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APPLICATION OF ARTIFICIAL INTELLIGENCE IN THE SECTOR OF INVESTMENT FUNDS

Undergraduate Thesis

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Zagreb, August 2019

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STATEMENT ON ACADEMIC INTEGRITY

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Abstract

Artificial intelligence is neither a new concept nor a completely new research topic. However, advances in data availability and accessibility of high computing power - combined with important achievements in the development of machine learning algorithms - have enabled an exponential growth of the field. By implementing artificial intelligence, investment fund management companies could see major benefits such as cost reduction and improved decision making across all of their departments. The main obstacles in leveraging artificial intelligence are data quality, lack of skilled personnel and maturity of existing technology infrastructure. In order to enable implementation of artificial intelligence in the investment funds sector, issues of auditability of machine learning models, bias of goal-directed models as well as potential implications for financial stability have to be properly addressed and regulated. Regulatory agency should aim to foster financial innovation, safeguard consumers and provide a simple and understandable regulatory framework at the same time.

Keywords: artificial intelligence, machine learning, investment funds, FinTech

1. Introduction

1.1. The aim of the paper

The purpose of this paper is to provide a comprehensive theoretical overview of the applications of artificial intelligence within the financial sector, with special emphasis being put on investment funds. The paper, therefore, aims to explain the many ways in which investment funds will be affected by rapid developments in the field of artificial intelligence and machine learning whilst covering the main opportunities and threats related to the implementation of these solutions from the perspective of consumers, financial corporations and regulatory agencies. The paper, moreover, examines the historical development of artificial intelligence and the main drivers behind its increasing applications to real world problems in recent years, as well as the specific challenges and risks for organizations which aim to implement artificial intelligence systems. The main focus of this thesis, building upon the aforementioned AI-related theory, are the implications of artificial intelligence applications to investment funds and the financial sector as a whole. Some of the important questions this paper thus addresses are the effects of improved efficiency of organizations on consumer satisfaction and access to affordable financial services, consequences of automation on the labor market within the financial sector, changes in the investment funds operations and increased profitability. Risks for the financial stability are also considered, as are the opportunities to utilize artificial intelligence in the regulatory and supervisory institutions in the financial industry.

1.2. Methodology

For the purpose of the thesis desk research methods were conducted, i.e. secondary data sources were used and further research was performed based on the available data. The sources include books and scientific articles from various databases, including Web of Science Core Collection and ProQuest Business Premium Collection. Furthermore, the paper used various resources available online, mainly official reports from international institutions as well as studies by research organizations, including business and management consultancy firms.

1.3. Structure of the paper

This paper consists of five main chapters. The first, introductory chapter serves to specify the aim of the paper, its methodology, the sources used upon conducting research, and to present the overview of the structure of the paper itself. The body of the thesis is divided into three chapters, with Chapter 2 examining the theoretical concept of artificial intelligence, Chapter 3 introducing the investment funds sector and finally Chapter 4 analyzing the applications of artificial intelligence in the investment funds sector. More specifically, Chapter 2 discusses increased scientific interest in the topic of artificial intelligence, describes its historical development in further detail, and examines different definitions and classifications of artificial intelligence in order to provide a concise theoretical overview of the field. Chapter 3 introduces the investment funds sector, covering the historical development of investment funds worldwide, the benefits of investing in mutual- and different types of investment funds, and an overview of the investment funds market both globally and in Croatia. Although Chapter 2 and Chapter 3 examine artificial intelligence and investment funds separately, Chapter 4 brings them together to address the main topic of the paper - the application of artificial intelligence in the investment funds sector. Different drivers of financial innovation are discussed, followed by an overview of current and potential applications of artificial intelligence in the investment funds sector. The main benefits and opportunities for leveraging this technology are further analyzed, as well as the challenges and limitations in implementation of artificial intelligence solutions. Risks and threats are not overlooked, as main issues and open questions when it comes to artificial intelligence systems are also presented in Chapter 4. Finally, Chapter 5 summarizes all of the key points of the thesis.

2. Artificial intelligence

2.1. Bibliometric analysis

Artificial intelligence (AI), although not a completely new discipline as will be discussed in the following chapter, has recently become an increasingly popular topic in the academic and business world. The developments in machine learning algorithms and, perhaps more importantly, the availability of data and accessibility of high computing power have enabled researchers and professionals to leverage artificial intelligence in order to solve a wide range of problems (Fliche and Yung, 2018). It is important and insightful to conduct the bibliometric analysis, as the research on artificial intelligence correlates with the developments in the field and subsequently its applications in the businesses across respective industries.

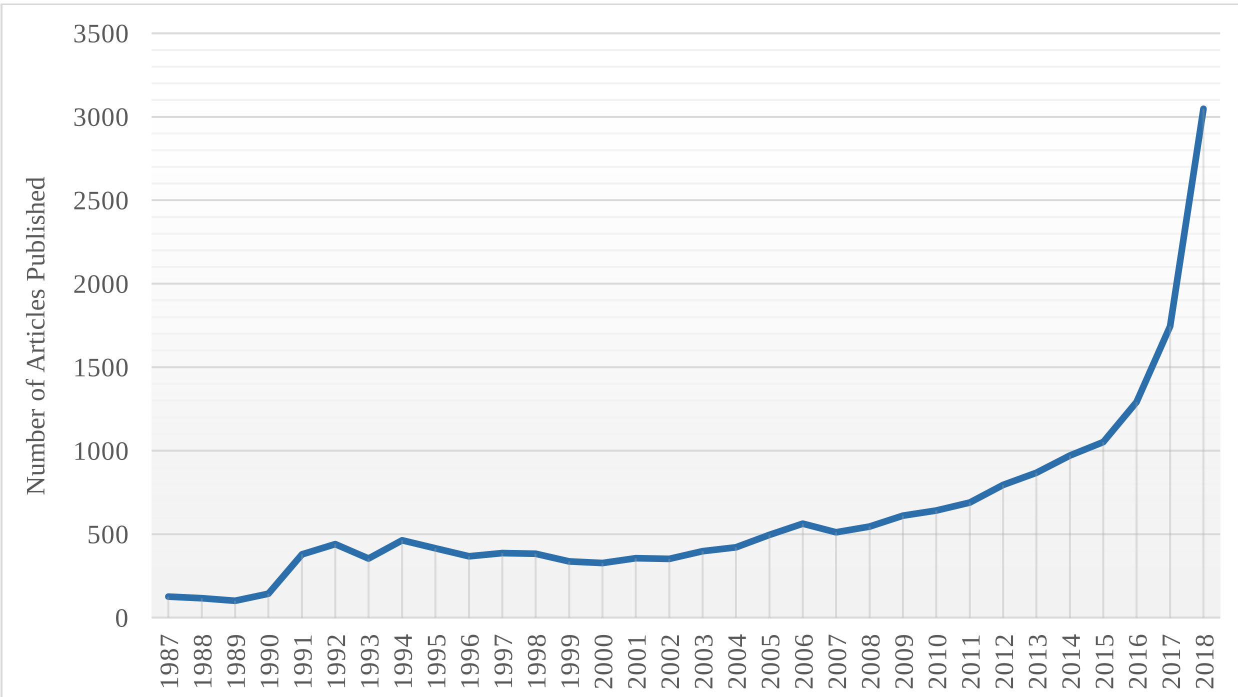
Figure 1 illustrates the exponential growth of published research on artificial intelligence which shows just how promising the field is. The first article with the topic of artificial intelligence[1] indexed in Web of Science was published in 1960, and only in 1987 did the number of articles published annually exceed 100. As can be seen from Appendix 1, it took researchers an additional 28 years to reach the 1,000 published papers in 2015, when the topic of artificial intelligence really starts to attract academic interest with more than 3,000 papers published in 2018. Moreover, the field of artificial intelligence, initially reserved for researchers specializing in computer science and applied mathematics, has increasingly become more of an interdisciplinary field of study. The table in Appendix 2 shows how scientific articles on artificial intelligence are distributed by subject category[2]. Although computer science and engineering still dominate the field, other scientific disciplines are becoming more involved in research. The fields of operations research, management, economics, and business are expanding their interest in artificial intelligence and applications of machine learning in their respective areas of research. However, the field of finance

[1]Articles indexed in Web of Science Core Collection with the topic of artificial intelligence. More specifically, the term “artificial intelligence” is included in the title, abstract or keywords of the article.

[2] Articles indexed in Web of Science Core Collection; articles can be classified in more than one subject category; number includes articles in all periods, date of data extraction 2019-08-27

seems to still be lagging behindwith less than 100 papers published with the topic of *business finance* as a subject category.

Figure 1 Number of Published Scientific Articles with the topic of Artificial Intelligence Indexed in Web of Science: distribution by years



Source: author's work based on Web of Science Core Collection data

2.2. Historical development

In order to fully comprehend the application and importance of contemporary artificial intelligence, one must first take a detailed look at its historical development. Indeed, artificial intelligence as we know it today stems from numerous recent events, yet its fundamental principles and rudimentary ideas date back to the Homeric Age itself – some 3000 years ago. As Nilsson (2009) points out in his book: "People have long imagined machines with human abilities – automata that move and devices that reason. Human-like machines are described in many stories and are pictured in sculptures, paintings, and drawings". These ideas have first been recorded in ancient Greek literature and have subsequently motivated many great historical figures – artists and scientists alike – to expand upon them, thus shaping the entire field in what it ultimately is today.

Arguably the oldest known story of something resembling artificial intelligence may be found in Homer's epic poem *Iliad*, whereby the author describes self-propelled chairs called "tripods" and golden "attendants" constructed by the blacksmith god Hephaestus. Having been born lame and thus unable to walk, Hephaestus created a set of handmaidens – all of whom possessed advanced reasoning and physical strength – to help him in his forge. Hephaestus was, supposedly, also responsible for the first "killer robot" named Talos: a mechanical bronze colossus which patrolled the shores of Crete, throwing massive boulders at potential invaders (Nilsson, 2009; Cave and Dihal, 2018). The ancient Greek philosopher Aristotle further touched upon the concepts of automation and artificial intelligence, weaving together the insights and fears of early Greek tradition with the careful analysis and methodological approach that have become standard in modern science. In his work *The Politics*, for example, Aristotle dismisses Homer's "tripods" as overambitious inventions that are ultimately impossible to construct and implement in Greek society (Nilsson, 2009). His main contribution to the field of artificial intelligence, however, comes through *Physics* – a collection of treatises that define "the philosophy of nature itself". Aristotle distinguished between the *matter* and *form* of things: a sculpture is fashioned from the *material* (*matter*) bronze and takes the *form* of a human. Change – the most fascinating aspect of nature according to Aristotle – occurs when the said sculpture is molded into a new form. This simple distinction ultimately provides the philosophical basis for modern notions such as symbolic computing and data abstraction. Differentiating between the form and the medium of its representation not only allows these forms to be manipulated computationally, but also supports the idea of artificial intelligence (Luger, 2009).

As Greece's power and influence slowly started to decline, the West entered a new millennium in which the skills of automation-making were lost, along with the hopes and ambitions associated with them. The ideas of mechanical beings and artificial intelligence did survive, however, having been preserved within the Byzantine Empire and the Arab world during those centuries. Often associated with the "exotic" and "infidel" East, automata were viewed with great suspicion – only to be rediscovered once more by Western philosophers during the 13th century (Cave and Dihal, 2018). Automata began appearing at courts as showpieces designed to impress visitors. Leonardo da Vinci himself sketched designs for a humanoid robot in the form of a medieval knight around the year 1495: this artificial knight was supposed to be able to sit up, move its arms and legs, turn its head, and open its jaw (Nilsson, 2009). Indeed, it was Renaissance thought, building upon ancient Greek tradition, that initiated the evolution of a different and powerful way of thinking about humanity and its relation to the natural world. Over the course of four centuries these ideas were further expanded upon and refined, with the seventeenth and eighteenth centuries witnessing a great deal of discussion on epistemological issues[3]. The most prominent and influential philosopher of the time was certainly René Descartes, whose theories greatly influenced the development of modern concepts of thought and theories of mind. In his *Meditations*, Descartes sought out to find a basis for reality purely through introspection. By rejecting the input of his senses as untrustworthy, Descartes was ultimately forced to doubt the existence of all physical things, instead relying purely on thought – even when it came to his own existence. This duality between the mind and the physical world underlines all of Descartes's thought, including his development of analytical geometry (Luger, 2009). One should note that Descartes's *mind*/*body* discussion is quite similar to that of Aristotle's *matter*/*form* one. Indeed, this is a reoccurring theme within this chapter and, according to Luger (2009), one that is essential for understanding artificial intelligence. According to the author, there are two main consequences of such an analysis:

1. By attempting to separate the mind from the body, Descartes and other related thinkers established that the structure of ideas about the world were not the same as the structure of their subject matter. This, in turn, underlies the methodology of artificial intelligence: mental processes have an existence of their own, follow their own laws, and may be studied on their own, irrespective of any physical components.

2. Once the body and mind have been separated and properly analysed, philosophers find it necessary to reconnect the two. The interplay between the mental (*res cognitas*) and the physical (*res extensa*) form an essential component of human existence.

[3] Defined narrowly, epistemology is the study of knowledge and justified belief. Since knowledge itself is at the very core of epistemology, the field aims to answer the following questions: What are the necessary and sufficient conditions of knowledge? What are its sources? What is its structure, and what are its limits? (Steup, 2018).

When looking at the historical context behind contemporary AI development, one can clearly see that early philosophers vastly contributed to our understanding of the *mind*, or, in later centuries, knowledge itself through epistemology. Yet for AI to truly function as a whole, one still requires a *body*. It was not until the advent of the computer, however, that artificial intelligence received a proper "physical engine" – one that could properly demonstrate intelligence. The development of a modern, digital electronic computer began almost simultaneously in three different countries during World War II, with the first operational model being accredited to Alan Turing. These early contraptions were used exclusively by British intelligence officers to decipher encrypted German messages, but by the end of the war in 1945 the *Colossus*[4] had already entered into everyday use (Russell and Norvig, 2009). Indeed, by the turn of the decade, computers had demonstrated their potential to provide sufficient processing power and capacity needed to run even more complex and intelligent programs: demonstrating intelligence had thus become a reality, further fuelled by the adoption and subsequent implementation of formal reasoning systems (Luger, 2009). This major milestone – one that effectively delivered the needed symbiosis between the mental and the physical – marked the beginning of modern AI development.

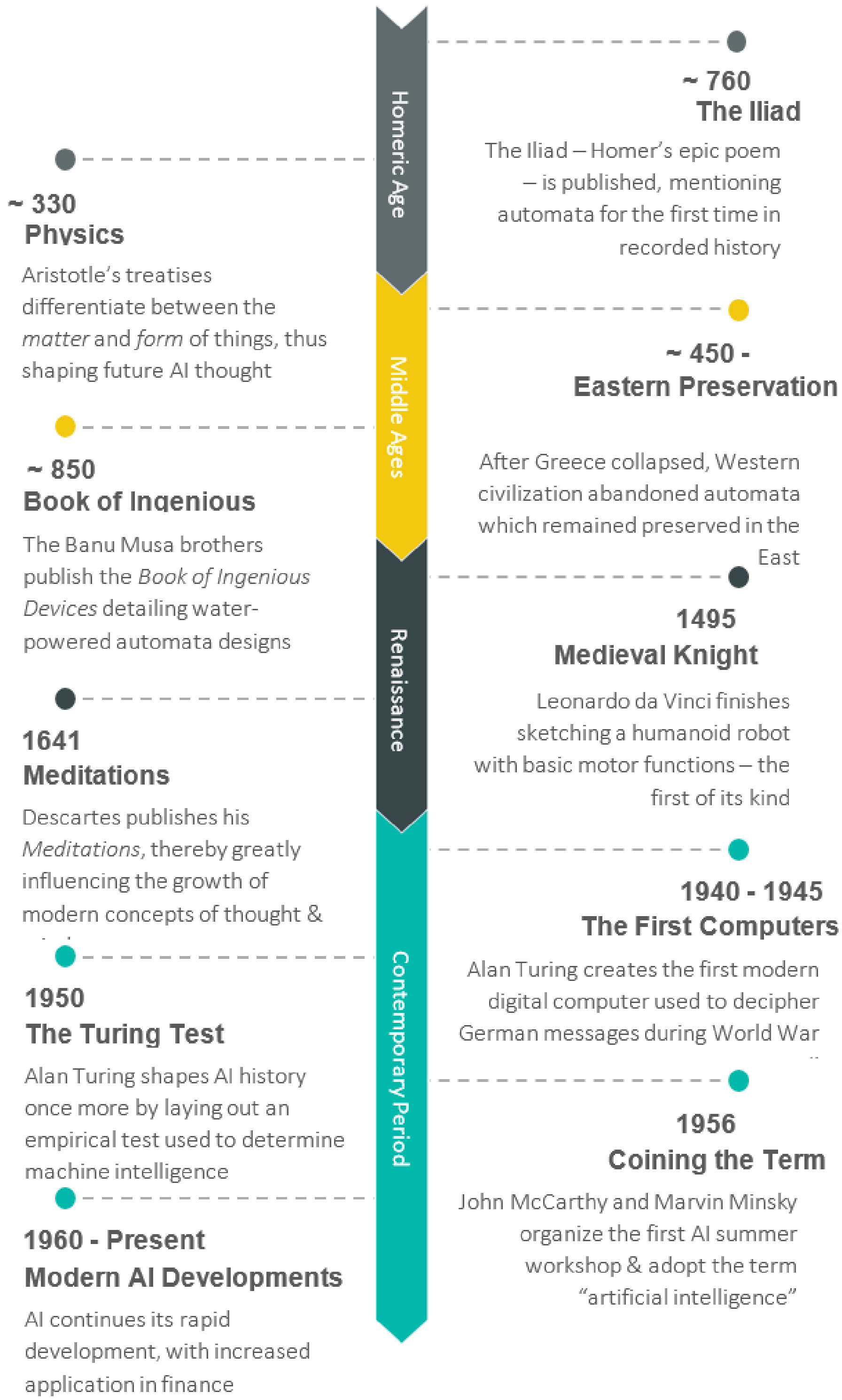
The first truly contemporary research on what is now commonly understood as *artificial intelligence* began in 1955 with two American scientists: John McCarthy and Marvin Minsky. McCarthy – having just graduated from Caltech – joined Dartmouth College in Hanover, New Hampshire, as an Assistant Professor of Mathematics. While at Dartmouth, he was invited to spend a few months at IBM's Rochester Information Research Department in Poughkeepsie, New York. During his time at IBM, McCarthy persuaded Minsky – then a Harvard junior fellow in mathematics and neurology – to join him in organizing a workshop at Dartmouth, one that was to be called a "Summer Research Project on Artificial Intelligence". Plans for the workshop were laid out in 1955, with the event taking place during six weeks of summer in 1956 (Nilsson, 2009). The workshop ended up having ten attendees in total, including Trenchard More from Princeton, Arthur Samuel from IBM, and Ray Solomonoff, as well as Oliver Selfridge, from MIT. Although the workshop did not lead to any major advancements, it did connect the major figures to one another, thus fundamentally altering the academic landscape for decades to come. The following

[4] *The Colossus* was effectively the second generation of Turing's wartime message-deciphering computers, built in 1943. It utilised vacuum tubes (as opposed to electromechanical relays found in Turing's first machine) in order to decipher more complex messages with greater efficiency (Russell and Norvig, 2009).

20 years were undeniably dominated by these researchers and their colleagues from MIT, CMU, Stanford, and IBM. The most significant – and lasting – thing to come out of this workshop, however, was a simple agreement (proposed by McCarthy himself) to formally adopt a new name for the field: artificial intelligence (Russell and Norvig, 2009).

Five years prior to McCarthy's and Minsky's historic and field-defining workshop on AI, another exceedingly important milestone took place – one that still influences artificial intelligence thought to this very day. Alan Turing, the aforementioned inventor of the first digital electronic computer, had only begun to tap into their potential after World War II. Turing reasoned that computers had the theoretical capability to do anything – even fully mimic human intelligence (Nilsson, 2009). This led him to publish *Computing Machinery and Intelligence* in 1950: a paper which tried to answer the question of whether or not a machine could actually be made to think. In order to avoid focusing on ambiguous questions (i.e. what constitutes a machine?; What is thinking?), Turing devised an empirical test that would replace the question of intelligence altogether; one subsequently dubbed *The Turing test*. This test measures the performance of a machine against that of a human – arguably the best (and only) standard for intelligent behavior. The test itself is simple: one human being and one machine are placed in individual rooms separate from the one where a second human being – often called the *interrogator* – is currently located. The interrogator is thus completely isolated and is unable to see or speak to either the machine or to the other human. Moreover, the only method of communication available to the interrogator is a textual device (terminal) located within the room. The interrogator is then asked to communicate to both entities via the terminal. The interrogator's ultimate goal, moreover, is to distinguish between the human and the machine solely based on their answers: if the interrogator is unable to achieve this task, then the machine is assumed to be intelligent (Luger, 2009). No single article in computer science – and, indeed, in academia itself – has generated so much controversy and discussion following its publication (French, 2000). The field of AI, although still highly influenced by Turing's theories, has gradually shifted its focus away from human interaction and towards reasoning patterns that are not necessarily based on human models (Russell and Norvig, 2009). Such contemporary AI models are further discussed within this paper, with special focus being put on their application in the financial funds sector. Artificial intelligence's historical development is further summed up in Figure 2 below:

Figure 2 Historical Development of the concept of Artificial Intelligence



Source: author's work based on various sources

2.3. Definition of Artificial Intelligence

As was discussed in the previous Chapter, the modern understanding of artificial intelligence originates with Alan Turing posing the question "Can machines think?" (Buchanan, 2019). Turing (1950) realized that definitions of terms *machines* and *to think* can lead to ambiguity, thus the famous Turing test's goal of answering the question by imitating humans, rather than by considering the definitions and the underlying problem. The term Artificial Intelligence was coined by John McCarthy in 1959 (Buchanan, 2019). The definition professor McCarthy used describes artificial intelligence as "the science and engineering of making intelligent machines". By intelligent machines, McCarthy was referring to "the computational part of the ability to achieve goals in the world" (McCarthy, 2007). This explanation again raises the question whether there is a definition of intelligence (or thinking) which doesn't depend on relating and comparing it to human intelligence. McCarthy (2007) states that that there is no such definition of intelligence, but adds that this doesn't mean that artificial intelligence is only about simulating human intelligence.

The contemporary definitions of artificial intelligence seem to fully rely on the concept of human intelligence. Kaplan (2016) defines artificial intelligence as "The theory and development of computer systems able to perform tasks that have traditionally required human intelligence". The Financial Stability Board (2017a) defines artificial intelligence broadly as "the application of computational tools to address tasks traditionally requiring human sophistication". The European Commission (2018), moreover, firstly proposed the following definition: "Artificial intelligence (AI) refers to systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals". The definition goes on to specify that artificial intelligence can be software-based or embedded into a certain hardware equipment (European Commission, 2018). However, the European Commission set up an independent High-level Expert Group on Artificial Intelligence consisting of 52 members from academia, civil society and industry which introduced an updated definition of artificial intelligence systems as "software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal“ (High-Level Expert Group on Artificial Intelligence, 2019).

2.4. Taxonomy of Artificial Intelligence

In order to fully grasp the (many) definitions of artificial intelligence, it is equally important to explore the taxonomy of this field. Although it seems they are converging, there are still many different definitions of artificial intelligence, many of which are used interchangeably by researchers, professionals and the media. These discrepancies in the definitions reflect diverse perspectives and different priorities and values of authors. As was discussed beforehand, although our understanding of the technical aspects of artificial intelligence increased during the last decade, the underlying principles of what artificial intelligence is and should be has not changed significantly. In order to fully comprehend the topic, it is important to get a firm grip on the many different aspects of artificial intelligence that authors often emphasize in their definitions, and to subsequently explore the different classifications of artificial intelligence.

2.4.1. Classifications according to the level of independence of AI

Russell and Norvig (2009) recognize some of the categories of artificial intelligence by highlighting eight distinct definitions classified into four categories based on what machines are able to achieve: Thinking Rationally, Acting Rationally, Thinking Humanly and Acting Humanly. Firstly, the definitions within the Thinking Rationally category consider the computations on logically expressed problems. Rao and Verweij (2017) call these type of algorithms assisted intelligence. It is used for automation of manual and routine tasks and the machines do not learn from interactions. Although solving these kind of problems does not require algorithms we currently classify as artificial intelligence, all problems could theoretically be expressed in a logical format. The real-world problems, however, are not easily translated to formal terms and computational power to solve more complex problems makes this approach inefficient. Moreover, the inputs in terms of data are often uncertain and incomplete which makes the problem unsolvable using solely this approach (Russel and Norvig, 2009).

The definitions in the Acting Rationally bucket require much more from the machine than just solving a perfectly framed logical problem. Software is expected to act as a rational agent and to "operate autonomously, perceive their environment, persist over a prolonged time period, adapt to change, and create and pursue goals" (Russel and Norvig, 2009). This approach is most similar to the field of operations research today, as it seeks to find a perfect solution given the constraints. Rao and Verweij (2017) name these sort of systems automated intelligence. Machines can automate even the cognitive and non-routine tasks, but only ones which do not require learning about new ways of performing tasks. However, the issue is the same as for the first approach - most of the problems encountered by organizations are too large and complex which points to a limitation in terms of computational capacity. The field of economics teaches us that in the world of scarce resources there will never be enough time to always find a perfect decision.

This leads us to Thinking Humanly definitions. This set of definitions, also known as cognitive modelling approach, combine the artificial intelligence algorithms with experimental techniques from psychology in the interdisciplinary field of cognitive science (Russel and Norvig, 2009). Rao and Verweij's (2017) equivalent is augmented intelligence – AI systems augment human decision making process and continuously learn from their interactions with humans and the environment.

Even though the idea of making machines think in the same way as humans do captures the essence of artificial intelligence as discussed in the previous chapters, the most demanding definitions of AI lie in the category of Acting Humanly. Machines should be able to pass what is known as the total Turing test to be classified into this category of AI definitions, which reveals the array of contemporary sub-fields of AI which should, if put together, aspire to fall under this set of definitions: natural language processing, knowledge representation, automated reasoning, machine learning, computer vision and robotics, some of which are now known as sub-categories of artificial intelligence (Russel and Norvig, 2009). Rao and Verweij (2017) call this ultimate version of AI autonomous intelligence – AI systems can adapt to different situations and can act autonomously without human assistance.

2.4.2. Difficulties in classification

There are two important considerations to keep in mind when discussing the definition and taxonomy of artificial intelligence. Firstly, not only is there no generally accepted definition of intelligence, the scope of what artificial intelligence is seems to change dynamically with the advances of the field. The Tesler's theorem[5] stating that artificial intelligence encompasses "whatever hasn't been done yet" is indicative of this (Allas et al., 2018). Secondly, the developments in the field of artificial intelligence are often mistakenly not attributed to the field, but rather claimed by different research topic due to the interdisciplinary nature of the field. Lastly, the applications of artificial intelligence usually take advantage of many distinct domains of artificial intelligence, which makes it even more difficult to properly and clearly differentiate between sub-categories of artificial intelligence (Allas et al., 2018).

2.4.3. Weak and strong AI

Another distinction which has to be made when explaining artificial intelligence is the one between narrow or weak artificial intelligence and general or strong artificial intelligence. The High-Level Expert Group on Artificial Intelligence (2019) clarify that strong artificial intelligence should be able to replicate most of the actions humans are able to perform. General artificial intelligence is still only a theoretical concept as technology has not yet advanced so far. This does not mean it should not be discussed, however. On the contrary, many successful and influential professionals and entrepreneurs warn that governments should regulate general artificial intelligence. However, the focus of this paper is weak or narrow artificial intelligence. Narrow AI focuses on specific tasks and solves them separately, and this is where the recent development of artificial intelligence is most visible (High-Level Expert Group on Artificial Intelligence, 2019).

2.4.4. Machine Learning

The most important field of artificial intelligence when it comes to application of algorithms is machine learning. Arthur Samuel coined the term Machine Learning in 1959 (Buchanan, 2019) following his article "Some Studies in Machine Learning Using the Game of Checkers". Smith used the following definition for Machine Learning: "a field of study that gives computers the ability to learn without being explicitly programmed" (Puget, 2016). Another influential author, Tom Mitchell, describes Machine Learning as "the study of algorithms that allow computer

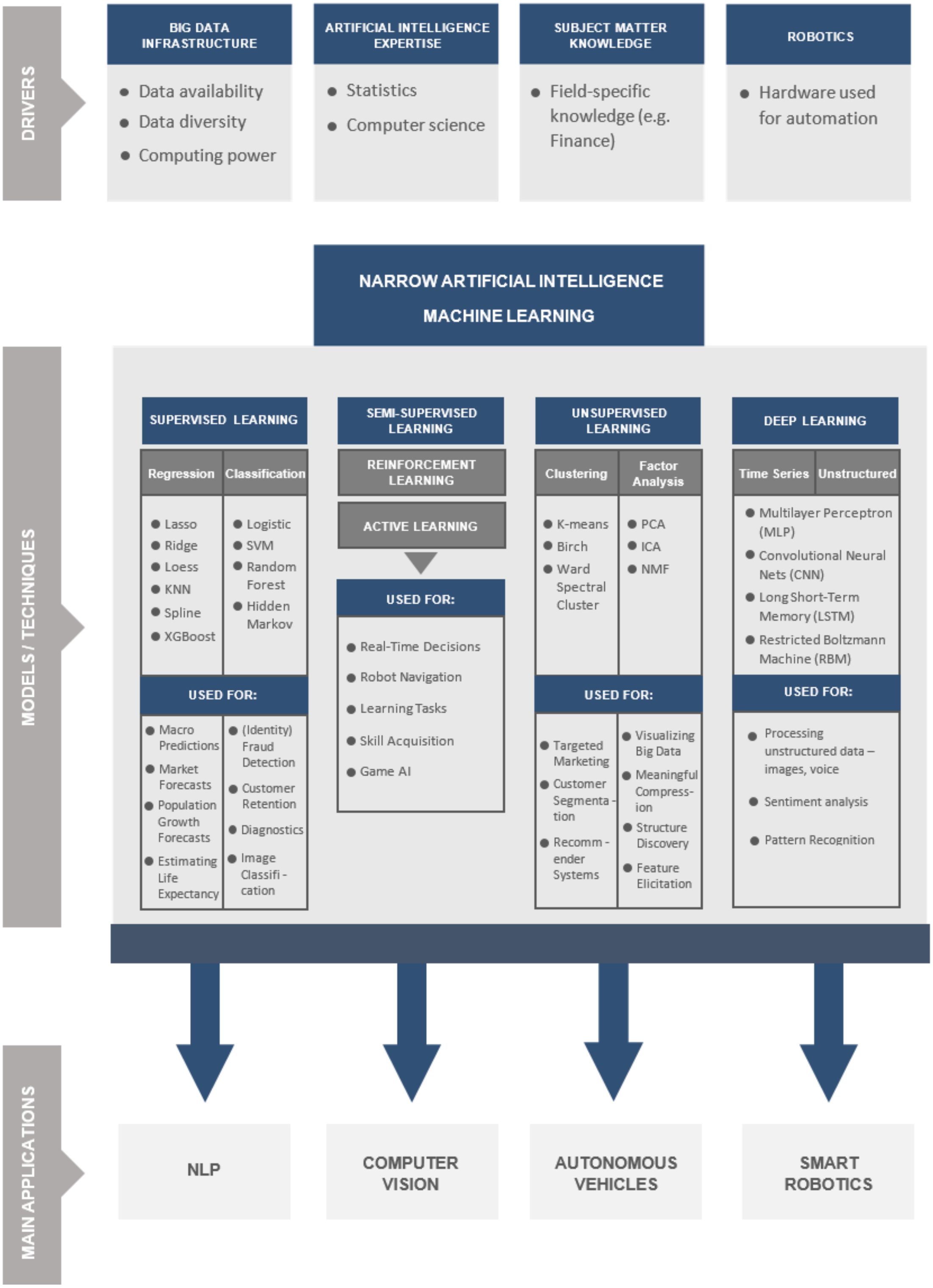
[5] Tesler's theorem is a quote attributed to Lawrence Gordon Tesler

programs to automatically improve through experience” (Mitchell, 1997). Both of these imply that a certain software is to solve a set problem with limited to no human intervention.

As illustrated in Figure 3, Kolanović and Krishnamachari (2017) classify Machine Learning into Supervised Learning, Unsupervised Learning, Deep Learning and other approaches such as Reinforcement Learning. Supervised Learning algorithms depend on dataset used for training the model containing a portion of the observations, usually historical data with both input and output variables (Kolanović, Krishnamachari, 2017). Intelligent agent then learns a function used to get from a set of input variables to outputs (Russell, Norvig, 2009). Unsupervised learning algorithms go one step further. Instead of observations in input-output pairs, the agent is given entire dataset without explicitly labeled dependent and independent variables (Financial Stability Board, 2017a). In reinforcement learning algorithms agents get more information than in unsupervised learning, but less than in supervised learning. Agents firstly get only unlabeled data as an input, but are also receiving feedback in form of rewards or reinforcements which support agent in learning (Russell, Norvig, 2009). Deep learning algorithms mimic the functioning of human brain by passing the data through multiple layers of artificial neural network (Kolanović, Krishnamachari, 2017).

There are many other classifications of artificial intelligence which can also aid better understanding of the field, but most of them are variations of the taxonomies explored in this chapter. To summarize, artificial intelligence applications mostly use a different combinations of following functions: pattern detection, forecasting, customization and categorization, decision-making and interaction with humans (McWaters et al., 2018).

Figure 3 Drivers, Taxonomy and Applications of Artificial Intelligence



Source: author's work based on HLEG (2019), FSB (2017a), Kolanović and Krishnamachari (2017) and other sources

3. Investment funds

3.1. History

The first investment fund in the world dates back to 1774, when it was established by a Dutch merchant Adriaan van Ketwich in Amsterdam (Mosselaar, 2018). The fund's motto was encapsulated in its name Eendragt Maakt Magt, which translates to Unity Creates Strength, already reflecting some of the positive aspects of investing in mutual funds. After the banking crisis in 1772-1773 in London and Amsterdam caused by the decline in the stock price of the famous English East India Company, investors became more cautious and aware of the risks associated with investing in stocks and bonds. With this in mind, Ketwich set up a closed-end fund which enabled small investors to invest in a diversified portfolio of bonds (Mosselaar, 2018). Since Eendragt Maakt Magt had types of investment classes specified in its prospectus, and because it had very low management fee of 0.2%, it could be considered as a passive investment fund. After the initial success of the first fund, Ketwich went on to open two new funds by 1799. They are important because the latter fund - introduced in 1776 by bankers in Utrecht - defined a possibility to invest a portion of assets in Eendragt Maakt Magt, which is considered as a fund-in-fund investment today. His third fund, Concordia Res Parvae Crescunt founded in 1799, is equally important to note as its prospectus stated that the fund would invest in undervalued securities, trading below their intrinsic value, which makes Concordia Res Parvae Crescunt the first actively managed fund lead by the same principles as some of the most successful and best-known funds today (Mosselaar, 2018).

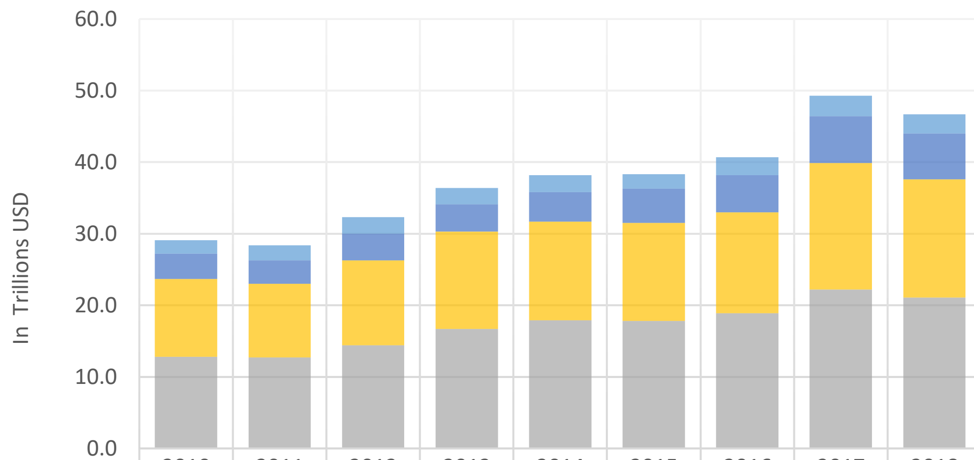
Foreign and Colonial Government Trust was, furthermore, the first British investment trust, founded in 1868 by Phillip Rose (Rutterford, 2009). Some of the benefits of investment funds widely known today were recognized in the trust's prospectus. The trust aimed to allow smaller, individual investors access to financial instruments such as bonds and stocks, usually only accessible to large capitalists, while lowering the risks by spreading the investment in a number of securities. The trust also emphasized the professional management which enabled clients to invest overseas without knowledge of the market and without the need to deal with all of the paperwork related to transactions on their own. Following the success of Foreign and Colonial Government Trust, a total of 18 trusts were listed on the London Stock Exchange by 1875. In the late 1880s the number of trusts skyrocketed, with 70 new trusts established and £45 million raised between 1887 and 1890 (Rutterford, 2009).

These Scottish and English trusts served as a guiding star for the early investment trusts in the United States, which experienced a boom in 1920s with the number of trusts exploding from 160 in 1926 to approximately 750 in 1929, just before the Wall Street Crash. investment trusts in the Unites States had a different management style than those in Britain, often focusing on achieving extraordinary returns by being highly-leveraged and relying on risky investment strategies such as market-timing and stock-picking (Rutterford, 2009). The failure of most of these trusts after the stock market crash revealed the need to increase supervision and transparency of investment funds. The first regulation introduced in 1933 was Securities Act, known as "truth in securities", and was enacted to regulate the registration and issuance of new securities to the public. The aim was to increase transparency and prohibit deceit, misrepresentation and other fraud in the sale of securities (U.S. Securities and Exchange Commission, 2019). The other important regulation was Investment Company Act of 1940, which regulated the organization, structure and operations of investment funds in order to minimize the conflict of interest (U.S. Securities and Exchange Commission, 2019).

With the new regulations in place and investors' preference for higher transparency standards, the popularity of open-ended funds was on the rise. The first open-end mutual fund structured similarly to the modern investment funds, with the idea of issuance of new shares as investors provide additional funds, was Massachusetts Investor Trust founded in Boston in 1924 (Mosselaar, 2018). From this point forward, the investment funds industry was increasing steadily, with rising popularity of open-ended mutual funds. By 1944 the open-end funds had more assets under management than the close-end funds in the United States (Mosselaar, 2018), and by 1951 there were more than 100 mutual funds with number of investors exceeding 1 million for the first time in history (Investment Company Institute, 2019). With the introduction of money market funds in 1971 and with Vanguard's founder John Bogle making the first market index fund available for retail clients in 1976, assets managed by investment funds skyrocketed: by 1990 total mutual fund assets surpassed $1 trillion, while exchange traded funds, first introduced in 1993, now have $4.7 trillion total net assets in 2019 (Investment Company Institute, 2019).

As can be seen in Figure 4, total assets of regulated open-end funds reached their peak in 2017 at $49.3 trillion.

Figure 4 Total Assets of Regulated Open-End Funds Worldwide by Region

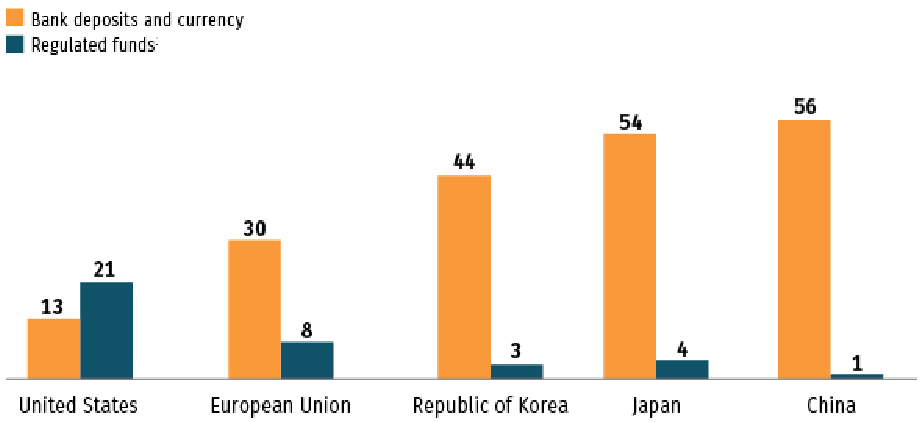


	2010	2011	2012	2013	2014	2015	2016	2017	2018
Rest of the world	1.9	2.1	2.3	2.3	2.4	2.0	2.5	2.9	2.7
Asia-Pacific	3.5	3.3	3.7	3.8	4.1	4.8	5.2	6.5	6.4
Europe	10.9	10.3	11.9	13.6	13.8	13.7	14.1	17.7	16.5
United States	12.8	12.7	14.4	16.7	17.9	17.8	18.9	22.2	21.1
Total	29.1	28.4	32.3	36.4	38.1	38.3	40.6	49.3	46.7

Source: author's work based on Investment Company Institute (2019)

The United States leads the world with $21.1 trillion of total assets in regulated open-funds, or 45% of assets globally. Following the US, Europe held 35% of the worldwide total assets in open-end funds with $16.5 trillion. The rest of the world has only 20% of world open-end funds assets, which is mostly due to the fact that households prefer to keep their wealth in bank products, such as deposits, rather than invest with mutual funds or similar companies. Figure 5 shows that United States households hold more of their wealth in the open-end funds than in bank deposits and currency with 21% of the household wealth being invested in regulated open-end funds, while Europeans are at only 8%. Asian households have especially low percentage of their assets invested in open-end funds, with Korea at 3%, Japan at 4% and China at 1%.

Figure 5 Percentage of Household's Wealth Invested in Open-End Funds[6]



Source: Investment Company Institute (2019)

Global investment funds sector has increased significantly not only in absolute, but also in relative terms. In 2010, worldwide regulated open-end funds accounted for 20% of worldwide capital markets, rising to 25% in 2018. Majority of debt and equity assets are still coming from other investors, including central banks, sovereign wealth funds, defined benefit pension plans, banks, insurance companies, hedge funds, broker-dealers, and households' direct holdings of stocks and bonds Investment Company Institute (2019).

3.2. Classification of investment funds

The terms *investment fund* and *mutual fund* are often used interchangeably. However, the term investment fund is broader and also include hedge funds, private equity funds, venture capital funds and other (Brigham, Ehrhardt, 2011). It is important to use a clear classification since different categories of funds are regulated differently around the globe. Investment Company Institute (2019), following the standards set by International Investment Funds Association uses the term regulated funds in their analysis, defining regulated funds as "collective investment pools that are substantively regulated, open-end investment funds". Funds can be categorized by many

[6] Data for the United States and Japan are as of 2018:Q4; data for the European Union and the Republic of Korea are as of 2018:Q3; and data for China are estimated as of 2014:Q4.

characteristics such as their size or type of their investors, as well as according to their organizational structure and type of securities they invest in.

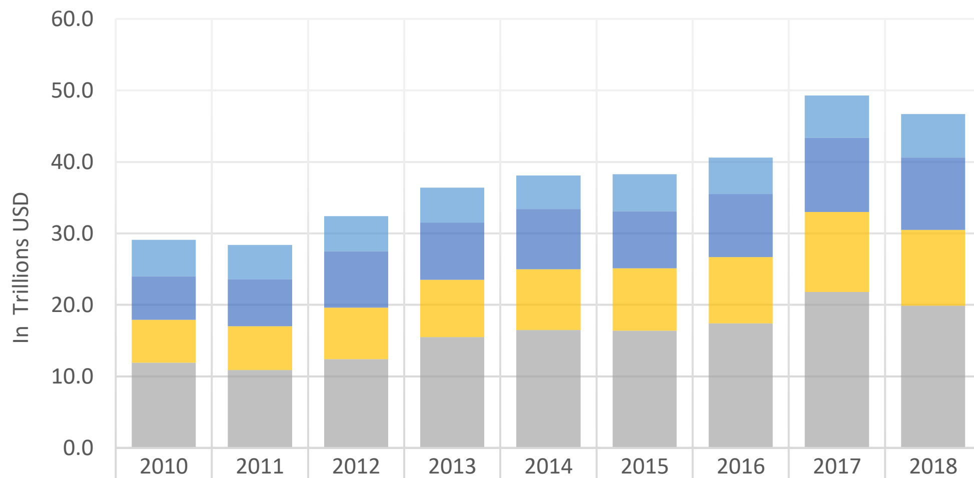
3.2.1. Open-end and Closed-end funds

It is important to distinguish between closed-end funds and open-end funds. Closed-end funds issue a fixed number of non-redeemable shares which can only be traded on the secondary market with other investors. Open-end funds, on the other hand, issue units or shares which are redeemable at any given point of time. Instead of trading the fixed amount of shares with other investors on secondary market, each investor can purchase or sell their shares and the fund will simply increase or decrease the number of shares (Mishkin, Eakins, 2018). Open-end funds are strictly and formally regulated, providing investors transparent overview of the organizational structure of investment company, investment funds' management and custody fees, valuation of funds' assets and restrictions on investments including diversification across asset classes and limits on leverage. By the definition of Investment Company Institute (2019), regulated open-end funds include mutual funds and exchange traded funds (ETF) in the United States, while in the European Union most common forms are Undertakings for Collective Investment in Transferable Securities (UCITS) and Alternative Investment Funds (AIF).

3.2.2. Types of investment funds by investment objective classes

The most common classification of investment funds is by investment objectives and by the type of securities they invest in (Orsag, 2011). Equity or stock funds invest in the shares of companies and are the riskiest type of mutual funds, but provide the highest expected return in the long term. Equity funds differ based on many other characteristics, such as the type of companies they invest in and region or industry they are focused on (Orsag, 2011). Bond funds invest in fixed-income securities such as government bonds, municipal bonds or corporate bonds. They are less risky than equity funds and provide a safer, but lower return to their investors. As equity funds, bond funds differ by type of bonds they purchase, geographical region they are focused on or the time horizon of the securities the fund invests in. Hybrid funds (also known as mixed funds or balanced funds) are a combination of the first two categories, investing a proportions of its assets in stocks and bonds. The limits of the respective proportions is specified in the prospectus. This makes balanced funds less risky than the equity funds, but more volatile than bond funds. Money market funds invest exclusively in money market securities, with holding period sometimes even less than a week. Money market funds have the purpose of capital protection, and offer low returns at very low risk (Mishkin, Eakins, 2018). The total assets of regulated open-end funds worldwide by type of fund can be seen in Figure 6 below.

Figure 6 Total Assets of Regulated Open-End Funds Worldwide by Type of Fund



	2010	2011	2012	2013	2014	2015	2016	2017	2018
Money market	5.1	4.8	4.9	4.9	4.7	5.2	5.1	5.9	6.1
Bond	6.1	6.6	7.9	8.0	8.4	8.0	8.8	10.4	10.1
Mixed/Other	6.0	6.1	7.2	8.0	8.5	8.7	9.3	11.2	10.6
Equity	11.9	10.9	12.4	15.5	16.5	16.4	17.4	21.8	19.9
Total	29.1	28.4	32.3	36.4	38.1	38.3	40.6	49.3	46.7

Source: author's work based on Investment Company Institute (2019)

A special type of investment funds are index funds. Index funds do not apply security selection strategy, but rather try to replicate a return of a certain benchmark, such as market index. These funds are considered to apply passive investment strategy and they do not require the same level of professional expertise as actively managed funds, therefore they usually have lower management fees. Funds of funds are those mutual funds which allocate their investments to other investment funds. These are sometimes funds under the same management company, but can also be index funds or any other mutual fund. While funds of funds usually provide extreme diversification, they often have high management fees offsetting these benefits.

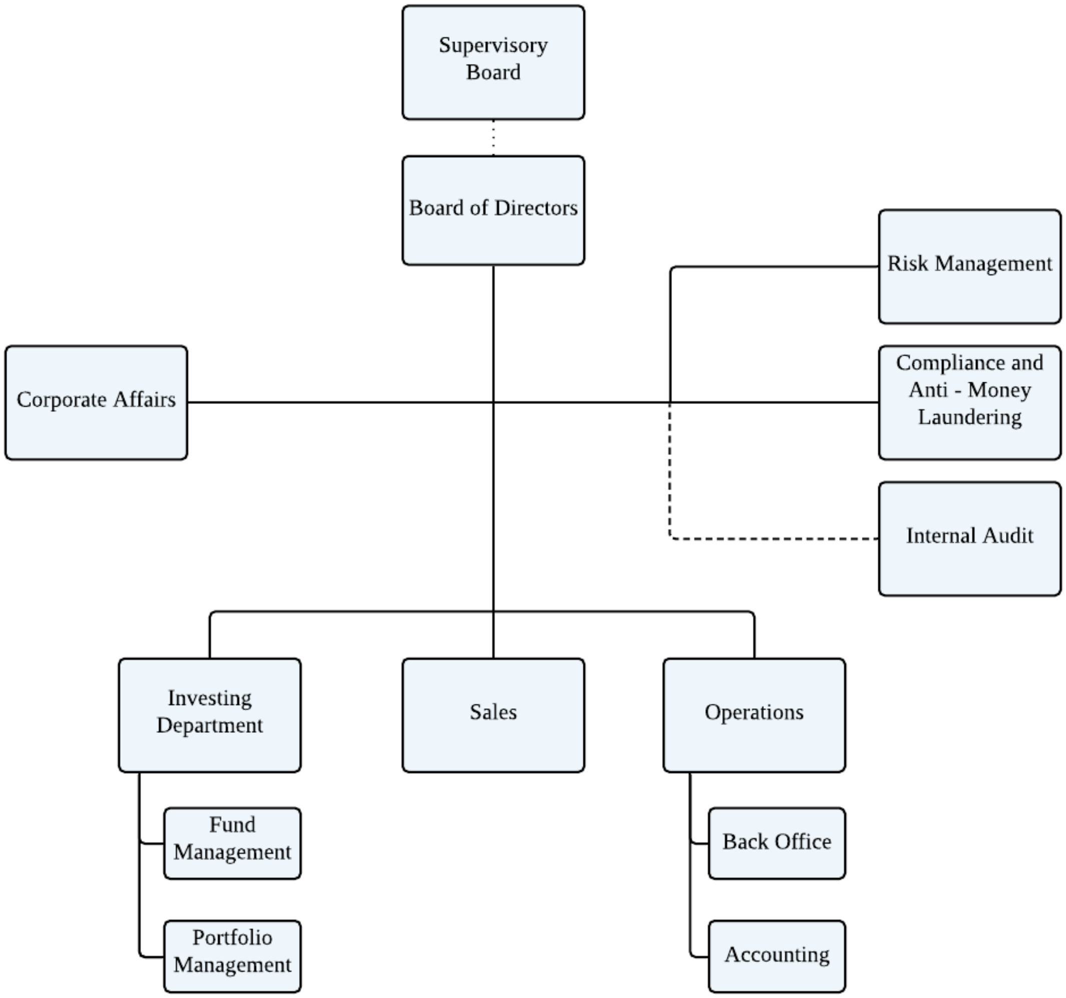
3.3. Benefits of investing in Mutual Funds

Some of the benefits of investment funds, such as diversification and professional management, were known to the founders of first mutual funds in the world. Mishkin and Eakins (2018) recognize five distinctive benefits of mutual funds: liquidity intermediation, denomination intermediation, diversification, cost advantages and managerial expertise. Liquidity intermediation means that mutual funds' clients can benefit from high liquidity of their investments, being able to convert their funds into cash easily, quickly and at a low cost which would not be otherwise possible. Denomination intermediation means that small, retail investors have the ability to invest in securities they could not have otherwise obtained. This is the case for some stocks with high market price per share, but is especially important for assets such as money market securities which are only accessible to small investors by pooling their resources as money market securities are rarely available in denominations lower than $100 thousands (Mishkin, Eakins, 2018). Diversification is another very important advantage of mutual funds as small investors do not usually have the necessary resources to acquire enough securities to reach the optimal level of diversification on their own. Furthermore, the transaction costs related to purchasing securities are much higher for small investors in relative terms, as a large portion of costs are fixed costs. Investing in mutual funds, therefore, brings significant cost advantages because the fees are split among many investors. Finally, the average retail investor does not have the required knowledge about the financial markets or know-how related to the procedures to acquire securities. Mutual funds bring managerial expertise allowing small clients to have their investment managed by professionals (Mishkin, Eakins, 2018).

3.4. Organizational structure of Investment Management Companies

It is important to review the organizational structure of investment management companies in order to better understand how each of the departments functions within the company, and how artificial intelligence could aid in increasing performance for each of them. The organizational structure of Investment Management Companies is regulated by the national supervisory agency. In Croatia the supervisory institution is the Croatian Financial Services Supervisory Agency (HANFA). Organizational structures must be publicly available and easily interpretable for each of the Investment Management Companies in Croatia. (Zakon o otvorenim investicijskim fondovima s javnom ponudom. NN 44/2016). An example of an organizational structure relating to an Investment Management Company in Croatia can be seen in Figure 7. The Board of Directors body serves as the head of the Investment Management Company, and is overlooked by the Supervisory Board. In this simplified view, the main departments of such an Investment Management Company are the Investing Department, or Front Office and the Operations Department, or Back Office, alongside the Sales department, Risk Management, Compliance and Anti-Monely Laundering departments (AML) and Internal Audit and Corporate Affairs. The Investing Department consists of Fund Management and Portfolio Management, while the Operations Department includes back Office and Accounting. The Investment Management Company can also have additional Committees and sub-departments, as well as additional departments with support functions such as Human Resources and Information Technology.

Figure 7 Example of Organizational Structure of Investment Management Company



Source: author's work based on the organizational structure of PBZ Invest (2019)

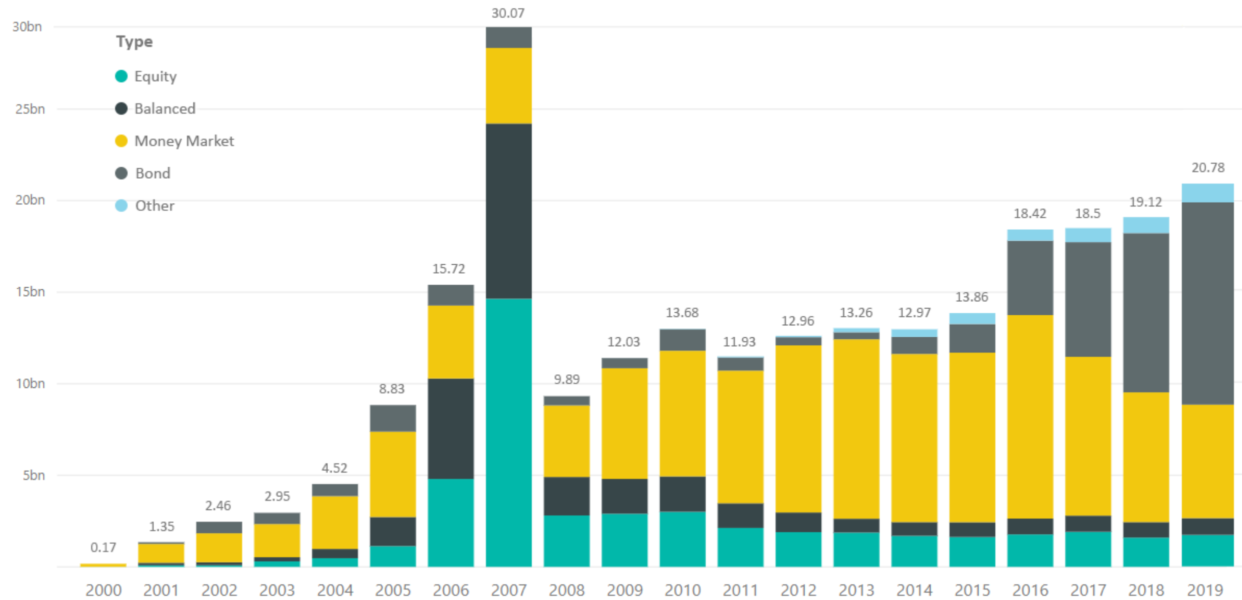
3.5. Investment funds in Croatia

The history of investment funds in Croatia begins only after 1995, with the first legislation enabling the registration of investment funds. The development of investment funds only really begun after the introduction of 7 Privatization investment funds[7] used primarily to transform companies from government to private ownership (Jurić, 2005). In 1997, Fondinvest[8] became the first investment

[7] In Croatian *Privatizacijski investicijski fondovi*, or PIFs
[8] Still functioning, currently under name KD Locusta fondovi as of 2015

fund management company to receive an operating license (Morić Milovanović, Galetić, 2006; KD Locusta fondovi, n.d.), while the first mutual funds in Croatia started their operations in 1999. The increase of total assets under management of mutual fund companies from 2000 by the type of fund in Croatia can is visible in Figure 8. Assets under management started increasing exponentially from HRK 2.95 billion in 2003, with figures almost doubling each consecutive year before reaching an all-time high at HRK 30.07 billion in 2007 just before the financial crisis. After the financial crisis funds experienced a slow, but continuous growth in total assets to HRK 20.78 billion - still not fully recovering to the all-time high level in 2007. Due to the different risk-return profiles of different types of funds, the decline and growth in assets under management was not the same for all types of funds. Equity funds rose from HRK 1.1 billion in 2005 to HRK 14.6 in 2007 and have not recovered ever since with only HRK 1.7 billion in 2019. Balanced funds, being the most risky fund type after equity funds, expectedly followed the same destiny as stock funds with assets going from HRK 1.6 billion in 2005 to HRK 9.6 billion in 2007, only to drop significantly due to the crisis and remain under HRK 1 billion up to 2019. Bond funds, on the other hand, did not hold more than HRK 1 billion of assets prior to the 2008 crisis and their increased popularity in the last years boosted assets under management from HRK 1.6 billion in 2015 to HRK 11 billion in July 2019.

Figure 8 Total Assets of Mutual Funds in Croatia by Type of Fund in HRK billions[9]

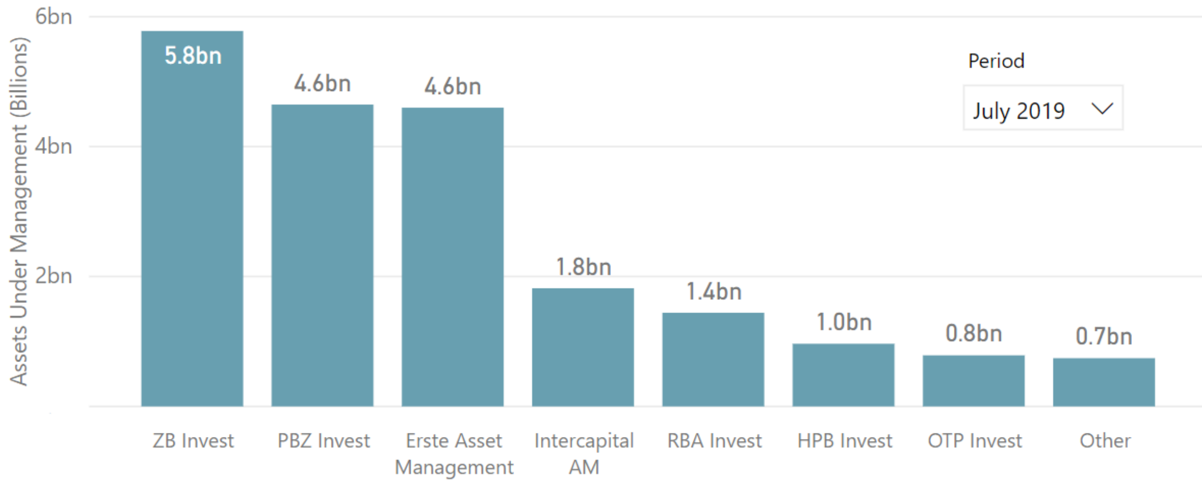


Source: author's work based on compiled data from Croatian Financial Services Supervisory Agency (HANFA)

The Croatian financial system is bank-based, with banks holding almost 70% of assets in the financial sector (Krišto et al, 2018) - which is why investment funds became more popular when leading banks opened their investment fund companies and attracted new capital to their mutual funds. Not only did the banks boost the development of mutual funds sector in Croatia, they also remained the market leaders when it comes to open-end mutual funds. As illustrated in Figure 9, the top 7 investment companies by assets under management in Croatia make up more than 95% of the market[10]. Within these top 7 investment management companies, only Intercapital Asset Management is not owned by a bank. Moreover, bank-owned investment companies hold almost 90% of the market[11]. As can be seen in Appendix 3 there were 95 active open-end mutual funds in Croatia in July 2019, managed by 15 investment companies.

[9] Assets under management in December of each year, except for 2019 where latest data available was July
[10] 96.43% with HRK 20.04 billion
[11] 87.67% with HRK 18.22 billion

Figure 9 Top Investment Companies by Assets under Management in Croatia



Source: author's work based on compiled data from Croatian Financial Services Supervisory Agency (HANFA)

4. Application of AI in investment fund sector

Artificial intelligence will certainly represent one of the key factors transforming the future of business across all industries, and financial secor is leading the race in terms of current AI adoption and future AI demand trajectory (Bughin et al., 2017). In McKinsey's report on asset management industry in Europe, Catania et al. (2018) include expanding digital modes of delivery, investing in innovative investment processes and implementation of advanced analytics across the entire value chain as the main challenges for the future. One of the most important financial innovations in the coming years is the application of artificial intelligence to various segments of business and transforming the investment management companies to be more flexible, efficient and profitable. Rao and Verweij (2017) estimate that artificial intelligence will have a strong impact on the industry of financial services, and that the transition will almost certainly happen until 2025.

4.1. Drivers of Financial Innovation

The three main categories of drivers of financial innovation are shifting consumer preferences, new and emerging technologies and changes in financial regulation (Financial Stability Board, 2017b). Changes in consumer preferences drive the financial innovation from the demand side. When customers desire a new mode of delivery for financial products, increased speed or lower costs, this drives the innovation in the financial sector from the consumer side. From the perspective of investment funds, however, demand factors include opportunities to increase profitability both through cost reductions and revenue gains as a result of leveraging artificial intelligence technology (Financial Stability Board, 2017a). Institutions can also benefit from improved risk management, but the main driver of investment in artificial intelligence may be competition within the investment funds industry and arms race to be the first mover in the application of new and promising technologies. Another demand factor are numerous regulation requirements for more detailed and more frequent reporting from investment funds, introducing the need for increased efficiency and automation in regulatory compliance (Financial Stability Board, 2017a). The summary of the factors which serve as drivers of financial innovation can be seen in Figure 10.

Figure 10 Main Drivers of Financial Innovation in Investment Funds Sector

SUPPLY			DEMAND		
Technology	**Investment Management Companies**	**Regulation**	**Consumer preferences**	**Profitability**	**Competition**
Computing power	Skilled personnel	Supervisory requirements	Lower costs	Cost reductions	For human capital
ML algorithms	Data availability	Business incentives	Convenience	Revenue gains	For first-mover advantage
Big Data	IT infrastructure	Restrictions	Speed	Risk-management	For reputation

Source: author's work based on FSB (2017a), FSB (2017b)

In this chapter more emphasis will be put on the supply side drivers of financial innovation, or, more specifically, on how evolving technologies influence innovation in the financial industry with a further and more detailed look on applications of artificial intelligence within the investment funds sector. The developments in artificial intelligence applications, as well as the adoption and the implementation of these technologies, were spurred by the increased availability of data, accessibility of higher computing power and advances in machine learning algorithms (Fliche and Yung, 2018). These three factors - availability and diversity of data, access to information technology necessary to process the data, and possession of intellectual capital - are the main prerequisites for successful utilization of artificial intelligence in organizations.

4.1.1. Data availability and diversity

Data availability pertains to large and diverse datasets accessible to organizations, coming from both internal and external sources. The availability of large quantities of data is facilitated by digitization of organizations, wide-spread use of internet and mobile phones. Increasing utilization of internet of things (IoT) solutions with embedded software which uses sensors to retrieve data on one hand, and popularity of social media on the other, also contribute significantly (Reinsel et al., 2018). Data is essential for good performance and high accuracy of artificial intelligence algorithms, and never has there been more data than today. Allas et al. (2018) report that there is new 2.2 exabytes, or 2.2 billion gigabytes of data created every day in the world, while Reinsel et al. (2018) estimate that global data will grow from 33 zettabytes in 2018 to 175 zettabytes by 2025[12]. Diversity of the data means that artificial intelligence models can use different types of data as an input, not relying only on tabular data with categorical and numerical values, but also images, videos, text, geographical location data and other types of data (Kolanović, Krishnamachari, 2017).

4.1.2. Increased computing power and cloud computing

With large datasets readily available for analysis and modelling, it is essential that organizations have the necessary computing power which is able to run the power-demanding algorithms. This is why the developments in graphics processing units (GPU) may also be considered as the drivers of increased applications of artificial intelligence in organizations. Allas et al. (2018) state that advances in the speed of graphics processing units enabled the training speed of deep learning algorithms to improve by more than 5 times in the last couple of years.

Another very important factor in reducing the cost of storing, processing and collecting data, as well as enabling execution of machine learning algorithms on large datasets, is the development of cloud datacenters. Reinsel et al. (2018) estimate that half of the world's data will reside in public cloud environments by 2025. Cloud computing solutions not only provide many benefits to the companies which want to implement artificial intelligence models, but are sometimes necessary and irreplaceable. The most notable benefits of cloud computing include flexibility in modulating the required data storage capacity, interoperability of software based on cloud between different devices and security and availability of data (Fliche and Yung, 2018).

[12] One zettabyte is equal to one billion terabytes or trillion gigabytes

4.2. Current applications of AI and opportunities

4.2.1. Trading with Machine Learning Algorithms

One of the most obvious utilizations of artificial intelligence in the investment funds sector is for analyzing financial data and adjusting the trading positions accordingly. Machine learning algorithms can be used to build models which will either help humans in the decision-making process, e.g. through certain warning signals, or autonomously execute transactions given the specific scenario and set of circumstances. Different machine learning techniques are used for numerous applications in trading by investment funds, namely those who primarily deal with quantitative investments. There are different approaches to application of artificial intelligence in the investment funds, which range from those aiming to do the tasks already performed in the investment funds more efficiently to the new values propositions of AI introducing radically different approaches to the existing problems (McWaters et al., 2018). Machine learning algorithms can enable flexible portfolio management and building of personalized asset-allocation models, processing and analyzing the potential risks in the real time and lowering the overall costs of portfolio management (McWaters, 2017).

Kolanović and Krishnamachari (2017) from J.P. Morgan listed an array of trading questions which can be answered with distinct methods of applying AI techniques, some of which are “Given set of inputs, predict asset price direction?”, “Which assets move together?”, “What factors are driving asset price?”, “What are the most common signs of market stress?”, “Predict volatility based on a large number of input variables?” etc. Kolanović and Krishnamachari (2017) provide an example of predicting the relationship between returns of different macroeconomic variables and commodities, such as gold, oil, inflation, foreign exchange rates etc. which can be performed used classical machine learning methods of supervised learning. Some unsupervised learning algorithms such as principal component analysis (PCA) are converted from statistics to machine learning without any changes, and can also be utilized in trading. PCA can be used by analysts to better understand the main factors that are driving the price of an asset (Kolanović and Krishnamachari, 2017).

4.2.2. Enhancing the research process

Large quantities of publicly available data previously not accessible makes it possible for investment funds to apply advanced analytics and utilize artificial intelligence solutions. By applying machine learning techniques such as natural language processing (NLP), current research processes in investment funds may be significantly enhanced (Doshi et al, 2019). One example Doshi et al. (2019) provide is using natural language processing to automate the analysis of financial reports, highlighting the most important and relevant changes since the last company's filing. This does not replace the work of an analyst but rather complements it, thus increasing the productivity of professionals. Furthermore, with the application of natural language processing, financial analysts can now go beyond traditionally used sources of information such as financial statements and benefit from various other sources of data widely available on the internet - such as customer reviews and social media sites. Sentiment analysis can provide a better understanding of the business and may serve as one of the key performance indicators for companies which is available even in between the filings of financial reports. Buchanan (2019) states that ML in sentiment analysis can discover new trends in financial activities of observed companies, and is able to replicate and enhance human intuition. The sentiment indicators can either be internally developed by the investment fund, or can be purchased from a data analytics company (Financial Stability Board, 2017a).

Using machine learning algorithms investment companies can also eliminate systemic biases from the investment decision process (Doshi et al., 2019). With the psychometric data about traders available, along with their trading history, communication patterns and times of the trades, companies can become aware of the influence of each of these conditions and potentially remove the traders' bias from the equation. Analysts can also compare their research with crowdsourced estimates of value of a given security, and experiment with the inclusion of this data in their valuation models, utilizing artificial intelligence to factor out their bias from the investment decisions.

4.2.3. Customer acquisition and retention

Advanced analytics and big data applications with embedded machine learning algorithms can help investment funds improve the understanding of their clients, which can be utilized to optimize distribution and service models. Consulting company McKinsey reports that behavior based segmentation can “free up 15% or more of existing salesforce capacity and increase sales from priority client relationships by up to 30%” (Doshi et al., 2019). By profound understanding of customer behavior and preferences, investment management companies can increase customer satisfaction and optimally customize the investor relationship experience. Investment funds can utilize the predictive capabilities of machine learning algorithms to improve both customer retention and customer acquisition. For example, customer at risk of redemption can be predicted by the algorithm, which will then preemptively suggest other financial products to be offered to the client. Doshi et al. (2019) report that these algorithms can have 80% accuracy and lead to sales results up to 10 times better than without these technologies.

Another important application of artificial intelligence is precision targeting of customers which will enable cost-reductions in marketing and sales due to increased efficiency and lower marginal costs of advertising. Investment management companies could market customized and personalized products which have the greatest probability to attract consumers with specific characteristics (Rao and Verweij, 2017).

4.2.4. Compliance, RegTech and Fraud Prevention

Artificial intelligence is not only going to benefit the individual companies, it has potential to produce positive effects for the entire financial system. One of the important ways every entity will benefit from AI is increased transparency and more efficient regulatory and supervisory agencies through RegTech[13]. RegTech can allow finvestment management companies to improve its compliance and risk management operations and address issues of regulator reporting, financial crime and operational risk (BIS, 2017). Natural language processing can be used to analyze unstructured data when detecting suspicious activities, such as text and voice communication of traders which could significantly enhance the supervision and control functions of regulatory agencies. Of course, this also raises ethical questions, such as what are the boundaries of surveillance of employees (Financial Stability Board, 2017a). Many banks have already turned to AI techniques to stop illegal financing and have successfully avoided large fines because of better

[13] RegTech – Regulatory technology

detection of illicit activities (Buchanan, 2019). This is crucial as there is a huge opportunity for high return on investment if fines for non-compliance can be avoided – cumulative financial penalties in the financial sector between 2009 and 2017 amounted to $342 billion gloabally (McWaters et al., 2018). Machine learning algorithms revolutionizes fraud detection – it can analyze the millions of data points transactions in real time. Although similar algorithms are used for anti-money laundering (AML) purposes, they are not as effective due to lack of large public datasets for analysis (Buchanan, 2019). This is why many financial institutions still use conventional rules-based systems for AML. There is proof, however, that machine learning techniques outperform the traditional approach which opens the door yet to another application of AI in financial sector (Buchanan, 2019).

Machine learning algorithms can also aid supervisory institutions to have a better and deeper understanding of the financial markets and to detect financial and economic signals relevant to the institution's function. U.S. Securities and Exchange Commission (SEC) is already using machine learning methods to detect possible fraud and misconduct (Financial Stability Board, 2017a). Central banks will also increase the use of machine learning algorithms, especially for forecasting economic indicators such as GDP, unemployment, inflation, tourism activity, housing prices and the business cycle (financial Stability Board, 2017a). The issue of classification of AI arises here again, as central banks use statistical methods which are considered to be machine learning. To provide two examples, Kunovac and Špalat (2014) use principal component analysis for nowcasting the Croatian GDP, while Kunovac et al. (2018) use PCA to analyze the financial cycles in euro area. While these techniques are considered as machine learning in other areas, modelling departments of central banks are familiar with these methods and label them as econometric models.

4.2.5. Process Automation

Artificial intelligence will affect all of the parts of investment funds' organization, including back office, Human Resources and the recruitment process. Summarizing the survey by The Boston Consulting Group, He et al. (2018) estimate that the introduction of artificial intelligence applications in financial sector will lead to job cut up to 25% by 2027. According to the same model, productivity of remaining employees will also be affected as working hours will decrease by 27%. The efficiency increase is estimated to be above 50% in the capital markets industry (He et al., 2018). These improvements in efficiency will come from many different sources, however probably the most notable one is automation of not only manual work, but also non-routine tasks and cognitive tasks. This can lead to enormous efficiency boosts – JP Morgan's COiN, for example, can review 12,000 documents in just a few seconds using NLP, while the same result would require astonishing 360.000 hours of human labor (Buchanan, 2019). Artificial intelligence will increase the efficiency of the interview process in the same way, analyzing potential new hires by comparing them to the existing successful employees based on various characteristics. The solutions will not only aid decision-making in human resources, but will also save time for interviewer since HR chatbots will be able to answer most of the candidate's questions and can help significantly in the early steps of recruitment (He et al., 2018).

4.3. Challenges and Limitations in implementation of AI

4.3.1. Lack of skilled personnel

Lack of skilled personnel is one of the main challenges organizations will face when trying to implement AI solutions. EY and MIT's (2019) survey conducted on the EmTech Digital conference, results of which are illustrated in Figure 11, showed that 45% of the senior business and technology decision-makers believe that their organizations lack the skilled personnel to implement AI. Another survey by CGI and IBM (2018) conducted in Finland shows that 44% of finance executives reported lack of skills of their current employees as a challenge for AI implementation in their company. While this can be solved with education of current employees, 54% of companies choose to hire external consultants (CGI and IBM, 2018). Kolanović and Krishnamachari (2017) state that there are many different types of professionals to be included in the organization in order for successful utilization of big data and machine learning. They add that there is a risk that fund managers will not understand the set of skills required from their staff to make use of AI, which can lead to culture clashes and misrepresentation of skills by employees who possess the soft-skills to understand the principles of machine learning, but lack the hard-skills necessary to implement them in the models (Kolanović and Krishnamachari, 2017). Bughin et al. (2017) add that there are two types of roles that companies will have to fill: data scientists and translators. Data scientists, or quants, are responsible for the tasks usually associated with AI:

designing, developing, deploying and training artificial intelligence models. Translators, on the other hand, are employees who possess enough technical knowledge to understand the AI techniques, but are at the same time familiar with the business and management side of the organization. These roles will become increasingly important because translators will bridge the gap between professionals who know how to implement AI solutions and high-level management who will develop a strategy to apply these solution to the real-world problems and ultimately benefit from the application of these technologies (Bughin et al., 2017).

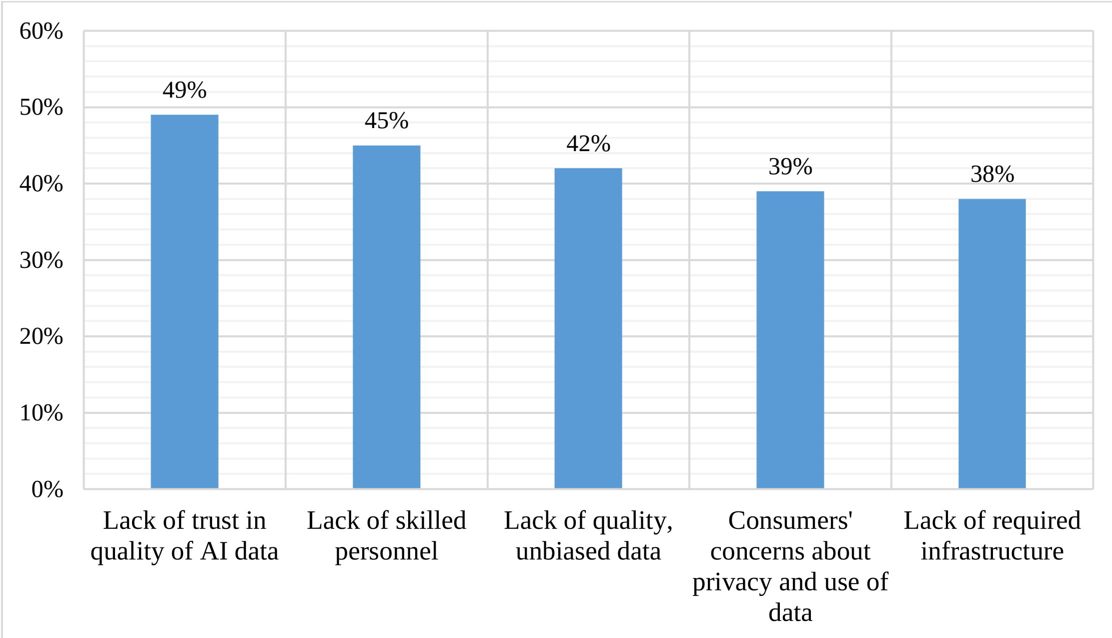
4.3.2. Data quality issues

EY and MIT's (2019) survey shows that 49% of professionals lack the trust in quality of AI data, which serves as a barrier to the implementation of AI, while 42% point to the lack of quality, unbiased data and 37% emphasize the lack of data interoperability. The issue of lack of trust are especially important, as the lack of customer trust due to privacy concerns can lead to data unavailability in the future (BaFin, 2018). All of these factors are connected to data quality, however there are distinct characteristics of big data which allow its full utilization. More specifically, when discussing about the data quality, one should consider not only the availability of data, but all of the five main characteristics of big data: volume, velocity, variety, value, validity and variability (Kolanović and Krishnamachari, 2017). While the volume stands for the quantity of available data, velocity represents speed at which data is being gathered and processed. Variety stands for different types of data, including structured and unstructured data and value represents the relevance of the data, i.e. how useful is the data as a resource to achieve a certain goal. Finally, validity or veracity is the reliability and trustworthiness of the data. The mentioned survey from CGI and IBM (2018) further confirms the importance of this issue, as 42% of finance executives point to poor data quality and missing data as a challenge for proper implementation of artificial intelligence solutions in their organizations. Bughin et al. (2017) see a solution in opening up public-sector data and introducing common data standards which would make public data readable by machines.

4.3.3. Maturity of existing technological infrastructure

Organizations will not be able to benefit from artificial intelligence if they do not ensure that required technology infrastructure is available. In the mentioned survey by CGI and IBM in Finland (2018) 30% of respondents stress that maturity of the available technologies does not allow their organizations to make use of the artificial intelligence. EY and MIT's (2019) survey supports these results as 38% of senior level managers report lack of required infrastructure as a barrier to implementation of AI solutions, with additional 27% adding siloed data and organizations as a challenge. Kolanović and Krishnamachari (2017) state that asset management companies should utilize cloud computing and sometimes even parallel computing in order to get the most out of the application of machine learning algorithms. A lot of investment management companies, however, still have not digitized all of the aspects of its business and hence needs to make significant investments in its IT infrastructure to be able to make use of artificial intelligence. Legacy code and systems will require enormous effort and investment to be re-engineered and prepared for AI implementation (McWaters et al., 2018). The overview of the main barriers to implementation of AI is visible in Figure 11 below.

Figure 11 Barriers to Successful Implementation of AI



Source: author's work based on EY and MIT (2019)

4.4. Risks and Threats

4.4.1. Data issues and Bias of AI

As artificial intelligence systems depend on the availability of large amounts of data, one must consider the issue of data quality when deciding to use a certain algorithm to solve a specific problem. One example could be that the dataset used for training is biased. This issue is well known to academics and statisticians who use an array of methods to test whether their data is representative and could be generalized upon. This issue should always be taken into account when using artificial intelligence and machine learning, especially supervised learning algorithms to drive decisions in the management environment (High-Level Expert Group on Artificial Intelligence, 2019). The problem of data bias emerges in the process of data collection and data processing, either through missing data or change in the datasets over time (BaFin, 2018). The potential risk occurs if the bias is not recognized because of the tests also having the same bias – which should be solved by using transparent models and examination of model's attributes before applying the algorithm (BaFin, 2018).

4.4.2. Black-box models: interpretability and auditability issues

Very common issue with artificial intelligence and machine learning algorithms used in predictive models is the explainability of results, as many of the models are difficult or impossible to interpret (Financial Stability Board, 2017a). This is especially important for those predictive models which are used for decision making. In central banks, for example, sophisticated econometric models are often employed to predict a set of variables such as gross domestic product or inflation. These models do not only have the purpose of predicting the dependent variable, but also to give insights what is driving the changes and based on this data a decision about policy implementation can be made. In financial sector and investment funds, high level of transparency is very important and being able to explain the reasoning behind the investment decision as well as other business decisions is key. As High-Level Expert Group on Artificial Intelligence (2019) emphasizes, some machine learning algorithms can very accurate relative to other techniques, but lack the ability to explain how decision has been made. These black-box models are given inputs and they produce outputs, but the process in between is unexplainable and decisions based on data cannot be traced back to the underlying reason. One of the crucial issues with implementation of black box models in investment funds and trading is the uncertainty about the level of risk these models bring to the strategy. Financial Stability Board (2017b) states that auditability issues with artificial intelligence models can even contribute to the macroeconomic risks if the risks are not properly and diligently managed by the microprudential supervisors.

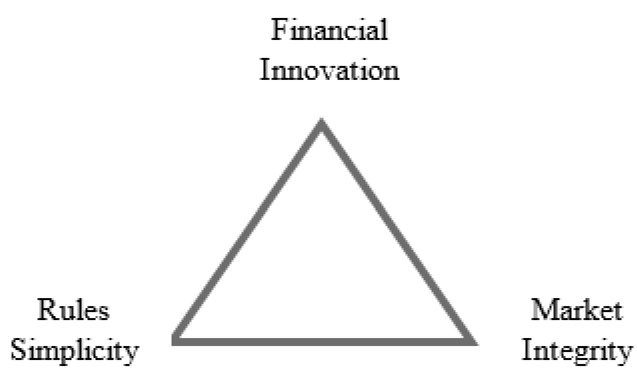
4.4.3. Goal-directed artificial intelligence

Another potential issue with the application of artificial intelligence in investment funds sector is goal-oriented artificial intelligence. Many artificial intelligence systems are designed in such a way that they are given a goal to achieve, without specifying the decisions to take to get the desired result (High-Level Expert Group on Artificial Intelligence, 2019). If artificial intelligence system receives only a final desired outcome as input, along with specific technique to achieve the goal, it will have the freedom to make decisions on how to achieve the result. This can lead to undesired effects even if the specified goal was achieved.

4.4.4. The innovation trilemma

Brummer and Yadav (2019) examine the concept of innovation trilemma in financial markets: the idea that between three main objectives of regulatory agency - financial innovation, market integrity and rules simplicity - regulatory agency is only able to properly address two at a single period. The innovation trilemma is illustrated in Figure 12. Market integrity in this context stands for consumer protection, combatting fraud and illicit activities and ensuring financial stability, while rules simplicity mean policies and regulations which are easy to understand, anticipate and apply (Brummer and Yadav, 2019). If regulatory agency wishes to foster financial innovation, while at the same time protecting consumers and safeguarding financial stability, it has to do so through a complex set of regulations. On the other hand, if they prioritize understandable and easily actionable regulations and aim to retain the market integrity at the same level, the policies end up being very broad, implicitly limiting the possibilities of financial innovation on the market. Finally, if supervisory agency puts facilitating financial innovation on the first place and desires to provide a simple and clear regulatory framework, it puts safety of consumers and market integrity at risk.

Figure 12 The Innovation Trilemma for Regulatory Agency



Source: Brummer and Yadav, 2019

To combat the innovation trilemma problem, regulatory agencies should cooperate internationally and introduce more flexible policies allowing financial innovation to foster in the environment of simple regulations, while at the same time safeguarding the final consumers by active supervision of the market. To do so, supervisory agency should be constantly reviewing new financial products, preferably through a dedicated department with specialized professionals. Regulatory agencies have a holistic approach to address the issue of AI regulation - they should learn from each other's approaches and practices in order to adopt the best practices when suitable, cooperate with other public institutions and ensure proper training for its personnel (BIS, 2017). Croatian Financial Services Supervisory Agency (HANFA) has certainly made a move in the right direction by establishing a regulatory Innovation Hub with the aim to support the development of innovative projects and help them enter the market, reduce regulatory uncertainty and to act as a catalyst in promotion of cooperation between academia, consumers and entrepreneurs (Croatian Financial Services Supervisory Agency, 2019).

4.5. Application of AI in Croatian Investment Funds Sector

Croatian investment funds sector could benefit from the application of artificial intelligence, but this potential is very limited by the size of the market. While total assets under management in Europe combined make 35% of world's total assets under management with $ 16.48 trillion, Croatia only makes a tiny share with 0.02% of European assets under management with $ 2.98 billion (Investment Company Institute, 2019). Moreover, with only 96 investment funds Croatian market is very small compared to 56 thousand funds in Europe, as can be seen in Figure 13. Although Croatian investment management companies are too small to make profitable investments in the development and implementation artificial intelligence tools on their own because of the high proportion of fixed costs and inability to use economies of scale, they can still utilize AI through different channels. Firstly, bank-owned investment management companies can make use of their parent company's size, which can pool their resources into investments on European or global level. Secondly, investment management companies can outsource parts of its operations to third parties who utilize artificial intelligence successfully. Applications of AI in the investment research process and trading show great potential, but will probably not be used in the Croatian investment funds because of limited number of securities most of investment companies consider for investments at the moment. Back office and compliance can see great improvements by application of automation tools, but probably the greatest potential is in personalization and automation of service and marketing. The fact that Croatian market is small can also be an advantage as it has the possibility to become a FinTech hub if supervisory agency provides a regulatory framework which incentivizes advances in new technology. Personalization of investor relations and full digitization of service, along with financial education of potential customers can lead to the development of the sector of investment funds in Croatia.

Figure 13 Total Assets under Management and Number of Funds in Europe in 2018

Country / Region	Total Assets Under Management (in $ billions)	Market Share in the Investment Funds Sector (in %)	Number of Funds
Austria	165,036	1.00%	1,603
Belgium	98,098	0.60%	735
Bulgaria	822	0.00%	123
Croatia	2,977	0.02%	96
Cyprus	2,803	0.02%	69
Czechia	12,514	0.08%	159
Denmark	138,232	0.84%	599
Finland	100,005	0.61%	404
France	2,074,766	12.59%	10,804
Germany	2,198,505	13.34%	6,149
Greece	4,744	0.03%	175
Hungary	15,486	0.09%	298
Ireland	2,772,568	16.83%	7,285
Italy	236,504	1.44%	866
Liechtenstein	50,871	0.31%	1,566
Luxembourg	4,654,017	28.24%	14,898
Malta	3,185	0.02%	143
Netherlands	858,681	5.21%	931
Norway	138,053	0.84%	865
Poland	39,769	0.24%	440
Portugal	13,572	0.08%	136
Romania	4,726	0.03%	78
Slovakia	7,563	0.05%	86
Slovenia	2,750	0.02%	98
Spain	324,856	1.97%	2,584
Sweden	336,156	2.04%	528
Switzerland	530,976	3.22%	887
Turkey	7,407	0.04%	398
United Kingdom	1,682,857	10.21%	3,033
Europe	**16,478,499**	**100.00%**	**56,036**

Source: author's work based on Investment Company Institute (2019)

5. Conclusion

Artificial intelligence has been a topic of research from the 1950s, but has only seen significant advances as a field in recent years. The availability and diversity of data, accessibility of computing power and cloud computing together with the advances in machine learning algorithms made it possible to apply artificial intelligence solutions in various industries, with financial sector leading the race. Some of the benefits of implementation of artificial intelligence in investment management companies are cost reductions from automations across all of its departments, revenue gains from more efficient sales and marketing and improved customer acquisition and customer retention. Most obvious application of artificial intelligence in asset management is for trading purposes. Machine learning algorithms prove to be more effective than traditionally used analytical methods in many specific problems, ranging from forecasting asset prices and analyzing the factors which drive the asset price to predicting market volatility based on macroeconomic variable. Natural language processing will enhance the investment research process allowing analysts to focus on more important tasks and decision making. Furthermore, sentiment analysis will enable analysts to use various external sources of unstructured data in their research, allowing them to go beyond the information in financial statements. The main obstacles to successful implementation of artificial intelligence are lack of skilled personnel, inadequate IT infrastructure and unavailability of data within the organization. The main risk which implementation of artificial intelligence presents to the financial sector is the question of auditability of machine learning algorithms. The reasoning behind black box models used by investment funds often cannot be explained and this problem of interpretability is in the focus of regulatory agencies. Supervisory agency needs to address these issues keeping in mind the innovation trilemma – a constant problem of trying to achieve the goals of fostering financial innovation, safeguarding consumers and having simple and understandable regulatory framework at the same time.

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Figures

Appendices

1. Number of Published Articles with the topic of Artificial Intelligence by year

Year	No. of Articles	Year	No. of Articles	Year	No. of Articles
1960	1	1981	26	2001	356
1961	2	1982	28	2002	352
1962	1	1983	36	2003	398
1963	1	1984	57	2004	422
1964	1	1985	98	2005	496
1966	4	1986	87	2006	562
1967	1	1987	126	2007	511
1968	3	1988	116	2008	545
1969	5	1989	101	2009	610
1970	5	1990	143	2010	642
1971	8	1991	379	2011	690
1972	2	1992	441	2012	794
1973	10	1993	354	2013	867
1974	11	1994	463	2014	971
1975	12	1995	416	2015	1051
1976	15	1996	367	2016	1291
1977	11	1997	386	2017	1746
1978	17	1998	383	2018	3048
1979	24	1999	337		
1980	19	2000	328		

Source: author's analysis based on bibliographic and citation database Web of Science Core Collection

2. Number of Articles with the topic of Artificial Intelligence by Subject Category

Journal subject category	No. of papers	Journal subject category	No. of papers	Journal subject category	No. of papers	Journal subject category	No. of papers
COMPUTER SCIENCE ARTIFICIAL INTELLIGENCE	4848	INFORMATION SCIENCE LIBRARY SCIENCE	396	STATISTICS PROBABILITY	183	METEOROLOGY ATMOSPHERIC SCIENCES	105
ENGINEERING ELECTRICAL ELECTRONIC	2870	WATER RESOURCES	387	NANOSCIENCE NANOTECHNOLOGY	182	CLINICAL NEUROLOGY	101
COMPUTER SCIENCE INFORMATION SYSTEMS	1953	NEUROSCIENCES	377	**BUSINESS**	**181**	ERGONOMICS	100
COMPUTER SCIENCE INTERDISCIPLINARY APPLICATIONS	1754	ROBOTICS	365	PHARMACOLOGY PHARMACY	179	SURGERY	98
COMPUTER SCIENCE THEORY METHODS	1330	COMPUTER SCIENCE HARDWARE ARCHITECTURE	362	PSYCHOLOGY MULTIDISCIPLINARY	174	AGRICULTURE MULTIDISCIPLINARY	96
OPERATIONS RESEARCH MANAGEMENT SCIENCE	**1169**	ENGINEERING BIOMEDICAL	328	MECHANICS	173	ENGINEERING AEROSPACE	90
ENGINEERING MULTIDISCIPLINARY	921	PHYSICS APPLIED	326	ONCOLOGY	165	REMOTE SENSING	87
COMPUTER SCIENCE SOFTWARE ENGINEERING	896	RADIOLOGY NUCLEAR MEDICINE MEDICAL IMAGING	320	BIOCHEMICAL RESEARCH METHODS	155	EDUCATION SCIENTIFIC DISCIPLINES	86
AUTOMATION CONTROL SYSTEMS	841	EDUCATION EDUCATIONAL RESEARCH	306	THERMODYNAMICS	154	MATHEMATICS	85
ENGINEERING CIVIL	642	GEOSCIENCES MULTIDISCIPLINARY	299	BIOCHEMISTRY MOLECULAR BIOLOGY	150	ECOLOGY	84
ENERGY FUELS	633	PHILOSOPHY	282	MEDICINE GENERAL INTERNAL	148	GENETICS HEREDITY	84
TELECOMMUNICATIONS	625	CHEMISTRY ANALYTICAL	268	ELECTROCHEMISTRY	145	LINGUISTICS	84
ENGINEERING MANUFACTURING	612	MATHEMATICS INTERDISCIPLINARY APPLICATIONS	241	IMAGING SCIENCE PHOTOGRAPHIC TECHNOLOGY	145	**BUSINESS FINANCE**	**83**
MANAGEMENT	**579**	MATHEMATICAL COMPUTATIONAL BIOLOGY	237	HISTORY PHILOSOPHY OF SCIENCE	140	ETHICS	83
MATERIALS SCIENCE MULTIDISCIPLINARY	541	**ECONOMICS**	**233**	HUMANITIES MULTIDISCIPLINARY	139	CARDIAC CARDIOVASCULAR SYSTEMS	82
MULTIDISCIPLINARY SCIENCES	526	CHEMISTRY PHYSICAL	223	METALLURGY METALLURGICAL ENGINEERING	128	LOGIC	82
ENVIRONMENTAL SCIENCES	505	HEALTH CARE SCIENCES SERVICES	222	NUCLEAR SCIENCE TECHNOLOGY	124	REGIONAL URBAN PLANNING	82
ENGINEERING INDUSTRIAL	477	BIOTECHNOLOGY APPLIED MICROBIOLOGY	219	OPTICS	118	SOCIAL ISSUES	77
CHEMISTRY MULTIDISCIPLINARY	435	GREEN SUSTAINABLE SCIENCE TECHNOLOGY	215	FOOD SCIENCE TECHNOLOGY	115	PHYSICS CONDENSED MATTER	75
COMPUTER SCIENCE CYBERNETICS	423	**SOCIAL SCIENCES INTERDISCIPLINARY**	**212**	MEDICINE RESEARCH EXPERIMENTAL	114	PUBLIC ENVIRONMENTAL OCCUPATIONAL HEALTH	75
ENGINEERING CHEMICAL	418	TRANSPORTATION SCIENCE TECHNOLOGY	210	ENVIRONMENTAL STUDIES	113	CHEMISTRY MEDICINAL	73
MATHEMATICS APPLIED	414	PSYCHOLOGY EXPERIMENTAL	204	PHYSICS MULTIDISCIPLINARY	112	PHYSICS ATOMIC MOLECULAR CHEMICAL	72
MEDICAL INFORMATICS	412	CONSTRUCTION BUILDING TECHNOLOGY	201	ENGINEERING PETROLEUM	111	RELIGION	72
INSTRUMENTS INSTRUMENTATION	401	ENGINEERING ENVIRONMENTAL	200	BIOLOGY	108	ENGINEERING GEOLOGICAL	71
ENGINEERING MECHANICAL	396	LAW	185	COMMUNICATION	105	ENGINEERING MARINE	71

Source: author's analysis based on bibliographic and citation database Web of Science Core Collection

3. Mutual Funds Market in Croatia in July 2019

Investment Management Company	Assets Under Management	Market Share	Funds run by Company
ZB Invest	5,779,271,734.58	27.81%	18
PBZ Invest	4,647,144,933.09	22.36%	13
Erste Asset Management	4,599,024,745.53	22.13%	8
Intercapital AM	1,819,301,856.25	8.75%	8
RBA Invest	1,442,040,162.10	6.94%	10
HPB Invest	964,704,259.24	4.64%	6
OTP Invest	786,514,915.53	3.78%	10
Allianz Invest	333,286,020.94	1.60%	3
KD Locusta Fondovi	215,550,691.58	1.04%	8
Auctor Invest	53,127,943.47	0.26%	1
ALTA Skladi	52,430,274.46	0.25%	3
Platinum Invest	34,360,703.86	0.17%	3
Global Invest	30,676,351.15	0.15%	2
SQ CAPITAL d.o.o.	17,732,334.45	0.09%	1
Alternative Invest	5,392,189.04	0.03%	1
Total	**20,780,559,115.28**	**100.00%**	**95**

Source: author’s analysis based on complied data from Croatian Financial Services Supervisory Agency (HANFA)