading global financial centres. In the Eastern Europe and Central Asia region, Astana takes the leading position, while Prague and Warsaw fall behind. Moscow dropped more than ten places in rank, whereas Athens, Sofia, and Riga all rose by ten or more places. In the Middle East and Africa, Dubai and Abu Dhabi are ranked first and second, respectively, with Casablanca as the leading financial centre in the African continent. In Latin America and the Caribbean Islands, according to the same index, Cayman Islands, Santiago, and Bermuda are the leading centres.

International financial centres (IFCs) have tax and regulatory policies that favour foreign investment (Hines, 2009). Establishing global finance centres generates additional financing for entrepreneurs in a country who might otherwise limit themselves to domestic financing (Kindleberger, 1973). Empirical studies provide evidence of IFCs' contribution to attracting additional investment finance (Hatayama, 2019), while also creating employment and promoting the efficient functioning of markets (Hines, 2009). IFCs facilitate the inflow of international investments into developing countries through three methods (Hatayama, 2019): attracting foreign direct investment, managing private equity funds, and intermediating funds sourced from development finance institutions.

3. How AI Impacts The Infrastructure of Financial Centres

3.1. The Infrastructure Components of Finance Centres

The main infrastructure components of financial centres are physical infrastructure such as skyscrapers housing private sector offices, residences, conference halls ("IFC Physical Infrastructure", nd), data centres, trade floors, and communication networks; technological infrastructure such as ultra-fast, world class internet and secure data storage; a well-established transparent and flexible regulatory framework; and a skilled workforce that can speak multiple languages. All these infrastructure components enable financial centres to handle complex financial transactions and serve as gateways to international markets.

In recent years, there has been significant progress in applying fintech to the infrastructure of financial institutions. Three primary factors driving this progress are the massive generation of data, advancements in computer algorithms, and increases in processing power (Sahay et al., 2020). These transformations have been made possible through the support of high-speed broadband internet, cloud computing, and AI. Financial centres benefit from fintech applications such as usage of blockchain technology, cloud computing, AI, and biometric data (WAIFC, nd). In this section, I will explore the applications of AI in the infrastructure components of financial centres.

3.2. Impact of AI on Physical Infrastructure

Although, at first glance, physical infrastructure does not seem to be related to technology, since the newly constructed IFCs are built under smart city concept, they include advanced technology. For example, the brand new Istanbul Financial Centre will have 1.3 million m^2 of office space with a shopping mall, a conference hall, a 5-star hotel, and a car park all of which are built under the concept of smart city ("IFC About", nd). These office buildings with residential complexes will consume high amount of energy. When AI is used together with Internet of Things (IoT) technologies that create interconnection among data-generating devices (Berry, 2021), the places where energy shortage exists can be detected by energy monitoring technology. Energy must be consumed at the same time it is produced. At some point, storage systems are required. The problem of where these storage systems should be installed can be solved with AI. Since this task involves the use of big data, solving it with human intelligence is not very likely, and classical optimization methods are not suitable for solving this problem either.

As financial centres consume a significant amount of energy that needs to be continuous, determining the optimal locations for these energy storage systems can be achieved with AI support. Another area where AI can be applied in financial centres is parking lots. Integrating AI systems into parking lots enables users to identify available parking spaces (Berry, 2021).

3.3. Impact of AI on Technological Infrastructure & Network Infrastructure

In financial centres, there are agglomeration of financial institutions such as banks, insurance companies, fintech startups, and investment firms. All these establishments require ultra-fast, world-class internet and secure data storage to facilitate their daily transactions. Key technological infrastructure components in financial centres encompass cloud computing, fiber-optic networks, and high-tech data centres. A financial cloud system functions as a cloud-based sharing platform, utilizing cloud computing technology to enable interoperability, data storage, and the deployment of computing resources (Wang and Song, 2019). Because of the processing of big data, both AI and cloud computing technology are needed to enhance the development of financial shared service centres while keeping rigorous oversight over risks such as information technology (IT), suppliers, and data security (Wang & Song, 2019).

AI, in collaboration with geodata infrastructure (GDI), supports the automation of fiber-optic network organization (“Open Telekom Cloud”, nd). This integration encompasses secure data storage and rapid geospatial data analysis, including the utilization of aerial photographs, laser scanner-generated point clouds, and digital camera images (“Open Telekom Cloud”, nd). Regarding financial centres, AI, in conjunction with GDI, can assist in analysing geospatial data to determine optimal routes for fiber-optic cables during the construction phase, continuously monitor the fiber-optic network to detect security breaches, and develop a contingency plan to address physical infrastructure issues in the event of a disaster. For example, if a city is located in a primary earthquake zone and experiences an earthquake, the previously developed contingency plan, aided by AI's ability to detect potential vulnerabilities, enables a rapid disaster response for the financial centre’s fiber-optic network.

Digitalization not only reduces operational costs but also opens the door to ultra-personalized financial services that could enhance the country's

financial industry (Wyss et al., 2021). AI, specifically ML, is used and has the potential to automate processes, process data, assess risks, implement anti-money-laundering measures, and detect fraud in financial institutions (Bredt, 2019; Wyss et al., 2021). In the future, the presence of fintech startups, the availability of ultra-customized financial products and services driven by data-driven insights, and the integration of conversational interfaces such as chatbots will further drive the adoption of ML (Wyss et al., 2021). Regarding security, AI helps identify software vulnerabilities that could be exploited by hackers and assists defenders in identifying and addressing these vulnerabilities, as well as detecting malicious code in their networks (Buchanan, 2020).

AI will increase the efficiency of the network system by providing trusted automation processes that decrease the network operation costs. This is achieved through the utilization of models trained on historical data. AI supports IT automation in various areas, including the management of network policies, the integration of zero-trust security solutions to ensure network consistency, and the identification and categorization of devices within the network By leveraging a network controller and a management dashboard, AI/ML technology analyses telemetry data from the network to detect anomalies, remove incorrect alerts, and suggest corrective measures ("What is Artificial Intelligence in Networking?", nd). It's worth noting that AI tasks often involve transmitting substantial data volumes across different system components, such as data storage, processing, and analytics. As a result, network design should efficiently meet these requirements, potentially incorporating advanced networking technologies like software-defined networking and network function virtualization (Frackiewicz, 2023).

Another technology where AI supports network infrastructure is machine reasoning (MR). It uses acquired knowledge to guide the user through several options to achieve the best possible result. In order to get benefit from MR, all available input should be provided beforehand by humans. This technology proves particularly valuable when addressing complex issues that demand deep domain expertise ("What is Artificial Intelligence in Networking?", nd).

3.4. Impact of AI on Regulatory Framework

For a well-functioning financial centre, a stable and transparent legal system is a necessity. Special administrative areas may be built in financial centres that have its own courts. Commercial and civil laws may be written

according to English common law to create integrity with other countries' regulations. The Dubai International Financial Centre is an example of such centres where their own courts and laws based on English common law exist (Pogliani & Wooldridge, 2022).

Financial institutions must accurately and promptly report their activities to financial regulatory bodies, such as the banking regulation and supervision agency and the capital markets board. Regulatory compliance processes involve the collection of data from various sources within specified timeframes (Okwechime, nd). Furthermore, reports should adhere to international rules and requirements. AI enhances these processes by automating data collection, accelerating and improving decision-making precision, and strengthening the organization's ability to meet regulatory compliance obligations.

Regulatory compliance processes can be facilitated by regulatory technology (RegTech), which involves the utilization of emerging technologies to support the way businesses handle their regulatory obligations (Ascend, nd). RegTech refers to any technology that assures corporations meet their regulatory obligations (Teichmann et al., 2023). The benefits of using RegTech for financial services include efficiency gains, greater accuracy and comprehensiveness, improved internal alignment, and enhanced risk management (Ascend, nd). AI is expected to support RegTech functionalities such as bias evaluations, automated evidence usage to track changes in AI models, and the enhancement of transparency and comprehensibility in AI systems (Adrian, 2021).

When considering this aspect within the context of financial centres, the potential advantages of RegTech appear to be substantial. Given that 75% of exchange trading volume occurs in cryptocurrency exchanges registered in offshore financial centres (Bains & Wu, 2023), there is an increasing need for greater regulatory clarity. The cryptocurrency market is recognized as one of the riskiest financial markets, with certain attributes of crypto assets increasing the risks of money laundering and financing of terrorism (Coelho, 2021). Furthermore, as financial centres host companies from various countries, each country's unique compliance requirements come into play. RegTech, supported by AI, can streamline reporting processes (IBM, 2018), establish early warning and fraud detection systems (IBM, 2018), identify legal threats (Dowd, 2023), and classify cryptocurrency assets according to diverse regulatory frameworks (Coelho et al., 2021).

3.5. Impact of AI on Skilled Workforce

In most financial firms, recruiting a skilled workforce is common practice. Likewise, in the context of financial centres, the increasing reliance on AI in operations necessitates the recruitment of individuals proficient in commonly used international languages and possessing high technological literacy. The likelihood of hiring someone who held a professional position 20 years ago in these centres is low due to technological advancements over the past decade, particularly with the acceleration toward a digital world brought on by COVID-19.

Typically, financial centres seek professionals capable of managing numerous statistically or AI-intensive applications (IBM, 2018). Nevertheless, there exists a trade-off between the costs of hiring such individuals and the efficiency gains from employing AI (IBM, 2018). While many tasks currently performed by humans will eventually be replaced by AI-supported machines over time, humans continue to play a vital role in decision-making processes due to their possession of common sense, a trait absent in machines. Universities should adapt to provide technology-intensive education that aligns with the demands of high-tech firms. Indeed, if technological education begins in pre-university stages, such as secondary or high schools, the adaptation process for individuals will be smoother, resulting in higher efficiency gains from this transition.

CONCLUSION

Financial centres provide several benefits, including facilitating international trade, increasing trade volume and financial competitiveness, fostering integration into global financial and capital markets, and contributing to sectors such as education, healthcare, and tourism that serve financial sector employees (Apak & Elverici, 2008; Tartan & Tetik, 2023). As the world transitions to a digital financial landscape, and adapts to increase digital financial inclusion, the importance of financial centres with high-tech infrastructure grows. The introduction of new technologies can be costly, but the agglomeration effect in financial centres enables firms to share these costs and leverage technological advantages at a lower cost.

This chapter explores how AI affects each infrastructure component of financial centres, from the regulatory framework to the skilled workforce. AI will support financial centres by developing new personalized products for

customers, accelerating algorithmic trading, and enhancing risk management—contributing to financial innovation. Furthermore, AI will assist in regulatory compliance by automating regulatory processes (Nachmany, 2023). Managing big data originating from numerous customers in financial centres would be nearly impossible without AI support in this era.

As technology advances, financial markets may become more efficient. It becomes easier for machines to generate profits through trading in such efficient markets. However, the persisting challenge lies in investor sentiment, a factor that remains unpredictable as long as human beings are involved. Regardless of how advanced technology becomes, forecasting human behaviour in advance remains a complex task. Consequently, there will always be a need for a skilled workforce capable of making informed decisions within financial centres. In the future, as fintech progresses further, an AI-dominated financial world will embrace individuals and firms, requiring adaption to such an environment. Therefore, the technological and financial literacy of individuals will play a critical role in utilizing the AI-supported services.

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Chapter II

THE EFFECT OF HUMAN-CENTERED ARTIFICIAL INTELLIGENCE ON DECISION-MAKING BEHAVIOR IN STRATEGIC MANAGEMENT

Ayşe Meriç Yazıcı

INTRODUCTION

In today's rapidly changing business world, the process of making strategic decisions to maintain or increase the sustainability and competitive advantage of organizations is becoming increasingly complex. Addressing this complexity and making the best decisions is critical to the success of organizations. At this point, artificial intelligence (AI), and especially human-centred artificial intelligence (HCAI), has the potential to radically change decision making processes (DMPs) in strategic management (SM).

HCAI offers a different approach from traditional AI systems. This approach is based on the idea of integrating technology into human collaboration and DMPs. Technologies such as AI algorithms, big data analysis, machine learning (ML) and deep learning (DL) help organizations make better informed and more strategic decisions. However, the adoption of a human-centred approach by these technologies can radically affect the decision-making behaviour of businesses.

In this study, the impact of HCAI on decision-making behaviour in SM is examined. First, the definition of HCAI and and how it Works will be examined, then, the role of this technology in SM and how it optimises DMPs will be analyzed. Finally, the way that the HCAI may enhance the competitive advantage of organizations will be addressed.

In conclusion, this study highlights the importance of using HCAI to improve DMPs in SM and to enable organizations to compete more effectively.

It aims to show that this new technology can lead to fundamental changes in the business world and support the sustainable success of organizations.

1. Human-Centred Artificial Intelligence

HCAI is an approach or philosophical perspective in the field of AI. This approach emphasises that AI should be more useful, ethical and human-centred for humans. HCAI is based on some basic principles. These basic principles are explained below (Mhlanga, 2022).

Focus on People's Needs: HCAI encourages the development of AI systems to solve the problems that people face in daily life. These mean that AI applications in various fields such as health, education, work, transport meet the needs of people (Xu, Dainoff, Ge and Gao, 2021).

Equality and Justice: HCAI advocates the protection of equality and justice during the creation and use of technology. This is especially important during the data collection, model training and implementation phases, as inaccurate or biased data can affect AI systems and contribute to social inequalities (Chen, Clayton, Novak, Anders and Malin, 2023).

Transparency and Understandability: HCAI systems should explain their decisions and functioning in a way that is understandable to humans. This enables users to understand and trust how AI systems work (Riedl, 2019).

Human and Machine Collaboration: HCAI encourages collaboration between humans and AI. This aims to enable AI systems to achieve better results by working together with humans and help people perform their daily tasks more efficiently (Schmager, Pappas and Vassilakopoulou, 2023).

Ethics and Responsibility: HCAI recommends that AI developers and users pay attention to the ethical use and responsibility of technology. This includes establishing policies and guidelines to prevent harmful or malicious use (Bingley, Curtis, Lockey, Bialkowski, Gillespie, Haslam and Worthy, 2023).

HCAI aims for advances in AI to improve people's quality of life and serve the overall benefit of society. Therefore, it is emphasised that AI development and implementation processes should be done with people's needs and values in mind.

2. Human-Centred Explainable Artificial Intelligence Techniques

Human-Centred Explainable Artificial Intelligence Techniques (HCXAI) techniques play a crucial role in HCAI systems. They aim to fill the gap between the opaque nature of traditional AI systems and the need for transparency and accountability in DMPs (Balasubramaniam, Kauppinen, Rannisto, Hiekkanen and Kujala, 2023). HCXAI techniques include rule-based systems, locally interpretable mode-agnostic explanations, Shapley values, counterfactual explanations, and user-interactive explanations. These techniques are described below:

Rule-Based Systems: Rule-based AI systems use a set of explicit rules to make decisions. These rules are usually defined by human experts and can be easily understood and interpreted by humans. Since the DMP is based on transparent rules, rule-based systems are inherently explainable (Zafar and Khan, 2021).

Locally Interpretable Model-Agnostic Explanations (LIME): LIME is a technique that provides explanations for decisions made by complex ML models. It produces locally interpretable explanations by approximating the behavior of a model around a given example. LIME makes it easier for people to understand and validate the logic of the model by highlighting the features that contribute most to the model's decision (Aas, Jullum and Løland, 2021).

Shapley Values: Shapley values come from cooperative game theory and are used to assign importance values to different features in a model. In the context of explainability, Shapley values can be applied to attribute contributions to individual features in a prediction, allowing people to understand how each feature affects the outcome (Olson, Khanna, Neal, Li and Wong, 2021).

Counterfactual Explanations: Counterfactual explanations involve generating alternative scenarios to explain why a particular decision was made. By providing counterfactual examples, people can understand how changing certain input characteristics would lead to different outcomes. This technique helps users identify the factors influencing the decision and explore potential interventions (Tocchetti, 2022).

User Interactive Annotations: User interaction plays a vital role in HCAI systems. Explanations can be made more effective by involving users in the process. Techniques such as interactive visualizations, natural language interfaces, and interactive debugging tools allow users to explore and refine

the explanations provided by AI systems, improving their understanding and confidence (Sarker, 2022).

The purpose of using HCXAI techniques is to make AI systems transparent, interpretable, and accountable.

3. Decision Making With the Help of Artificial Intelligence

3.1. Organizational Decision Making

AI is a powerful tool to optimise organizational DMPs and achieve better results (Sinnaiah, Adam and Mahadi, 2023). AI can analyse large data sets quickly and effectively. This helps to gain important insights for future decisions by examining the past performance of organizations (Bajwa, Munir, Nori and Williams, 2021).

ML algorithms can be used to predict future events. For example, AI can be used for demand forecasting, inventory management and analysing market trends. AI-based decision-support systems provide information to decision makers and can simulate the results of different decision options. This can help the decision makers to make better decisions (De Mauro, Sestino and Bacconi, 2022).

AI can be used to identify and assess organizational risks. It is especially effective in financial decisions, risk management and security issues. AI can help managers to provide more personalised services by analysing customer data. For example, recommendation systems and customer support bots can be used (Zhao and Fariñas, 2023). AI can help managers to direct human resources to more strategic tasks by automating routine tasks. AI continuously learns from an organization's data and can use this information to improve DMPs (Mishra, 2023). However, the integration of AI into organizational DMPs must be done carefully. In addition, important issues such as data privacy, ethical and legal responsibilities should be considered. It is also important to develop a good strategy on when and how to use AI technologies.

AI can help organizations deliver personalized experiences to their customers. By analyzing customer data and preferences, AI algorithms can create personalized recommendations, product recommendations, and targeted marketing campaigns. This can lead to increased customer satisfaction, increased sales, and better decisions regarding product development and marketing strategies (Haleem, Javaid, Qadri, Singh and Suman, 2022).

It is important to note that while AI can greatly assist organizational decision-making, human judgment, and expertise remain necessary. AI technologies should be seen as tools to support and strengthen human decision-making rather than replace it entirely (Jarrahi, 2018). Organizations should carefully consider the ethical implications and potential biases associated with AI algorithms to ensure fair and responsible DMPs (Bankins and Formosa, 2023).

3.2. Basic Process for Organizational Decision-Making under Uncertainty

Organizational decision-making under uncertainty involves making choices and taking actions when there is a lack of complete information or when outcomes cannot be predicted. While there is no one-size-fits-all approach, there are some basic steps that organizations can follow when making decisions under uncertainty. A description of these basic steps is listed below (Nutt, 1999; Stanton and Roelich, 2021; Savioni, Triberti, Durosini and Praventtoni, 2023):

- Relevant data and information should be gathered from various sources to better understand the situation.
- The degree of uncertainty surrounding the decision should be assessed.
- Multiple potential courses of action or alternatives should be formulated and evaluated.
- The risks and trade-offs associated with each alternative need to be assessed.
- Based on the analysis and evaluation of the alternatives, the decision that seems most appropriate under the existing conditions needs to be made.
- An action plan should be developed to implement the chosen decision.
- Implementation of the decision and continuous monitoring of the results should be carried out.

Corporate decision making under uncertainty is a process where an organization is faced with the need to manage future uncertainties and risks, and this process can be complex. However, following the basic steps above can help to make more informed and effective decisions. It is also important to tailor the DMP to the specific needs and objectives of your organization.

4. Using Artificial Intelligence to Support Strategic Corporate Dmps

The use of AI is a highly valuable tool to support strategic corporate DMPs. AI can analyse big data, and predict future trends and possible scenarios as a result of these analyses. This makes strategic DMPs informed. For example, AI can be used to predict market trends or understand customer behaviour. AI can make decisions or provide decision recommendations based on certain criteria. This can help making strategic decisions more quickly and objectively. For example, AI recommendations can be used when managing an investment portfolio (Dash, Shakyawar, Sharm and Kaushi, 2019).

Strategic decisions often involve certain risks. AI can be used to assess risks and identify potential hazards. It can also help develop strategies for mitigating or managing risks. By analysing customer data, AI can also provide personalised product and service recommendations. This can increase customer satisfaction and provide a competitive advantage. Many stages of strategic DMPs can be automated. AI can make these processes more efficient and focus human resources on more strategic tasks. AI can be used to monitor competitors' activities and strategies. This can help a company to understand it’s position in the market better, and create competitive advantages (Kumar, Koul, Singla and Ijaz, 2023). AI can be a powerful tool to improve strategic corporate DMPs and provide competitive advantage, but this technology needs to be used consciously and carefully.

AI can explore different scenarios and their consequences by considering different variables and potential impacts on the DMP. This can help with strategic planning, evaluating alternative courses of action, and selecting the most appropriate strategies. It is important to note that although AI can provide valuable insights and recommendations, human judgment and expertise remain important in the DMP (Pena, Carballal, Rodríguez-Fernández, Santos and Romero, 2021).

However, AI should be seen as a tool that augments human capabilities, and provides additional information, rather than replacing human decision-making,. Organizations should ensure transparency, fairness, and accountability in the AI systems they use and consider ethical implications when using AI for strategic decisions making decision-making (De Cremer and Narayanan, 2023).

4.1. Ethical Perspectives on the Use of Artificial Intelligence in Strategic Corporate DMPs

The use of AI in strategic corporate decision-making raises various ethical issues. AI algorithms can be trained on biased or incomplete data, which can lead to biased decision-making outcomes. This can perpetuate existing inequalities and discriminate against certain individuals or groups (Belenguer, 2022). Ethical concerns arise when AI systems reinforce social, gender, or racial biases in strategic DMPs. Ensuring fairness, transparency, and accountability in the design, development, and deployment of AI systems is crucial (Li, Ruij and Lu, 2023). AI algorithms such as DL models often operate as black boxes, making it difficult to understand the logic behind their decisions. This lack of transparency raises concerns about accountability and the ability to challenge or correct erroneous decisions (Linardatos, Papastefanopoulos and Kotsiantis, 2021). Ethical perspectives require the development of explainable AI systems that allow stakeholders to understand the rationale behind strategic decisions made by AI algorithms. AI relies on large amounts of data to make informed decisions. However, the use of personal or sensitive data in strategic DMPs may violate individuals' privacy rights (Perifanis and Kitsios, 2023). It is crucial that organizations ensure appropriate data management practices, such as obtaining informed consent, anonymizing data where possible, and implementing robust security measures to protect personal information (Quach, Thaichon, Martin, Weaven and Palmmatier, 2022).

AI systems can potentially automate or augment DMPs traditionally performed by humans. This shift raises concerns about the impact on human autonomy and the delegation of decision-making authority to machines (Laitinen and Sahlgren, 2021). Ethical perspectives emphasize the need to maintain human accountability and responsibility in strategic decision-making and state that AI serves as a tool to enhance, rather than completely replace, human decision-making. The inclusion of AI in strategic DMPs can have significant economic and social consequences (Ryan and Stahl, 2021).

The internal working logic of AI systems can be complex and decision processes can become incomprehensible. This can make it difficult for people to trust these systems. Therefore, it is important to explain the way AI systems work and ensure that they are understandable. AI has the potential to automate some jobs. This may cause changes in the labour market and unemployment. Therefore, there is an ethical responsibility to deal with

labour force changes. Issues related to how AI systems will be integrated into legal regulations and the justice system are a source of ethical concern. It is important that the use of AI is compatible with legal frameworks and ensures justice. It is important that society understands and accepts AI technologies. Education and awareness raising are important to promote ethical use. AI systems carry risks of failure or misuse. It is important to develop appropriate risk management strategies to recognise and mitigate these risks (Nguyen, Ngo, Hong, Dang and Nguyen, 2023).

The use of AI in strategic organizational DMPs should be carefully planned and implemented with these and similar ethical issues in mind. Ethical principles provide guidance for maximising the potential of AI technology to deliver societal benefits.

4.2. The Effect of Using Artificial Intelligence in Strategic Corporate DMPs on Task Distribution Between Humans and Machines

The impact of the use of AI on the distribution of tasks between humans and machines in strategic corporate DMPs is very important (Ahmed, Krishna, Ganeshkumar, and Manivel, 2023). This effect helps businesses make more efficient, faster and more accurate decisions (Coombs, Hislop, Taneva and Barnard, 2020).

AI technologies such as ML and natural language processing can extract insights from large amounts of data at a speed and scale beyond human capabilities. This enables more informed decision-making and empowers humans with data-driven recommendations and insights. AI algorithms can perform tasks faster and with greater accuracy than humans. By leveraging AI, organizations can streamline processes, reduce errors and achieve higher operational efficiency. This allows human employees to focus on tasks that require creativity, critical thinking, and subjective judgment (Wamba-Taguimdje, Fosso Wamba, Kala Kamdjoug and Tchatchouang Wanko, 2020). AI systems can assist human decision-making in complex scenarios by providing relevant information, scenario analysis, and predictive modeling. AI-supported algorithms can process large amounts of data, simulate various scenarios, and provide recommendations to enhance human decision-making capabilities (Soori, Arezoo and Dastres, 2023).

As AI takes on more decision-making tasks, ensuring ethical and responsible use becomes crucial. Humans need to oversee AI systems, set

parameters and establish guidelines to ensure compliance with ethical and societal considerations. Humans also play a critical role in reviewing and validating recommendations generated by AI to avoid biases or errors (Pflanzer, Traylor, Lyons, Dubljević and Nam, 2023). Humans are responsible for making the final decision based on the data provided by AI. AI provides the necessary data to optimise the decision-making process, but humans make the final decision. Humans monitor the results of strategic decisions and learn continuously. AI constantly analyses new data and improves its algorithms. It can work on data sets that are too large for humans to handle (Zirar, Ali and Islam, 2023).

As a result, the impact of AI in strategic corporate DMPs can optimise collaboration and task allocation between humans and machines. While humans contribute with their creative thinking, ethical judgement and experience, AI can quickly analyse large data sets and make decision processes knowledge-driven and data-supported. This can give businesses a competitive advantage and help them make better strategic decisions. However, it is also important to consider the ethical and security issues of this technology, and humans must maintain oversight and direction of these processes.

CONCLUSION

This study was conducted to examine the impact of human-centred AI on decision-making behaviour in SM. The research results show that human-centred AI significantly affects the DMPs of organizations. The results provide important information on the advantages of using AI in SM and the effects of this technology.

HCAI refers to AI systems equipped with human-like thinking and learning capabilities. These systems are used to support strategic decisions of organizations using technologies such as big data analytics, ML and natural language processing. This study investigated how this technology is integrated into SM processes and how it affects decision-making behaviour. HCAI provides the ability to predict future trends by analysing large data sets. This makes strategic planning processes more accurate and knowledge-based. AI can process large amounts of data instantly, which helps managers make quick decisions. This provides a great advantage in a competitive business world. HCAI can analyse data to identify and manage potential risks. This helps organisations minimise risks. ML enables AI to continuously learn new information. This allows to continuously improve and adapt SM processes.

Based on the results of this research, here are some recommendations to help organizations more effectively adopt the use of AI by managers in SM:

Managers and employees should be trained to understand and utilise AI technologies. This helps them to fully realise the potential of the technology. Data privacy and security is of paramount importance. Organisations should strengthen their data security policies when using AI systems. AI can collaborate with human decision makers. Managers should encourage this collaboration and facilitate communication between human and AI. It is important to continuously update and improve AI systems. Organizations should continuously improve this technology instead of using it in a static way.

In conclusion, human-centred AI is a technology with great potential in SM. Managers can make their organizations more competitive by using this technology effectively. However, careful planning should be done to integrate and manage this technology properly.

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Chapter III

ARTIFICIAL INTELLIGENCE AND EMPLOYMENT

Can Bekaroğlu

INTRODUCTION

It is an indisputable fact that technology is a crucial and indispensable instrument for socio-economic development, higher incomes, expanded opportunities, and improved quality of life. Thanks to advancing technology, we now lead longer and higher-quality lives with more opportunities, all without having to endure the exhausting and arduous work hours as we used to do in the past. We enjoy a better environment, access to superior food, improved health, and enhanced education.

However, the impact of technology on employment has been the subject of endless debates, with no real consensus emerging. Technological change, as has repeatedly been observed, both creates and destroys jobs. At the close of the 20th century, there were more jobs than ever before, suggesting at first glance that the overall effect of this creatively destructive process must be positive, as some researchers argue.

Nevertheless, real life is more complex than this. A deeper examination of working hours suggests just the opposite: we are working fewer hours than ever before! This reduction in working hours is one of the key factors contributing to our improved quality of life. Five-day work weeks and eight-hour workdays provide us with the opportunity to grow and enjoy life, a far cry from the six-day work weeks and 12-hour workdays of the past.

Although the total number of working hours has significantly decreased over the past century, as we will demonstrate in this chapter, the total number of jobs has not decreased. This is largely thanks to the deliberate, forward-thinking, and comprehensive policies and practices of governments worldwide, which were implemented to foster human and economic development. Changing cultural norms and smaller households have

significantly contributed to increased employment, particularly for women, thanks to the marketization of previously domestic work. An expanding female workforce created additional demand and job opportunities in areas such as childcare, education, and catering services. Additionally, economically independent women contributed to increased demand in various industries rather than relying solely on their husbands or practicing thriftiness.

However, developments in artificial intelligence (AI) appear somewhat distinct, not only due to their inherent characteristics, as discussed in this chapter, but also because of their timing. The challenge here is that there is no more room to go. Total working hours have been steadily declining since 1900. Most of the domestic work is already commercialized, and family units are as small as they can be. There is no more child labor to eliminate in the West, and the number of working retirees is not decreasing but rather increasing.

Therefore, this chapter, in which we will tackle the topics mentioned above, comprises three sections in addition to the introduction, conclusion, and references. The first section introduces and elucidates basic concepts such as artificial intelligence, technology, and employment. The second section delves into a comprehensive discussion of technological change in the literature. The third section, considering AI as the latest manifestation of technological change, examines the literature and discusses both the similarities and differences between AI and previous technological shifts, along with its expected impact on various aspects of employment. Finally, we conclude the chapter with possible future scenarios and recommended government policies based on our deductions and past research.

1. Basic Concepts

1.1. What is AI?

Alan Turing's work on artificial intelligence (AI), which he initiated with his 1950 publication and was later digitally published by Springer (Turing, 2009), has now evolved into a major breakthrough that is destined to dramatically shape our present and future world in unprecedented ways. Before delving further into the discussion on artificial intelligence, let's first examine how the concept of artificial intelligence, a term whose definition and scope have evolved over time, is described in the literature.

In a narrow sense, artificial intelligence can be defined as "the science and engineering of making intelligent computer programs" (McCarthy, 2007) or as "the endeavor to perform tasks that require human intelligence, such as the ability to reason and exhibit cognitive processes" (Luger, 2008). In a broader sense, however, it can be described as "the study of designing intelligent agents and systems that can perceive their environment, reason about it, and take actions to achieve specific goals" (Russell & Norvig, 2016). In a classical economic context, artificial intelligence is best described as a field that investigates "how to make machines do things that would require intelligence if done by humans using limited resources" (Rich & Knight, 1991).

Over time, the concept of artificial intelligence has come to be considered as a subfield of the evolving and expanding discipline of computer science. In this context, artificial intelligence is defined as "a branch of computer science concerned with the automation of intelligent behavior" (Nilsson, 1998) or, more broadly, as "the area of computer science that aims to mimic human-like cognitive functions such as learning, reasoning, problem-solving, perception, and decision-making using machines" (Poole et al., 1998). Artificial intelligence also encompasses the development of systems capable of learning from experience, understanding natural language, perceiving complex environments, and reasoning to achieve predefined goals (Poole et al., 1998). In a general sense, artificial intelligence is an interdisciplinary field that focuses on developing computer systems capable of performing tasks that typically require human intelligence, including natural language processing, computer vision, and machine learning (Shoham & Leyton-Brown, 2016).

1.2. AI: Beyond Common Sense and Intiution

The developments in artificial intelligence can simply be considered an extension of the technological change, which is the main drive of the economic growth for centuries. However, there are two main reasons why AI goes beyond that as a probable cure for the recent technological stagnation due to factors such as slow productivity growth (Baldwin, & Teulings, 2014) or decreasing rate of innovation (Jones, 2009). The first concept is related to “common sense” or “intuition”. It has been observed that human intuition and instincts, which enable quick, simple, rational, and accurate decisions for most situations and most of the time within our limited cognitive capacity, do not always yield the most precise or accurate results when capacity is enhanced.

Artificial intelligence, on the other hand, often makes choices that appear counterintuitive and illogical to human intuition but are more accurate and precise (Russell & Norvig, 2021).

The second concept is “tacit knowledge”, which is originally discussed by Michael Polanyi in his work published in 1966 (Polanyi, 2009) and later coined as the "Polanyi Paradox" by Autor (2014), can be succinctly defined as "knowing more than we can tell, transmit, or communicate through a channel." A person who knows how to ride a bike, for instance, cannot easily explain or transmit this skill or knowledge directly; however, he or she can facilitate learning for others by sharing their own learning experiences. Similarly, artificial intelligence, unlike conventional technological advancements, has the capability to learn and transfer this tacit knowledge through machine learning (ML), thereby exponentially enhancing efficiency.

1.3. What is ML?

ML, particularly in recent years, has emerged as one of the most rapidly advancing subfields within the field of artificial intelligence (Goodfellow, 2016) under the overall umbrella of computer science. Therefore, let's first provide a general framework of a definition for ML based on the literature. ML, which is a subfield of artificial intelligence aimed at minimizing human intervention, involves the development of algorithms and statistical models that enable computers or similar systems to learn from data-driven experiences, make predictions and decisions without explicit programming, utilize statistical techniques to identify trends, and autonomously improve themselves. (Mitchell, 1997; Alpaydin, 2010; Bishop, 2006; Hastie et al., 2009; Shalev-Shwartz & Ben-David, 2014; Murphy, 2012).

The rapid development of ML in recent years can be attributed to several key factors such as the availability of large datasets (Deng, 2014), exponential growth in computer processing capabilities (Chorowski et al., 2015), advances in computer modeling, mathematical, and statistical modeling of algorithms (LeCun et al., 2015), remarkable progress in deep learning and neural networks (Schmidhuber, 2015), image recognition technologies (Krizhevsky et al., 2012), natural language processing technologies (Goldberg, 2017), and developments in speech synthesis technologies (Oord et al., 2016).

1.4. What is Technological Change?

Technological change, based on the literature, can be defined as:

a) a process that involves the progression, alterations, and enhancements within existing technologies or the invention of entirely novel technologies, leading to the reformation of production methods, products, and services (Rosenberg, 1982).
b) a process that encompasses the creation and integration of innovative methods, techniques, tools, or systems, resulting in enhancements in efficiency, productivity, and the overall performance across various sectors (Freeman & Perez, 1988).
c) a process through which fresh knowledge, ideas, or innovations are harnessed and integrated into production and organizational practices, inducing shifts in the manner economic activities are executed (Dosi, 1988).
d) the dynamic evolution of techniques, processes, and methods that facilitate the generation, diffusion, and application of novel knowledge and innovations, ultimately leading to enhancements in economic growth and development (Aghion & Howitt, 1992).
e) the ongoing advancement and transformation of knowledge, tools, and systems, which contribute to the augmentation of production capacities, economic efficiency, and competitive prowess (Nelson & Winter, 1982).

1.5. What is (Un)employment?

Employment is commonly defined as the integration of labor (individuals) into the production process, often in exchange for financial compensation (Ülgener, 1980:73). Unemployment refers to a scenario wherein individuals who possess the capability and willingness to work are unable to secure employment even after an extended period of job searching (Ünsal, 2000: 14) or simply the absence of work, causing capable and eager individuals to be excluded from productive activities (Ekin, 2003). To be officially categorized as unemployed, a person must actively seek employment and be open to accepting a legitimate job offer at the prevailing market wage (Reynolds, 1974:125). Diverse definitions and measurements of unemployment exist and vary across different countries. For example, the American Bureau of Labor Statistics outlines six distinct metrics for gauging unemployment (U.S. Bureau of Labor Statistics, 2022a).

2. Technological Change and Employment

2.1. The Rise of Technology

The impact of technology on employment has been a subject of debate in economics for a long time, particularly in the field of labor economics. However, no consensus has been reached, as technology does not uniformly affect employment; bolstering certain industries while hurting others. The effect of technology varies in terms of time, conditions, society, and the existing level of technology, and it is also shaped by decisions made and economic policies implemented. Technology not only affects employment but also deeply influences economic development.

2.2. Marginal Productivity of Labor (MPL)

The most fundamental concept that economists focus on from a theoretical perspective is the concept of the Marginal Productivity of Labor (MPL). In economic theory, the MPL is directly proportional to the levels of capital and technology. Increasing levels of capital and technology, whether qualitative or quantitative, lead to increased labor efficiency and a rise in MPL. The growing demand for more efficient labor results in an increase in the equilibrium wage and employment level[4].

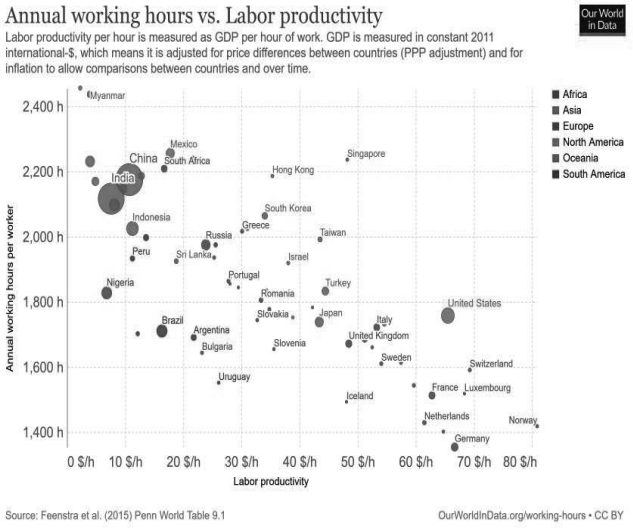
In this context, technological development can be seen as a highly positive development for labor, increasing both employment and wages as evidenced by Cardullo & Ansal (1997). The assumption here that an increase in MPL leads to an increase in labor demand has become a widely accepted and almost unquestioned law in economic literature. Unlike the fundamental neo-classical economic and particularly labor economics assumptions mentioned above, the demand for goods in the market is not unlimited, and labor is not the sole factor for production. The demand for labor is influenced not only by the MPL but also by the demand for products using labor and other factors affecting product supply. If production is not unlimited, an increased MPL will eventually lead to a reduction in employment. Likewise, in the presence of other binding constraints to production, productivity increases beyond a certain level of labor will only result in reduced employment. Therefore, even within the classical economic framework, the positive impact of technological development on employment will be conditional upon circumstances.

[4] For a more detailed analysis and thorough explanation on this topic, please consult references such as Borjas (2010) or Biçerli (2018).

2.3. Diminishing Hours of Work

The relationship between labor demand and labor wage represents an inverse correlation between the amount of labor demanded and the wage. An increase in wages does not necessarily imply an increase in labor demand. While an increase in productivity may partially increase labor demand, the (negative) effect of labor-saving resulting from increased productivity and its impact on equilibrium labor quantity, and its consequent increase in wages, are largely ignored in the literature. However, as it is widely agreed upon in almost all of economics literature, does an increase in labor productivity not lead to an increase in labor demand?

The most important point overlooked here is that the relationship is often examined only in the short and medium term and solely through wages. As Feldstein (2008) points out, real wages are expected to increase precisely in line with the MPL. In fact, the increasing productivity-pay gap shows that wage increases have been lagging way behind productivity rises ever since late 1970s (Fleck et al., 2011). In other words, a significant portion of the increase in wages is due to a decrease in labor supply, which is theoretically discussed in (Borjas, 1980), and recently been analyzed in detail by Bekaroglu (2022). Long story short, this decrease primarily reflects a continuous and significant reduction in the hours of labor employed rather than a decrease in the number of employed individuals (Oh et al., 2011) as demonstrated in Graph 1 below (Our World in Data, 2022).



Graph 1 – The Negative Correlation between Worldwide Working Hours and Labor Productivity

2.4. Productivity-Pay Gap

The productivity-pay gap that is demonstrated by Fleck et al. (2011) as a result of technological advancements from the 1980s onwards is often attributed to increasing income inequality by authors such as Mishel & Gee (2012) and Cooper & Mishell (2015). This is, in fact, a fallacy since increasing income inequality is not a cause but a result. The nature and mechanisms of technological developments did not change over night; rather, the factors in the mix changed. Despite the continuous decrease in the amount of labor throughout the 20th century, which prevented the devaluation of labor and kept real wages high, the average working hours in the United States decreased only by 3.5 hours, from 38.2 hours per week in 1980 to 34.7 hours in 2020 (Fred, 2022a). Since working hours cannot be reduced as much as in previous years (keeping the labor supply relatively abundant), wage increases have fallen well below expectations. OECD (2018), one of the few studies that address this issue, attributes at least half of the differences in wages to the decreasing share of labor in GDP, while the other half is attributed to increasing inequality. The focus should be on the decreasing share of labor.

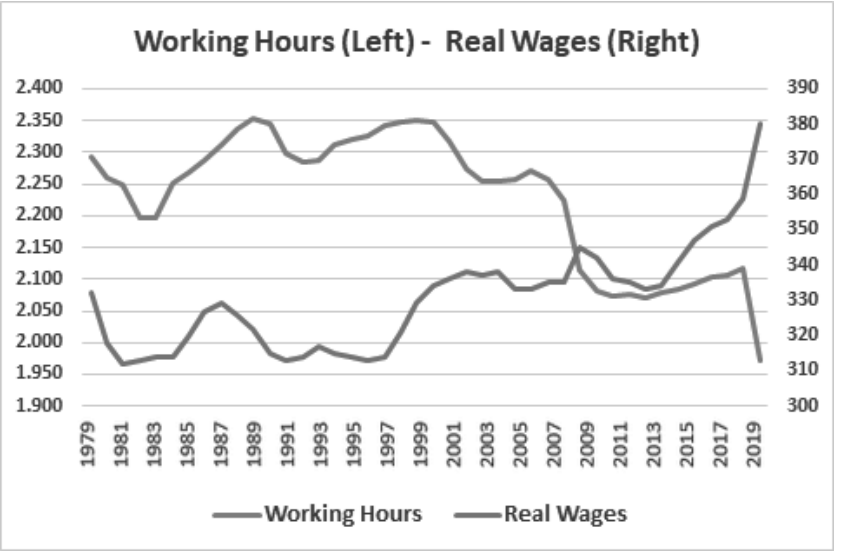
2.5. Rising Productivity and Decreasing Demand for Labor

The employment and wage data obtained from the Bureau of Labor Statistics (BLS) after 1979 (Fred, 2022a; 2022b; 2022c) show a clear inverse relationship between the employment rate and wages in the United States. Comparing employment quantities in hours, rather than employment numbers, to wage levels in the United States from 1979 to 2020 reveals a much clearer picture. A statistically significant, strong negative correlation (-0.69) between wage and employment levels is evident for both genders (please see Graphs 2a and 2b). Additionally, over a span of 40 years, average real wages in the US have increased a meager 14% despite a 50% increase in productivity. In essence, relatively stagnant real wages and constantly reduced employment (hours) signal a decrease in labor supply. Therefore, we can conclude that the main drive for wage increases is the constant decline in labor supply (in terms of hours), and the net effect of MPL must be a parallel decrease in labor demand to keep wages relatively stagnant. Cross-sectional data accross the globe illustrated in Graph 2 reveals that productivity increases are inversely related to labor accross virtually all countries from

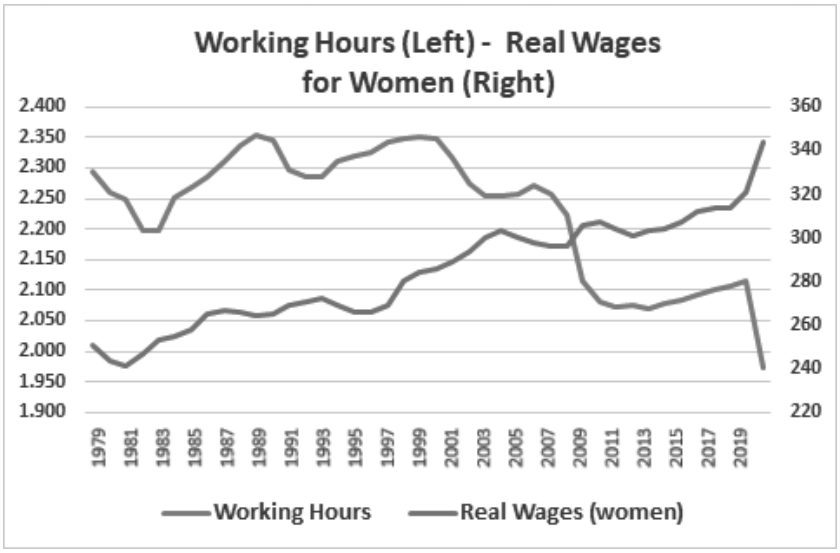
various development levels. The higher development and productivity level of a country, the lower the average number of work hours (employment in hour terms). The evidence is decisive, productivity increases (which is a natural result of technological change) undeniably reduces the demand of hours of labor.

2.6. Does Technology Create or Destroy Jobs?

The relationship between technological change and employment boils down to two major points: whether the technological change is capital- or labor-intensive. Capital-intensive technology is characterized by a production method that utilizes a relatively larger proportion of capital than labor, placing significant emphasis on utilizing machinery, equipment, and infrastructure for production tasks and leading to increased output efficiency for each unit of labor employed, or simply MPL (Shapiro & Stiglitz, 1984). Capital-intensive technology often results in labor substitution, as the increased utilization of machinery and capital equipment often leads to a decreased demand for human labor in the production process (Brynjolfsson & McAfee, 2014).



Graph 2a – The Negative Correlation between the US Real Wages and Average Hours of Work (Overall)



Graph 2b – The Negative Correlation between the US Real Wages and Average Hours of Work (Women)

2.7. Capital Intensive (Labor Saving) Technological Change

The well-established relationship regarding capital intensive technological changes has been demonstrated by authors such as Charles et al. (2013) and Jaimovich & Siu (2012), particularly in sectors involving routine tasks such as manufacturing and retail, and has been shown to lead to structural shifts by researchers like Goos & Manning (2007) and Autor & Dorn (2013). Moreover, the degree to which capital substitutes for labor increases with technological advancement and capital accumulation. The labor share of production is destined to fall in this process due to both higher productivity and a lower preference for labor (Pinheiro & Yang, 2018). This phenomenon is expected to be particularly pronounced in areas such as electronic and virtual markets, as well as financial and monetary markets, or in fields heavily reliant on online applications, like education (Frey & Osborne, 2017). Furthermore, post-computer revolution automation and labor substitution, contrary to the claims of Levy and Murnane (2004), have extended beyond routine jobs, encompassing a broader spectrum (Brynjolfsson & McAfee, 2011).

Keynes (1930) had envisioned a scenario where the rate of technological advancement outpaced the rate of job creation, where we could not create as many jobs as we destroyed, resulting in a decrease in working hours for

individuals. While Keynes's predictions did not fully materialize, Western countries, particularly the US, since the 1980s have been characterized by non-employment-generating economic growth (Brynjolfsson & McAfee, 2011). Following Akst's (2013) article on "Automation Anxiety," recent years have witnessed discussions on labor-substituting capital and technology gaining momentum, with a spotlight on machine automation and labor substitution, as emphasized by Acemoglu & Restrepo (2016; 2020). In an environment where technology fails to create new jobs, increasing automation is likely to decrease wages and employment (Acemoglu & Restrepo, 2016). The impact of automation, driven by technology and robotization, has shifted towards labor substitution, accompanied by other strategies such as outsourcing, which target routine tasks and echo trends from before the 1990s (Acemoglu & Restrepo, 2020). These developments have raised concerns among authors, like Benzell et al. (2019), who suggest that future automation could reduce labor demand, necessitating government intervention for income redistribution.

On the other hand, while Graetz & Michaels (2018) show that automation indeed reduces labor demand. They argue that concerns are largely exaggerated and misplaced, albeit acknowledging its negative impact on low-skilled workers and income equality. Similarly, Autor (2015) contends that the long-standing automation trend has not led to the doomsday scenarios predicted and highlights the existence of significantly more jobs in the market than anticipated. However, it is crucial to remember that both studies overlook the gradual reduction in labor supply in hours and the relatively modest increases in wages. Furthermore, Hemous and Olsen (2022) state that technological progress tends to substitute any form of labor it can replace profitably, ultimately asserting the insignificance of productivity growth in this process[5].

Throughout this process, it is evident that low-skilled workers have lagged behind both in terms of job opportunities and wage levels, and the literature, in general, agrees that wages tend to increase for highly skilled and more educated individuals due to productivity gains (Katz & Murphy, 1992). Despite the steady increase in education levels since World War II, however, the return on education has exhibited volatile fluctuations, resulting in only modest gains in average real wage levels (Acemoglu, 2002). Interestingly, wages for low-skilled workers, despite their higher education levels compared

5 The reader is advised to consult on Casey (2018) study for summary and general framework of the labor-substituting technology in the literature.

to earlier periods, have notably declined, contrary to theoretical expectations, thus exacerbating income inequality. Authors like Ingram and Neumann (2006) attribute this inconsistency and return variability to education's inability to accurately reflect skill levels, yet they fall short of explaining why wage growth significantly lags behind average productivity increases, contributing to widening inequality. Caplan (2018) contends that higher education primarily functions as a signal to market participants about individuals' skill levels (Spence, 1973), rather than substantially enhancing skills and productivity. From this perspective, the market more precisely distinguishes between low- and high-skilled individuals, thereby diminishing the potential impact of productivity growth.

2.8. Labor Augmenting Technology and The Prevailing Literature

Some widely acknowledged facts in the literature are as follows; a) The role of technological change in augmenting individuals' and societies' well-being through factors like productivity growth is indisputable; b) While technological advancements erode numerous jobs, occupations, and sectors, they also give rise to fresh opportunities or lay the groundwork for them; c) Though the immediate count of jobs obviated by technology indeed surpasses those generated, the ultimate implications remain open to debate; d) Weekly working hours and labor availability in terms of hours remain in a constant descent (Vivarelli, 1995).

Conversely, a conspicuous omission in the literature is the continuous and enduring reduction in working hours. To be precise, the deduction is clear: technological evolution gradually trims down employment in tandem with the ascent of productivity (Bekaroğlu, 2022). For many years, the prevailing stance in labor economics literature has relegated concerns, such as those echoed by Hansen (1939), to the realm of exaggerated or unfounded apprehensions. The sentiment prevalent in the literature can be succinctly encapsulated by the words attributed to former US President Kennedy: "If man has the ability to invent machines that take away people's jobs, then he also has the ability to give them jobs again" (The Economist, 1995).

Mokyr et al. (2015) contend that these fears about automation are not novel; such instances of panic have arisen before, yet the economy has consistently rebounded to full employment levels, suggesting the current scenario no different. Graetz & Michaels (2018) deem concerns regarding

automation valid but transient and overstated. Similarly, Özcan (2019) and Georgiou (2009) assert that robotics and technological change don't exert prolonged pressure on employment; instead, intricate and multifaceted relationships yield a net positive impact. Nübler (2016) even suggests the potential for technology to usher in a golden age of employment if societies can adjust their skills to match contemporary demands. Offering an all-encompassing review of the literature, Çelik (2020) highlights that technology-driven changes oriented towards products tend to foster job creation, whereas process-oriented changes tend to erode them (Vivarelli, 2014). This implies confusion within the literature while emphasizing technology's affirmative influence on employment, especially in countries with low productivity and employment like Türkiye.

Underscoring the divergent models within the literature concerning technological change and unemployment, Mortensen and Pissarides (1998) note the inverse correlation according to Aghion and Howitt (1994) and a direct one according to Pissarides (2000), and suggest that rapid, and productivity-boosting technological advancement tends to eliminate more jobs than it creates, whereas low-cost and gradual changes tend to elevate net employment. In essence, the velocity of technological change is inextricably linked with the process of job attrition. Similarly, Mortensen and Pissarides (1994) affirm that the ebb and flow of job destruction, while more volatile than job creation, doesn't primarily steer fluctuations in unemployment. In a nutshell, long-term employment (and unemployment) emerges as a byproduct of productivity and labor supply.

Another facet of technology's advancement is its increasing cost, reduced accessibility, diminished competitiveness, and higher concentration (Tang & Zannetos, 1992). Consequently, within a technology market characterized by elevated costs and monopolistic tendencies, many markets will exhibit comparable inclinations in the background (Mukhopadhyay, 1985). Considerable capital accumulations and advanced technology facilitate vertical and horizontal corporate mergers, obliterating specific employment and cost components (Ma et al., 2022). This not only enables heightened automation but also facilitates advanced labor substitution beyond what was previously achievable (Brynjolfsson & McAfee, 2011).

Furthermore, emerging data and findings under the Industry 4.0 and artificial intelligence framework, coupled with scholarly studies, accentuate the advent of a new economic revolution, thereby underscoring the imminent

transformation of employment. Flynn et al. (2017) lay out the conceptual framework of Industry 4.0 and present findings about awareness in the UK. Sümer (2018) quantifies the substitutability of occupational groups on a national scale in Türkiye, highlighting that without aligning the employment market (in accordance with its routines) with the requisites of Industry 4.0, a substantial unemployment issue will arise. The seminal article on artificial intelligence by Nilsson (1984) actually illuminates the economic revolution catalyzed by Industry 4.0. The rapid progression of automation and ensuing cybernetwork structures inevitably leads to a reduction in labor demand.

3. Artificial Intelligence (AI) and Employment

3.1. The end of Increasing Jobs

As Rotman (2013) clearly reveals in his study, the increase in employment levels has come to a halt in the vast majority of Western, and particularly Anglophone, countries. For instance, in the US, the increase in employment levels has dropped from 31.3% in the 1960s to a mere 19.8% in the 1990s, with a relatively stagnant overall employment level between 1960 (56.7%) and 2020 (58%). The total working hours, on the other hand, have diminished by 12.8% in the same time frame (Fred, 2022a; 2022c).

The findings of Bekaroglu (2022) show that the average (and total) paid working hours in the US has shrunk by 30% (and to a greater extent in Europe). To make things worse, housework has also shrunk by 70–80%, while child labor is virtually eliminated in the developed world. On top of that, people over 65 had a drastic drop in their employment rate from 65% to a mere 20%. Even worse, total employment rates have also started to decline, especially after 2008 (Fred, 2022c), with increasingly weaker rates of employment growth. There is one thing for sure: in terms of total hours, we are working much less, and the trend shows no signs of slowing.

We have also shown in Part 2 that increasing productivity does not actually lead to a net increase in labor demand as predicted in economic theory (Solow, 1957; Romer, 1990; Aghion & Howitt, 1992), but in fact leads to a decline in labor demand in terms of working hours. In other words, the main reason why the total number of jobs did not actually decrease is that the drastic decreases in working hours per capita were accompanied by productivity increases (Fernald, 2014), as well as the marketization of domestic work and the drastic changes in the family unit (Hochschild &

Machung, 2012; Glenn, 1992). The problem is that there is no more room to go. Practically all domestic work is already marketed; there are already more single people than married people (Fry & Parker, 2021). There is no more child labor to get rid of (Moehling, 1999), while the number of retirees working is no longer shrinking but on the rise (Costa, 1998), which is even more dramatic in Türkiye with the number of retirees nearing 16 million (Özsever, 2023).

3.2. Incoming Productivity Boom

Although the literature overwhelmingly finds that AI will increase labor productivity (e.g., Brynjolfsson & McAfee, 2014; Mokyr et al., 2015), whether the current, rather sluggish productivity growth trends will persist is a matter of heated discussion. After Makridakis (2017) ignited a furious plethora of discussions in academic circles regarding the impact of AI on labor productivity, many authors, such as Cockburn et al. (2019) and Agrawal et al. (2019), emphasized the positive expectations of AI through increased productivity due to higher automation, a reduction in uncertainty, and a new generation of innovations. Other authors, however, suggest that the productivity slowdown will persist due to increased inequalities (Gries & Naudie, 2018), learning costs (Jones, 2009), ideas and innovations getting increasingly harder to find (Bloom et al., 2020), and the relatively less disruptive nature of AI compared to previous technological breakthroughs (Gordon, 2018).

Brynjolfsson et al. (2018) befuddledly examine the post-1970s notorious productivity slowdown in the US economy, partly associating it with "the clash of expectations" in the study. They admit that productivity is much smaller than expected, calling it a "productivity paradox" (Brynjolfsson, 1993), and suggest that AI will restore higher productivity growth rates by breaking new ground. Jorgenson et al. (2008), by looking at the resurgence of productivity growth in the late 1990s and early 2000s, suggest the digital revolution has restored productivity growth. This proves to be premature, however, as Erber et al. (2017), among others, finds that the productivity resurgence was short-lived across G7 countries and that the productivity slowdown resumed in the 2000s.

In one of the very few empirical studies on the impact of automation on employment across 7 countries between 1993 and 2007, (Graetz & Michaels

(2018) finds that while increasing automation did increase labor productivity, it did not have a significant impact on overall labor employment, but it did indeed decrease the share of low-skilled labor. While a newer study by Alderucci (2020) finds that the impacts of AI are far more pervasive than before, indeed leading to rapid increases in labor productivity and wage inequality as well as AI-related or complementary employment. Another study by Damioli et al. (2021) also finds a positive impact of AI in the service industry, especially among small and medium-size firms, but fails to find such an increase in the manufacturing industry, theorizing the nascent nature of AI and sluggish adjustment by large firms. Finally, a European Commission study (Jäger et al., 2016) concurs with these findings, associating higher levels of labor productivity with robotization.

3.3. Changing Landscape of Wages

Even though economic theory generally assumes a positive correlation between productivity increase and labor demand (Solow, 1957), hardly any study in the literature finds further wage increases, regardless of the expectations regarding the AI's impact on employment numbers. For instance, Brynjolfsson & McAfee, (2012) point to the decoupling of wages and productivity growth, stating that real wage growth has been stagnant since the 1970s, which is corroborated by Shambaugh et al. (2017), showing an increasing chasm between the actual and estimated real wages based on productivity gains. Pessoa & Van Reenen (2013), on the other hand, claim that the gap disappears when non-wage compensations such as benefits are factored in, rendering the "net decoupling" close to zero for the UK and US. However, this does not change the fact that real wages at the higher income brackets have been increasing as expected and the purchasing power of wages has been decreasing (Shambaugh et al., 2017) especially due to skyrocketing prices of healthcare (Chen & Goldman, 2016) and education (Kerr & Wood, 2022).

Given the stagnant real wages since the 1970s, coupled with the expected pressure from increasing automation, most thinkers in the field expect and advise the populace and policymakers alike to embrace declines in real wages. Shambaugh et al. (2017) find that wages have long been stagnant and are expected to decline, at least for low-skill jobs, leading to increasing wage inequality and a lower share of labor income. Acemoglu & Restrepo (2020) also find that labor demand will likely decrease, particularly for routine tasks

and slightly for non-routine tasks, leading to decreasing wages throughout as well as increasing wage inequality. Even Brynjolfsson and McAfee (2012, 2014), who insist on a breakthrough in labor productivity, find that the demand for routine jobs will decrease, accompanied by lower employment for routine jobs and overall lower wages, leading to increasing wage inequality. Webb (2019), on the contrary, suggests that AI primarily affects high-skill employment, leading to declining wages for high-skill labor as well as diminishing wage inequality. He also suggests that older individuals will be more adversely affected than the young, who are relatively more mobile and adaptable.

3.4. Decreasing Employment and Labor Share of Income

Most authors in the literature, such as Acemoglu & Restrepo (2018, 2020), Autor (2019), Autor & Salomons (2018), Dauth et al. (2018), and Manyika et al. (2017), find or expect a decline in routine tasks and an increase in non-routine tasks regarding employment. Acemoglu et al. (2020), in their empirical study, alarmingly find that employment regarding both routine and non-routine tasks will decrease, along with overall wages, although non-routine tasks will only be slightly affected. Fleming et al. (2019) find similar results, where the demand for both routine and, to a lesser degree, non-routine tasks diminish. The report, however, notes that jobs will not necessarily disappear, and provided that policymakers take the necessary steps to accommodate the changing economic landscape, the number of jobs may be sustained thanks to policy changes regarding lower working hours per capita, which can be afforded due to productivity gains.

Interestingly, Michaels et al. (2014), in their panel study covering 11 countries over 25 years, find increasing demand for low- and high-skill labor but conversely decreasing demand for middle-skill labor, leading to an employment gap and increasing income inequality, which is called "skill polarization". Similarly, the Beaudry & Green (2019) study suggests a "great reversal of demand", implying that AI and increasing robotization have actually decreased the demand for skilled labor and cognitive tasks, leading to increased automatization of tasks that are both routine and cognitive. This hollows out the jobs that are typically carried out by the middle class. The demand for non-cognitive routine tasks as well as complex cognitive tasks, however, remains high, leading to increasing wage inequality and polarization of the market.

As we stated repeatedly in the chapter, the labor share of income has been decreasing, which is mirrored by the decreasing annual working hours in contrast to increasing labor productivity (Our World in Data, 2022). Literature overwhelmingly corroborates the decreasing share of labor income and expects this trend to continue (Acemoglu & Restrepo, 2018; Dauth et al., 2018; Shambaugh et al., 2017). Simply put, when the share of capital (income) increases, so does the labor productivity, but on the other hand, when the share of labor (income) decreases, along with the annual working hours, they also need to be decreasing. There are very few studies, such as Autor and Salomons (2018), that actually challenge this view, who suggest that the trajectory for the share of labor income in the future is ambiguous, claiming that automation, through creative destruction, will cause a heterogenous U-shaped pattern in employment across sectors, where middle-skilled labor is most vulnerable.

3.5. Total Annual and Weekly Hours of Work

As Bekaroglu (2022) found in his study, which draws from numerous seminal studies evaluating historical data in the field, including but not limited to Jones (1963), Altman (1999), Costa (2000), Rones et al. (2001), Fisk (2001), Hubermann (2004), Greenwood & Vandenbroucke (2005), Mosisa & Hipple (2006), Levine (2010), Restuccia & Vandenbroucke (2013), and Donnovan (2015), historical annual and weekly working hours have consistently decreased. This trend persists even when accounting for periodic increases in employment rates and job numbers.

Moreover, newer studies are emerging that reinforce this ongoing trend, particularly with the increasing prevalence of AI. For example, Carbonaro (2023) estimates that AI will reduce annual work hours by approximately 390, equivalent to 1.5 hours per day. Similarly, Huang et al. (2022) find significant potential for reducing working hours for nurses in the healthcare industry, while Kim et al. (2023) suggest that AI has the capacity to significantly decrease working hours, especially in labor- and knowledge-intensive fields, serving as an efficiency-enhancing tool.

Recently discussed concepts in the literature, such as Industry 4.0, and news disseminated by governments worldwide, either directly or indirectly, suggest that this transformation will gain momentum and take on a more revolutionary character, similar to the post-Great Depression period. For

example, Scott and Spadavecchia (2011) found that reducing the working hours from 54 to 48 per week in 1919 England did not lead to job losses or decreased competitiveness. Such findings subtly hint to contemporary government leaders to consider reducing working hours to avoid unemployment in the future. Government officials who receive this message, like Finland's young female Prime Minister Sanna Marin, propose plans for a four-day workweek or six-hour workdays (Teivainen, 2019). Business leaders initiate pilot programs (Paul, 2019), and media outlets portray current working conditions as strenuous and stressful for employees, arguing that reducing working hours would boost productivity (Khan, 2018). They even contend that it would make employees happier and healthier individuals (Heath, 2017). They commission semi-scientific articles for business managers (Glaveski, 2018) and even suggest that they could be beneficial for addressing climate change (Spicer, 2019). As a result, they prepare public opinion through the media (Booth, 2019) for the new market conditions by gauging the market and reflecting on the responses encountered, almost like a dialectical process.

3.6. The Varying Impact of AI on Employment and Gender

Technology and cultural changes have made it possible for women to leave the traditional family setup and enter the professional labor force in increasing numbers. This not only led to the creation of new industries through the marketization of domestic work or other means, but also gave businesses the opportunity to substitute female labor for male labor. In other words, the demand for female labor increased while the demand for male labor fell. As a result, over the 20th century, there was a substantial decrease in male employment (International Labor Organization, 2019a) in contrast to an even larger increase in female employment (International Labor Organization, 2019b), in addition to increasing wages (up to 34%) for women and decreasing wages (up to 9%) for men (Shambaugh et al., 2017).

One of the fundamental differences between AI-related changes in employment will be the reversal of relative labor demand in terms of gender. Despite the limited number of direct studies on the issue, it is highly unlikely that the aforementioned trend will continue, given the record number of female labor force participants and the significant decline in the gender wage gap. Brussevich (2019), for instance, finds that women are overrepresented in

routine jobs, which are more susceptible to automatization, which also helps explain the gender wage gap through routine task intensity (RTI). A report from McKinsey Global Institute (Timsit, 2023) suggests that more than a quarter of the female-intensive sectors, such as retail, education, and food sectors, are at high risk of automatization, which can also be inferred from general systematic studies such as Frey & Osborne (2017) without specific or direct mention.

3.7. Call for Government Action

In the academic world, there is a near-consensus regarding the inevitable and fundamental change in employment and labor demand. There is also a strong emphasis on investing in human capital and retraining to facilitate a smoother and more successful transition and fight structural unemployment (Jorgenson et al., 2008; Michaels, 2014; Mokyr, 2015; Brynjolfsson & Mitchell, 2017; Manyika et al., 2017; Autor, 2019; Brussevich et al., 2019; Acemoglu et al., 2020).

Furthermore, as we navigate the evolving socioeconomic landscape, it becomes apparent that additional measures may be required. Some experts propose strategies like progressive taxation (Acemoglu & Restrepo, 2018) or wage subsidies (Acemoglu & Restrepo, 2020), and even a combination of both (Brynjolfsson & Mitchell, 2017). These proposals are motivated by concerns about the increasing wage inequality and the erosion of the middle class, a phenomenon observed not only in individual countries (Michaels et al., 2014; Beaudry & Green, 2019) but also across the world (Kokkonen, 2017).

Moreover, researchers such as Brussevich et al. (2019) and Timsit (2023) draw attention to gender disparities in the context of automation. They highlight a bias toward female-intensive sectors in the automation process. Additionally, scholars like Webb (2019) underscore the role of age in occupational mobility, with elderly individuals facing a growing risk due to limited adaptability. Furthermore, it's crucial to recognize that the risk of automation is not uniform across countries with varying levels of development. More economically advanced and capital-intensive nations face a higher risk of job displacement due to automation and the widespread adoption of AI, compared to less developed countries that may find technology adoption relatively costlier (Manyika et al., 2017).

CONCLUSION

While it is challenging to draw absolute conclusions, historical trends allow us to paint a relatively clear picture of the future of employment. Firstly, automation and robotization will increasingly become integral and commonplace in modern work life, significantly impacting both the professional and domestic spheres. This will result in:

1. Substantial productivity increases, which may sometimes be challenging to detect or measure.
2. Job losses due to substitution, observed non-uniformly across numerous industries.

With the marketization of domestic work nearing completion and family units as small as possible, total employment is expected to decrease due to further productivity gains and the impending population decline. This will have several effects on the labor force:

- Young people will enter the labor force at later stages.
- The elderly will face challenges adapting to the evolving landscape of AI-driven technological changes.
- Labor demand polarization may erode middle-class jobs and potentially exacerbate gender disparities, given the overrepresentation of women in highly automated sectors.

On one hand, reduced working hours through shorter workdays or workweeks can enhance leisure and human development. On the other hand, stagnant or decreasing wages, rising wage inequality, and growing disparities will prompt governments to take proactive measures and implement necessary policies. According to Leontieff (1982), this is an idyllic paradise scenario wehere people who do not work are happy and blessed. However, the problem lies in the fact that people not working would suffer from hunger in heaven due to the absence of income. Therefore, the necessary policies may include:

1. Investment in human capital and labor force retraining to address structural unemployment.
2. Income redistribution through measures like wage compensation and progressive taxation.

3. In the event of unprecedented unemployment levels, more assertive policies, such as universal income, may be required.

In our perspective, the decline in employment due to increasing automation and widespread AI usage may not be as daunting as anticipated. A significant portion of this reduction will manifest as reduced working hours per capita, driven by productivity gains and official regulations aimed at improving quality of life. Contrarily, AI could prove beneficial for countries experiencing declining populations worldwide (Lutz, 2001), particularly in Europe (Koehler et al., 2002), although it may pose challenges in nations with fast-growing or relatively young populations.

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Chapter IV

ARTIFICIAL INTELLIGENCE ASSISTED RECRUITMENT FROM A STRATEGIC MANAGEMENT PERSPECTIVE

Mesut Öztırak

INTRODUCTION

Today's increasingly competitive environment indeed requires organizations to think and act more strategically. This need has made strategic management one of the most important management techniques. Strategic management includes management activities aimed at achieving organizational success, improving the performance of employees, and maximizing product and service quality. Elements of strategic management are determining goals, objectives, mission, vision, strategies, policies, tactics, and values; carrying out the plans and programs at a good level; and establishing cooperation between employees and management.

With the development of information and artificial intelligence (AI) technology, the use of AI in human resources management (HRM) is increasing and deepening. AI technology in HRM helps to reduce the workload of managers and employees in a company by choosing the right person for the job, support skill acquisition, and predict staffing ratios in the workplace. It also helps to minimize the potential error, maintain workflow between various departments, increase employee engagement, and minimize bias in the decision-making process (Gur, Ayden and Yucel, 2019). Thus, it is necessary to make changes in areas such as security, work, economy, social relations, and psychology in accordance with the developments in AI, virtual reality, robotics, machine learning (ML), autonomous devices, data processing, etc. Large companies are investing heavily to take advantage of rapidly developing AI technology, and it is becoming a unique industry. AI

applications are therefore becoming a permanent component of the business world in general and corporate strategic HRM in particular.

The 4th Industrial Revolution has brought many developments, the age of automation has rationalized activities in many fields, and AI has been used as the driving force of an era that promises many conveniences in various fields (Purwaamijaya et al., 2021). Various businesses are using AI in making better, faster, and more reliable decisions (Singh et al., 2021). It provides important insights into key areas such as productivity, management efficiency, employee engagement, and talent assessment; which resulted in a massive influx of data in the human resources (HR) sector that are often overlooked,. AI helps HR managers to better understand their workforce, predict workforce trends and proactively identify problematic areas (Haque et al., 2021). AI can perform tasks such as personnel selection, deployment, adaptation, training, and evaluation of personnel much faster and with higher quality than humans (Tappaskhanova et al., 2020). It can process large amounts of data faster than humans. AI algorithms can find the causal relationship between the qualifications of the employees and the job content, predict who will be hired, scans the applications, and determines the best candidate for the job (Taşlıyan and Yılmaz, 2022).

The process starts with candidate screening. At this stage, the job application will be examined or reviewed. AI selects candidates from the database who fulfill certain requirements. HR managers then match the candidate's profile with the job description and sort the candidates according to their profiles. At this point, their administrative work is slightly reduced and they save time from processing large amounts of data. This allows recruiters to harness the power of AI through various tools (Lakshmi, Sowdamini and Kumar, 2020). AI solutions not only provide end-users with independence, instant data access, and self-support, but also reduce the workload of HR professionals (HRPs) when routine tasks and queries are taken into account. HRPs can focus on high-value tasks to take the business to another level (Macıjauskienė and Stankevičiūtė, 2021; Akkaya, Özkan and Özkan, 2021). HR managers should combine HR activities with science and technology, use AI to improve management efficiency and decision-making quality, and create strategic plans for this. As a result, HRM in the age of AI plays an important role in the adaptation of leaders and organizations to technology, and employees to new business models (Nagar and Saxena, 2020).

1. Strategic Management

1.1. Definition, Importance and Purpose

The word “strategy”, which is originated from military terminology, means the objective view of a company's future planning process. With the increase in the competition after the strategic management started to take shape (Bircan, 1999). Strategic management (SM) is defined as: to prepare and implement plans by taking into account the elements of risk and uncertainty in all processes of management functions (Pearce and Robinson, 2015), or, as: a management activity carried out to realize the vision that emerges after creative strategic thinking to implement the strategy (White, 2004).

SM deals with strategic issues related to the organization's long-term larger goals and outcomes, whereas classical management deals with activities related to day-to-day business and operations, and in this respect strategic management is superior to classical management. This management approach involves many uncertainties and should be considered before the management function as it is an attempt to predict future situations. Success would be unlikely if action is taken without resolving these uncertainties. SM is the ability of an organization to approach to different situations, adapt into inevitable changes, and solve problems arising from environmental uncertainty (Karakaya, 2004).

Businesses have to use different management styles and forms to increase activities and productivity in intense competitive conditions. In recent years, especially with the economic, political, and social changes, it should have a very good management system to ensure the harmony of relations, to be minimally affected by sudden changes, and to achieve success. It is the top management that bears the biggest burden to ensure the harmony within the business in instant change situations. Top management has many duties in this regard. These operations can be listed as follows (Serdar, 2001):

- Businesses determine and implement strategies.
- Determine the duties and responsibilities of managers to organize the relationship between the business and its environment.
- Participate in social events and celebrations organized on special occasions.
- To do the necessary preliminary work for the company to survive in case of crisis;

- Providing manpower requirements and necessary training;
- Determine work standards.

In the developing and changing world conditions, uncertainty is increasing and companies are trying to maintain and protect their existence in this uncertain environment. In this process, the most important trump card of a company is environmental adaptation. Adapting into the changes in line with the needs and demands of the country in which the company operates, it is indispensable to make accurate predictions and to read the changes well, that is, to analyze and take preventive measures. To achieve this, it is necessary to identify environmental factors and determine their possible effects on the company's future. Nowadays, it has become increasingly clear how important forecasts for the future are in companies implementing SM processes, as they guide the organization toward long-term goals (Kamaşak, 2014).

Tapera (2014), based on some research, states that there are two main reasons why strategy is important. Accordingly, the first issue is to organize the administrative structure and design it proactively. Secondly, a strategy-focused enterprise has a strong bottom line. Therefore, strategic management is important for the sustainability of the business.

David (2003) points out that strategic management techniques are very effective in determining a systematic and logical path, saying that companies can formulate healthier strategies with a rational perspective. He emphasizes that dialogue and participation mechanisms established in addition to communication are some of the basic elements of strategic management that make managers and employees feel themselves a part of the company. Another advantage of strategic management is that it allows managers to easily apply financial and non-financial benefits to their businesses.

Aydemir (2011) states that SM serves to increase the productivity of employees, recognize external risks and threats, adapt to innovations, and understand competitive strategies, which represents the increasing value of a business. High-performing organizations, therefore, tend to make systematic plans for adverse factors or fluctuations that may occur in their environment. Organizations with planning systems whose approaches are consistent with SM show relatively high levels of financial performance.

Mintzberg (1987) states that strategic thinking and subsequent SM provide direction to businesses, give them an advantage over competitors in the industry, and enable them to resist threats in the business environment.

Similarly, Aksoy (2021) points out that strategy and SM are very important in making the coordination in businesses more effective, and ensuring that people focus on goals. Therefore, SM has an important value in guiding every individual in an organization toward the determined goals and objectives.

The basis of the SM approach is the idea of developing a strategy toward the goals to be achieved, executing this strategy meticulously, and taking the right steps towards the results. SM requires decisions to be made according to the strengths, weaknesses, and available resources of the organization under changing environmental conditions. These decisions make it easier for companies to adopt a knowledge-driven, open style of development management and to understand long-term change in a planned way. In this way, the growth and success of the business are planned and controlled by protecting it from the negative effects of external factors (Şeker, 2012).

In this sense, it is important to take current business situations into account. The aim of SM is to increase business efficiency, and maximize performance in the long term. The business should consider the importance of achieving goals based on teamwork. Companies should also analyze internal and external environments. This allows companies to respond to internal and external expectations, predict the future, direct institutions to common goals, and engage in environmentally friendly activities (Çakmak, 2012). SM is a big part of the business management process. SM allows businesses to make decisions about which steps to be taken, and how to move forward.

The main objectives of SM are (Aşkın, 2021): determining the purpose of the organization, planning objectives, implementation of these objectives, and audit and control of the objectives. This would provide the following to a company: competitive advantage, above-average profit, long-term survival, and final result.

1.2. Basic Concepts Related to SM

1.2.1. Strategy

In Latin, the word “strategy” is derived from the word “strategic” , which means “way”, “route”, “head of government” in Latin. It was first used as a military term and afterwards in the sense of “planning and managing with the aim of success” (Bayraktar and Yıldız, 2007). Strategy can be expressed as long-term, dynamic decisions that enable a person to achieve goals more

easily, follow the situation of competitors, and focus on the result (Ülgen and Mirze, 2016). In other words, strategy is the process of encouraging, motivating, and mobilizing the eemployees of a company in a dynamic and complex organizational structure (Aktaş, 2015). It can also be defined as: the ways and methods to be followed by using all human and non-human means to achieve a determined goal or objective (Çevik, 2001). Strategy is the process of continuously analyzing an organization and its environment, planning activities, and determining objectives that will adapt to the environment by reusing the necessary tools and resources that will guide the organization (Dinçer, 1998). The concept of the strategy includes long-term thinking, good awareness of the environment, the harmony between goals and the environment, and looking to the future (Hughes, 2003). Strategy is related to the future of an organization, rather than it's current situation, and is about regulating the relationship between the organization and it's environment (Yüksel, 2002).

In the business literature, the common features of strategy definitions for private sector organizations are orientation towards the future, environmental analysis, and long-term basic objectives. In other words, strategy is a broad perspective, i.e., a general perspective that do not get drowned in the details, and an orientation (Caulfield and Schultz, 1989). When strategy is mentioned; a clear vision, future direction, planned actions and methods, and predetermined goals and objectives come to mind. Therefore, in the field of management science, strategy refers to the ways and methods to be followed by a private or public sector organization to achieve its goals (Çevik, 2001). "Strategy, which is a set of goals, policies, and plans to achieve the determined goals, is related to the future and is a set of decisions that a company chooses to achieve the best results" (Çınar Altıntaş, 2003). "Strategy is a conscious endeavor. Strategy does not necessarily mean making big, radical plans. The companies can also aim to achieve long-term change through small, incremental changes. The basic strategic choice should be made between these two points" (Yılmaz, 2002).

1.2.2. Vision

A company's vision is its sense of the future. Vision is expressed as a picture describing the future of the company for all managers and employees of it. It is a design that explains how a business can achieve its goals and what the future will look like. In other words, vision is defined as the idea of a

situation that may occur in the future. Therefore, making assumptions about the future of a company means acting as if it were real. It tells where the company will be in the future, and what it will achieve by taking the necessary measures. Simply put, a vision describes what the company wants to be in the future. It is an idea that makes it clear what a company should do to achieve a solid goal (Muslu, 2014). It is a simple statement of where the company defines where the company wants to be in the long term and includes the world vision in its forward-looking expectations and statements. In this case, the world vision does not include a dream or an expectation, but an intellectual evaluation that shows how the future can be achieved .

To create a vision; it is necessary to determine the values that represent the basic beliefs that the company represents what the company wants to do in the future, and the goals it aims to achieve (Karakaya and Gürel, 2012).

Some basic principles to consider when determining the vision are: Goals should be expressed realistically, clearly, and in an eye-catching way; defining the future brightly; being compatible with business values, culture, and vision (Kanbaz, 2014).

1.2.3. Mission

"Mission is an organization's reason for being. It clearly states what the organization does, how it does it, for whom it does it" (DPT, 2003) The mission briefly explains what the organization does and why it does it. A mission is a guiding statement that expresses the purpose of an organization's existence. The main components of the mission are the organization's purpose, basic rules, corporate identity, organizational policies, and values (Akyüz, 2001). An organization's mission/goal-statement increases commitment of employees to the organization, and helps to communicate with and inform the public. A mission is an effective guide that directs the activities and analyses to be carried out during strategic planning, helps to ensure coordination between activities, and ensures compliance with these objectives in the execution of the strategic decision-making activities.

The vision and mission of an organization are paradigms that determine its organizational culture, world view, view of the future, and perception of the universe. These paradigms form the theoretical basis of the belief system on which the business (organization) is based; this system conditions the interpretation of the environment in terms of opportunities and threats, future orientation, proactive spirit, and dynamism (Barca, 2002).

1.3. Strategic Management Process

The SM process can be defined as the steps of planning the path to be followed and the activities to be carried out to achieve the mission and vision of the organization, to use opportunities such as capital, HR, and technology for the organization, to carry the process forward, to implement and follow the determined strategy. The SM process consists of analyzing the internal and external environment of the organization, i.e. strategic analysis, strategic orientation, strategy formulation, strategic implementation, and strategic monitoring (control) stages (Şahin, 2012; Bay, Akpınar and Yılmazer, 2016; Başol, 2015; Erdem, 2021). It is the activities related to the collection, analysis, selection, decision-making, and implementation of information for an organization to exist for a long time and have a sustainable competitive advantage (Ülgen and Mirze, 2016; Erdem, 2021). In other words, the SM process is the planning and evaluation of projects, service delivery, project management, the establishment of performance measurement systems and the creation of strategies to determine the values, mission, and vision of the organization (Poister and Streib, 1999).

SM is the efficient use of production resources such as labor, capital, natural resources, HR, raw materials, machinery, etc. to achieve structural and sustainable goals (Ülgen and Mirze, 2016). Based on these statements, ongoing management can be seen as making and implementing plans, and determining alternatives in the face of situations that may be encountered. SM aims to ensure that sustainability is maintained under environmental conditions and to improve adaptation (Chakravarthy, 1982). Another aim of SM is to create a common meaning system that is organized to facilitate and sustain the activities of the organization (Smircich and Stubbart, 1995). Audit and information processing systems are harmonized (David, 2011).

The characteristics of SM can be listed as follows (Jasper and Crossan, 2012):

- Ensure that the overall workforce of the organization is known or that employees are included in the workforce.
- Promote harmony between the organization and the external environment.
- We plan for the future by promoting innovation and excellence and encourage quick response to situations.

- Identify processes for change and organizational development, focusing on organizational performance and achievement of objectives.
- Facilitate decision-making and communicate them to management. Strategic management is the process of identifying, organizing, and maintaining the relationship between the organization and the environment, systematizing the evaluation of organizational performance, and determining the long-term development direction of the organization (Hatten, 1982).

SM, which refers to the direct implementation of developed business strategies within an organization, analyses the internal and external environment to maximize the use of resources appropriate to the objectives (Bracker, 1980). In addition, SM continuously examines the environment to ensure that the organization and its environment are compatible, to take advantage of competitive advantage, to evaluate opportunities, to develop missions, to accelerate decision-making, to ensure internal and environmental control, and to obtain information to minimize environmental threats. SM helps organizations cope with future uncertainties by developing capabilities and defining procedures in the face of change (Stead and Stead, 2008).

1.3.1. Stages of SM

The implementation process of the SM process is from the top level to the bottom level. It is the responsibility of top management to determine the strategic direction of the organization. SM, which is a systematic approach that reflects strategic thinking in life, consists of certain steps. The basic steps of strategic management is strategy formulation, **strategy implementation and strategic learning. Strategy formulation,** this can be considered as a process of 'strategic thinking' in which a strategy is finally formed. **Strategy implementation,** It is the stage where the strategy created for the business is realized. **If strategic learning,** this is the stage where new knowledge and experiences gained through the implemented strategies contribute to the creation of new strategies (Durur, 2009).

The steps of SM can be pointed as follows (Durur, 2009): Making an analysis of the environment, setting the goals, analysing the strategic options,

choosing from the strategic options, implementing a strategy, and control and evaluation of that strategy. The process of SM starts with strategy

formulation, continues with strategy implementation, and ends with strategic learning.

1.3.2. Benefits of SM

SM involves the strategic planning, implementation, and review/control of an organization's strategy. All modern organizations work within the scope of SM to achieve desired levels of performance. There are many benefits of an organization's strategic management. (Collins et al., 2004; Betz, 2010; Bryson, 1988).

Strategic direction is determined by the company. The SM process clearly defines the desired level of performance (mission/goals/objectives) and sets direction so that everyone in the organization knows where they are going. Strategic management serves as a roadmap for everyone in the organization and clearly defines the path to reach the end goal/desired level of performance. The companies should focus on the important elements of the organization. SM identifies the critical factors that are strategically important to the organization. Once the critical factors are identified, the company can analyze and take necessary actions to ensure satisfactory performance in these areas. The companies should understand the changing environment. SM anticipates changes that may occur in the future. Anticipating future changes helps the organization to respond proactively and take the necessary steps to manage change through change planning and change management strategies. The companies are achieving sustainable competitive advantage. This is the most important and decisive benefit of strategic planning. A successful SM process should enable a company to create a competitive advantage that can withstand overtime without being imitated or overwhelmed by competitors. SM identifies the competitive advantages that can arise from an organization's strengths and takes the necessary measures to realize them effectively (Betz, 2010). The companies orientation toward better performance. Successful SM should ensure that the company performs very well and generates profits for its owners. Once the competitive advantage is established, the company can build on it to generate revenue and record good performance. The companiesensure organizational continuity. SM identifies opportunities and threats that affect organizational performance. The company seizes opportunities and minimizes threats to ensure its sustainability in the market by outperforming its competitors. The companies make simplify complex scenarios and develop appropriate strategies. The current business world is

very complex, volatile, and dynamic. Companies lacking strategic management have to interpret the complexities facing their organizations. In contrast, through strategic management, businesses simplify complexity, anticipate future dynamics, and take proactive steps to minimize threats and seize opportunities (Collins et al., 2004).

A comprehensive analysis of a representative sample of companies with different profiles, sizes, and economic and financial conditions clearly shows the advantages of strategic management practices and the results they bring to the business world. The most important advantages can be summarised as follows (Efil, 2010; Ülgen and Mirze, 2016; Çoban, 2010):

- It ensures the company's ability to prevent problems. Managers who focus the attention of their employees on planning benefit from monitoring and planning the responsibilities of their subordinates who realize the necessity of strategic planning- It ensures unity of understanding and action at all hierarchical levels within the company.
- The strategy consists of partial strategies, policies, plans, programs, responsibilities, etc., even if the company's units and sub-components have a high level of functional autonomy. The overall strategy of the company is the common denominator to which management continuously reports. The business strategy and its elements, determined by top management, form the basis for the elaboration of the relevant elements for each unit and sub-unit at each level of management.
- It ensures that strategic decisions are consistent with current and tactical decisions and enables better coordination of all functional units within the company.
- It contributes to the clarification and understanding of the mission and purpose of the organization and thus creates and develops a business culture that plays an important role in effective management and increases the employment of all employees for success and corporate strategy.
- Defining a clear strategy, taking into account the three dimensions offered by broad and broad participation and the close combination of strategy formulation and implementation, helps to increase employee motivation and reduce resistance to change through better understanding. Identify performance-reward relationships, limiting

factors, and alternatives. Create a favorable environment for the improvement of company performance and performance, which is an important prerequisite of the country's economic potential and a source of growth.

- SM is the most appropriate form of management to anticipate the opportunities, opportunities, and threats that a company will have in the future, given the ever-increasing pace of change in many areas of business.
- The most important advantage of SM is that it significantly improves the economic and financial results of the company, allows it to develop rapidly and strengthen its position in the market, and significantly increases its competitiveness. Extensive research on this subject has shown that companies that apply SM are much better off because this form of management is irrelevant and employees in the first category are more motivated.

2. AI and Ai-Assisted Recruitment

2.1. Definition, Importance and Objectives of AI

One of the structures that have attracted the most interest of researchers from the past to the present is the human brain. Although new technologies try to imitate the functions of the human brain, machines that can think and act like humans have not yet been produced. Starting in the 18th century and going through three revolutions, the fourth industrial revolution, or Industry 4.0, is still fully experienced today. AI, which has become the most important concept of the latest technology, is one of the technological developments of Industry 4.0, where machines reproduce processes based on human intelligence. Big data, cloud computing, the Internet of Things, cyber security, nanotechnology, and robotics are among these developments (Öztırak, 2023; Oswal, Khaleeli and Alarmoti, 2020). The technological developments that emerged as a result of this revolution have reshaped and transformed various business processes.

AI, which is believed to have entered our lives with Industry 4.0, was first used in 1950 by the British mathematician Alan Turing with the question “Can machines think?”. The companies can see this mentioned in an article where he addressed the question. This method, developed by Turing and also known as the “Turing Test”, aims to determine whether a machine is intelligent or

not. The test is a kind of imitation game that asks questions to the AI and humans through the computer screen. Turing's paper containing this test is thought to mark the beginning of AI (Russell and Norvig, 2016).

The term AI was coined by John McCarthy in 1956. McCarthy defined it as the science and engineering of producing intelligent machines. AI is a branch of computer science that deals with the study and design of intelligent agents that perceive their environment and take actions to maximize their chances of success. The scientific goal of AI is to understand intelligence by creating computer programs that exhibit intelligent behavior using symbolic reasoning or inference within the machine. The definition of AI is that it is not time-independent and all system decisions are made taking into account time (Winfield, 2020).

Although AI applications have been used in health and industry for at least 30 years, their use in social sciences is a recent trend. In a social context, AI can provide useful tools for discovering new social phenomena and testing existing theories. The foundations of these AI systems can be found in computational graph theory, which has been proven to work well in computer networks (Rangaswamy and Gurusamy, 2018 as cited in Cai, Ramis Ferrer, and Luis Martinez Lastra, 2019).

The results of a study conducted by Robila and Robila (2020) show that AI methodologies have been successfully applied to three main areas of social sciences.

- Increasing the effectiveness in the diagnosis and prediction of various diseases,
- Increase understanding of human development and functioning;
- To increase the efficiency of data management in various social and humanitarian services.

The general aim of AI research is to model the working logic of the human brain and to develop computer systems that can make decisions, think, and learn like humans. AI allows organizations to make decisions based on priorities and tackle complexity and uncertainty. They are capable of performing human-like processes including adaptation, learning, synthesis, and modification. It has also provided an opportunity for all organizations to strengthen effective and efficient governance systems (Alam, Dhar and Munira, 2020). Judgments regarding AI applications are not affected by factors such as emotions, feelings, desires, and needs. They have better memory and

can process large amounts of information (Kshetri, 2021). Realizing the importance of AI, the world's leading companies such as Microsoft, Facebook, Google, IBM, Telsa Motors, Amazon, Nvidia, and Baidu invest heavily in AI applications (Alam, Dhar and Munira, 2020).

In a highly competitive and dynamic market environment, corporate decision-making has become highly complex. These conditions can delay decisions. In addition, the amount of data to be analyzed has increased significantly. Today, with the advancement of big data technology and the increase in computing power, the importance of AI in the business world is increasing. AI traditionally refers to a broad range of technologies that enable computers to perform tasks that usually require human cognition, including adaptive decision-making. In other words, AI focuses on solving human problems or performing tasks through the use of computer-based systems (Khalil, 1993).

AI, which focuses on systems making decisions on their own and developing structures that can implement these decisions, helps people solve problems and transfers human cognitive efforts to the global brain (Öztırak, 2023; Vardarlier and Zafer, 2020; Chen, 2023). AI technology helps companies to reduce delays in business decisions, minimize unwanted situations, and increase revenue opportunities (Thakur, 2012). Given that business decision-making processes are characterized by uncertainty, complexity, and chaos, AI will provide a more holistic and intuitive approach to eliminate uncertainty in decision-making through greater computational capacity and analytical approaches (Jarrahi, 2018). Especially in the current era, with the effect of information technologies, companies have the opportunity to access much data and gain the ability to use these data for their purposes thanks to these technologies. Companies face many problems in the decision-making phase and AI technologies and methods are needed to solve them. Therefore, AI, which provides a large amount of information and professional skills, can have a significant impact on corporate decision-making and change the dynamics of corporate decision-making (Lawrence, 1991; Stock and Rauscher, 1996).

Rapid changes in the business environment require a quick response. Therefore, there is a need to create a natural interface system instead of the traditional approach to information system development. AI technologies, which focus on replicating the principles of human intelligence functions, meet these requirements (Buzko et al., 2016). In the process of simulating the information processes of human consciousness and thought, AI can quickly

search databases, obtain information, efficiently respond to our doubts, and provide the best answers directly and rationally (Jia et al., 2018). It may be useful for companies to look at AI technologies through the lens of business capabilities. Davenport and Ronanki (2018) state in general that AI can support three important business requirements: Automating business processes, gaining insights through data analytics, and interacting with customers and employees.

2.2. AI Technologies

2.2.1. AI Based on Symbolic Logic

Symbolic AI refers to a set of approaches that aim to reproduce human reasoning mechanisms (Wang, Wagner and Rondinelli, 2019). These mechanisms, expressed in logical form, are created by pre-modeling logical rules and information to perform the task at hand (Garnelo and Shanahan, 2019). An outstanding example of symbolic AI technology is expert system algorithms that can generate inferences from known facts and rules. For example, diagnostic rules defined by a doctor are automatically transformed to create a diagnosis. These techniques require, as an a priori approach, the division of the objects processed by the algorithm into fixed classes according to some predefined characteristics. It is therefore quite difficult to capture the complexity of the real world and create fixed categories (Toiviainen, 2013).

2.2.2. Machine Learning

ML investigates the study and creation of algorithms that can learn from data and make predictions. In other words, ML generally refers to a broad set of techniques that create algorithms that learn from data to predict outcomes (Munoz, 2014; Tambe et al., 2019). ML, considered a subset of AI, can use computational algorithms to learn and improve analytics while learning based on experience compared to human intelligence. These algorithms use big data to perform effective learning to recognize patterns and train machines to make autonomous recommendations or decisions. After a sufficient number of iterations and modifications to the algorithm, the machine can take inputs and predict outputs based on these inputs. The output is then compared to a known set of results to determine the accuracy of the algorithm and iteratively improved to perfect its ability to predict subsequent results (Naylor, 2018; Bini, 2018; Haeberle and Kaplan, 2019).

ML is used for many computing tasks where it is difficult or impossible to design and program explicit algorithms with good performance. Examples include email filtering, detecting network intruders, and detecting malicious actors seeking to exfiltrate data (Dickson, 2016). ML models have had great success in learning complex patterns that can make predictions about unobserved data. In addition to using prediction models, the ability to interpret what they have learned is receiving increasing attention (Murdoch et al., 2019). ML, which focuses on building algorithms that use experience with a class of tasks and feedback in the form of performance metrics to improve performance on those tasks, is a broad and rapidly changing field. In general, ML is divided into three types: supervised learning, unsupervised learning, and reinforcement learning (Bartneck et al., 2021).

It includes methods such as supervised learning, regression and classification. In order to make a classification, experiences in the form of data are labeled according to some target classification. The labeling process is done by examining each piece of data and recording people's experiences to label the data. For supervised learning classifications, performance is measured by calculating the true positive rate and false positive rate. The result of this machine learning process is called a classifier. Supervised learning is the process in which unlabeled data is fed to a developing classifier and the performance of the classifier improves over the course of working on some training data. A second data set needs to be used to test the classifier.

Unsupervised learning focuses on understanding data patterns and the relationships of these patterns rather than prediction. This learning includes methods such as principal components analysis and clustering, which are often used as exploratory precursors to supervised learning methods.

Reinforcement learning is different from supervised and unsupervised learning. Reinforcement learning differs from supervised learning and unsupervised learning because it does not use a pre-existing sample set as input. This is because it does not use an existing example set as input. Instead, bending occurs directly through interaction with the environment (Lu and Hong, 2019). The machine performs an action, changes the state of the environment according to this action, and receives a reward according to the result. Rewards enable the machine to find the best action according to the outcome it is trying to achieve. A recent and famous example of reinforcement learning is AlphaGo. Here, the action is the movement on the board, the environment is the board with the pieces, and the reward is the result of winning or losing the game (Ongsulli, 2017).

2.2.3. Deep Learning

Deep learning (DL) models, which are frequently used in AI research, consist of deep neural networks designed with various architectures. Deep neural networks contain millions of neurons, learnable parameters, and many deep layers. Systems trained with DL models produce different outputs by learning the data they encounter (Deliloğlu and Çakmak Pehlivanoğlu, 2021). Deep learning is a form of machine learning that allows computers to learn from experience and understand the world in terms of a hierarchy of concepts (Kim, 2016). There have been many studies using deep learning in the literature and in practice. Deep learning applications are being developed in a wide variety of subjects such as natural language processing, image and video processing, biomedical signal and image processing, object recognition, robotics, chemistry, advertising, finance, search engines, and autonomous vehicle systems (Şeker, Diri and Balık, 2017). Deep learning is generally based on learning from the representation of data.

Explainable AI (XAI) approaches have emerged to represent increasingly complex DL models as black boxes and to enable humans to understand and interpret the outputs produced by these models (Terzi, 2021). Classification results, such as a simple machine-predicted cat/dog, may not necessarily be explainable. However, the system that will help decision makers in the field of medicine and health must be able to explain its predictions about whether a tissue is cancerous or not. Otherwise, a surgeon who only relies on the machine's predictive decision may operate on a healthy person unnecessarily. Similarly, in serious projects with high budgets such as railways, it is important that the output produced by the system is explainable. It should not be forgotten that the machine also has a margin of error. When the decisions made by the machine are explainable, the human being, who is the main decision maker, can use his will to implement the decision by looking at the explanation information. In this way, incorrect actions can be prevented. With explainable artificial intelligence, explanation maps showing the infrastructure of the decisions made by the system are shown to humans. When a human examines the explanation maps, he or she can perceptually recognize a possible wrong decision made by the machine and prevent a wrong action from being shown.

DL algorithms, another subfield of AI, improve the efficiency of understanding speech, text, and images by determining the location of components as a classification of ML algorithms. The analysis system works with an algorithm that uses natural language processing (NLP), a subfield of AI

(Umachandran, 2021). The main task of NLP, one of the most important functions of AI, is to automatically process human language. The NLP approach refers to a system that understands and learns natural language using humans as models, similar to how humans learn language through experience (Hemaletha et al., 2021).

2.2.4. Image and Video Recognition

Interpreting images and recognizing people, objects and the surrounding environment is a relatively easy task for humans. Our brains easily process complex visual information every day. However, this is a very difficult task for computers (Suen et al., 2019). The social media platform uses convolutional neural networks to recognize faces in photos. After a photo is uploaded to the platform, the system classifies the new face by matching it with labeled faces in the database (Maras and Alexandrou, 2019).

2.2.5. Translation

Creating translation software starts with creating a large database of texts translated by translators that serve as models. These translations usually come from books, official documents, and approved websites from international organizations (United Nations, European Commission) (Prates, Avelar and Lamb, 2019). The neural network then processes the text to find statistical patterns. These patterns create equivalence between sequences of words, which makes the unknown text possible. However, the translation software produces fewer translated documents for some language pairs. For example, more articles are translated from French into Spanish than from Danish into Romanian. Therefore, the quality of translation varies greatly from language to language (Adami, 2015).

2.2.6. Content Suggestion

AI systems, which work according to different approaches than the learning techniques described above, are used to recommend content to users, online marketplaces, or live streaming platforms. Here, the input data consists of past choices made by the user. This dataset is used to create fake user profiles and product categories. Here we represent fake average user behavior. Due to the variety of users and products, it is not possible to extract consumption behavior categories directly from the consumption options. The organizations can then analyze each user through these fake categories. This

allows us to calculate the fake affinity between users more reliably than just counting the number of ordered items. The system then selects based on the preferences of fake users who are similar to a particular user, so that various products can be recommended that are likely to match that user's preferences (Pan, 2016).

2.3. AI Assisted Recruitment Process

The recruitment process, which is one of the most important functions of HRM, includes determining personnel needs based on HR planning, announcing open positions through the right channels, receiving candidate applications, conducting tests and interviews, and accepting successful candidates (Karaboğa and Vardarlıer, 2020). This process aims to ensure that the competencies of the individuals match the skill requirements of the organization. To achieve this, the recruitment process involves the search, selection, and recruitment of people who are suitable for the qualifications required by the company. It also aims to ensure that these people are compatible with the organizational culture and strategy (Vardarlier and Zafer, 2020).

AI is one of the emerging trends affecting the recruitment process (Köchling, Wehner and Warkocz, 2022). In the age of digital transformation, companies prefer to apply AI and algorithmic decision-making methods instead of traditional selection processes (Köchling, Wehner and Warkocz, 2022; Bhatt, 2023). Most hiring managers use AI technologies to improve the quality of recruitment and automate the process of searching for promising candidates that match their parameters by scanning profiles from various sources such as social media, job portals, networking sites, etc. (Vedapradha, Hariharan and Shivakami, 2019).

The application of AI to various decision-making stages of the recruitment process (sourcing, screening, matching, and evaluation) is becoming increasingly common (Figueroa Armijos et al., 2022).

The use of AI-based systems can facilitate the arduous and time-consuming task of identifying and evaluating potential candidates for decision-makers and provide a more consistent and fair decision-making process (Kupfer et al., 2023). The traditional recruitment method of Hilton, a global hotel chain, takes an average of 42 days, but this time was shortened to an average of 5 days by applying an AI-based video interview method (Karaboğa and Vardarlier, 2020). One of the application areas of AI in

recruitment is AI-assisted CV screening, which algorithmically analyses words and specific criteria to predict a candidate's suitability for a job without human intervention (Köchling and Wehner, 2023). Filtering algorithms allow candidates to be evaluated according to various criteria such as graduation status, work experience, and field experience. Based on these assessments, recruiters can directly weed out candidates who do not fulfill the basic requirements of the job. These benefits allow companies to complete the recruitment process quickly, saving time and effort (Vardarlier and Zafer, 2020). Besides CV screening, web-based and non-interactive AI-assisted interviewing (also known as asynchronous video interviewing or automated interviewing) is another application that has recently become widespread (Köchling and Wehner, 2021).

In the recruitment process, candidate interviews are conducted through a chatbot created with an AI algorithm. Chatbots are software that can communicate with candidates through certain pre-virtualized scenarios, ask questions to candidates, and answer candidates' questions (Vardarlier and Zafer, 2020). Chatbots are AI-based assistants that provide personal interaction with candidates. These assistants interact with job seekers via e-mail, text message, or chat boxes. As a result of the communication with the candidate, the chatbot transfers the experience of the candidate to the recruiter (Upadhyay and Khandelwal, 2018). These robots are set up to analyze the needs and questions of real or virtual interlocutors and provide answers, information, guidance, and services (Allal-Ch'erif, Aránega and Sánchez, 2021). It generates the candidate’s CV and automatically matches the requirements with the candidate's skill set (Vedapradha, Hariharan and Shivakami, 2019).

Another important innovation brought by AI technology to the recruitment process is video interview applications. Thanks to AI-based video interview technology, face recognition technology, voice-to-text conversion, and voice tone analysis functions, HR managers can identify suitable candidates more easily. Utah-based HireVue is one of these companies. After interviewing the best candidate for the job, HireVue records the candidate's facial expressions, changes in voice tone, and micro gestures during the interview using an AI algorithm rhythm. Unilever has been working with HireVue in the recruitment process since 2016 and has used AI technology to evaluate 250,000 applications. Unilever announced that digitalization reduced the recruitment process from four months to four weeks, saving 50,000 hours (Vardarlier and Zafer, 2020).

2.4. The Use of AI in Recruitment Process

In the study on the use of AI technology in the recruitment process; There are very few companies that use AI in the recruitment process, and AI is only used for preliminary interviews and personality tests. It is believed that AI can be used in most cases such as CV selection, personality test application and performance evaluation. It is stated that individuals cannot be replaced or decided only by the use of AI in the personnel selection process, and human control is considered to be necessary (Karaboğa, 2020).

In research on the changes that AI can bring to HR processes and awareness levels; Integrating AI into the recruitment process for HR personnel and managers will reduce the stress experienced in finding suitable candidates, the perception of reaching more qualified candidates, and the inclusion of AI technology in education and training will lead to development. interest in courses, time spent, and training will decrease. If AI is used in the performance evaluation process, motivation will not disappear and performance evaluation standards will be determined correctly. With the awareness that AI will help the person to plan his/her career, it has been concluded that promotions are given to those who are deserving, and salaries and surcharges are determined by using AI technology in the salary and career management process fairly. It is said that the results show that HR managers and employees want to measure their performance with AI technology (Kambur, 2020).

In the study on the application of artificial intelligence in standard staff calculations in personnel planning, it is possible to estimate the normative number of personnel by using the learning ability of the artificial neural network. This provides the opportunity to increase the performance of the artificial neural network by increasing the reliability of future predictions and reducing the error rate. It is stated that companies can train their own networks by processing the results in the next process with the results obtained, the information obtained is protected throughout the network and the manager can make future plans more accurately by using these results. Thus, it will play a more active role in personnel planning in institutions (Yılmaz, 2012).

AI is both a machine and an improved algorithm. It is a tool that improves performance by using human intelligence in various fields. AI can help HR professionals do their jobs more easily and have a positive impact on recruitment and orientation processes. Moreover, AI has more technologies. Some of them are (Upendra Nishad and Gurav, 2020):

- **Recruitment and onboarding:** In the future, every organization will need AI to recruit the best talent. AI helps recruiters analyze the CVs received during the recruitment period, compare them with the CVs of existing employees working in the same job, and select the most suitable candidate. AI can process more CVs than humans to find the perfect set of candidates, and it can also evaluate a large pool of talent, taking into account parameters such as experience, value, skills, and achievements that perfectly match the transaction requirements.
- **Talent Retention:** The loss of skilled employees is not only a business loss. It is not only an unacceptable depletion of resources, but also a very significant loss of carefully constructed value. AI can monitor several tangible and somewhat intangible parameters to retain talent. From identifying employees who should be rewarded with salary increases and bonuses to monitoring work-life balance, AI can help address the root causes of talent dissatisfaction with their current jobs and work environments.
- **Training and Performance Analysis:** Changes in technology and processes are constant requirements that organizations must meet. AI allows HR departments to develop and organize training programs for the entire team of employees, as well as automate the process, taking into account the needs, schedules, and wishes of individual employees. In general, AI helps to analyze the skills and behavior of specific candidates for various positions. Customization of a training program using AI is very important as everyone's style and ability are different. In addition, these customization activities act as a bridge between employers and employees.
- **Conversational AI:** AI can gather insights through employee interactions, gathering information about employee satisfaction, productivity, and motivation to participate. Conversational AI systems can perform activities ranging from collecting feedback from employees to initiating the review process.

The reasons why organizations prefer AI in HR are as follows (Mathew et al., 2021):

- **Showing the right candidates:** When a candidate applies to the company for a vacant position, artificial intelligence interacts to assist the candidate.

- **Advanced analytics integration:** HR managers want to select candidates based on their experience. AI tools help increase business efficiency by select candidates faster from the pool of their current candidates profiles and improving recruitment efficiency.
- **Improve hiring quality:** Recruiting suitable candidates from a wide candidate pool to the right positions is an important task for HR departments.
- **Automation and unbiased judgment:** As the saying goes, time is money and time is a crucial factor in any organization. AI tools can help businesses save time, money, and other resources by helping businesses search for the right candidate profile for the right position from a pool of applicants. In addition, AI tools can be used to review applicants' CVs and online data entered when applying for open positions to reduce biased judgments due to human intervention and make fair decisions.
- **Employee development and motivation:** Companies should organize regular quality learning and training programs for their employees. This helps employees feel more motivated to do their jobs and therefore focus more on their career and organizational development. As learning is a continuous process, employees may need to spend additional time outside working hours. AI tools allow to personalize any learning and training program and employee training programs can be carried out at the most convenient time with minimal human intervention.
- **Fair treatment of all employees:** Treating all employees fairly is critical to a company's growth and development. Companies should provide regular updates on job policies, promotion and salary increase criteria, benefits, and holidays, and answer all employees' questions about health and grievance issues. Using AI tools, all work policies can be customized and employee queries or complaints can be communicated to company officials through a chat box or virtual meeting call. With the help of AI tools, HR can develop a set of measurable goals for each employee, as well as more easily manage employee feedback and surveys conducted by the organization.
- **Organizational benefits:** Companies using AI tools can have a more comprehensive understanding of their employees. The organizations can monitor emotions and performance throughout the working day. As a result, companies can take any corrective action for their

employees and find opportunities to further strengthen the bond with their employees, which can result in greater employee engagement. By using AI in HR, HR have optimized the recruitment process to be more accurate and efficient, reducing costs and improving the quality of recruitment. In addition, AI has brought several challenges.

Using AI in recruitment can help the organizations save money and time, receive more applications, and select more suitable candidates for the job. In addition, supporting recruitment professionals by utilizing AI instead of conducting all recruitment processes alone can help companies and employees achieve more successful results (Kırılmaz and Ateş, 2021). Candidate screening is another task that can be automated with AI technology. This technology allows to collect data from candidates' social media profiles, previous online job records, and other online sources.

AI can identify the most promising candidates for a job in a short time by effectively sourcing and screening the admission criteria set by the company (Ahmed, 2018). Some positions require the recruitment of a large number of employees, which makes it difficult to conduct interviews at the same time and significantly increases recruitment costs. AI can manage a large number of applications. AI performs calculations to select from a large number of CVs those that meet the department's requirements or match recommendations based on job requirements. Moreover, AI is not limited by time and space. The manpower burden can be greatly reduced by conducting structured interviews for different applicants at the same time or conducting voice interviews using voice robots. In addition, AI greatly increases the efficiency of employee training and improves the quality of training by providing personalized learning feedback (Qiu and Zhao, 2018).

AI can perceptually recommend videos or learning programs to employees based on their work and experience. This software automatically reads documents and designs microlearning programs, as well as generates keys that suggest learning intervals by reading and interpreting tasks or achievements written by employees. Furthermore, AI converts written documents into visuals to provide personalized or individualized (Sangivukumar and Thamodaran, 2020).

AI simplifies the recruitment process and increases candidate engagement through appropriate communication. This keeps the organization in a tight talent environment while attracting and hiring a pool of candidates (Lakshmi et al., 2020). AI-powered chat systems that effectively communicate and screen candidates help recruiters manage employer branding, candidate

management, and more. They find time to focus on more strategic functions (Nagar and Saxena, 2020). Using AI in talent acquisition helps the recruitment process and improves the candidate experience. Providing real-time answers to candidates' questions during job interviews, providing quick feedback, and suggesting future actions develop a good relationship between the organization and the candidate. This technology allows candidates to save both time and effort (Lakshmi et al., 2020).

AI offers solutions to help solve various important business challenges in HR (Macijauskıenė and Stankevičiūtė, 2021). AI technology helps to reduce the possibility of bias or bias when selecting candidates based on appearance, skills, and language (Saini and Tarkar, 2022). AI can collect information from users and create its knowledge base and database. Performance evaluation indicators can therefore become more data-driven and more closely match real-world situations. AI in performance appraisal can not only prevent the randomness of subjective appraisal but also enable more objective and fair appraisal, making the appraisal results more accurate and convincing (Qiu and Zhao, 2018).

Applying AI to the recruitment function can automate parts of the recruitment process, help recruiters connect with top talent faster, allow recruiters to be more engaged in recruitment, and improve their relationships with hiring managers (Singh et al., 2021). HR recruiters use AI algorithms to speed up the recruitment process and gain more talent in the overall recruitment and selection process (Singh et al., 2021).

CONCLUSION

Since it is important for companies to select employees who will ensure the continuity of the organization's operations, the recruitment process is very important. Having employees who will contribute to achieving business goals is now seen as a completely separate field of activity from other departments of the business. Over time, companies have realized that the most important element required to achieve their goals is their employees, and therefore it has become essential to select good and qualified people to achieve their goals over time. However, the process of recruiting people who meet the standards set by the company and who will help the company achieve its goals is not easy for the company. This challenging process led to the establishment of the HR department. The process in question involves determining the personnel

needs of the enterprise, finding the people who meet these needs, and co-operating with the people who meet the objectives and requirements of the enterprise (Fındıkçı, 2009).

The main purpose of strategic HRM is to harmonize business and human factors within a company and to ensure that human factors achieve the company's goals (Vardarlier, 2014). From this point of view, it is important to take the necessary preventive measures and to conduct research to increase the efficiency of HR. One of the innovations that have started to be applied in the field of HR is the use of AI. The field of AI endeavors to understand and construct intelligent beings. Simply put, AI can be defined as a computer or computer program that can perform intelligent functions. It is difficult to make a more precise definition since AI can be related to all kinds of tasks and covers a wide range of subfields (Russel and Norvig, 2016). In the developing business world, AI is starting to appear in every field and HR departments of companies are starting to manage the recruitment process. In the age of technology, as new technologies are adopted, business structures need to adapt to new designs and as a result, the performance of business processes needs to be improved (Vardarlier and Zafer, 2020).

In the interview process, AI helps HR managers make pre-selection, reveals the degree of match between the interviewee and the position, even supports decision-making, and helps HR managers predict job change intentions. In terms of staffing, the career evaluation system provided by AI can more accurately identify the expertise of employees, transform the value of each employee's talent into intuitive data, and better position employees for realization using scientific algorithms. The organizations can provide them with expertise and skills, and assign them to business goals and tasks that will best demonstrate their talents (Shao and Shi, 2020). In addition, AI facilitates various HRM activities. There is a general awareness among human resource managers that AI will replace human resource managers shortly. In reality, however, AI facilitates the work of human resource managers by continuously automating tasks without intellectual bias. AI is an advanced computer program with extraordinary abilities to structure, plan, decide, and adapt in a way that mimics human thinking (Sangivukumar and Thamodaran, 2020). Companies need to take full advantage of AI, learn from successful model companies, and create an environment where the general workforce can adapt to the latest needs of the new era (Qiu and Zhao, 2018).

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Chapter V

ARTIFICIAL INTELLIGENCE APPLICATIONS IN HEALTHCARE

Şebnem Yücel - Recep Yücel - Havva Nur Atalay

INTRODUCTION

Artificial intelligence (AI), also called machine intelligence, means the ability of computer systems to learn from inputs or historical data (Gupta et al., 2021). AI aims to mimic human cognitive functions (Al Kuwaiti et al., 2023; Jiang et al., 2017). The field of AI includes the theory and the development of computer systems that can perform tasks that normally require human intelligence, such as sensory perception and decision making (Misra et al., 2022). In order to benefit from the developed computer systems, artificial intelligence applications are used in both production and service sectors such as agriculture, industry, food, tourism. Healthcare is one of the service sectors where AI is used. AI is a vast and diverse field of data, algorithms, analytics, deep learning, neural networks and insights that is constantly expanding and been tailored to meet the needs of the healthcare industry and patients (Kumar et al., 2023). AI can use developed algorithms to 'learn' from large volumes of healthcare data and use the insights gained to aid clinical practice. It can also be equipped with feedback-based learning and self-correction capabilities to increase its accuracy (Jiang et al., 2017, p. 230). The recent increase in clinical, biological (genomic and immunological) and imaging data creates an opportunity for personalized medicine. The integration of multiple information flows and their appropriate interpretation are important. AI techniques are seen as beneficial in this respect (Lee et al., 2017). For example, personalized treatment in cancer is an attempt to supply the right treatment to the right patient by taking into account several types of patient data including current drugs, genomics variants, imaging genomics, living and working environment, and lifestyle (Shamshirband et al., 2021). Information processing is needed in order to realize the stages in the effective

management of health services. AI applications can also act as an information processing in health services at this point (Panch et al., 2018). AI can help to identify precise demographics or environmental areas where disease frequency or high-risk behaviors are found (Kumar et al., 2023). Yao et al. (2021), who conducted a systematic review to determine the effectiveness of AI applications in kidney diseases, found that AI would be an excellent aid in clinical settings to improve patient outcomes. However, they stated that there are some problems related to data quality and quantity, patient privacy, information security, medical responsibility, AI-clinician and physician-patient relations, and ethical regulations. In this section, the concept of AI is explained and the areas, purposes, and the way that the AI applications are used in health services are examined.

1. Artificial Intelligence (AI)

When Google Trends data is examined, it is seen that the concept of AI has continued to be a subject of interest for more than ten years (Misra et al., 2022, p. 6305). AI emerged when the famous mathematician and computer science expert Alan Turing, one of the best names in computer software that emerged with World War II, created the test about machine intelligence (Lombardo et al., 2022; Uzun, 2020). In addition, the term "artificial intellegigence" was proposed by John McCarthy at the Dartmouth conference in 1956 and thus the field of AI emerged as a name (Liu et al., 2020). Many studies were carried out in this field in 1980-1990, but its use became possible in the 2000s. Today, many programs such as shopping sites, social media platforms, text analysis, translation and face recognition programs operate on the basis of AI (Erturk & Erturk, 2021, p. 40). AI consists of the concepts of "artificial" and "intelligence". The concept of "artificial" refers to "man-made" and "intelligence" refers to the "capacity to think" (Hosgor & Gungordu, 2022). AI can be defined as computers and computer softwares that are capable of intelligent behavior such as analysis and learning (Buyukgoze & Dereli, 2019). AI is perhaps the oldest field of computer science and is very broad; It deals with all aspects of real-world problem solving and mimicking the cognitive functions of humans to create systems that learn and think (Holzinger et al., 2019). AI is a technology created to enable computer-generated robots to think and act just like a human (Sucu, 2019). *AI, in other words, is "the ability of a system to accurately interpret external data, learn from such data and use it to achieve specific goals and tasks through flexible adaptation*" (Kaplan & Haenlein, 2019). The definition of AI in OECD's AI Council is as follows:*"An AI*

system is a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy" (OECD Legal Instruments, 2019). AI are systems designed to solve complex operations, which are obtained by adapting the human thinking and consciousness structure into the machine, by designing a hardware structure on the computer that is similar to the human-brain structure (Akalın & Veranyurt, 2020, p. 134). Based on these definitions; it can be said that AI is a system that enables the computers to think, process information, learn and make decisions in a human-like manner.

1.1. Machine Learning and Deep Learning

Simply describing AI may not be enough to understand its functions. Therefore, the concepts of deep learning (DL) and machine learning (ML) should also be explained. The field of ML has a more critical value for developing and changing AI (Ozturk Dilek, 2019). ML is one of the important areas of AI that continues its work in the formation of learning systems and machines, and it is a vital aspect of machines. ML is considered as a subfield of AI. Computer scientists have been making efforts in ML since the 1950s (Shinde & Shah, 2018). The hierarchy of relationships between AI and ML, as well as ML and DL, is shown in Figure 1 (Shinde and Shah 2018).

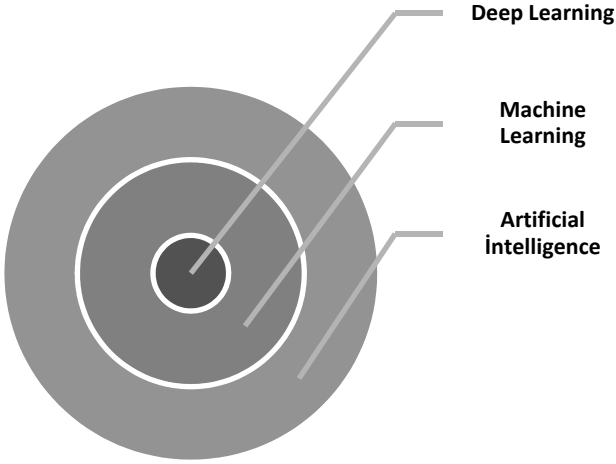


Figure 1: Artificial Intelligence, Machine Learning and Deep Learning Hierarchy

ML is carried out in three ways as supervised learning (SL), unsupervised learning (uSL) and reinforced/reinforcement learning (RL). While the input and output are directed with certain training sets in SL, this type of orientation is relatively less in the inputs in uSL. In RL, on the other hand, without any input and output pairs, the ML system is unleashed and is often quite useful in closed systems such as games. Goodfellow et al. (2020) stated that the most used ML model is SL. Goodfellow et al. (2020) this situation; *"supervised learning can often achieve more than human accuracy after the training process is complete and is therefore integrated into many products and services."* explained as.

ML is an umbrella term that refers to a wide variety of algorithms that perform intelligent predictions based on a dataset. These datasets are often large and consist of perhaps millions of unique data points (Nichols et al., 2019). Such learned models are then applied to perform or guide certain tasks and make predictions (OECD Legal Instruments, 2019). In other words, ML represents various techniques for solving complex problems with big data by identifying interaction patterns between variables (Krittanawong et al., 2017). Recent advances in ML seem to have reached a human level of semantic understanding and information extraction, and the ability to detect abstract patterns, sometimes with higher accuracy than experts (Nichols et al., 2019). Since the last few years, tremendous efforts have been made in advances in machine learning. This leads to higher expectations from machines.

DL, a subset of ML, is a result of these efforts (Shinde & Shah, 2018). DL has obtained a crucial place in recent years in pattern recognition and ML (Ravì et al., 2017, p. 17). The rapid development of modern computing makes DL possible to create neural networks with multiple layers, which is not possible for classical neural networks. Therefore, DL can discover more complex nonlinear patterns in data (Jiang et al., 2017). In fact, DL mimics the functioning of the human brain by using multiple layers of artificial neuronal networks capable of generating automated predictions from inputs (training datasets) (Krittanawong et al., 2017). DL methods encompass multi-step feature learning approaches, wherein data is progressively refined through a series of cascading layers (Shamshirband et al., 2021). Deep learning will be invaluable in the context of big data as it extracts high-level information from huge volumes of data (Rusk, 2016; Q. Zhang et al., 2018). On the contrary, the creation of systematic big data is considered very important in terms of DL. In general, DL is known to play an important role in providing big data predictive

analytics solutions as data continues to grow, especially with increasing processing power and advances in graphics processors (Chen & Lin, 2014). In this sense, healthcare services have also become one of the areas where big data is formed, got complicated, and AI is started to be applied.

2. Artificial Intelligence in Healthcare

The use of healthcare data has increased thanks to the rapid development of big data analytics methods that made the successful applications of AI in healthcare possible (Jiang et al., 2017). AI reduces administrative and clinical costs by reengineering healthcare service processes. In clinical processes; it accelerates processes such as diagnosis, diagnosis and treatment and aims to increase service quality by reducing human interaction (Akalın & Veranyurt, 2020). AI provides many advantages in the execution of healthcare services and thus treatments can be performed more accurately and in shorter times which affects the psychological well-being of the patients (Hosgor & Gungordu, 2022).

While AI is unlikely to completely replace healthcare providers, it can perform certain tasks with greater consistency, speed, and repeatability than humans (He et al., 2019). However, it is likely that AI will put an end to traditional medicines in healthcare and will pave the way for the transition to personalized medicine by developing drugs that are suitable for each person's DNA (Hosgor & Gungordu, 2022). One of the notable aspects of AI applications is that it provides support for comprehensive healthcare management. These applications support physicians, nurses and health managers in their work (Secinaro et al., 2021). Accordingly, the four areas where AI-assisted healthcare delivery will likely have the most impact: health management, clinical decision support, patient monitoring, and health interventions (Reddy et al., 2019). With the development of AI, disease screening systems based on AI algorithms are emerging in the medical field. Such systems can be used in primary screening of diseases to relieve pressure on primary health care services (M. Zhang et al., 2023). AI systems are also used in tele-health applications. Virtual nursing, remote treatment, and Neuro-Linguistic Programming (NLP)-based diagnosis and referral systems are being used and developed in a period when physical communication with hospitals should be absent (Akalın & Veranyurt, 2020). In this way, the workload and error rate of physically working health service providers are reduced.

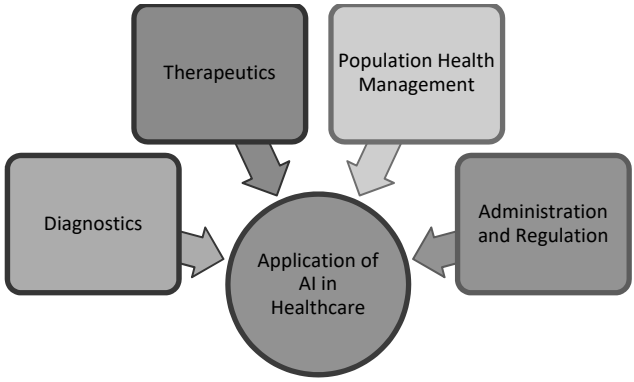


Figure 2: Potentional Roles of AI-based Technologies in Healthcare

Potential roles of AI-powered technologies in healthcare can be classified as diagnostics, therapeutics, population health management, administration, and regulation (He et al., 2019), as seen in figure 2. Thus, AI technologies enable diseases to be diagnosed using personal health data and medical imaging records. In addition, human and AI integration is getting effective with the use of big data in hospitals in processes like: robotic surgery, treatment of common diseases, developing information systems and public health that will promote a healthy lifestyle, management and regulation.

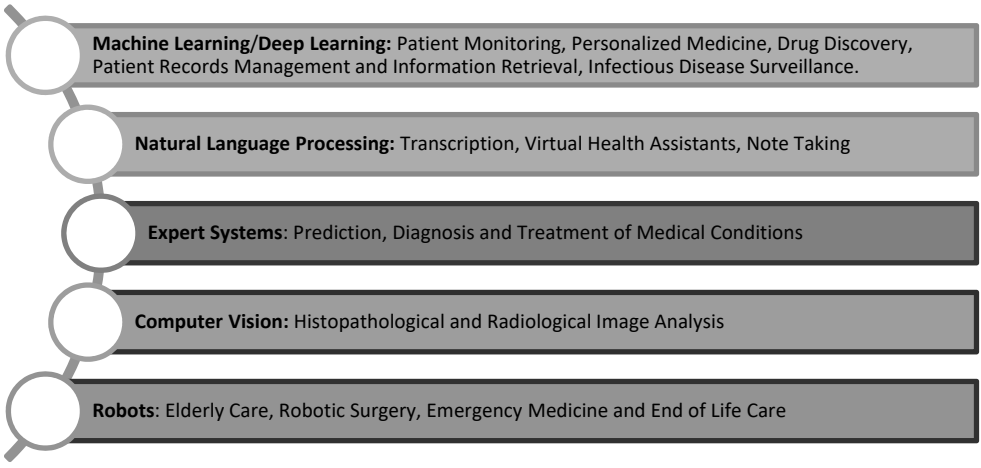


Figure 3: Application of AI Techniques in Healthcare

The application areas of AI in healthcare are given in Figure 3 (Reddy et al., 2019). Accordingly, the use of AI personal therapy data in healthcare is used for administrative and clinical purposes with medical imaging, diagnostics and parts, and robotic surgery (Reddy et al., 2019) as well as medicine for clinicians to interpret radiological images quickly and accurately, and to speed up workflow and minimize errors for healthcare systems (Alıcılar & Çöl, 2021, p. 151). According to Bennett and Hauser (2013), AI algorithms can contribute to clinical decisions by speeding up the amount of care provided and the process, and reducing the cost of healthcare services.

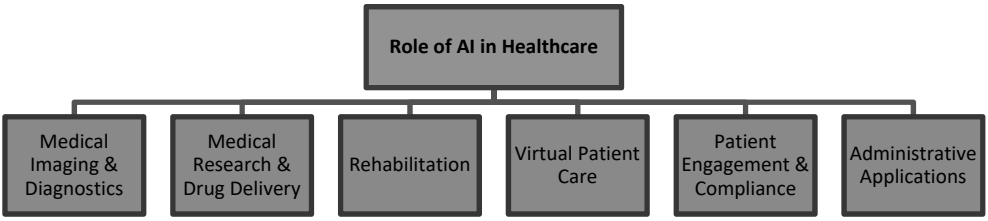


Figure 4: Application of AI in Various Aspects of Healthcare

The usage areas of AI were classified as in Figure 4 (Al Kuwaiti et al., 2023). In addition to the classification made by Al Kuwaiti et al., (2023), the rehabilitation dimension was added by Reddy et al. (2019). In addition, in a systematic review study conducted by Secinaro et al. (2021), AI techniques applications in health services were discussed under four headings: health services management, patient data and diagnostics, clinical decision-making, and predictive medicine.

The striking point in this classification is that the "management" title, which was examined as "administrative applications" by Kuwaiti et al. (2023) and as "administration and regulation" by He at al., (2019), was integrated into health management as "health services management". In healthcare management, the intended use of AI is to minimize errors in decision-making. Case-Based Reasoning (CBR) and Artificial Neural Network (ANN) techniques are ways to apply AI in medical decision making (Amaitik & Amaitik, 2010; Dabowsa et al., 2017). Areas where AI enables healthcare services to operate more efficiently (Secinaro et al. 2021) listed as follows:

- Clinicians have instant access to data when they need it.
- Nurses can provide a higher level of patient safety while administering medication.

- Patients can have information about their care/health by communicating with healthcare teams during their stay in the hospital.

The following are carried out using AI in the field of health informatics: disease prediction, data mining, and human behavior monitoring applications. Electronic health records, blood/lab tests, and big medical datasets are used as inputs in these applications (Che et al., 2015; Lipton et al., 2017; Miotto et al., 2016; Nie et al., 2015; Putin et al., 2016). A study was conducted by Patel et al. (2018) to detect Heart Failure disease with Preserved Ejection Fraction (HFpEF) based on electronic health records. NPL and ML methods were used as AI applications in the study. As a result of the study, it has been determined that the algorithm created in the study can be used in other researches to diagnose HFpEF disease by using other electronic data records. In the literature, there are studies in the fields of cancer diagnosis and drug design using gene expression, and molecular compound inputs. For example, in a study conducted by Fakoor et al. (2013), using DL, different types of cancer were classified by AI and gene sequences were created. In this way, AI succeeded in separating later cancerous cells from non-cancerous cells. A review study was conducted by Gupta et al. (2021) to examine the role of AI in drug development. As a result of this study, it has been determined that NLP, image and voice recognition, ML, and DL areas of AI are used in drug development and more studies are needed to develop drugs. In addition, it was stated in the study that AI used in drug development reduces costs, saves time, and reduces errors. Thus, an issue that needs attention in the study is underlined. This is due to the fact that most countries do not patent inventions produced with AI technology, and companies go through a difficult process to obtain the copyright of their work in order to secure their patent rights. In this direction, it can be stated that these developments as a result of digitalization should also be included in national and international law.

Another critical area of medicine, where AI has an impact, is clinical decision making and disease diagnosis (Secinaro et al., 2021). AI can use advanced algorithms to 'learn' features from large volumes of healthcare data and then use the results to aid clinical practice. In addition, these algorithms can be equipped with learning and self-correction capabilities to increase the feedback-based accuracy of the decisions made (Jiang et al., 2017). AI is a powerful image analysis tool that is increasingly used by radiologists to reduce diagnostic errors in the context of early detection and prevention of different diseases. Similarly, AI is a smart and potential tool for analyzing ECG and echocardiography charts that cardiologists use to support their decision making (Al Kuwaiti et al., 2023). In a study by Dabowsa et al. (2017), a

backpropagation neural network was used in the diagnosis of skin disease to achieve the highest level of accuracy.

Dabowsa et al. (2017) used real personal health data collected from the dermatology department. In the study, a computer system was created using Microsoft Visual BASIC. A database of five tables was designed, containing the details of the cases, the login ranges, and the user login details. In the study; The system created by the authors was found applicable, good performance and acceptable. In addition to other factors such as physical examination and analysis, knowledge and experience, the developed system provides dermatologists and relevant clinical personnel; it is expected to assist in determining the correct diagnosis and then providing/administering the appropriate treatment to prevent further deterioration of the patient's skin. Rathod et al. (2018), on the other hand, propose an automated image-based system using ML classification for diagnosing various skin diseases. This system analyzes disease images, gives a result report, and assists clinicians in decision making.

CONCLUSIONS

This chapter underlines once again that data is needed for AI to learn, infer and monitor. It should also be underlined that accurate datasets must be produced for the development of AI. On the other hand, it should be mentioned that, data protection and confidentiality are also required while using AI applications, as hackers and malicious software developers focus on these important health records (Al Kuwaiti et al., 2023). This situation is stated by Gupta et al. (2021) as: “Security is also a major concern, as AI-driven personalized medicine requires person’s genetic code for which personal information will be required.” Therefore, for the development of AI applications in health, it is necessary to eliminate the concerns about the access and misuse of personal health data/records by third parties.

AI basically includes the theories that computers realize intelligence and produce computers as intelligent as the human brain, enabling them to perform high-level applications (Xu et al., 2022). The age of augmented intelligence in healthcare stems from the idea that intelligent algorithms can support providers in diagnosis, treatment, and outcome prediction, especially with increasing digital and connected patient data, and advances in computational capabilities (Abedi et al., 2020; Lee et al., 2017; Patel et al., 2018). Moreover, Kaptanoglu (2020) expresses this thought that artificial intelligence will be effective in all steps of health services as follows: “Artificial intelligence promises to be a transformational force in health services, both in primary, secondary, and tertiary levels.”

Based on these data; It is possible to say that AI applications are spreading in the areas of health services such as diagnosis, treatment, rehabilitation, medical imaging, health management and so on , as well as other business sectors.

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Chapter VI

TECHNOLOGIES AND FUTURE OF ARTIFICIAL INTELLIGENCE

Mustafa Coşar

INTRODUCTION

The stunning developments in the field of Information Technologies (IT) in recent years offer humanity a faster and easier life. The most striking of these developments is artificial intelligence (AI). AI is a type of intelligence that enables all actions that can be done with human intelligence to be performed by an artificial system. Human intelligence is an entity that can extract information from the data it collects through its sensory organs towards an object and phenomenon, can think analyse, solve problems and make decisions by learning from these processes.

Although the history of AI dates back centuries, important progress has been made in the last 60 years. John McCarthy first defined the concept of artificial intelligence in 1956 as "the science and engineering of making intelligent machines and especially intelligent computer programs" (McCarthy, 2007). AI, which has started to develop as a branch of science, has become a system that can be applied to all fields. This system has the ability to learn by processing the data, it collects and stores with its various sensors, very quickly and with high performance. The purpose of AI is to identify, teach and apply the mental and physical functions and skills of human intelligence to artificial systems with computer algorithms.

Today, it is possible to see AI applications in every field. It has a wide range of uses, from text, audio and image processing in daily life to industrial production lines. AI, which has managed to eliminate many obstacles, can transform individuals' education into more adaptable learning environments.

Robotics systems in Dark factories, which entered our lives with Industry 4.0, can produce non-stop all day long. In addition, successful results are obtained by using autonomous vehicles with AI in jobs that put human life at risk. The spread of AI technologies removes many obstacles and brings quality, efficiency and profitability.

Since IT is used extensively in private and business life, we experience a continuous process of creating and sharing data. These data come together in terms of meaning, scope and type and form big data. Big data enables a system with AI to come to life. This life becomes smart with data mining, data analysis and data learning.

AI, whose life adventure starts with data and develops with learning, needs some technologies to become operational. These technologies come into play in the classification, identification, analysis and interpretation of data. These technologies, which include logical, mathematical and statistical formulas, functions and theorems, are called AI algorithms. In this section of the book, these important AI technologies that make AI operational are mentioned in detail.

1. Artificial Intelligence

AI is the branch of science and engineering that deals with systems that can imitate human behavior that shows signs of intelligence (Tecuci, 2011). AI, which started to develop after the 1950s, is closely related to fields such as logic, machine learning (ML) and symbolic reasoning. According to Angelov et al. (2021), looking at recent applications, AI and ML technologies have proven themselves in civil and official fields with their performance in recent years. Particularly in some applications such as text analysis, speech and image recognition, performance rates have reached or even begun to exceed human performance levels.

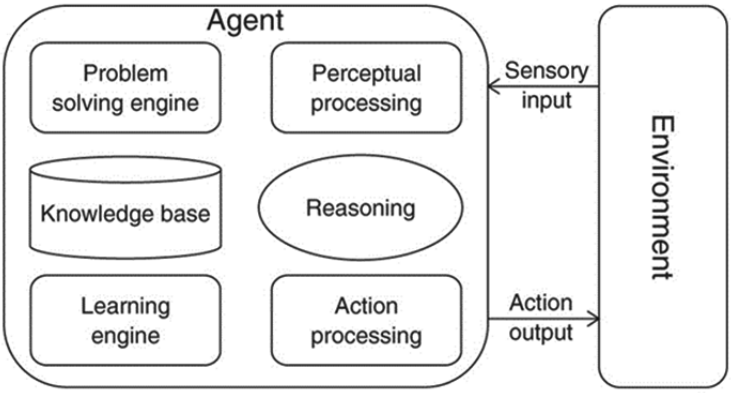


Figure 1. Architecture of a Knowledge-Based AI System (Tecuci, 2011).

Figure 1 shows a conceptual architecture that defines the main components of an intelligent entity. An intelligent being is a knowledge-based system that can collect and process data by perceiving its environment through various sensory organs. This system is involved in the process of interpreting perceptions, analysing them, solving problems, determining actions and performing tasks. Additionally, this entity can continuously improve the capacity and performance of its knowledge base, the source of intelligence it creates by learning from its new data, humans, other intelligent systems, and its own problem-solving experiences.

It cannot be said that every artificial intelligence system has all the components in Figure 1. Some existing species may have limited purposes, functions and capacities. For example, an internet user can contact an AI chat robot system to resolve some connection issues. This system may have advanced speech, natural language processing and reasoning capabilities, but may not have visual data processing capabilities. In contrast, a system that only has visual data sensing and processing capabilities may not have text and speech processing capabilities (Tecuci, 2011).

In recent years, as the use of AI in human-oriented applications has increased, the concepts of benefit-harm, ethical and legal dimensions have come to the fore. These concepts determine the operability and performance of the artificial intelligence system, as well as its interpretability. Because algorithmic decisions made by artificial intelligence systems may contain significant threats and put human lives at risk.

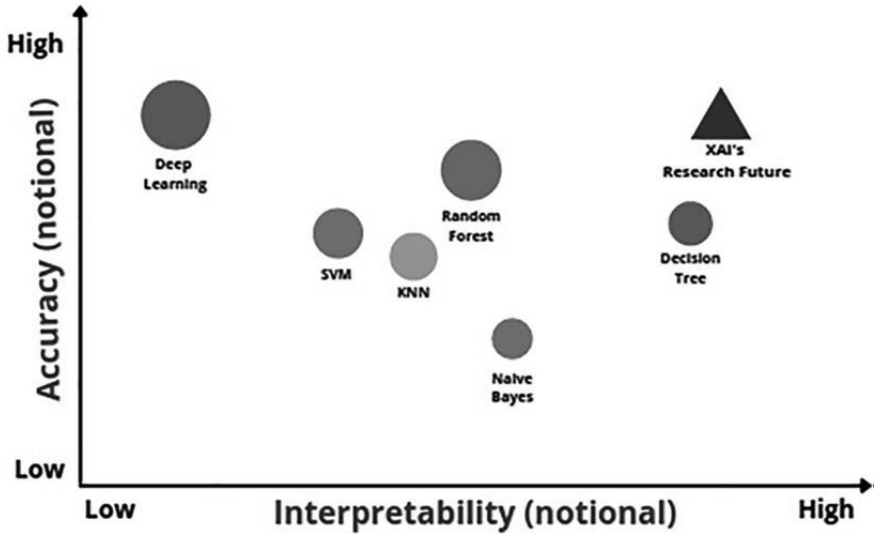


Figure 2. Comparison of Accuracy and Interpretability Rates of AI Methods (Angelov et all, 2021)

Figure 2 compares the accuracy rates and interpretability of AI methods. According to this figure, it is emphasized that an AI with a high level of accuracy can only be the subject of future research if it is at a high level of interpretability. The concept of interpretability is the clear and accurate expression of all aspects of artificial intelligence systems. This concept includes transparency in the purpose of creating an artificial intelligence, its data collection method, its learning model and all other aspects. In this way, people can establish the relationship between benefits and harms and make their usage preferences freely.

Artificial intelligence is divided into three types in terms of its historical development, capabilities and capacity criteria. These types are called Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI) and Artificial Super Intelligence (ASI). Among these types, only ANI applications can be seen yet. Others are still in the thought and planning stages (Girasa, 2020). The details of these types are as follows.

- *ANI:* It is the first type of artificial intelligence developed and has limited features and capacity. This is the type we see and use today. For examples; Google Translate, Chatbot, Apple Siri and IBM Watson.
- *AGI:* It is planned to be a system that can imitate the mental characteristics of humans and behave like them. Such systems are expected to learn in a short time and make the right decisions.

- *ASI:* It is considered as an intelligence that emerges as a result of a system with AGI, which exceeds it and exhibits high level learning ability, accurate predictions and superhuman skills.

2. AI Technologies

AI needs some basic components to exist in a system. These components come together and enable AI to work in a process. The first of these components is 'Big data'. Big data starts to be processed thanks to the 'data mining', that is the second component, and is made ready for the desired information extraction. The 'data processing', is the third component, now enables AI to identify, make sense of and associate the object with the help of data. The 'data analytics', is the fourth component. Data analytics (analysis) is a component that carries out the meaning-making, problem-solving and decision-making processes after processing the data. The 'learning', which is the fifth component, which makes sense of the provided big data, with the help of rules and algorithms, by transforming this input into output. Finally, the 'experiencing phase', which is the last component, in which the AI system solves a problem on its own.

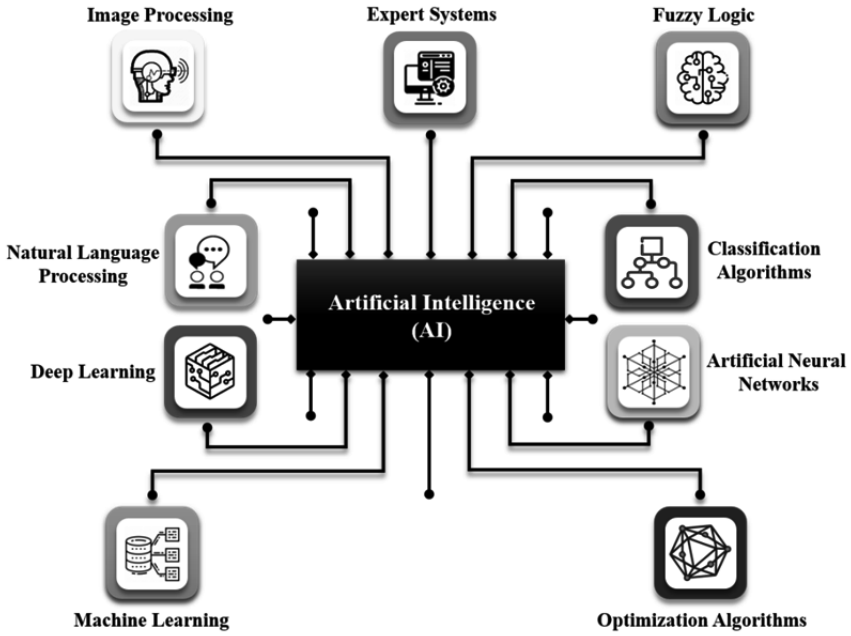


Figure 3. Best Known AI Technologies

Some AI technologies are used to ensure that the components of AI systems operate as a successful process. These technologies listed in Figure 3 are; Expert System (ES), Fuzzy Logic (FL), Classification Algorithms (CAs), Decision Tree (DT), Artificial Neural Network (ANN), Optimization Algorithms (OAs), ML, DL, Image Processing (IP) and Natural Language Processing (NLP).

These technologies make the artificial intelligence system operational through mathematical, logical, statistical and algorithmic methods. Artificial intelligence systems, developed with the aid of these technologies, can be found in various aspects of both business and personal life. This includes instances such as language translation programs, voice-activated televisions, intelligent robotic vacuum cleaners, web assistants, chatbot software, and self-driving vehicles. A detailed explanation of these technologies is presented in the sub-titles below.

2.1. Expert System

ES are software that digitizes the data used by artificial intelligence to solve existing problems and transfers it to the computer environment. ES can establish a cause-and-effect relationship during the problem-solving process with the help of expert knowledge and opinions. The first expert system is considered to be the MYCIN ES, developed by a group of doctors at Stanford University in 1970. MYCIN ES is still widely used in the healthcare sector in the diagnosis and treatment of some diseases (Buchanan & Smith, 1988).

The development and proliferation of ES are considered the first stages of AI and the first step in the AI industry. ES can solve certain problems by bringing human problem-solving expertise in many areas to the computer environment. ES in general; It is used in fields such as medical diagnosis, engineering design, military planning or intelligence analysis (Buchanan & Shortliffe, 1984).

While solving large and complex problems, the ES can solve the problem by decomposing it into sub-problems. This process is called ‘solving the problem by reduction and synthesis’. This type of solution method is also used for comprehensive tasks such as planning, designing and modelling. In this method, a problem is first reduced to simpler sub-problems from top to bottom. Then, solutions to these sub-problems are sought. Finally, the solution

to the original problem is tried to be obtained by combining these solutions from bottom to top.

A general structure of ES is given in Figure 4. ES consist of a block that includes the user interface, analysis engine and knowledge base. A feedback mechanism providing expert, user and external support is connected to this blog. Therefore, it is a system that works directly dependent on the user and the expert.

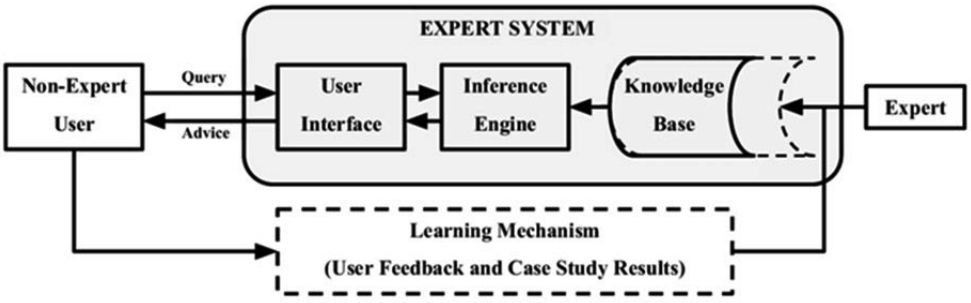


Figure 4. A Standard Expert System Architecture (Ozden et all., 2016)

ES does not have the ability to fully learn because it is fed from previous data in the knowledge base and sample solutions to the problem and works with the help of an expert. Therefore, they may fail when faced with a new situation or problem. According to Leondes (2002), the use of ES is generally concentrated in areas such as military, health, production, transportation and trade. Although Liao (2005) classified ES into 11 application-based categories, it is divided into 5 main categories. These categories are Rule Base ES, Knowledge Base ES, Neural ES, Fuzzy ES, Neuro-Fuzzy ES.

Although ES are examined in five different categories hybrid structure emerges by using more than one expert system in solving some problems. Nagori and Trivedi (2014) define hybrid systems as: 'an AI technology that emerges with the combination of two or more expert systems'. Then, they divide the hybrid ES into two types: Neural ES, and Neuro-Fuzzy ES.

2.2. Fuzzy Logic

Fuzzy Logic (FL) is a technology that tries to reveal the meaningfulness and accuracy of short, vague and complex expressions used in daily life. FL is used to make decisions about real-world problems, especially those that consist of uncertain, unreliable and fragmented information. It is possible to talk about two types of FL.

Representing some of the uncertainty, which is the subject of FL, with sets formed by numbers in the range (0, 1) is considered as Type-1 FL. However, for more complex and difficult problems where Type-1 FL cannot find a solution, Type-2 FL, which is an improved version of Type-1, is used. In cases where Type-1 FL methods cannot fully reveal the ambiguity of a language term, Type-2 FL methods come into play (Mittal et al., 2020).

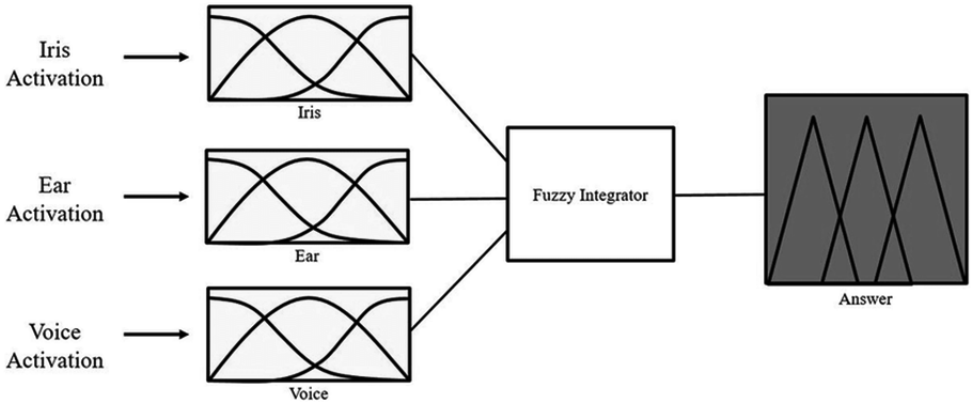


Figure 5. FL Architecture Used for Pattern Recognition (Melin & Sanchez, 2019)

Type-2 FL has a very strong ability to manage the dynamic parameters arising from the environment and the natural uncertainties found in the models. This situation is generally referred to as 'noise removal'. The example in Figure 5 shows a general process of pattern recognition based on three biometric data with FL methods. The usage architecture of both types of FL in pattern recognition problems is the same. Such applications are widely used for identification.

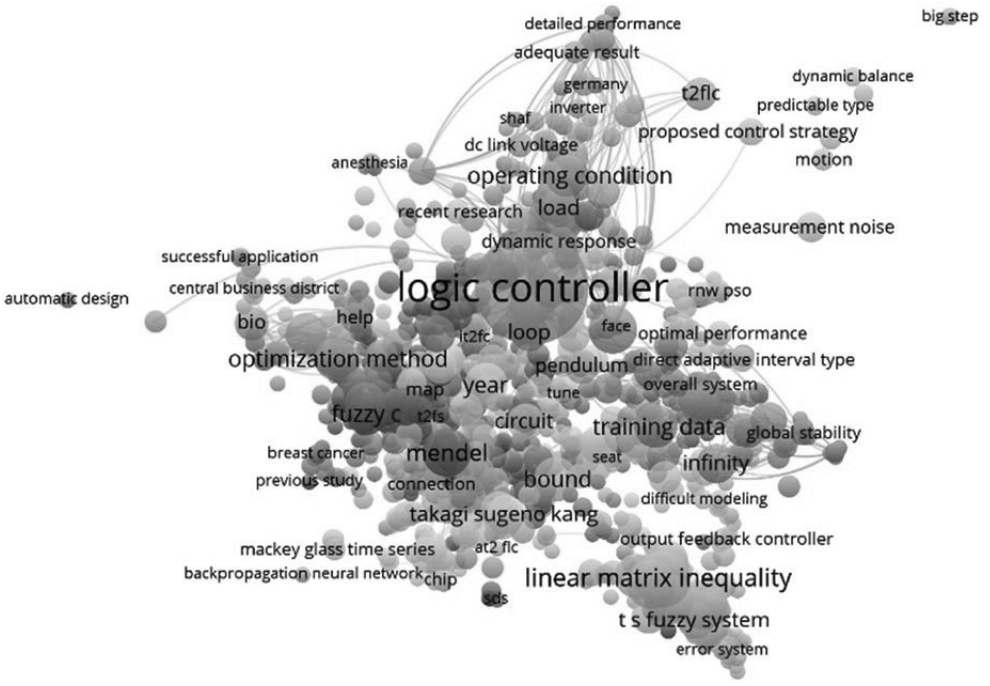


Figure 6. Keyword-based Literature Density Map of FL (Mittal, 2020).

According to Boolean Logic, a situation can be associated with 0 or 1. However, real-life problems can have countless possible solutions between 0 and 1. This uncertainty is called fuzziness. For example, in addition to hot and cold climate conditions in weather; It is possible to be in intermediate states such as warm, cool, very hot and very cold. These uncertain possible values fall within the scope of FL. Figure 6 shows the keyword-based density distribution of publications related to FL. According to this figure, it is possible to see research involving many topics such as logic control, optimization, operation status related to FL.

2.3. Classification Algorithms

Classification Algorithms (CAs) are classify data, objects and states within the scope of predetermined properties and rules. In the classification process, the probability of a new object falling into one of the specified classes and categories is calculated by CAs. CA produce an output by reflecting the information learned from the trained data onto the test data. This type of classification process is applied to many areas, especially text, speech and

image classification (Deniz, Erbay & Coşar, 2019). The main classification algorithms are Support Vector Machines, Naive Bayes, Decision Tree, Logistic Regression, Random Forest and K-Nearest Neighbours. Figure 7 shows the comparison of various classifiers in Scikit-learn on artificial datasets.

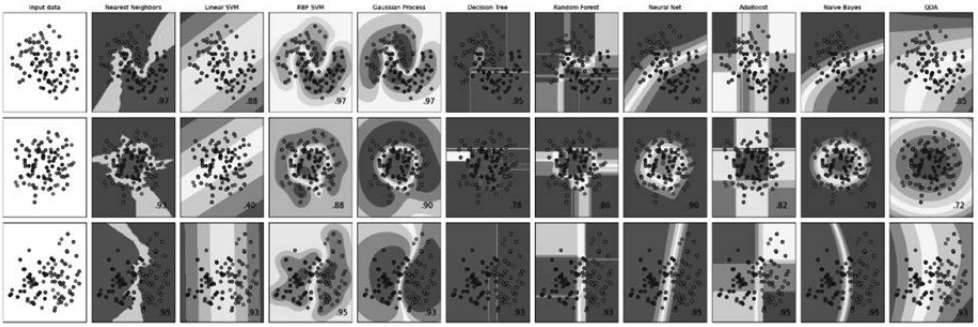


Figure 7. Analysis Comparisons of Sample Data Set with Classification Algorithms (Scikit-learn, 2023)

In particular, in multidimensional data spaces, data can be more easily analysed linearly. The performance of classifiers such as Naive Bayes and Linear SVM may be higher than that obtained with other classifiers. Below, the most known and used classification algorithms are briefly explained.

Random Forest: It is an algorithm that develops predictions by creating multiple independent decision trees on a randomly selected data subset. Different outputs are obtained from these decision trees. A method called "voting" is used to make the best prediction from these outputs. Given that each decision tree votes for an output class, Random Forest selects the class with the maximum votes as the final prediction (Sailasya & Kumari, 2021).

Logistic Regression: Also known as the logit model. It is a model that develops a classification and prediction based on a data set. This model calculates the parameter probability of a particular independent variable in the data set according to the dependent variables. As the regression value is based on a probabilistic calculation, the dependent variable can only take values between 0 and 1. In the regression calculation, the logit transformation method obtained by the ratio of success and failure probabilities is used. This calculation method is also called the natural logarithm of odds (IBM, 2023a).

Decision Tree: It is a non-parametric supervised learning method preferred for classification and regression purposes on a data set. A decision

tree created as a result of the analysis contains a single root node, branches arising from the root node, internal nodes belonging to the branches, and leaf nodes connected to these internal nodes. In this structure, internal nodes represent decision nodes and leaf nodes represent all possible outcomes in the dataset (IBM, 2023b).

Naive Bayes: It is an algorithm used to calculate whether a particular feature in one class of a classified data set is associated with any other feature. As a result, the situation of no relationship is revealed. It is based on Bayes' theorem. This algorithm is based on the principle that "each classified feature or attribute is independent of each other" (Zhang, 2004).

K-Nearest Neighbors: It is used to classify a data point in terms of features over the data set and to estimate its proximity to other points. It is used as a classification algorithm that calculates the degree of closeness of similar points to each other, usually with Euclidean distance. It is also used in regression problems (Cover & Hart, 1967).

Support Vector Machine: It is an algorithm used to determine a feature from the data set through classification and regression analysis. It has a supervised learning model. They are based on the logic of finding a hyperplane that separates different classes in a multidimensional space. The distance between the hyperplane drawn in the multidimensional variable space and the closest data points is called support vectors. These distances are used to define the hyperplane. This plane allows estimating the class of the point based on their distance (Cortes & Vapnik, 1995).

2.4. Artificial Neural Network

ANN is a network model that tries to define the relationship between data by taking the structural features of the human brain as an example. ANN has non-linearity, generalization, learning and decision-making stages. ANN is firstly based on neurobiologists' discovery of the working mechanism of the human brain. It is a mathematical method that models the information processing process of the biological central nervous system based on the logic of creating a network topology. Thanks to adaptive feature learning over the data set, ANN creates a rule by classifying models or examples among themselves according to the given inputs. In this way, it can achieve a good performance ratio between the expected output and the calculated output.

ANN consist of many interconnected computing units. This information processing unit is called artificial neuron. The biological neuron consists of three structures: cell body, axon and dendrite. The artificial neuron designed inspired by this structure; There are input nodes, multi-link weights, transfer function and activation function components.

ANNs are divided into three groups in terms of their network structure, number of nodes, intended use and other features. These are Deep Neural Network (DNN), Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN). Thanks to new DNN algorithms, objects on image recordings can be recognized and classified (IBM, 2023c)

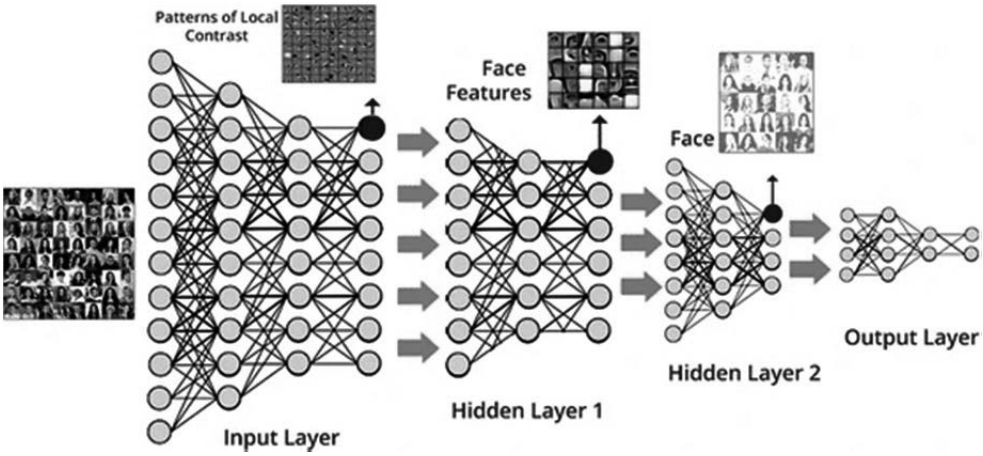


Figure 8. Deep Neural Network Model Used for Face Recognition Application (Grigsby, 2018)

Figure 8 shows an image recognition application processed with the DNN algorithm. The first step in the application; The raw image dataset is presented to the first neural network layer of the learning system. In this layer, classification and association of facial images are performed based on features such as color and brightness. In the second layer, which comes as a hidden layer, the components that make up the human face and their features are determined and fixed to the places they should be in the template. In the third layer, the second hidden layer, the correct face image will be found by comparing the face in the template with the facial expressions from the data set and will be transmitted to the output layer. Thus, the artificial intelligence system performs image processing over a layered network model. A few extra hidden layers can be added to the DNN layered model to increase the performance rate of such applications or to solve more complex problems.

2.5. Optimization Algorithms

OAs are programming that work in the architecture of finding the most suitable solution by searching through the data set. For this reason, it is widely used in optimization problems. Optimization algorithms are used to solve real-life problems that have arisen in many fields in recent years. It is especially suitable for calculating and recommending the optimum alternative solutions to problems that have high costs in terms of time, money and energy.

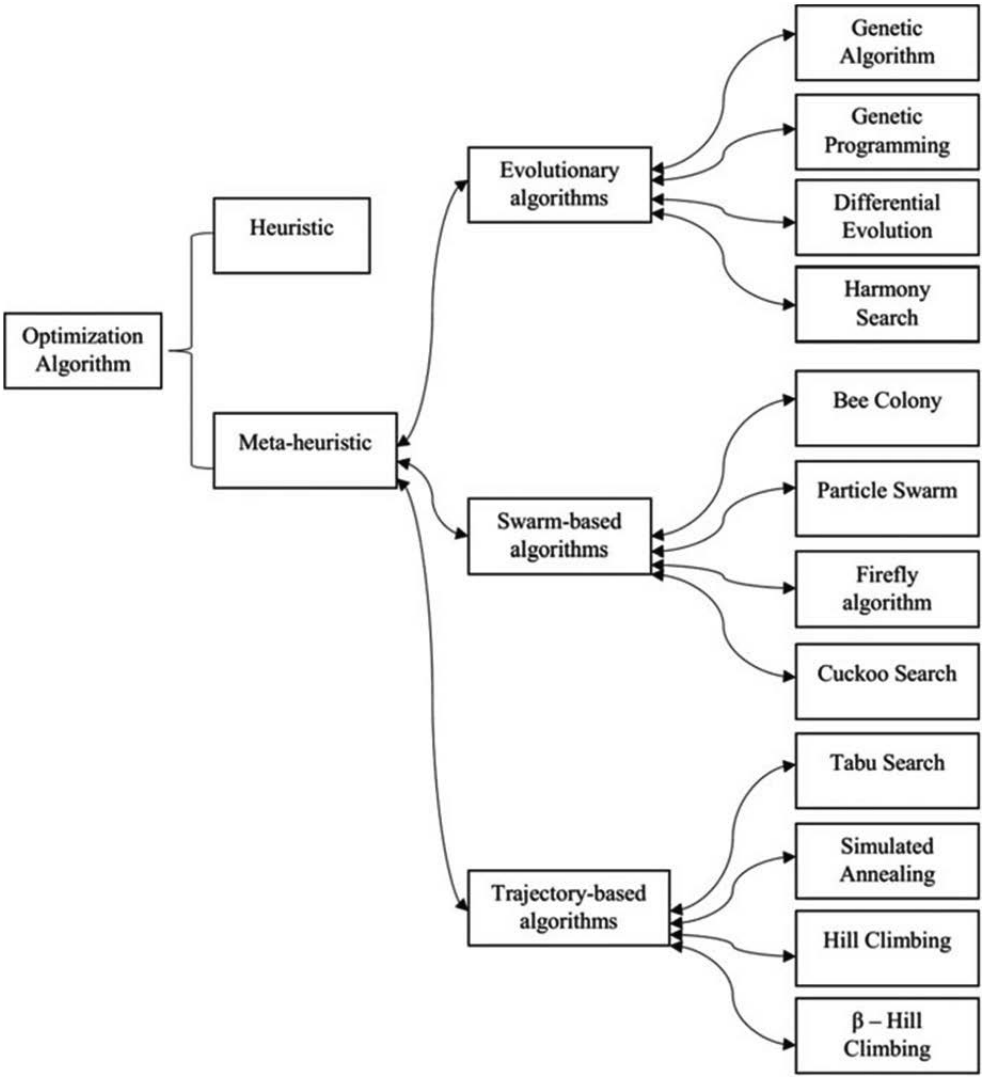


Figure 9. Optimization Algorithms (Das et al., 2020)

A list of algorithms used for optimization problems is given in Figure 9. When using these algorithms, determining the type of the problem and the data set structure is important. In some problems, more than one algorithm can be used to choose the one with the best accuracy. Das et al. (2020) suggest that one of the algorithms with the best accuracy in speech recognition problem is the Cuckoo Search.

Generally, a problem has an approximate or best-possibly exact solution. Algorithms that find the optimum solution to problems with approximate solutions are in two classes: heuristic and meta-heuristic. Examples of heuristic algorithms: Simulated annealing, Greedy approach, Beam search and A* algorithm can be shown. Meta-heuristic algorithms have subclasses as swarm-based algorithms (Bee colony, Particle swarm, Firefly algorithm, etc.), evolutionary algorithms (Genetic algorithm, Fitness search, etc.) and trajectory-based algorithms (Simulated annealing, Tabu search, Hill climbing, etc.) (Desale, Rasool, Andhale, & Rane, 2015).

OAs are algorithms that can provide near-optimal solutions in an acceptable time for large-sized optimization problems. Heuristic or meta-heuristic algorithms reveal techniques based on learning and discovery for problem solving. When a comprehensive solution is not practical, they find approximate solution by using heuristics. Heuristic methods contain rule sets, some conscious guesses, and the intuition to choose the most appropriate one among the guesses. Meta-heuristic algorithms, on the other hand, can make very few hypotheses about the solution of the optimization problem, but rather, they try to improve the solution with iterative calculations to find the ideal solution.

2.6. Machine Learning

People create concept maps that reveal the similarities and differences of data regarding any object and phenomenon, and learn by making inferences from these maps. In Machine Learning (ML) parameters are determined through the data set with the help of some algorithms, and learning occurs by calculating the weight of this parameters. Therefore, while humans learn by looking at the similarities and differences of features, an AI trained with ML learns through statistical calculations. In this context, ML is a learning method that enables learning from a data set and making predictions automatically for a task, directly and without the need for programming. Therefore, in the learning process, the aim is to sequence the steps, relate them to each other, establish a cause-and-effect relationship and reach the result. Then, after

solving a problem through analogy, this solution is transferred and adapted to new situations and problems.



Figure 10. 7-Step ML Process

ML is a core element of AI due to its advantages in terms of both learning and technology. The 7-step process in Figure 10 shows the processes that occur from the beginning to the end of machine learning. It should not be forgotten that the success rate of learning will increase when the appropriate model and algorithm is used in each step of this process.

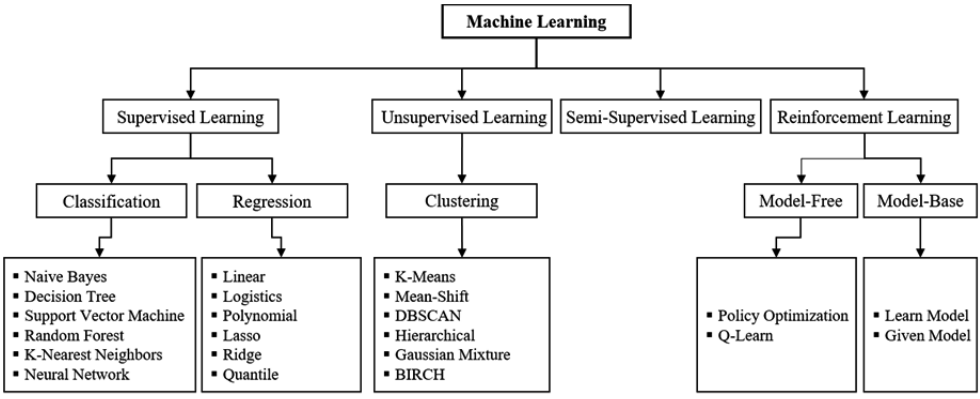


Figure 11. ML Methods

Figure 11 shows the classification of ML according to various parameters. These ML classification methods show some changes depending on the capacity of the data set, the type of problem and solution methods. Here, a separate machine learning algorithm is preferred if a probability-based calculation is to be made, while it is necessary to use a different algorithm if it is to be determined in which class the object or event will take place.

ML forms the basis of AI because the system can operate on its own, solve the problem with one of the previously learned solutions, and continuously learn. In general terms, machine learning is the process of making predictions and judgments on new data by learning rules and relationships from the old

data set with the help of some algorithms. This is a learning that enables the system to make decisions like humans (Wang, Fan & Wang, 2021).

2.7. Deep Learning

Deep Learning (DL) is the technology that enables turning the learning process of AI systems into human-like learning. While ML offers a single-layer learning model, DL offers a multi-layer learning model. DL is a slightly more advanced learning method than ML because it contains a programmable neural network. Thanks to this advantage, it can create outputs using various algorithms on the entire data set without any human intervention. DL is a machine learning technique that can create outputs using various algorithms on entire data sets without any human intervention. Its primary purpose is to teach the system to filter, classify, and make predictions on input in the plain text format, audio, and images.

It is estimated that over 2.6 quintillion bytes of unclassified digital data are created and circulated daily as people increasingly use digital world technologies (IBM, 2020). It does not seem possible for traditional computers to cope with this enormous amount of unclassified data and to draw conclusions from these. For this reason, DL, which becomes more efficient as the amount of data increases, consolidates its place among the rising trends. Because the more data it works with, the more precise and accurate the results become.

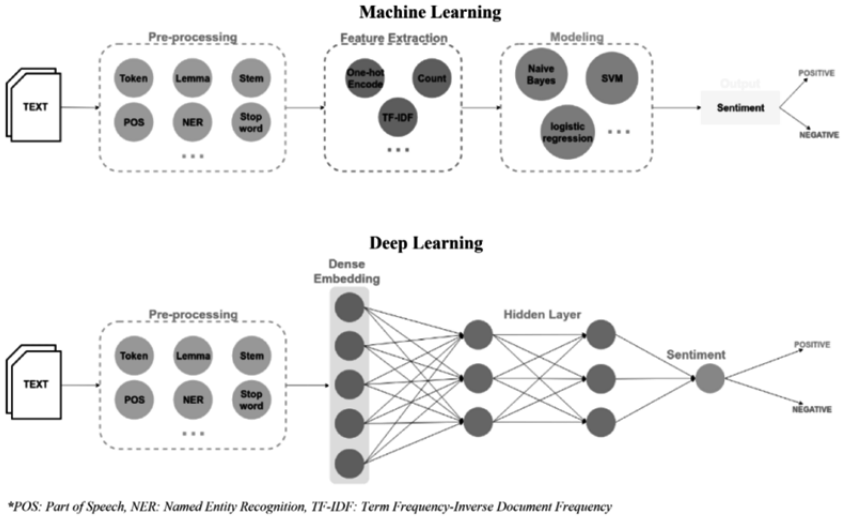


Figure 12. Difference Between ML and DL Architectures (Dang et al. 2020)

Figure 12 shows the differences between ML and DL approach in emotion polarity classification AI and DL are known as technologies that offer the best solutions in natural language processing, text classification, speech and image processing applications.

2.8. Natural Language Processing

Natural Language Processing (NLP) is an AI technology that analyses written or spoken words and sentences collected from the languages people use. The ideal example of this technology is chatbots. ChatGPT, which has been making a name for itself lately, is an advanced chatbot. ChatGPT can create its own data set on any subject and make meaningful definitions and comments within it.

People have been creating text files and storing them in digital environments for many years. Researching and revealing a topic from these text files requires a lot of time and effort. For this reason, extracting topics from large file stacks in a short time and easily has paved the way for the development of text mining and language processing technologies.

In the text classification process with NLP, four stages are applied from creating the data set to obtaining the output. These stages, seen in Figure 13, are respectively; creation of the data set, feature extraction, dimensionality reduction, classifier learning model selection and output evaluation.

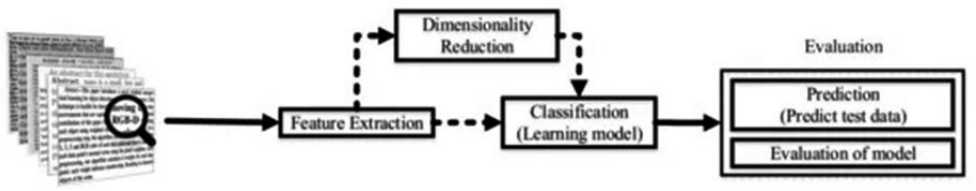


Figure 13. Stages of Text Classification (Kowsari et al. 2019).

The first stage of the system shown in Figure 13 is to give raw text data as input. In the second stage, this text data is divided into various levels such as plain text, paragraph, sentence and sub-sentence. Then, features are extracted from these separated structures. Meanwhile, in a sub-stage, the documents are cleaned of unnecessary words, spaces and other errors. Then, formal features

are extracted according to the usage intensity and categories of the words. In this sub-stage, which is referred to as dimension reduction, the process is continued by removing some of the features using various methods to save time and resources. In the third step, a learning model is run with classification algorithms. In the final stage, the learning outcomes and the model itself are evaluated. An estimated inference can be made based on the test data.

Speech recognition and processing is a slightly more difficult field than text classification. Because speech contains differences in pronunciation, accent and other personal characteristics. These differences make the process a little difficult. However, new techniques and methods can overcome this. The success of the speech recognition and processing process depends on creating a large data set, accurate labeling of sounds, and establishing a good training model.

Speech recognition and processing is a slightly more difficult field than text classification. Because speech contains differences in pronunciation, accent and other personal characteristics. These differences make the process a little difficult. However, new techniques and methods can overcome this. The success of the speech recognition and processing process depends on the creation of a large data set, accurate labeling of sounds and the establishment of a good training model.

Models in speech recognition can be divided into acoustic model and language model. The acoustic model describes the process of converting sound signals into some kind of phonetic representation. It includes frequency analysis and processing of the audio signal. The language model contains domain information about the vocabulary, grammar and sentence structure of the language. Hidden Markov models are considered the traditional speech recognition solution (Rabiner & Juang, 2006). Voice Assistants on mobile phones are one of the most well-known types of applications in the field of speech recognition and processing. Microsoft's Catana, Apple's Siri, Amazon's Alexa and Alphabet's Google Assistant use voice commands to receive, process, and respond.

2.9. Image Processing

Image Processing (IP) is a technology used to enhance an image, recognize image pattern, and image matching. (Huang, Schreiber & Tretiak,

1971). In the IP process, first the image data set is created and this set is digitized to be transferred to the computer. Then, the image begins to be processed with the help of some calculations and algorithms. The IP method is divided into several steps that include image acquisition and processing. These steps are given in stages in Figure 14.

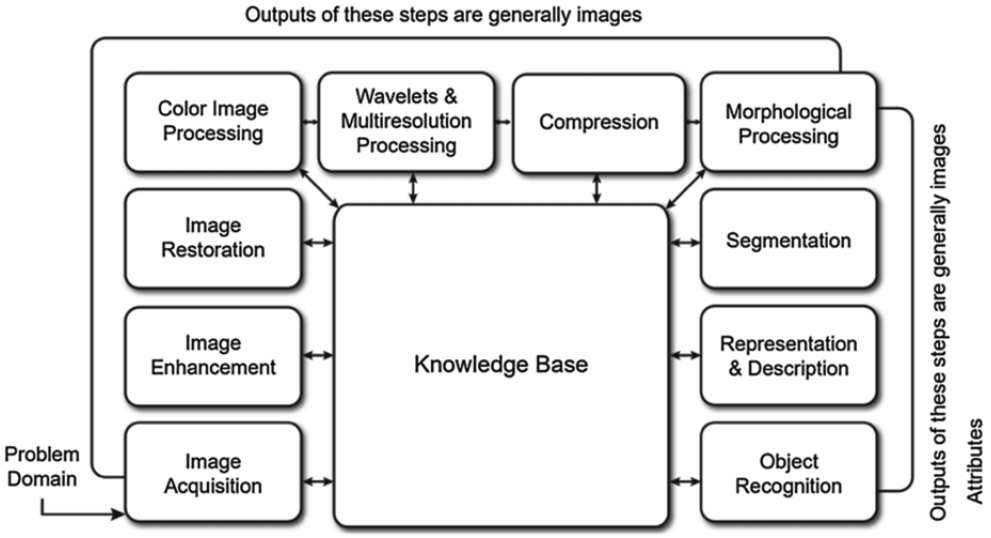


Figure 14. Image Processing Architecture (Gandhi, Kamdar & Shah, 2020)

It starts with the first step, which is obtaining and digitizing the image. The second stage is the enhancement of digital image data. In the third stage, the noise and errors on the picture are removed and restoration is done. At this stage, the contrast and brightness of the image are adjusted according to some parameters, highlighting important areas in the image. Then, the color processing of the picture, which is an important step, which is the fourth, begins. Thus, a color model of the picture is created. In the fifth step, the Wavelet method is used to obtain images at various resolutions. The sixth stage is the compression stage. At this stage, compression is applied to reduce the capacity of the image and increase the processing speed. The seventh step is Morphological Processing. This processing is used to identify important details from the image and define the object shape based on predefined features. In the segmentation phase, which is the eighth, the image is divided into multiple parts to identify individual objects in the image whose details are determined. The boundaries of each segment point are determined. Thus, the

resulting draft image is converted into a format suitable for later processes. In the description phase, which is the ninth, various features analysed from the image are brought together and described. Then, the scale, color and boundaries of the objects on the image are determined and the recognition phase, which is the tenth, begins. At this stage, a label is assigned to the image and the object in the image, using the data set and the output of the description stage. The last stage is the knowledge base stage, which is associated with all stages. This determines whether other details about the image are processed beyond a tagging process. Thus, object details and shapes are identified from the image (Gandhi, Kamdar & Shah, 2020). In the IP process, it should be noted that when there is an image with many edges, the system cannot fully process it. This makes it difficult to detect the objects in the picture.

A camera is required to digitize the image. Cameras usually have a frame grabber that converts the image from analog to numeric information. Numeric information is basic information that includes image size, color type, and intensity. Another important numerical information is the grey color values that define the brightness of each point in the image, called pixels. While the human eye can perceive a 5-bit (5-bit, 25 -between 0 and 64) image quite well, a digital image can process 8-bit grey color values (8-bit, 28 -between 0 and 256). However, there may be errors and distortions called 'noise' in the image. These artificial intelligence algorithms offer various methods to minimize these errors and distortions during image processing. For example, expanding the brightness scale by extending the histogram over the entire available range is the simplest way to improve the contrast of an image (Oberholzer et al. 1996).

CONCLUSION

AI is viewed by some people as a technology that will replace humans and even bring about the end of the human race. It is viewed by some people as a useful technology for society that can transform life and the world into a more liveable one. Therefore, it is not exactly known whether we should be afraid from or look at it as a more useful technology.

AI, from the level of simple computer game when it was first released, has now reached to a level where it can assist humanity. However, the transition

from the ANI level to an AGI level which is expected to result in the AI's combatting the real-world problems, has not been achieved yet. It seems that a lot of time and work is needed in order to reach this level. At the moment, it is believed that a lot of time, knowledge and experience is needed in order to rise the ASI up to a level that will turn it into a system that thinks, learns and creates just like the human intelligence does, and even exceeds it. In order to accelerate this process, the first condition may be that individuals, societies and states be ready for this change and its power. Then, AI researchers need to focus on some basic goals and objectives and put all their energy in this direction. Finally, the ethical and legal basis will need to be prepared to AI at the AGI and ASI level.

Although AI systems have produced successful results in recent years, following challenges need to be overcome to realize.

- Excessive speed, capacity and energy demands on the software and hardware side of computing systems are increasing.
- In order for the success rate to be high, the data set given as input must exceed a certain level in terms of number and capacity.
- After the artificial intelligence system is trained about an object, it is expected to produce successful results for similar objects. However, after the system learns, when it encounters different objects and events, it may not be able to establish a relationship and may give unsuccessful results. Therefore, the relevant learning ability needs to be developed.
- The instant real-time learning capabilities of an ANI level AI are very weak. Therefore, its use in situations with dynamic variables reduces performance.
- A task-based artificial intelligence has a low tolerance for instantaneous errors. If there is a solution to this error in its own knowledge base, it will be able to deal with the situation. Otherwise, it may not be able to cope.

As a result of eliminating these negative factors, the development of AI can be accelerated more easily. In particular, the coordination of the basic components such as data, users, software, hardware, applications and infrastructure that make up the cyber world will further accelerate this development. The point that should not be forgotten is that the principles of

confidentiality and security of information should not be neglected during the digitalization phase.

Another factor affecting the development of AI is the capacity of the technologies in which artificial intelligence is developed. Improving the number, features and capacities of these technologies will indirectly contribute to the development of AI. In this context, it is necessary to look at it from an interdisciplinary perspective and scientists working in these fields should focus on the same points.

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