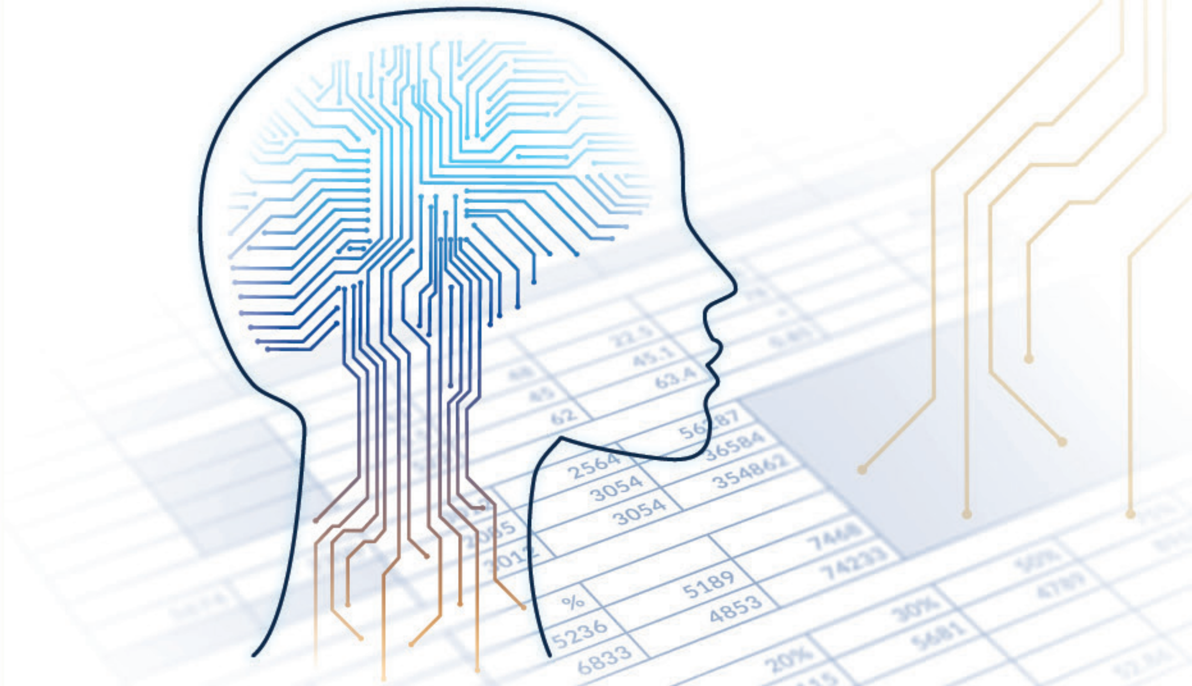
JACEK KALINOWSKI PIOTR KALINOWSKI

# ARTIFICIAL INTELLIGENCE IN ACCOUNTING



## What the past and present mean for the future

# ARTIFICIAL INTELLIGENCE
## IN ACCOUNTING

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ŁÓDZKIEGO

JACEK KALINOWSKI
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LODZ UNIVERSITY PRESS
Lodz 2025

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https://doi.org/10.18778/8331-880-6

Published by Lodz University Press
First Edition. W.11855.25.0.K

Publisher's sheets 7,6; printing sheets 7,375

ISNB 978-83-8331-879-0
e-ISBN 978-83-8331-880-6

Lodz University Press
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# Introduction

The rapid development of Artificial Intelligence (AI), and more recently generative models, has been transforming the landscape of accounting and finance. For decades, the field relied mainly on manual data processing and human judgment, but today it is being redefined by advanced algorithms capable of automating complex tasks, detecting patterns in vast datasets, and even generating human-like narratives. This monograph explores how AI, and especially generative models, intersect with accounting practice—highlighting both the opportunities they offer and the challenges they pose.

AI in accounting is not merely a technological trend but a defining element of the current digital era, with significant implications for the profession and society as a whole. Modern accountants must navigate an environment where efficiency, transparency, and data-driven analysis are paramount, while at the same time facing new challenges and the need to redefine their professional roles. AI technologies—from machine learning algorithms to generative models—can significantly support these areas, but they also bring risks such as algorithmic bias, loss of professional judgment, and difficulties in maintaining trust. The historical context, including successive industrial revolutions, reminds us that each technological change has brought not only improvements but also new questions about the role of humans and the future of professions. Understanding this history allows for a better assessment of today's challenges and conscious shaping of the future of accounting in the face of another digital revolution.

The aim of this monograph is to examine the impact of artificial intelligence and generative models on accounting, focusing on assessing the opportunities and threats associated with their application in practice. The work emphasizes the importance of historical conditions that have shaped the development of accounting tools and influence how new technologies are perceived today and what their consequences may be for the future of the profession. Additionally, it also systematizes and explains fundamental concepts related to AI and generative models to help practitioners better understand these issues and their significance in everyday work.

To guide the analysis and achieve the aim of the study, the following research questions were formulated:

1. What historical technological conditions have shaped the development of accounting, and how do they influence today's perception of AI and generative models?
2. How are AI and generative models used in accounting practice, and what results and effects do they bring?
3. What opportunities and challenges—technical, organizational, and social—are associated with implementing AI in accounting from the practitioners' perspective?
4. What key concepts and notions related to AI and generative models should be understood by accounting practitioners to use these technologies consciously?

To achieve the aim of the study, the following research methods were applied:

- literature review, covering academic publications, industry reports, and historical documents,
- historical analysis, capturing the evolution of accounting technologies in the context of successive industrial revolutions,
- case studies, presenting examples of AI and generative model implementations in selected organizations, showing practical applications and conclusions,
- inductive and deductive reasoning to formulate generalizations based on observed examples and to verify assumptions in light of the collected data,
- experiment involving the use of various AI tools described by the authors to enhance the value of the presented content and organize the material, while maintaining the authors' full substantive independence.

The monograph consists of four chapters and a conclusion. Its structure was carefully designed so that the reader can smoothly transition from explanations of basic definitions and terms related to AI technology, through a discussion of the historical context and contemporary applications, to practical case studies, ensuring a coherent and logical narrative and a better understanding of the entire process of transformation in accounting.

In the first chapter, basic information about artificial intelligence is presented—its definitions, history, and tools. This chapter thoroughly introduces key concepts and terminology, presents the most important definitions of AI and generative models, discusses key milestones in their development over decades, and explains which tools and models are most commonly used in practice today. The chapter concludes with a comprehensive review of currently used basic AI tools along with their characteristics, which forms an important foundation for understanding the subsequent parts of the work.

The second chapter explores the history of technology and artificial intelligence in accounting—from inventions to automation. The authors provide a broad historical context of technological innovations in accounting. They show how successive stages of development—from the earliest counting tools, through mechanization and computerization, to intelligent systems—gradually shaped the organization of accounting and prepared the ground for modern AI applications. It is also emphasized that the experiences of the past help to better recognize the challenges and opportunities that the implementation of new technologies brings and constitute an important background for the further analyses presented in the monograph.

The third chapter is devoted to analysing contemporary applications of AI in accounting—directions and processes. It marks the transition to the empirical part of the study, where examples of current AI implementations in accounting are presented, showing how these technologies support strategic decisions, automate processes, and facilitate predictive analyses. The chapter also develops issues related to practical examples of AI use in different areas of accounting, indicating both their effectiveness and the challenges that arise during their implementation.

The final, fourth chapter of the monograph serves as its empirical culmination. Various case studies are described here, illustrating the practical implementation of AI tools and generative models in accounting, showcasing specific deployments, their results, achieved benefits, and encountered difficulties. The authors highlight the diversity of approaches to introducing AI in practice, showing both successes and challenges that may inspire or warn against mistakes in future implementation projects.

The monograph concludes with a comprehensive summary that synthesizes the main findings of the entire study, answers the formulated research questions, and indicates practical implications derived from the analysis. Additionally, possible directions for further research are presented, and the reader is encouraged to reflect on the role of artificial intelligence in accounting. The importance of both historical aspects and contemporary implementations, which together provide the context for further exploration and discussion about the future of the profession, is highlighted.

Due to the dynamic nature of AI, it should be expected that the contemporary products discussed in this monograph (particularly in chapter 1) will become out of date. New technologies are being developed remarkably quickly and thus make it impossible to predict when information “stop” being current. This monograph is designed to be up to date as of June 30th 2025.

Chapter 1

# Understanding Artificial Intelligence — Definitions, History, and Tools

Piotr Kalinowski

## 1.1. Artificial Intelligence — Definitions, Boundaries, and Meanings

What is a computer program? One would think that it's a synonym of "algorithm"—a set of instructions for a machine to achieve a particular outcome. However, the flaws of this definition become apparent when examining Artificial Intelligence. Artificial Intelligence is man's attempt to create, as the name implies, intelligence other than his own. Through complex Machine Learning (ML) algorithms, manual reinforcement and a massive amount of training data, these programs essentially mimic human actions and reasoning in performing their tasks.

It is important to emphasize that these new creations were, and still are, unlike other algorithms. The main difference highlighted while attempting to define AI is that these algorithms can "learn". In practice a more rigorous explanation of "learning" as pertaining to a computer program may be: "refining their output based not only on their code, but also their experiences—training data" (Ozkaya, 2020).

In lieu of these complexities the first formal definition of AI was proposed in 1955 by John McCarthy—"the science and engineering of making intelligent machines". This definition however, proved to be insufficient and so more attempts have been made do formalize this concept. In their 1991 book, Ellaine Rich and Kevin Knight proposed a more pragmatic definition: "Artificial Intelligence is the study of how to make computers do things which, at the moment, people do better". This approach provides a link between AI's definition, and its practical usage—something which earlier attempts sorely lacked. Yet even the authors themselves, in the very book they posed this definition, did not neglect to highlight its shortcomings, for instance its rather narrow scope of "things that […] people do better", which fails to consider problems that people can't solve, yet machines can or problems that neither man nor machine can solve at the moment (McCarthy, 2007; Rich et al., 1991).

It's no wonder that even defining or attempting to explain what AI is difficult. The monumental, some would say, complexity of AI itself necessarily results in complexity of its definition. After all, even though humanity has been using Mathematics for thousands of years to build the very foundations of our civilisation, no formal definition exists, and those that do exist, are both radically different from each other, and widely controversial (Cajori, 1893; Mura, 1995).

Having concluded that strictly defining AI falls beyond the scope of this book, we will accept a working definition of AI posed by Professor Dalvinder Singh Grewal in his 2014 article on the very subject of defining AI: "Artificial Intelligence is the mechanical simulation system of collecting knowledge and information and processing intelligence of universe: (collating and interpreting) and disseminating it to the eligible in the form of actionable intelligence" (Grewal, 2014).

The presented definitions have several implications. If AI is designed to learn and adapt (simplifying) it follows that, in principle, these algorithms could do most of the things humans do, and several that humans cannot do. Simply put, as AI is a very broad term, it is reasonable to expect its uses and applications to be quite varied.

And indeed, that is what we observe. For years now Machine Learning algorithms have been used: to analyse large data sets, create predictions in financial markets, simulate evolution, model our planets climate and so much more. Of all the uses, however, perhaps the most recognizable is NLP or Natural Language Processing, as this is the branch of the AI tree that gave us Large Language Models (LLM) such as GPT-4o which, at the time of writing, most commonly[1] powers the well known ChatGPT.

In the next part of this chapter, we will attempt to discover the history of AI. This is in hope that through understanding the roots of a thing, we can better understand the thing itself. Before we do that however, we believe that it will become useful to divide AI and its history into two parts: History of Chatbots, and History of AI itself. Our reasoning for this distinction is that chatbots have begun their development independently from AI and only later merged with a small subset of AI—Natural Language Processing. We will begin with the story of the, comparatively, simpler technology—Chatbots.

It is not too brave to say that every one of us has at some point used, or at least heard of tools such as ChatGPT, Gemini, Claude, Perplexity, DeepSeek and so much more. Even so, most of us don't realise that these tools, while innovative, are not necessarily new and didn't "come out of nowhere". Indeed, in this chapter we will find that the *chatbots* we use today have their beginnings stretching back to the time of great scientific innovation which put man on the moon—the 1960's.

1 As we will show in later parts of this chapter, tools such as ChatGPT can use several models depending on user preference.

## 1.2. The History of Chatbots — Conversations That Changed the World

### 1.2.1. ELIZA — The Ancestor

It is 1966 at the Massachusetts Institute of Technology (MIT). A bright computer scientist fascinated with the ever-expanding uses of computer systems and "making computers appear intelligent"[2] named Joseph Weizenbaum publishes a program called ELIZA. It was an attempt mimic human to human interactions based on relatively simple word processing. ELIZA was designed to "play the part" of a particular character its creator meticulously pre-programmed. The most influential and well-known role, sometimes called a persona, was DOCTOR. In this state, modelled to play the role of an empathetic psychotherapist, ELIZA would ask questions that encouraged the user to share more about their feelings, experiences and life story. Weizenbaum himself was confounded by the attention and engagement his creation was getting from people. Almost a decade later he wrote:

> I was startled to see how quickly and how very deeply people conversing with the DOCTOR became emotionally involved with the computer and how unequivocally they anthropomorphized it… [This was] clear evidence that people were conversing with the computer as if it were a person who could be appropriately and usefully addressed in intimate terms (Agassi & Weizenbaum, 1976).

What set ELIZA apart from the scarce but existing, other "chatbots"[3] was its believability. Users firmly believed that ELIZA could understand their messages and respond as if it was really a psychotherapist. This innate human tendency to read too much into programmes' output that even remotely resembles human communication, has been dubbed "The ELIZA effect". This phenomenon we still observe elicited by modern chatbots, perhaps to a greater extent with the rise of models specifically built to serve the role of a companion.[4] Ultimately these, some would say, unhealthy relationships with ELIZA (and later creations), are what drove its creator into being one of the most prominent critics of AI in his time.

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2 Weizenbaum published a paper entitled "How to Make a Computer Appear Intelligent" in which he proposed a "intelligent" strategy used to write a program to win a simple board game—Gomoku.

3 While the term chatbot was coined much later it can be posed that ELIZA was the first notable chatbot as defined in the English Lexico Dictionary. For more reading, see (Adamopoulou & Moussiades, 2020).

4 Post 2022, there has been a surge in AI powered apps that mimic human romantic or otherwise close connections. An example would be Nomi.ai, advertised as "An AI Companion with Memory and a Soul".

As discussed earlier, ELIZA's users believed that the program understood and even cared about them. Who could really blame them seeing as how the program was built to create this effect. But was that belief true? Could ELIZA really think and talk not unlike a human?

The short answer is—no, it most definitely could not. While Weizenbaum's creation was ground-breaking and set the stage for later innovations, it was also quite primitive. ELIZA relied on basic keyword detection to detect which pre-programmed patterns fit the current user message, and then responded with, again, pre-programmed phrases that matched its playbook. A common example used to describe conversing with ELIZA is as follows: The user might type "I am feeling sad today" and the program would respond with "Why do you say you are feeling sad?". ELIZA could not understand that the user is expressing an internal sensation of an emotional pain, indeed it couldn't understand anything at all. All it did was matched the user's words to a set list and reformulated it into its message. While there is sadly no way to test this theory, we would venture to suggest that if the user typed "sad I feeling am today" it would elicit the same response from ELIZA.

This will become relevant later when we discuss how that contrasts to today's leading chatbots.

### 1.2.2. PARRY — The Vision of Chatbots' Potential

ELIZA's unexpected impact inspired others to experiment with chatbots and similar tools. A direct successor was created in 1972 by psychiatrist Kenneth Colby. PARRY, as it was named, was designed as a direct counterpart to ELIZA with the former playing the role of a psychiatric patient, specifically one suffering from paranoid schizophrenia (Adamopoulou & Moussiades, 2020).

PARRY is notable because it was quite a bit more advanced than its predecessor. For instance, Colby programmed it to have a "personality". In practice, this meant that while ELIZA simply reformulated its user's messages, PARRY had a rudimentary cognitive structure that was a very primitive form of Natural Language Processing.[5] It primarily controlled its responses based on implicit (not revealed to the user) assessments of "emotional responses" based on the changes of the user's messages. It is again important to note that PARRY had its shortcomings, namely it still had low language understanding and emotion expression capabilities, slow response times, and the inability to learn from conversations (Adamopoulou & Moussiades, 2020).

Following on Colby's previous plan to create a PARRY was put through a modified version of an experiment called "The Turing Test" (Colby et al., 1971).

5 The term "NLP" today is often conflated with its subset – Statistical NLP, used in modern systems. However, the term was first coined to refer to Symbolic NLP which relied on exhaustive lists of hand-written rules.

Named after its creator—and arguably one of the most influential researchers in computing—Alan Turing, the test was relatively simple and aimed to assess if a computer program could fool humans into thinking they were speaking to a member of their species. The standard test, as proposed by Turing in his revolutionary 1950 paper can be summarized like so: a human "interrogator" is asked to converse with a programme without any prior knowledge. After a conversation where the interrogator may ask any question they wish, they are asked to judge—did they speak to a human or a machine? (Turing, 1950).[6]

Despite its simplicity, the test was considered outlandish at a time when computers didn't yet exist. Almost 30 years later in PARRY's time, the test and the questions it posed were beginning to become more and more reasonable, as people realized that a "thinking machine" may be, in fact, possible.

As mentioned earlier, the Turing test challenging PARRY was modified somewhat, and comprised of two parts. A panel of five psychiatrist interrogators (called interview judges) were tasked (separately) with diagnosing two patients—one was a human suffering from schizophrenia, and the other was PARRY. Additionally, another 33 psychiatrists were randomly selected (called protocol judges) and asked to read a transcript of the interview judges' conversations. None of the judges were alerted to the fact that one of the patients was not a real human being, instead they rated the degree of paranoia on a scale from 0 to 9 to see if any of them would notice irregularities that would suggest the patient wasn't real.

The interview judges' "hidden test" results were as follows: "The first psychiatrist gave two correct diagnoses; another gave two incorrect ones. The third considered that both subjects were real patients, and the other two diagnosed that both subjects were chatbots" (Adamopoulou & Moussiades, 2020; Heiser et al., 1979).

As for the protocol judges, they were overall more likely to distinguish between the model and the patient, however the researchers running the test ruled that the results show the model and the patient were close to indistinguishable with the judges making the correct judgement only 48% of the time—a score obtainable simply by guessing randomly (Colby et al., 1972).

### 1.2.3. Jaberwacky — Addressing the Limitations

We now jump 16 years later into another notable advancement in the field of chatbots, particularly in the context of the aim of this book. Jaberwacky[7] was created in 1988 by developer Rollo Carpenter and was crucial because it was the first explicit use of artificial intelligence algorithms to simulate conversation. Compared

6 For a more „hands-on" (and gamified) experience with the Turing test, see: https://humanornot.so/

7 Not to be confused with „Jaberwock", a chatbot developed by Jurgen Pirner. As there are next to none sources, academic or otherwise, concerning Jaberwock it's unclear when exactly it was created, let alone how it worked.

to ELIZA, which used a keyword-based approach to match user input into a set list, Jaberwacky was the first major implementation of a rule-based approach. Instead of hard-coded lists of words and sentences, it used templates to match entire patterns. Perhaps even more revolutionarily however, Jaberwacky was also capable of basic context awareness, due to explicit detection mechanisms, and being able to include previous discussions in its processing. Carpenter's program addressed many of the main limitations and shortcomings suffered by its predecessors (namely ELIZA and PARRY), but it had some of its own—it was considered quite slow and couldn't handle many users at the same time. This brings us to another innovation—in 1997 Jaberwacky was made available to the general public through the internet and therefore was one of the first chatbots to handle many users at the same time. As an interesting fact we can mention that even though the original Jaberwacky website was discontinued, its, slightly modified, successor Cleverbot is available to this day (Adamopoulou & Moussiades, 2020).[8]

Later years brought further advancements to the field of AI and chatbots, one we might mention is the development of Artificial Intelligence Markup Language (AIML) which used XML to standardize and streamline building Knowledge Bases,[9] with ALICE,[10] a chatbot developed in 1995, being the first chatbot to use this standard.

### 1.2.4. Siri — The Impact of Chatbots

The next leap in chatbots was more sociological than strictly technological. In 2010 Apple Inc. developed Siri—a popular digital assistant that has become integral to the "Apple ecosystem". The reasons this chatbot is so notable are twofold. Firstly, Siri uses advanced machine learning for speech recognition which allowed users to talk to their "assistant" which was substantially more convincing than typing each message (in this case most often a command). Secondly, a year after its release, Siri was integrated into iOS and later into iPadOS macOS[11] and other Apple operating systems. This meant that millions of users now had direct access to a chatbot, and in turn began to wonder about its potential. The increased awareness (and demand) of chatbots bore fruit as early as 2014 when Microsoft released their own assistant—Cortana. They were soon followed by Amazon, Google and

8 To chat with Cleverbot see: (Cleverboat, 2025).

9 Knowledge Bases was a more organized way to create a set of sentences for the chatbot to "know" and use. It can be considered an evolution of the earlier template and keyword sets used by Jaberwacky and ELIZA respectively.

10 Artificial Linguistic Internet Computer Entity (ALICE) is a chatbot developed by Richard Wallace that pioneered the use of AIML for notating heuristic rules that governed its responses.

11 iOS, iPadOS and macOS are Apple's names the operating systems running on iPhones, iPads and Mac computers respectively.

several others as virtual assistants, which only increased the interest, awareness and demand for advanced chatbots and personal AI in general.

This highlights another consideration—technological innovation is only as robust as the public demands it. Indeed, since research speed can be traced directly to funding, almost every field of scientific advancements will benefit from public attention and potential commercial applications. We have ventured through the history of chatbots and explained how they were created, so before we move to the history of AI in general, we shall consider WHY chatbots were being developed.

Let's return to the previously mentioned "ELIZA effect". Weizenbaum in his time became concerned not only with the personal connections users were forming with his creation, but also the potential for, to put it bluntly, the parasocial relationships to spiral out of control. Nevertheless, as chatbots became more "intelligent" and communicative, the ELIZA effect only grew stronger, with users "feel[ing] chatbots as friendly companions and not just as mere assistants" (Adamopoulou & Moussiades, 2020; Costa, 2018). The effect was strong enough, in fact, that according to a study conducted by IBM researchers showed that around 40% of users' interactions with various chatbots can be classified as emotional, rather than practical or informational (Xu et al., 2017).

We will leave the ethical considerations of such an arrangement for now and instead note the benefits. As more and more people were introduced to the concepts and potential of AI chatbots for their personal use, the demand quickly rose. As the great innovator Steve Jobs said: "People don't know what they want until you show it to them". Now the people did know what they wanted, and the accelerated rate of improvement of chatbot technology is its direct result.

Knowing what the general public wanted, gave innovators in this space direction and motivation. It's well known, however, that motivation alone won't suffice in achieving large goals. For instance, someone might like to visit the moon, but no matter how motivated they were, there would always be one thing missing—funds. Similarly, AI and chatbots had to prove themselves to be profitable or at least to have the potential of profitability which would secure funding for research and development.

This fortunately was not difficult. Chatbots' potential to cut costs, especially in domains such as customer service and marketing is, and was, readily apparent to investors. Chatbots can effortlessly provide direct support to, potentially, thousands of customers simultaneously and can work 24 hours a day, 7 days a week with no extra cost such as wages. Additionally, the potential of AI in general has not been overlooked. Implementation of technologies such as machine vision for validating production lines, deep learning and predictive algorithms for financial institutions has been dreamed of for decades and, after a turbulent period of development, its research been sufficiently funded. Today these solutions are commonplace in almost every area of life.

## 1.3. The History of Artificial Intelligence — From Dreams to First Successes

### 1.3.1. Humanity's Early Dream

We now know why and how chatbots were created. This was, however, just the beginning of our exploration of computation history. Now we must venture deep into the story of how AI has begun and grown into the great monuments of today's technology. This story begins, of all places, in legends and myths.

Humans have been fascinated in "playing god"—creating intelligent, artificial beings. The first hints of this curiosity can be found in Greek mythology. *Talos* was a bronze creature, resembling a human being, forged by Hephaestus[12]—a smithing god serving as the blacksmith of the gods. Talos was gifted to Minos, the mythical king of Crete, to serve as the benevolent protector of his kingdom.

Depictions of artificial "men" continued throughout our centuries-old history. In the Middle Ages we find legends of *Brazen heads* created by wizards or alchemists to answer any possible question, golems created by animating a clay statue to do its creator's bidding.

But the yearning for artificial intelligence didn't stop at legends. In 1206 Al-Jazzari, a Mesopotamian polymath, in his *Book of Knowledge of Ingenious Mechanical Devices* created one of the first programmable automata. His creation was a boat carrying four mechanical musicians that were controlled by a set of cams that, when colliding with a set of levers, caused the musicians to play. It was considered programmable, because if the pegs (cams) were moved around, the machine would play a different rhythm, not unlike today's wind-up music boxes. An era later, the first known chess bot was constructed, one of many to come.[13] A Spanish engineer Leonardo Torres y Quevedo designed and demonstrated *El Ajedrecista*—an electromagnet-based chess playing machine that could reliably win against human players in a king + rook vs. king endgame.

### 1.3.2. The Dawn of the Age of AI

While people continued to build advanced automated machines, none could compare to the true power of the digital computer. We now return to "the father of

12 There exist, as often is the case with Greek mythology, several accounts of the origin of Talos. An alternative to the one we chose is him being created by Zeus himself and given to Europa.

13 Because of its rigid rules and necessity for numerus and in-depth calculations to play, chess quickly became an area of particular interest for programmers who created both traditional algorithms and later AI to create the best possible machine chess player. The human record for the highest chess ELO rating in history is currently held by Magnus Carlsen and measures 2882, while the computer record is held by Stockfish, which crushes Carlsen's score with a value of 3644.

computation" —Alan Turing,[14] and his contributions to Artificial Intelligence. Turing's theoretical work on computable numbers and his introduction of the hypothetical Turing machine, proved that a mechanical device of a relatively simple construction could imitate any mathematical operation by methodically manipulating symbols on, essentially, a strip of paper. This theoretical foundation, and the newfound potential for computing, with the development of early computing machines like ENIAC in Turing's time, caused scientists and engineers to consider more deeply building an "electronic brain".

1943 marked one of the most important theoretical inventions pertaining to Artificial Intelligence and Machine Learning. In their paper entitled "A Logical Calculus of the Ideas Immanent in Nervous Activity", McCulloch & Pitts (1943) translate human neuronal activity into the language of mathematical logic. This pivotal step enabled the later creation of Artificial Neural Networks (ANN's)[15] which aim to imitate the very biological processes that enable human thought.

In 1951 researchers Marvin Minsky and Dean Edmonds decided to push the concept of emulating a human brain through Neural Networks a step further. Instead of simply making an algorithm that could "think like us",[16] they attempted to make a system to "learn like us". SNARC or Stochastic Neural Analog Reinforcement Calculator was a system designed to use reinforcement learning—a technique where a program is "rewarded" for finding a better solution to a particular problem, and being "punished" for the opposite. The idea was to simulate the behaviour of a rat navigating a maze with the machine mimicking the way animals learn through rewards and punishment—adjusting its output (in this case movement) over time based on feedback. This early network, containing only 40 simulated neurons (sometimes called nodes) is considered tiny by modern standards[17] but was still able to learn and improve from the reward and punishment system.

Just a year later Arthur Samuel created the Samuel Checkers-Playing Program—the world's first fully self-learning program capable of, as the name suggests, of learning, and playing the game of Checkers. His program consisted of a set of predefined rules that dictated how it evaluated its effectiveness in past games and fine tuned its parameters to optimize its score. Samuel's work, beyond its obvious technological innovation, had two sociological consequences with the first being that it was him who coined the, now abundantly used, term "Machine Learning". The

14 For and introduction to Alan Turing, see chapter 1.2.2.

15 Later sources started omitting the word "Artificial" and today the model is simply called a Neural Network.

16 This statement could be considered controversial, as Neural Networks today, let alone more than 70 years ago, are rudimentary compared to the natural complexities of a human brain. Having acknowledged this, we still believe useful parallels can be drawn between machine "brains" and biological ones.

17 Transformer-based neural networks of today, such as GPT-3 have largely moved on from their biological inspiration, but to give a sense of scale, this particular network is estimated to comprise of around 6 million neurons.

other effect was more subtle, his results clearly showed that the program's skill eventually far surpassed that of its creator, which started questions and debates about AI becoming smarter than humans.

### 1.3.3. Perceptron — The First Spark of Machine Intelligence

Early neural networks were disorganized and limited in capabilities. To reach the advanced algorithms created by system architects today, more theoretical components were needed to be developed. In 1957 Frank Rosenblatt developed the *Perceptron* which, unlike its name might suggest, was not a science fiction robot, but a way to organize neural network in distinct layers. These layers vastly increased the learning potential of the network by enabling pattern recognition in the system. For now the only relevant information is that today there is no practical limit on the number of layers a network has. This is thanks to the supplementary development of back propagation—a computation method that allowed for the network to efficiently update (learn) through many layers when training. While the early concept was can be traced to just 5 years after the perceptron (1962), it had crippling limitations that made practical implementations impossible until as late as 1982. Since learning curves for error correction for large perceptron networks have not yet been successfully and universally modelled, research could only rely on empirical data collected from experimentally training the network. This disallowed any predictions of how the model would behave, which in turn made training the network inefficient, unreliable and time-consuming. The author himself stated: "Nonetheless, the three-layer series—coupled perceptron clearly falls far short of biological systems in some respects. The differences lie not in what the system can learn to do, but rather in the speed, efficiency, economy, and reliability of learning or adaptation" (Rosenblatt, 1962).

### 1.3.4. AI Winters — Roadblocks in Development

We may now take a short break from the technical challenges which AI researchers needed to overcome and instead talk about the socio-economic (and political) roadblocks in the path to AI. As established earlier, the backbone of most research is funding, and funding for AI was turbulent to say the least. The field experienced several cycles of increased interest with innovators overstating the, already inflated, potential applications. This was inevitably followed by a period of disillusionment when the field failed to reach its promised potential which caused pessimism in the AI development community and later the press. This resulted in a severe cutback in funding and the research being effectively "frozen"—this is why these periods have been dubbed the "AI winters".

The exact beginning and end dates of the AI winters are not universally agreed upon. The first is generally considered to have started in the mid-1970s, after initial optimism in the 1960s about symbolic AI and general problem solvers could not deliver practical results. A 1969 report by Minsky and Papert critically analysed the limitations of perceptrons, leading to diminished enthusiasm in neural networks. Compounding the problem was the 1973 Lighthill Report in the UK, which declared most AI research a failure, resulting in the withdrawal of government support (McCorduck, 2004; Minsky & Papert, 2017; Lighthill et al., 1998).

The second major winter began in the late 1980s, when the commercial success of expert systems like XCON was followed by a saturation of the market, unmanageable system maintenance costs, and growing awareness that expert systems were too brittle and narrow. This disillusionment was further exacerbated by economic downturns and the collapse of Japan's Fifth Generation Computer Systems project (Hendler, 2008).

Yet despite these icy periods, important foundational work continued quietly in the background. Research in probabilistic reasoning, neural networks, and machine learning laid the groundwork for the rebirth of AI in the 21st century (Russell & Norvig, 2021).

### 1.3.5. The Resurgence of AI — Breakthroughs in Backpropagation

One of the turning points that lifted AI out of its second winter occurred in 1985, when several researchers—including David Rumelhart, Geoffrey Hinton, and Ronald J. Williams—revived the concept of backpropagation. Backpropagation is a method that helps a neural network learn by figuring out what it got wrong and making small corrections by sending an "error score" backward through the system to update itself and perform better next time. This process helps the network gradually improve and make better decisions over time (Rumelhart et al., 1986).

This was more than just mathematical theory. Backpropagation enabled something called "deep learning" by making it feasible to train networks with multiple layers—a feat that had been near impossible due to earlier lack of suitable learning algorithms which were way too inefficient. With backpropagation, the brakes have been taken of neural networks, so to speak—the training of multilayer perceptrons became systematic and scalable. In effect, the algorithm transformed neural networks from mere curiosities (as they were mockingly named in the AI winters) into functional systems capable of solving real-world problems.

A few years later, in 1989, Yann LeCun applied backpropagation to convolutional neural networks (CNNs) for the purpose of recognizing handwritten digits. It was soon adopted as a proof-of-concept in automating postal services. His system could look at a scan of a postcard, figure out the important parts on its own, and then decide what digit it was seeing—all in one go. It was trained by showing it lots of examples and helping it learn from its mistakes each time. This model, known as LeNet-5, was one of the first examples of a truly practical AI system that combined theory with large-scale implementation (LeCun et al., 1989).

These breakthroughs were historically significant for three reasons. First, they demonstrated that neural networks could handle complex tasks, fulfilling the unmet expectations that caused so much disillusionment that caused much turmoil a few years before. Second, they showed that the algorithms could learn without any human "teaching" them manually, instead effectively identifying useful features from raw data. Third, they paved the way for future deep learning architectures that now power image recognition, speech processing, and natural language understanding systems across the globe.

What had once been dismissed as a theoretical dead-end now became the foundation of a new AI renaissance, one driven not by symbolic rules or handcrafted logic but by data, learning, and computation.

## 1.4. The History of Artificial Intelligence — Breakthroughs, Crises, and New Hopes

### 1.4.1. New Models, New Potential — Bayesian Networks and LSTM

Among the quiet developments during and after the AI winters were models that tackled some of the core weaknesses of earlier systems. One of the most important of these was the development of Bayesian networks. These networks made it possible to represent uncertain knowledge and reason with probabilities. Instead of needing perfect information, Bayesian networks could make intelligent guesses based on likelihoods. This was a major breakthrough for AI in areas like medical diagnosis, speech recognition, and robotics—where outcomes are rarely black and white, and often depend on incomplete or noisy information.

Another important breakthrough came in 1997 with the introduction of Long Short-Term Memory networks, or LSTMs. These were a special kind of neural network designed to remember information over time. Unlike traditional models that quickly forgot previous inputs, LSTMs could keep track of patterns and sequences—like the structure of a sentence or the rhythm of a song. This made them ideal for language modelling, machine translation, and later, even music generation.

Both Bayesian networks and LSTMs helped expand AI's reach in crucial ways. Bayesian networks, first formalized by Judea Pearl in the 1980s, brought reasoning under uncertainty into AI by allowing systems to weigh possibilities and make probabilistic decisions when data was incomplete or noisy (Pearl, 1988). This capability became a cornerstone for expert systems in medicine, speech recognition, and fault diagnosis, offering machines a framework to 'guess wisely'—a major shift from rigid rule-based thinking (Pearl, 1988).

Long Short-Term Memory networks (LSTMs), introduced by Hochreiter and Schmidhuber in 1997, overcame a key weakness of earlier neural networks: the inability to remember important information over long periods (Hochreiter & Schmidhuber, 1997). By using special memory cells that could hold and manage information across many time steps, LSTMs enabled breakthroughs in fields where sequence matters—such as speech recognition, language translation, and even handwriting generation. Their structure mimicked a basic form of short- and long-term memory, making them more human-like in learning from context (Hochreiter & Schmidhuber, 1997).

Together, these two innovations helped AI move beyond simple, static inputs to deal with the real-world complexity of language, decision-making, and time-based data—setting the stage for many of the intelligent systems we use today.

### 1.4.2. Deep Blue — The Machine That Beat the World Champion

In 1997, a major milestone in the public perception of artificial intelligence occurred when IBM's Deep Blue, a chess-playing supercomputer, defeated the reigning world chess champion Garry Kasparov in a six-game match. This was the first time a machine had beaten a world champion in a standard tournament setting, and it caused a global stir.

Technically speaking, Deep Blue did not "think" in the way humans do. It relied on brute-force computation: it could evaluate up to 200 million chess positions per second, using a combination of sophisticated algorithms and a vast database of grandmaster games and opening strategies. Its strength came not from creativity or intuition, but from speed and depth—analysing thousands of possible future moves to find the best possible outcome in any given situation(Campbell et al., 2002).

What made Deep Blue's victory so significant wasn't just its performance on the chessboard—it was the psychological and cultural shift it created. Many people saw chess as one of the ultimate tests of human intelligence, a game requiring foresight, strategy, and intuition. The fact that a machine could surpass even the best human player shook the public's belief in human uniqueness. News headlines at the time reflected both awe and concern, with some viewing Deep Blue's win as the dawn of a new era and others fearing it signalled a loss of control over our own creations.

Sociologically, the match ignited widespread interest in the potential—and the risks—of AI. For the first time, people outside the research community were confronted with a powerful, visible example of a computer outperforming a human expert. Debates surged about what other domains might be "conquered" by machines next: medicine, education, law? Kasparov himself reflected afterward that he had underestimated the machine's capabilities and later became a speaker on the cooperation between humans and AI.

Deep Blue didn't lead directly to today's intelligent systems, but it marked a turning point in how the world perceived them. It demonstrated that AI could take on expert-level tasks—and win. While Deep Blue was a specialized system with no intelligence beyond chess, its victory set the stage for broader societal awareness of artificial intelligence and helped shift the conversation from theoretical possibility to tangible reality (Campbell et al., 2002).

### 1.4.3. The Deep Learning Revolution — Hinton's Legacy

With the foundation of neural networks and backpropagation well-established, the next major leap came from Geoffrey Hinton and colleagues in the mid-2000s. They revived interest in what is now called 'deep learning'—a way to build neural networks with many layers that could learn to recognize patterns from raw data.

It's easy to confuse deep learning with backpropagation, since they are often discussed together. But they're not the same. Backpropagation is a learning method—a way for a neural network to improve by adjusting its internal settings based on the mistakes it makes. Deep learning, on the other hand, is a design approach: it uses multiple layers of neural networks to learn more complex features and patterns. Backpropagation is the tool that makes deep learning possible, but deep learning is the structure that allows for real depth in AI systems.

Instead of requiring human programmers to define rules for identifying shapes or speech sounds, deep learning models could learn these patterns themselves just by seeing enough examples. Hinton's work showed that, given enough data and the right computing power, these deep systems could surpass traditional approaches in tasks like image recognition, speech processing, and even reading comprehension (Hinton et al., 2006).

### 1.4.4. GPUs — Fuelling the Data-Hungry Brain

Much of this became possible thanks to the rise of Graphics Processing Units, or GPUs. The idea of a separate graphics processor emerged in the early 1980s, but it was in 1999 that NVIDIA introduced the first commercial GPU, the GeForce 256, branding it a "graphics processing unit" for the first time. It was built to accelerate graphics rendering in video games—handling lighting, shading, and image transformations.

What made GPUs particularly suited for AI was their ability to handle many small tasks in parallel. While CPUs (Central Processing Units) are designed for versatility and can perform a few complex tasks very quickly, GPUs are optimized for doing thousands of simple tasks simultaneously. In the gaming world, this meant rendering rich, complex scenes smoothly. In AI, it meant being able to train neural networks far more efficiently.

The CPU can be thought of as a multipurpose tool, good at handling individual jobs, and a GPU as a giant assembly line of simple tools working together. This made GPUs the ideal engine for processing the enormous number of calculations involved in training deep neural networks. The gaming industry's demand for realism had, somewhat by accident, built exactly the hardware that AI researchers needed for their data-hungry algorithms.

### 1.4.5. GANs — Machines that Imagine

In 2014, another breakthrough arrived with the invention of Generative Adversarial Networks (GANs) by Ian Goodfellow and his team. GANs introduced a creative twist: two networks in competition. One network (the 'generator') tried to create fake content—like photos of people who don't exist—while the other (the 'discriminator') tried to tell real from fake. As they played this game, both improved dramatically.

The technology behind GANs was built using deep learning methods, particularly multilayer neural networks trained through backpropagation. What made GANs innovative was not just their use of neural networks, but the adversarial setup that enabled the system to self-improve without needing explicitly labelled training data. By constantly trying to outsmart one another, the two networks pushed each other to get better, leading to surprisingly realistic and creative outputs.

The first practical applications of GANs were seen in areas such as image enhancement (e.g., turning blurry images into high-resolution ones), style transfer (e.g., applying the style of one painting to another image), and photo-realistic image generation. GANs were also used in medical imaging to simulate data for training other models, and even in fashion and architecture to generate new designs. GANs excited the public and researchers alike, opening doors to AI-generated media and raising new questions about originality, art, and authenticity (Goodfellow et al., 2020).

### 1.4.6. GPT's — Giving Machines a Voice

The next leap came with the introduction of large language models, beginning with the first version of the Generative Pre-trained Transformer (GPT) by OpenAI in 2018. The name itself explains how it works: "Generative" means it can produce text, "Pre-trained" means it learns from large amounts of information before being fine-tuned, and "Transformer" refers to the specific type of model architecture it uses—one that excels at handling sequences of data like language.

This model was trained by reading vast amounts of textbooks, articles, websites—and learning to predict the next word in a sentence. While the task sounds simple, doing it well meant the model absorbed grammar, facts, tone, and even reasoning. GPT was suddenly able to write short stories, explain ideas, and chat in ways that felt surprisingly human. This marked a shift: AI was no longer just analysing our language. It was starting to speak.

But it was the release of GPT-3 in 2020 that truly shocked the world. Built with 175 billion parameters—an enormous leap in scale—GPT-3 displayed a remarkable ability to generate natural, often insightful language. It could answer trivia, write code, summarize articles, and compose poetry—all from a single prompt. Unlike older models that needed task-specific training, GPT-3 could generalize, working across many domains with only a little guidance. The result was a machine that, to many, felt intelligent. For others, it raised ethical concerns: if AI could write convincingly, could it also deceive? Could it replace jobs?

In the months and years immediately following its release, GPT-3 was adopted in a wide range of experimental and commercial applications. Developers used it to build writing assistants, programming aids, chatbots, and customer service agents. It powered idea generation tools for marketers, scriptwriting aids for storytellers, and even tutoring bots in education. APIs made available by OpenAI allowed developers to test and integrate GPT-3 into websites and apps with minimal setup. Some companies used it to draft business reports and emails, while others explored more creative uses like poetry, songwriting, or roleplaying companions.

While the general public didn't interact with the model directly in the beginning, these uses quietly laid the groundwork for what would eventually become ChatGPT—a more guided, accessible, and socially integrated interface built on the same core model. In a sense, GPT-3's release was not just a technological milestone, but a preview of the AI-infused tools and platforms that were to follow.

### 1.4.7. AlphaFold 2 — AI Meets Biology

Also in 2020, DeepMind announced AlphaFold 2, a model designed not to write or speak, but to understand life itself. The system tackled one of biology's hardest problems: predicting how proteins fold. Proteins are essential molecules, and their shape determines how they work in the body. Scientists had struggled with this for decades. AlphaFold 2 could predict shapes with such accuracy that it rivalled laboratory experiments. This wasn't just an AI milestone—it was a moment of transformation for science, opening the door to faster drug discovery, better understanding of disease, and even synthetic biology (Jumper et al., 2021).

During the COVID-19 pandemic, AlphaFold's technology was rapidly integrated into global research efforts. It was notably used within the Folding@Home initiative, a distributed computing project involving volunteers around the world, to model proteins associated with the SARS-CoV-2 virus. While AlphaFold was not directly used to produce vaccines, its structural insights significantly accelerated the understanding of viral mechanisms—helping researchers identify potential drug targets and deepen our molecular understanding of how the virus functioned.

### 1.4.8. From DALL·E and Sora — AI in Art

After GPT-3, OpenAI began releasing models that pushed the boundaries of creativity. In 2021, DALL·E emerged as a powerful tool that could generate unique and often whimsical images from text prompts—like "an armchair in the shape of an avocado" or "a futuristic city underwater". It was based on the same transformer architecture used in GPT models, but instead of learning to predict the next word in a sentence, DALL·E learned to predict the next pixel—or patch of an image—based on a text description. This made it a model that understood both language and visual form, blending them in a coherent and often surprising way.

DALL·E showed how generative AI could expand beyond words into imagery, and it sparked public curiosity around how machines could "imagine" visual scenes never before seen. Although still limited in precision and resolution, it became a stepping stone toward general-purpose creative AI.

Jumping forward a bit, in 2024, OpenAI unveiled Sora, a video generation model that took things even further. Given a few lines of description, Sora could create entire video scenes—merging storytelling, image generation, and motion. Nowadays there of course exist more advanced video generation tools, for instance the recently released Veo 3 from Google. However, Sora was the first tool to be used widely and thus can be said to have had greater sociological impact. It marked the convergence of language, vision, and animation, and signalled that AI was no longer just responding—it was co-creating with us.

### 1.4.9. The Oracle — ChatGPT and Its Impact

30.11.2022 is a day that changed our world forever, without most people even realising it. On that Wednesday OpenAI released ChatGPT—a moment many consider to be the beginning of "The AI Era". GPT models weren't new (as discussed earlier) but it was the release of ChatGPT that took the underlying GPT model and presented it in a way that felt intuitive and conversational. By fine-tuning GPT to respond in a more dialogue-friendly format, OpenAI created an interface that millions could engage with naturally. Suddenly, people were chatting with an AI like they might with a friend or a colleague—asking for advice, explanations, or even companionship.

The sociological effects of ChatGPT's release were immediate and profound. For the first time, a broad population had continuous access to a powerful language model that could answer questions, help with writing, simulate conversations, and even serve as emotional support. In educational settings, students began using it as a tutoring aid, often turning to ChatGPT before a teacher or textbook. In creative fields, it became a brainstorming partner, assisting with writing, coding, and idea generation. People with limited access to professional services, such as legal, psychological, or medical advice, began consulting the model as a first step.

At the same time, ChatGPT raised important questions about the nature of intelligence and authorship. Could work generated with ChatGPT be considered original? Should students be allowed to use it in academic settings? Was the model simply a tool, or something more interactive and relational? These debates intensified as its presence became embedded in daily life.

ChatGPT also sparked anxiety over misinformation, job automation, and surveillance. While many users celebrated its helpfulness, critics pointed out the ease with which it could generate persuasive yet false or biased information. Professions reliant on writing, communication, or customer interaction began to reassess their future.

Culturally, ChatGPT helped normalize the idea of conversing with a machine. What once felt futuristic or niche became commonplace: people began naming their bots, sharing conversations online, and incorporating ChatGPT into routines. It did not just change the way people accessed information—it subtly changed how they thought about knowledge, trust, and interaction in a digital society.

## 1.5. The AI Ecosystem — Introduction and Its Practical Relevance

### 1.5.1. A First Look at Today's AI Ecosystem

We have explored how the development of chatbots naturally merged with the development of AI and, perhaps more importantly, the motivations fuelling this progress. From the early ambition of creating autonomous machines, through the first learning algorithms and machines that "speak" and "learn". Where does this story lead? Having understood history, we are now almost properly equipped to discuss the present.

However, while we know the technical terms that describe AI tools, we don't yet know the organizational structure the creators of these tools use to group and distinguish them from one another. To address this, we introduce a structured framework that clarifies how to interpret and differentiate the various tools, companies, and technologies present in the AI landscape.

To understand the modern AI environment, it is crucial to distinguish between three key layers:

**Platform** – The interface the user interacts with. A platform is the actual product that delivers AI to the end-user. For example, ChatGPT is a platform accessible at chat.openai.com, Claude (by Anthropic) at claude.ai or Gemini at gemini.google.com.

**Provider** – The organization responsible for releasing and maintaining the platform or the underlying models. Providers can develop their own models or license models from others. For instance, OpenAI provides ChatGPT, Anthropic provides Claude, and Google DeepMind provides Gemini.

**Model** – The Large Language Model itself—the core engine that powers AI functionality. Models such as GPT-4o (by OpenAI, powering ChatGPT), Claude 3 Opus (by Anthropic), and Gemini 1.5 Pro (by Google) are the underlying technologies that determine the platform's capabilities.

Obviously, it can't be that simple. Certain platforms (e.g., ChatGPT, Perplexity, Copilot) are built upon multiple models while some models are reused across providers and platforms (e.g., GPT-4o is used both by ChatGPT and Microsoft Copilot). Others, such as Meta's LLaMA or DeepSeek-R1, are open-source and therefore can be used by anyone to build any service they wish. These, however, are exceptions to a rule that will still be helpful in understanding the most commonly used tools.

As a word of conclusion, understanding the contemporary platforms and ecosystems of artificial intelligence reveals how diverse and advanced today's tools are, enabling the implementation of AI in business and accounting practice. This knowledge is the last piece in the story of AI's development and will render us ready for the following chapters of the monograph, which will explore the impact of AI on accounting and its practical applications.

### 1.5.2. ChatGPT (Platform by OpenAI)

**Provider**: OpenAI
**Models**: GPT-4o, GPT-4.5, GPT-5, GPT-5 Thinking and many others
**Use Case**: Multimodal[18] assistant for general-purpose productivity, creativity, education, and research

ChatGPT is the most well-known AI assistant available today. Its strength can be arguably attributed, at least in part, to its enormous library of features both related and unrelated to the actual models used. ChatGPT supports text, code, and images which is quite typical for a chatbot these days. What makes ChatGPT different are the integrated improvements—for instance Canvas—a feature that allows users to write alongside the AI in an unprecedented way or the bot's ability to write and run code by itself which opens endless possibilities for tackling more challenging prompts. ChatGPT's provider—OpenAI also offers powerful customization through the so-called Custom GPTs, which allow users to and create tailored versions of ChatGPT with unique instructions, behaviours, or tools. Alternatively, OpenAI created an entire ecosystem of purpose-built renditions of ChatGPT through their "GPT Store". These features significantly extend the utility of the base model by adapting it to specific tasks or audiences.

18 Multimodality is the ability to process and generate multiple types of input and output such as text, images, and audio, allowing for richer interaction and broader application scenarios.

### 1.5.3. Claude (Platform by Anthropic)

**Provider**: Anthropic
**Models**: Opus 4, Opus 4.1, Sonnet 4, Sonnet 4.5, Haiku 3.5
**Use Case**: Professional analysis, legal and technical writing, structured reasoning

Claude is known for its emphasis on safety, structured reasoning, and long-form, high-quality output, making it well-suited for professional and academic work. It excels at coding and analytical tasks with remarkable precision, able to explain algorithms step-by-step, review and refactor code, and even generate entire modules tailored to specific requirements. In legal and technical writing, it produces clear, logically-structured documents, supports drafting and reviewing contracts, and aids in building robust arguments with detailed citations. Its thoughtful, context-aware responses in complex domains make it particularly valued for scenarios that demand rigorous reasoning and high reliability.

Recent benchmark results place Claude—especially its Claude 4 (Opus 4/ Sonnet 4) iteration—at the top of AI coding rankings. Claude Opus 4 achieved a record-setting 72.5% on SWE-bench and 43.2% on Terminal-bench,[19] the highest among all models tested, outperforming OpenAI's GPT-4.1 and Google's Gemini 2.5 Pro (Anthropic, 2025). In real-world use, the model sustains independent code refactoring tasks for up to seven hours of continuous operation, cementing its position as the go-to assistant for complex, multi-hour software development projects.

### 1.5.4. Gemini (Platform by Google DeepMind)

**Provider**: Google DeepMind
**Models**: Gemini 2.5 Pro, Gemini 2.5 Flash, Gemini 2.5 Flash-Lite
**Use Case**: Integrated assistant across Google Workspace (Docs, Gmail, Android, etc.) with multimodal and long-context abilities[20]

Gemini integrates deeply with Google's ecosystem, enhancing productivity tools such as Gmail, Docs, and Android with AI-powered assistance. This tight integration enables seamless collaboration across emails, meetings, and documents, allowing workflows that span calendar events, chat discussions, and document editing without leaving the ecosystem. It excels at handling long, multimodal workflows, learning from a user's documents, emails, and notes to deliver contextually relevant and media-rich support.

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19 SWE-bench and Terminal-bench are benchmarks for evaluating large language models on realistic software tasks. SWE-bench measures a model's ability to resolve real-world GitHub issues by generating code that passes project tests. Terminal-bench assesses a model's proficiency in completing command-line tasks in a Linux terminal. Scores in both benchmarks represent the percentage of tasks successfully completed.

20 Context or a context window is the model's capacity to retain and consider prior input in a single conversation. A large context window enables more coherent dialogue and better handling of complex, multi-step tasks.

Beyond this, Gemini leverages Google's search, cloud storage, and even Android OS-level hooks to offer context-aware suggestions, summarize threads, draft documents using existing knowledge bases, and streamline repetitive tasks, making it a natural fit for users already embedded in Google's tools and services.

### 1.5.5. Copilot (Platform by Microsoft)

**Provider**: Microsoft
**Models**: GPT-4, GPT-4o, GPT 5, GPT-5 Thinking (via Azure OpenAI)
**Use Case**: Embedded AI for Microsoft 365 apps (Word, Excel, PowerPoint, Outlook, Teams), Windows OS, Edge browser, and Copilot mobile apps

Copilot is Microsoft's AI platform for enterprise users, integrated into Microsoft 365 and Windows. It automates tasks like drafting documents in Word, analyzing data in Excel, summarizing in Teams, and managing schedules in Outlook, and its deep integration enables context-aware assistance across these applications—for example, it can pull insights from emails into reports, generate presentations from meeting notes, or create Excel models based on Word documents.

The introduction of 'Copilot+ PCs' with dedicated AI hardware further enhances its performance with on-device capabilities. Equipped with powerful NPUs, these PCs enable instant AI features like live captions, background removal, voice focus, image enhancement, and faster, more responsive Office integration—all running locally for improved speed, privacy, and extended battery life, making workflows even smoother and more capable within the familiar Office environment.

### 1.5.6. Perplexity (Platform by Perplexity AI)

**Provider**: Perplexity AI
**Models**: GPT-4o, GPT-5, GPT-5 Thinking (OpenAI), Claude 3.7 Sonnet (Anthropic), Claude Instant (Anthropic), Perplexity (own search models), Mixtral (multi-model AI architecture), Gemini (Google AI, selected features)
**Use Case**: Search-focused factual assistant with source citations and browsing tools

Perplexity combines live web search with LLM output, producing concise, citation-backed answers ideal for fact-checking and research. It demonstrates unparalleled proficiency in academic research by surfacing credible, up-to-date sources, generating structured bibliographies, suggesting related research questions, and even helping draft abstracts or literature reviews. It can analyse uploaded papers to find gaps, summarize findings, and recommend follow-up readings. Features include follow-up threads, document uploads, and shareable 'Perplexity Pages' while letting users choose among multiple models for a customized experience focused on accuracy, depth, and traceability, making it a powerful tool for students, researchers, and professionals alike.

### 1.5.7. Grok (Platform by xAI)

**Provider**: xAI (Elon Musk)
**Models**: Grok-3 Mini, Grok-3, Grok-4 Fast, Grok-4 Heavy, Grok-4
**Use Case**: Conversational AI for entertainment, real-time web browsing, and integration with X (formerly Twitter)

Grok is designed for engaging, edgy conversation, with direct access to live content from X (formerly Twitter). It draws on trending topics, recent posts, and breaking news, offering timely cultural commentary and social-media-driven insights. Unique among chatbots, it allows users to mention Grok (*@grok*) directly in the comments of an X post and receive context-aware replies based on that post, seamlessly integrating into social conversations.

Beyond its appeal to users who value humor, real-time awareness, and cultural relevance, Grok also supports more serious use cases—summarizing threads, analyzing sentiment, providing quick fact-checks, and offering context-rich responses to ongoing discussions. These capabilities make it suitable not only for entertainment and live event discussion but also for media monitoring, brand engagement, and staying informed on dynamic topics in professional settings.

### 1.5.8. DeepSeek (Platform by DeepSeek AI)

**Provider**: DeepSeek AI (China)
**Models**: DeepSeek-V3, DeepSeek-R1, DeepSeek-V3.2-Exp, DeepSeek-VL2, DeepSeek-Coder-V2, DeepSeek-R2
**Use Case**: Advanced AI applications including complex reasoning, coding, scientific and mathematical tasks, multimodal understanding with text and images, efficient handling of very long contexts (up to 128K tokens), and open access with strong performance benchmarks

DeepSeek offers high-accuracy technical models, open-sourced for developers and researchers, with a focus on reproducibility[21] and structured logic—clearly organized and stepwise problem-solving capabilities that excel in domains like mathematics and programming. However, DeepSeek has also drawn criticism over its ties to the Chinese government, with allegations of potential misuse related to censorship and state surveillance. These concerns stem from broader geopolitical apprehensions about China's regulatory environment and the possibility of LLMs being co-opted for monitoring, content control, or influence operations. Although no direct evidence has confirmed DeepSeek's involvement in such practices, its national origin and open-access policy have prompted caution among security experts, particularly in Western contexts where data sovereignty and transparency are central to trust.

21 In this context reproducibility means the ability for others to independently verify results using the same model and data.

### 1.5.9. LLaMA[22]-Based Tools (Various Platforms)

**Provider**: Complicated—The creator is Meta AI (Facebook), but the open-source models are provided on various other platforms, for instance—*Hugging Face*
**Models**: LLaMA 2, LLaMA 3, LLaMA 4 (including specialized variants such as LLaMA 4 Turbo and LLaMA 4 Vision)
**Use Case**: Widely adopted open-source foundation models for LLM[23] research, fine-tuning, multimodal tasks, and deployment across various platforms including Hugging Face and enterprise solutions, supporting advanced applications from custom model development to integration of vision and language capabilities

LLaMA models are among the most widely used in the open-source community, serving as foundational architectures for developers, startups, and academic institutions aiming to fine-tune[24] and deploy models without relying on proprietary systems. These models enable customization for specific use cases such as coding assistants, domain-specific chatbots, or in theme with this monograph even an accounting assistant. Platforms like Hugging Face play a central role in this ecosystem by hosting pre-trained model checkpoints, facilitating collaboration through shared repositories, and providing easy-to-use APIs[25] for inference[26] and training. Hugging Face's 'transformers' library, combined with its Model Hub, allows users to access, deploy, and experiment with thousands of LLM variants in a standardized environment—democratizing access to cutting-edge AI technology and encouraging transparency, interoperability, and innovation in the AI community.

**Table 1.** A brief comparison of current AI chatbots

| Platform/Tool | Provider | Main Models | Key Strengths & Use Case |
|---|---|---|---|
| **ChatGPT** | OpenAI | GPT-4o, GPT-4.5, GPT-5, GPT-5 Thinking | General-purpose, multimodal assistant with unique tools (Canvas, Custom GPTs, GPT Store) for creativity, productivity, education, and coding |
| **Claude** | Anthropic | Opus 4, Opus 4.1, Sonnet 4, Sonnet 4.5, Haiku 3.5 | Professional analysis, legal & technical writing, superior coding & reasoning, high reliability for complex, long tasks |

22 Large Language Model Meta AI (LLaMA) is a family of open-weight large language models released by Meta starting in early 2023. They are characterised by being smaller (easier to run on a local machine), open source (freely available for anyone to download, modify and use locally) and great efficiency (resource requirement to model performance ratio).

23 As a reminder LLM stands for Large Language Models—the "inner cores" of AI chatbots.

24 Fine-tuning in the context of LLM's is the process of retraining a pre-existing model on a specific dataset or for a specific task to improve performance in a targeted domain, such as legal advice, customer support, or biomedical research.

25 Application Programming Interfaces allow developers to access and interact with models (or other software) directly over the internet.

26 Inference, here, is the process of running a trained model to generate predictions or outputs based on input data.

**Table 1** (cont.)

| Platform/Tool | Provider | Main Models | Key Strengths & Use Case |
|---|---|---|---|
| **Gemini** | Google DeepMind | Gemini 2.5 Pro, Gemini 2.5 Flash, Gemini 2.5 Flash-Lite | Deep integration with Google Workspace (Docs, Gmail, Android), excels at multimodal, long-context workflows within Google ecosystem |
| **Copilot** | Microsoft | GPT-4, GPT-4o, GPT 5, GPT-5 Thinking (via Azure OpenAI) | Embedded AI for Microsoft 365 apps (Word, Excel, PowerPoint, Outlook, Teams), Windows OS, Edge browser, and Copilot mobile apps |
| **Perplexity** | Perplexity AI | GPT-4o, GPT-5, GPT-5 Thinking, Claude 3.7 Sonnet, Claude Instant Perplexity (own search models), Mixtral, Gemini 2.5 | Search-focused, citation-backed answers, outstanding for research & fact-checking, bibliographies, document analysis |
| **Grok** | xAI (Elon Musk) | Grok-3 Mini, Grok-3, Grok-4 Fast, Grok-4 Heavy, Grok-4 | Conversational, real-time social media integration, especially with X (Twitter), humorous yet insightful commentary & monitoring |
| **DeepSeek** | DeepSeek AI (China) | DeepSeek-V3, DeepSeek-R1, DeepSeek-V3.2-Exp, DeepSeek-VL2, DeepSeek-Coder-V2, DeepSeek-R2 | Advanced AI applications including complex reasoning, coding, scientific and mathematical tasks, multimodal understanding with text and images, efficient handling of very long contexts (up to 128K tokens), and open access with strong performance benchmarks |
| **LLaMA-based tools** | Meta AI & open community | LLaMA 2, LLaMA 3, LLaMA 4 (including specialized variants such as LLaMA 4 Turbo and LLaMA 4 Vision) | Open-source foundation for LLM experimentation & fine-tuning, widely used on Hugging Face for research, customization, and transparency |

**Source:** own study.

Chapter 2

# The History of Technology and Artificial Intelligence in Accounting — From Invention to Automation

Jacek Kalinowski

## 2.1. The History of Invention — From Fire to Algorithm as the Context for AI Development

### 2.1.1. The Technological March of Humanity Toward Intelligence

Human History is an epic tale of the spirit of discovery, of a relentless effort to tame nature, to organise society, and to fathom the mysteries of existence. As Plato wrote in "The Republic", true wisdom is achieved through constant striving to know what is unchangeable and eternal. Each era has brought inventions that not only changed the practical aspects of life but often initiated a revolution in the way of thinking about man and the world. In the context of the development of artificial intelligence—a tool capable of emulating human mental structures and processes—it is worth looking retrospectively at the breakthroughs that marked the successive phases of civilisation's march towards the advancements we now enjoy, thus placing it in the broader context of the history of human invention (Plato, 2013).

In the following paragraphs, we will look at nine historical breakthroughs that played a fundamental role in the development of civilisation: from the Neolithic Revolution, through the Metal Age, to computers and generative models (see Figure 1, a chronological overview of nine key turning points in the history of civilisation).

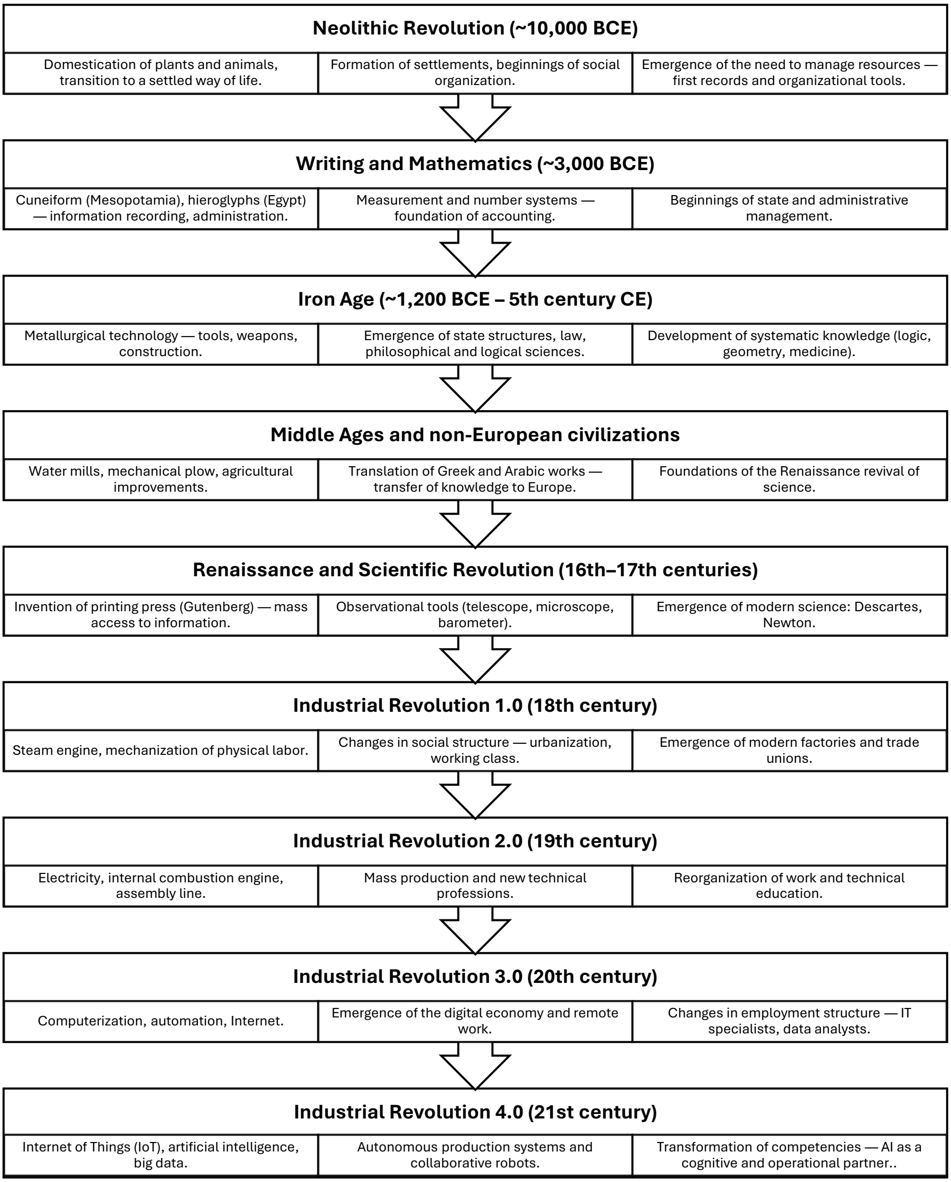


**Figure 1.** The most important technological breakthroughs in human history: from the Neolithic revolution to the age of data and artificial intelligence.
**Source:** own study.

Each of these moments changed not only the way we live but also the way we think about the world and ourselves. The foundations of knowledge, the structures of power, the ways of communication and interpretation of reality have changed—from mystical tribal thinking, through Greek rationalism, to the digital logic of algorithms. Successive inventions have redefined the conceptualisations of work, community, and knowledge, creating cultural paradigms in which we embed our social and economic actions.

### 2.1.2. Inventions as a Mirror of Social and Economic Changes

One of the first breakthroughs is considered to be the so-called Neolithic Revolution which, around 10,000 years BCE, brought the domestication of plants and animals. This event not only changed the way food was obtained but also led to a sociocultural breakthrough: people abandoned the nomadic lifestyle and began to create settlements, which became the nucleus of future cities and beginnings of state structures. Agriculture, although originally primitive, over time gave rise to the need to organise work, store surplus food and thus manage natural resources. In response to these needs, the first administrative institutions began to emerge, accounting tools appeared, and with them writing and systems of measurement, especially in Mesopotamia and Egypt. They gave rise to what today we would call information and knowledge management.

Another great civilisational leap was the mastery of metallurgy, especially iron processing, which took place between the 12th century BC and the 5th century AD. New materials allowed for the creation of more efficient tools, better weapons, and durable architectural structures. At the same time, state, religious and philosophical systems were being developed, and civilisations such as the Greek and the Romans began to systematise knowledge. It was in this era that the foundations of the sciences appeared: logic, geometry, medicine and rhetoric, as well as institutions of law, which have survived to this day. Technical and intellectual development went hand in hand here, which was of fundamental importance for later Europe.

The Middle Ages, often wrongly perceived as an era of stagnation, was in fact a period of numerous technical innovations. The development of water mills, the invention of the mechanical clock, the improvement of sailing and agricultural techniques contributed to economic growth and the stabilisation of social life. Of particular importance was also the exchange of knowledge with Muslim and Far Eastern civilisations, which at that time surpassed Europe in terms of the development of natural and mathematical sciences. Due to the translations of Greek and Arabic works, the thoughts of Aristotle and Euclid returned to Europe, which became the intellectual foundation of the later Renaissance.

However, the real explosion of knowledge and inventiveness occurred in the Renaissance era and during the scientific revolution of the 17th century. Gutenberg's invention of the printing press made it possible for ideas to spread *en masse*. Galileo's telescope, Leeuwenhoek's microscope, and Torricelli's barometer have expanded human senses beyond natural limits. The new cognitive paradigms, shaped by Descartes and Newton, assumed that the world was knowable, measurable, and describable in the language of mathematics. Science has gained momentum and great technology followed.

### 2.1.3. Four Industrial Revolutions: From the Steam Engine to Algorithms

The eighteenth century brought another radical transformation—the invention of the steam engine. This milestone triggered the first Industrial Revolution (Industry 1.0), which lasted from about 1760 to 1840. It was during this era that machines began to replace human and animal physical force on a massive scale for the first time in history. The main areas of application of the new technologies were textile and metal industries, as well as transport—rail and river. New energy sources such as steam have enabled the creation of factories that have changed Europe's economic and spatial structure. Large agglomerations were created, working classes formed, and with them new social and economic problems. Some traditional professions disappeared, such as craft weavers, blacksmiths, or furriers, whose work was taken over by machines. At the same time, however, completely new specialisations appeared: machine operators, mechanics, engineers, railwaymen, or factory and warehouse workers. The transition from manufactory to mechanised serial production did not so much eliminate employment but profoundly changed its nature, structure, and social relations. It also opened the way for the emergence of workers' movements, trade unions, and modern forms of work organisation. The Industrial Revolution 1.0 thus marked the beginning of the modern era, laying the foundations for the next waves of technological and social change. This was followed by inventions such as the internal combustion engine, the light bulb and the telephone, which reinforced the dynamics of change and led to the second industrial revolution (Industry 2.0; c. 1871–1914), based on electricity, assembly line and mass production. During this period, the number of strictly industrial professions exploded, but at the same time new roles appeared: electricians, installers, assembly line engineers, telegraph and telephony technicians.

The twentieth century was an era of technological acceleration. It was the third industrial revolution (Industry 3.0; from the 1940s to about 2000), which was based on electronics, computers and process automation. The invention of the computer and the electronic calculator at the turn of the 1940s and 1950s of the twentieth century gradually replaced the need for manual counting and calculations performed, for example, by accountants, leading to the development of office automation. In the following decades, personal computers appeared, which revolutionised information management and led to the emergence of new professions: programmers, data analysts, system administrators. Subsequently, the Internet, developed since the 1970s, became a global medium that enabled the almost instantaneous flow of information and the birth of the digital economy. Similarly, automation and robotization in industry have led to a decrease in the demand for some forms of physical labour, but at the same time created a demand for new specialists—automation engineers, control system operators, IT specialists. All these changes are the foundation for the fourth industrial revolution (Industry 4.0), which began after 2011, when a new concept was proposed in Germany to integrate digital technologies into production processes. Industry 4.0 includes solutions such as the Internet of Things (IoT), cyberphysical manufacturing systems, artificial intelligence, big data analytics, and collaborative robots (cobots). In the factories of the future, machines communicate autonomously, making decisions and learning from data. Again, his phase does not so much reduce the number of jobs but forces deep changes in competences—the need to retrain employees and develop professions based on knowledge management, data and complex technological systems. The history of technological change thus shows that inventions rarely lead to the complete displacement of people from the labour market—much more often they result in the transformation of their role, require retraining and open up space for new forms of employment.

### 2.1.4. Toward Intelligent Systems — The Birth of Thinking Machines

Artificial intelligence is one of the most groundbreaking technologies of the 21st century, which initially emerged as a philosophical hypothesis, and today functions as a real set of tools capable of transforming entire sectors of social and economic life. It is no longer the domain of science fiction literature or the subject of experiments in academic laboratories—AI has become a part of our everyday life. From shopping recommendations and automatic translation of texts, to support for medical diagnostics, to the generation of visual and linguistic content at a level indistinguishable from human work, artificial intelligence is redefining our understanding of work, knowledge, decisions and responsibility. Learning models, pattern recognition, natural language processing, and mass data analysis indicate that AI is no longer just an enablement tool—it is a transformative platform that changes the structure of decision-making and the nature of our interaction with reality. Just as the steam engine once ushered in a new era of production, today artificial intelligence opens up an era of assisted reflection, automated cognition and new forms of human-technology interaction.

Exploring this path—from fire and hoe to algorithms and generative models—is not just an exercise in reconstructing the past. It is an attempt to grasp the universal pattern of technological development that has accompanied humanity since the dawn of time, and which allows us to better understand where we stand in civilisation. Understanding this trajectory has a practical side to it: it allows us to better prepare for a future in which artificial intelligence will not play a marginal role but will become one of the basic mechanisms organising social and economic structures.

While we continue on our mental journey, we will soon find that intelligent technologies gradually permeating into all areas of life: education, medicine, finance, public administration, culture and art. They will not only support our decisions, but more and more often co-create them. For this reason, it is necessary not only to know the potential of AI, but also to reflect on its ethical, legal and social consequences. As George Santayana aptly put it: "Those who cannot remember the past are condemned to repeat it" (Santayana, 1927, p. 284). In the case of artificial intelligence—this "thinking machine"—the stake is not only repeating the mistakes of the past but also shaping a new horizon of technological responsibility. Important ethical questions arise: Who is responsible for the decisions made by algorithms? Is it possible to program justice, empathy, care for the common good? How do we prevent bias in the data that systems teach and how do we avoid creating technologies that exacerbate social inequality? Equally worrying are the challenges related to the automation of workplaces, surveillance, cognitive addiction[1] or the possibility of abuse in areas such as military tactics, general disinformation or manipulation of public opinion. Therefore, the development of AI must go hand in hand with the development of technological ethics, transparency of activities and building a responsible regulatory framework that will protect the public interest, human rights and the long-term common good.

## 2.2. The Origins of Counting — From Myths and the Abacus to Early Computational Practices

### 2.2.1. The Abacus — The First "Digital" Accounting Tool

One of the earliest and most influential tools for supporting arithmetic calculations in human history was the abacus. Its use, documented since ancient times, dates back to at least the 7th century BCE, when it appeared in Greek culture in response to the growing needs of trade, public administration and tax practices. The form of the abacus was based on a frame or surface divided into columns on which jetons (stones, tokens, beads) were moved, representing numbers in the decimal system. This allowed the user to perform basic mathematical operations—addition, subtraction, multiplication and division—without the need for written notation. As summarized by Sugden (1981), this construction was intuitive, based on logical principles of grouping and moving elements, which made it accessible even to illiterate people. Despite the subsequent introduction of Arabic numerals and algorithmic written methods, the abacus remained a tool widely used in

1 Cognitive addiction is the act of inadvertently transferring the responsibility of thinking, judgement and decision-making onto intelligent systems such as AI.

Europe for more than six centuries, demonstrating its functionality, durability, and deep-rooted role in accounting practice.

As Sugden (1981) emphasizes, the fundamental importance of abacus for the development of Western accounting and mathematics was not only due to its universality but, above all to the fact that it was the first effective, practical representation of the decimal system, based on the natural reference to ten fingers. The role of abacus in the consolidation of the decimal number system cannot be overestimated: The numerals represented not only the nominal value, but also the positional structure, which was later taken over by the numerical system. In this sense, the abacus served not only as an accounting tool but also as an educational one, allowing users to intuitively assimilate the principles of number and arithmetic systems.

In the context of the history of accounting technology, the abacus should be considered the progenitor of modern calculators, a device that made it possible to perform complex mathematical operations without the need to use numerical notation. Thanks to its versatility and independence from the accepted numerical notation, the abacus was especially valued in cultures whose writing systems or numerals were unwieldy to perform calculations, as was the case in ancient Greece, Rome or the Near East. Importantly, the abacus made it possible to operate on large numbers and facilitated repetitive accounting activities, making it a tool commonly used in retail trade as well as in tax and military administration.

Sugden (1981) also notes that despite technological and material limitations, the abacus was such an effective tool that its basic design and principles of operation remained virtually unchanged for over two thousand years. Only the materials and the cultural context of its use have changed. In the Middle Ages, it was present not only in marketplaces, but also in royal chancelleries and monasteries, where it was used to keep accounts of church property. Moreover, its presence was noted not only in merchant circles, but also in state and educational institutions, confirming its key role in shaping accounting practices in premodern civilisations. Even after the introduction of the Arabic numeral system, the abacus retained its position as a reliable, durable, handwriting-free tool and resistant to accounting errors.

### 2.2.2. From Myth to Logic — Ancient Sources of Accounting Technologies

As pointed out in Chapter 1, the ability of humans to create abstract ideas about artificial intelligence dates back to ancient times. Already in the oldest mythologies, humanity presented visions of beings created by man or by gods, who were equipped with the ability to move, reason or perform specific functional functions. Long before technological advances that made it possible to construct autonomous devices, the ideas of creating artificial life and mechanical beings were present in mythological narratives, constituting primordial forms of reflection on the relationship between technology and humanity (Mayor, 2018).

The beginnings of ideas resembling artificial intelligence can be seen, among others, in Greek mythology. Homer in the "Iliad" describes how Hephaestus—the divine blacksmith—constructed mechanical tripods equipped with wheels, which could move around the palace of the gods on their own, serving during feasts on Olympus. In addition, he created golden servants who not only performed household chores but also had the ability to speak and act independently.[2] These are examples of mythological automatons that met the criteria attributed to intelligent machines today: autonomy, the ability to communicate and perform complex functions (Mayor, 2018, pp. 60–70).

Such images were not limited to the Greek tradition. In Jewish mythology, there was a Golem—a creature made of clay—that came to life as a result of ritual formulas. Chinese and Indian literature as well, there are mentions of mechanical servants, figures moved by hidden mechanisms or automatic musicians playing at the command of the ruler. The common denominator of these narratives is the perception of the man-made entity as a carrier of executive and sometimes cognitive competences that reflect the basic functions of artificial intelligence.

From the perspective of the history of ideas, it can therefore be considered that the roots of today's AI technologies are deeply embedded in the cultural and philosophical heritage of humanity. This shows that the dream of creating machines in the image and likeness of man—capable of thinking and acting—is not only a product of modernity but is a continuation of ancient aspirations and technological myths (Mayor, 2018).

In turn, in the fourth century BCE, Aristotle proposed syllogistic logic[3] in "First Analysts" as the first known system of formal deductive reasoning (Aristotle, 1998). This was a breakthrough achievement in the history of logical thought, which made it possible to reason systematically on the basis of general premises leading to specific conclusions. Aristotle thus conceptualised the basic forms of argumentation, which were later reflected not only in science but also in practical computer science applications. His approach was based on structured reasoning and classification of types of inference, which laid the groundwork for the development of information theory, rule systems, and structural knowledge bases. In this sense, syllogistic logic represents one of the earliest models of formalised information processing, which we find today in the logical architectures of AI systems.

2 In the Iliad, Book XVIII, Homer writes: "And two statues in the shape of two virgins made with an uncertain step supported the uncertain step: And motion, and voice, and reason, the gods gave them, and industry [ingenuity], capable of making more wonderful works" (Homerus (c. 8th century BCE), 2019). They are artificial, anthropomorphic automatons, made of metal, but possessing speech, consciousness and intelligence—which from today's perspective can be compared to androids or AI with a humanoid body.

3 It is also known in literature as Aristotle's classical logic or the logic of categorical propositions. Its main goal was to study the correctness of deductive inferences, especially those based on syllogisms consisting of three elements: two premises and a conclusion. All of them are categorical sentences (i.e. predicates, concerning belonging to a class).

This approach gained particular value in the context of the development of expert systems in the second half of the twentieth century, where the decision-making process was based on a set of rules such as “if… then…”, corresponding to the structures of the classical syllogism (Nilsson, 2010).

In the history of accounting technology, the importance of syllogistic logic is particularly evident in the transition from manual bookkeeping methods to automated financial data processing systems. The formalisation of decision-making processes, based on the inference structures proposed by Aristotle, allowed for the construction of business rules determining the method of classification, verification and reporting of accounting data. With the development of computerisation in accounting, a logical approach to information processing began to be implemented in decision support systems, including modules supporting management accounting, auditing and financial controlling.

The properties of the syllogism explained earlier—clarity of structure, unambiguity of premises and predictability of conclusions—turned out to be extremely useful in the construction of early expert systems. In particular, the application of the logic “if… then…” was reflected in automatic rules for controlling the correctness of accounting entries, classification of economic operations and anomaly detection, which was widely described, in research Appelbaum et al. (2017). This approach has made it possible to create transparent decision-making paths, understandable for both system designers and end users—accountants, auditors and managers.

Although modern AI solutions today also use more advanced methods—such as fuzzy or probabilistic logic—their foundations still refer to the structural concept of formal reasoning, the classic expression of which can be found in syllogistic logic. Thus, Aristotle’s achievements can be considered one of the pillars of the historical development of accounting technology, combining philosophical reflection with practical application in the area of processing and interpretation of financial information.

Thanks to the formalisation of such logical structures, it became possible to later develop rule-based algorithms that were used in accounting and auditing, especially in anomaly analysis, forecasting and decision support (Appelbaum et al., 2017). In this way, historical philosophical and mathematical foundations have been transformed into practical technological applications, which are an integral part of modern financial and accounting systems.

# 2.3. The Age of Mechanical Dreams — Inventions That Transformed Accounting

## 2.3.1. Leibniz's Calculating Machine — The Mechanical Dream of Intelligence

When analysing the history of technology in accounting, it is impossible to ignore the figure of Gottfried Wilhelm Leibniz (1646–1716)—one of the most outstanding scholars of the Baroque era, whose achievements had a far-reaching impact on the development of modern science, and indirectly also on the technologies used in accounting. Leibniz was not only a philosopher and mathematician, but also an engineer of ideas, who combined abstract considerations with practical mechanical concepts with extraordinary precision. Already in the seventeenth century, he formulated pioneering logical and structural ideas, which are the foundations of computer science, formal logic and artificial intelligence (Hasan, 2022).

One of Leibniz's most groundbreaking undertakings was the construction of a computing machine, later called Leibniz's calculation machine. The mechanism was based on gear cylinders and was an improvement on Blaise Pascal's earlier design. Significantly, unlike Pascal's calculator, which only supported addition and subtraction, Leibniz's machine introduced multiplication and division as a process of multiple addition or subtraction—a significant step towards automating more complex calculations(Buchanan, 2005).

From the point of view of the development of accounting technology, this machine was one of the first examples of transforming intellectual operations into mechanical ones. For Leibniz, calculation was an act of reasoning, and since reasoning can be formalised, it can also be written in the form of a mechanical diagram. In this sense, its construction was not simply a tool, but also a philosophical experiment that was to prove that reasoning, also in the areas of accounting practice, can be transferred to the world of machines.

This idea of rationalising disputes with the use of machines was a precursor to machine logic and expert systems, which are currently used in accounting to verify transactions, detect anomalies or model future predictions. The belief forged by Leibniz's machine, that the operation of the mind could be captured in a procedure, became an inspiration for later computer scientists, including George Boole, Charles Babbage, Alan Turing and John von Neumann, whose work led to the creation of next-generation computing machines.

It is worth noting that although Leibniz's machine itself did not find widespread practical application in his time, its impact on later thinking about information processing was fundamental. It was a prototype of a device that was designed for the first time with versatility in mind, not just a utility function. Thus, it can be considered the spiritual progenitor of both the calculator and the digital computer—tools that in the 21st century form the basis of technologies used in accounting, from simple accounting applications to advanced systems based on artificial intelligence.

In the context of accounting, the Leibniz machine symbolises the moment of transition from accounting supported only by manual tools (such as abacus) to the concept of mechanical and algorithmic accounting. This change had not only technological but also epistemological consequences: It initiated the drive to transform accounting into a formalised, predictable and partially automated process. Modern ERP systems, RPA (Robotic Process Automation) tools, as well as AI solutions, develop precisely the ideas that Leibniz formulated over 300 years ago.

### 2.3.2. Mechanization and Digitization — From the Burroughs Machine to Mainframes

The beginnings of mechanised accounting are directly related to the dynamic development of industry and trade in the 19th century, which created a demand for more effective and automated methods of keeping accounting books. This phenomenon should be interpreted in the broader context of the so-called second industrial revolution (Industry 2.0), the essence of which was the popularisation of electricity, the development of industrial infrastructure, mechanical technologies and the standardisation of production and administrative processes. The rapid development of enterprises and the growing importance of international exchange have led to an increase in the number and complexity of transactions, which has forced the development of tools supporting financial control, including modern forms of mechanical and computational accounting (Scapens & Jazayeri, 2003).

As indicated in point 1 of this chapter, each stage of the industrial revolution brought new requirements and opportunities for accounting. In the first stage (Industry 1.0), based on the mechanisation of production, accounting had a record function and was used to control production assets. In the second phase (Industry 2.0), the development of mass production and supply chain management in an environment of increased scale of operations created the need for more complex forms of cost recording, unit calculations and budgeting. At the same time, there were first attempts to use computing machines, such as the Burroughs machine, which were able to automate basic arithmetic operations and allow faster registration of economic operations (Encyclopædia Britannica, 2025).

In the next stages—in particular in the third industrial revolution (Industry 3.0), related to the development of information technology and microcomputers—integrated information systems appeared, and accounting itself began to play not only an operational function, but also an information and analytical one. As Granlund (2011, pp. 4–5) emphasises, it was during this period that the need to integrate accounting with IT systems that enabled faster access to financial data and supported real-time management control increased.

However, in the current phase, i.e., the fourth industrial revolution (Industry 4.0), accounting is based on data-oriented systems—supported by artificial intelligence, predictive analytics and cloud technologies. As Brynjolfsson et al. (2014) note, modern organisations must adapt to a world dominated by digital information, where the speed and precision of accounting data processing is becoming a key factor in competitive advantage.

With each subsequent phase of industrialisation, the need not only to accurately record economic events, but also to analyse, model and integrate them into management processes grew. Therefore, the development of accounting technology should be understood not only as an evolution of tools, but also as a response to the growing complexity of economic structures and the information needs of managers. As Dechow et al. (2006) emphasize, modern accounting increasingly plays the role of a control and management system, not just a system of records, which is reflected in the technological and functional evolution of the tools used by modern accountants and financial controllers.

As companies became larger and more complex, the requirements for accounting information systems also grew—not only the recording of economic events, but also their ongoing analysis and synthesis of management information were expected. The complexity of trading operations and the need for faster and more precise processing of financial data have forced the search for technological solutions that could meet new organisational and operational challenges. Dechow et al. (2006) indicate that already in the mid-twentieth century, accounting became part of the management infrastructure in companies with a complex structure, and its functions had to change—from passive registration of transactions to an active component of control and management.

One of the breakthrough moments was the construction of the first effectively working mechanical accounting machine by William Seward Burroughs in 1888. The device, known as the "Adding and Listing Machine", was able to automatically add numbers and print the results on paper tape, which was a revolution in recording financial transactions (Encyclopædia Britannica, 2025). The Burroughs machine not only eliminated the need for manual addition but also made it possible to immediately obtain transaction documentation in the form of a printout, which greatly increased the transparency and accuracy of the accounts.

The design of the device was based on a precisely calibrated mechanism of levers, rollers and racks, which allowed for quick and repeatable arithmetic calculations. The device has been recognized for its reliability and ease of use, requiring no specialized training, making it ideal for a wide range of users, including bank clerks, accountants, and administrators. These features have earned Burroughs' machine the status of one of the most innovative and groundbreaking inventions in the history of accounting technology (cf. Encyclopædia Britannica, 2025; Granlund, 2011).

In a short time, the device was adopted by numerous financial institutions, offices and commercial companies in the United States and Europe. Its implementation made it possible to significantly speed up accounting processes, minimize the number of errors in settlements and reduce administrative costs. This machine also inspired broader thinking about accounting automation, providing a starting point for the further development of office and accounting technologies in the 20th century.

In the literature on the subject, it is noted that Burroughs' invention not only improved the technical aspects of bookkeeping but also initiated a number of organizational changes—from changing the role of accountants to introducing new work standards in accounting offices. As Granlund (2011) points out, automated calculation tools such as the Burroughs machine have contributed to the redefinition of the professional competences of accountants, shifting their role from purely manual work towards supervision, control and interpretation of financial results. In this sense, the machine was not just a mechanical tool, but an important impetus towards transforming accounting into a function supporting knowledge management in organizations.

In the mid-twentieth century, the first mainframe computers appeared—large, central computing units designed to support many users at the same time, with the ability to perform thousands of operations per second and store and process large volumes of data. Mainframes were characterized by high reliability, high uptime and the ability to simultaneously manage the information resources of different departments of the organization. They were typically installed in large data centres and operated by specialized technical personnel (Granlund, 2011).

Models such as the IBM 650 (1954) and IBM System/360 (1964) were a breakthrough in the use of computational technologies in accounting and management. IBM System/360, considered the first all-in-one computer for business applications, enabled the storage and processing of financial data on a scale previously unattainable. As Granlund (2011) points out, the new generation of computing systems introduced the possibility of automated management of settlements and financial reporting, enabling the creation of more comprehensive and timely management reports and budget plans.

The first integrated software packages also appeared—the precursors of later ERP systems—that allowed financial accounting to be combined with other organizational functions, such as logistics, human resources, and production planning (Scapens & Jazayeri, 2003). This was a milestone towards the integration of data and functions in the organization, and thus—increasing the quality of management decisions and the consistency of financial information used in strategic management.

The use of mainframe computers has significantly contributed to changes in control and organizational practices—as emphasized by Karamatova (2017) and Scapens & Jazayeri (2003), information systems have come to be perceived not only as data processing tools, but as a transformative force for management accounting and internal control. They enabled faster reconciliation of interdepartmental data, automatic generation of reports and better analysis of deviations in real time, which strengthened the role of accounting information as an element of strategic control.

In this context, accounting has gained a new dimension: it has become an active function, capable of influencing management decisions and operational planning processes. The implementation of mainframe-based systems can be considered the beginning of the era of computerization of accounting, the consequence of which was the reorientation of the role of the accountant—from contractor to analyst, system designer and co-decision-maker. These systems enabled not only the recording of operations, but also their analysis, aggregation and presentation in a way tailored to the strategic needs of the organization.

Thus, accounting has entered a new era—the era of integrated systems, logical data structures and digital flow of information between organizational units. This change also had an ethical and social dimension: the automation of processes and the integration of financial systems created new challenges regarding data accountability, transparency of decision-making algorithms and equal access to information in management structures (Granlund, 2011).

In the face of these changes, it was increasingly emphasized that accounting—despite the high technological level—cannot function in isolation from humans. It is the human, not the algorithm, who makes sense of the information, interprets the data, identifies the context and makes decisions. As Granlund (2011) notes, despite increasing automation, the accounting specialist remains the central figure of the organization's information system. Technology is a tool—powerful but not autonomous—whose value depends on the competence, professional ethics and analytical skills of the user.

The development of integrated information systems has brought benefits in terms of efficiency and control, but at the same time it has raised questions about who is responsible for interpreting data and whether it is possible to misuse or misanalyse it under automation conditions. The literature points out that the transition to the digital age requires not only technical training, but also in-depth ethical reflection and soft skills such as critical thinking, collaborative ability, and professional responsibility (Scapens & Jazayeri, 2003).

For this reason, modern accounting cannot be identified only with technology—its essence remains a human being, who, as a user, creator and supervisor of accounting systems, must be prepared not only for changes in tools, but above all for changes in the logic of information systems. The future of accounting—in the era of big data, AI and machine learning—depends on the extent to which it is possible to maintain a balance between automation and human reflection, between the speed of the system and the accuracy of decisions made.

## 2.4. The Dawn of the Digital Era — Microcomputers and Integrated Accounting Systems

### 2.4.1. The Microcomputer Revolution and the Birth of Accounting Software

The beginning of the 80s of the twentieth century brought a breakthrough moment in the history of accounting technology—the advent of the microcomputer revolution. Personal computers (PCs), previously unavailable or unprofitable for most enterprises, have begun to be increasingly adopted in small and medium-sized companies. Their importance lay not only in technical innovation, but above all in accessibility: microcomputers were much cheaper and smaller than existing mainframe systems, which made it possible to install and use them without the need for an expensive IT infrastructure. As a result, the microcomputer revolution was not reserved for large corporations, but also included the SME sector, public institutions, and even one-person accounting offices.

In the United States, which was a pioneer in the production and implementation of microcomputers (IBM PC, Apple II, Commodore), there has been a rapid increase in the number of users of information technology in the financial sector. This development was supported by dynamic investments in IT education and the culture of technological entrepreneurship of Silicon Valley. Microcomputers were relatively cheap, compact and intuitive to use, which favoured their rapid implementation in both the business sector and public administration (Campbell-Kelly et al., 2018, pp. 225–228).

In Europe, the pace of implementation of new technologies was more diverse—Western European countries, such as Germany, Great Britain and France, adopted new solutions relatively quickly, although the barrier was often higher costs of importing equipment, differences in technical standards and lower availability of specialized software in local languages. In the United Kingdom, the development of microcomputers was supported, among other things, by government educational initiatives (such as the BBC Computer Literacy Project) and by companies such as Amstrad and Acorn, which introduced computers into schools and accounting offices (Ceruzzi, 2003, pp. 225–230). Germany, on the other hand, focused on industrial solutions, which was reflected, for example, in the development of specialized software for the engineering and manufacturing sectors, while France invested in national hardware alternatives (e.g., Thomson TO7) and developed ICT systems such as Minitel, supported by the state as part of a strategy of digital sovereignty and modernization of public services (Ceruzzi, 2003, pp. 232–235).

In the countries of Central and Eastern Europe, this development was additionally limited by political and economic factors, characteristic of the period before the later political transformations. Lack of access to Western technologies, foreign exchange restrictions and centrally controlled markets meant that microcomputers were implemented to a limited extent—often using locally produced equivalents (e.g. ZX Spectrum in a cloned version). This situation changed only in the 1990s, when economic liberalization allowed for greater investment in IT infrastructure and technologies supporting accounting.

This phenomenon was part of the broader context of the third industrial revolution (Industry 3.0), which was based on the wide use of electronics and information technologies in production and services, including finance and accounting (Brynjolfsson et al., 2014, pp. 57–61).

Microcomputers have made it possible to implement decentralised accounting systems, breaking with the previous model of centralised data processing. Thanks to the availability of computers such as IBM PC, Apple II or Commodore, it has become possible to run simple accounting applications in local finance and accounting departments without the need for expensive mainframes. This has enabled small and medium-sized companies to access technological tools that were previously only the domain of large corporations and thus democratize access to modern accounting (Granlund, 2011, p. 5).

The first accounting programs, such as *VisiCalc*, *Lotus 1-2-3* or the later *QuickBooks*, offered users a simple interface based on spreadsheets and the ability to perform basic accounting operations—from recording documents, through keeping a general ledger, to creating statements and reports. These were standardized solutions, not custom-written ones, which enabled their wide dissemination and adaptation to various sectors of the economy. As Granlund (2011, pp. 6–7) notes, this type of software has become an impulse for the transformation of accounting from a purely record-keeping function to a role supporting decision-making processes.

As Karamatova (2017, pp. 5–6) points out, the spread of personal computers has also created new opportunities in the field of financial management and management accounting. Thanks to microcomputers, it has become possible to use local systems for cost simulation, budget analyses and scenario modelling, which significantly increases the flexibility of control functions in organizations. Accounting software has also become the foundation for the creation of Business Intelligence (BI) tools, enabling the combination of data from various sources and its interpretation in real time.

The introduction of graphical user interfaces (GUIs) and subsequent integration with printers, scanners and databases have made accounting software increasingly functional and user-friendly. These systems not only accelerated data processing, but also minimized the risk of human error, enabled backups, and later—also integration with tax, warehouse, HR and payroll modules. As Scapens & Jazayeri (2003, pp. 208–210) emphasize, the development of accounting software has influenced not only the efficiency of processes, but also the transformation of the role of the accountant, who has become an active user of the technology, and not just a beneficiary of its results.

From the perspective of the development of accounting, the microcomputer revolution democratized access to financial technology. Accountants gained the ability to independently operate systems supporting their work, which translated into an increase in productivity, flexibility and organizational independence. It was also a breakthrough in professional competence—from that moment on, accountants were expected to know not only accounting regulations and principles, but also the ability to use computers and financial software. Along with this transformation, challenges arose—both in terms of data security and the ethics of using financial information.

In the context of the socio-technological changes of this era, it should also be noted that microcomputers have ushered in a new culture of accounting work—more dynamic, flexible and end-user-oriented. As Granlund (2011, pp. 6–7) points out, it was during this period that the centre of gravity shifted from central accounting departments to frontline users—managers, analysts and specialists, who thanks to microcomputers gained tools for independent financial analysis.

Microcomputing solutions have set the course for further technological evolution—they have set the stage for the development of integrated ERP systems, cloud-based accounting platforms and financial analytics tools, whose functions are no longer limited to data recording, but also support analytics, forecasting and risk management (Scapens & Jazayeri, 2003, pp. 211–213). In this context, the microcomputer revolution turned out to be not only a technological breakthrough, but also an intellectual one—changing the way accounting is perceived in an organization. It is the human being—the accountant, analyst, manager—who still remains at the centre of this system, and technology plays a supportive, not determining, role. Maintaining this proportion—technology as a tool, not a decision-maker—is one of the main challenges for accounting in the 21st century.

### 2.4.2. From ERP to RPA — On the Integration and Automation of Accounting Systems

A direct consequence of the microcomputer revolution, which enabled a decentralized and affordable approach to financial data management, was the transition to more advanced and comprehensive information systems. The evolution of accounting software and the growing importance of technology in the work of financial departments have created a natural space for the birth of integrated ERP (Enterprise Resource Planning) solutions.

At the turn of the 80s and 90s of the twentieth century, a new stage in accounting technology began—the development of integrated ERP-class IT systems. These systems offered a coherent platform for managing many of the company's functions: from accounting, through warehousing, to human resources and production management. A key feature of ERP was the ability to collect, process, and analyse data in real time, within a single database and a unified logical architecture (Scapens & Jazayeri, 2003, p. 206).

In the context of accounting, ERP systems were a revolution because for the first time they made it possible to integrate all financial processes into a single, common computer system that combines all financial data and functions in one place, enabling them to be analysed and controlled on an ongoing basis. This eliminates data redundancy, i.e. duplication of the same information in different places in the system, which reduces the risk of errors and facilitates consistent information management, increases information transparency and supports consistency and internal control. As Granlund & Mouritsen (2003, p. 6) indicate, ERP implementations have led to a change in the role of accounting departments—from passive transaction recorders to active participants in decision-making processes, responsible for analysis, interpretation and formulation of strategic recommendations.

This transformation took place in parallel with the general trend of digitization and the progressive automation of internal processes, both in the corporate sector and in public administration. It covered in particular the areas of finance, logistics and human resources, where new information technologies began to support or replace traditional manual procedures on a large scale. As a result, accounting specialists were expected not only to know the regulations, but also to have technological and analytical competences. ERP systems enabled the integration of various accounting subsystems—financial, management, tax—and their coordination with the company's operational processes. In practice, this meant that real-time data could be immediately used for decision-making, budget planning, cost control, and risk management.

As Granlund (2011, pp. 10–12) emphasizes, ERP systems have also enabled the transformation of accounting information architecture by digitally tracking full transaction cycles. This not only enabled better documentation management but also facilitated audit and verification activities.

Simultaneously with the development of ERP, the era of automating repetitive accounting tasks using RPA (Robotic Process Automation) technology began. RPA tools enable routine tasks such as data entry, reconciliation of balances, invoice processing, and report generation to be programmable performed without the need for human involvement. Unlike traditional IT systems, software robots operate at the user interface level, which allows them to be quickly deployed in existing environments without having to interfere with the source code (Appelbaum et al., 2017, p. 7).

Implementing RPA has brought tangible benefits to organizations: shortening process lead times, eliminating errors related to human factor, and reducing operating costs. In addition, process automation has contributed to greater standardization of accounting practices and increased transparency in internal control and regulatory compliance. It is worth noting that RPA systems often play a "bridge" function between traditional systems and modern solutions based on artificial intelligence—they allow for quick increase in efficiency without the need for costly and long-lasting implementations of new IT systems.

More broadly, ERP and RPA should be considered as stages in the development of the digital accounting ecosystem. ERP can be thought of as an "accounting ecosystem" providing a place to store and organize large amounts of financial data while also facilitating common accounting processes. RPA builds upon this ecosystem by serving alongside accountants to help them automate certain tasks essentially being a layer between the user and ERP. The combination of both approaches creates a foundation for further innovation—including the implementation of systems based on machine learning, predictive analytics or artificial intelligence understood as the ability of a system to make adaptive decisions based on dynamic financial data (Brynjolfsson et al., 2014, pp. 111–114).

Thus, ERP and RPA are not the end, but a transitional stage—part of the paradigm of the fourth industrial revolution (Industry 4.0), which is characterized by the integration of cyber-physical systems,[4] the Internet of Things (IoT), cloud computing and artificial intelligence in economic processes. In this phase, automation is no longer just a way to increase operational efficiency but becomes the basis for the implementation of intelligent management systems that independently process, analyse and recommend actions based on financial data.

In the context of accounting, Industry 4.0 means a redefinition of its role—from an administrative and reporting function to a strategic one, based on real-time data and predictive analysis. ERP systems integrated with AI, RPA, as well as cloud and blockchain technologies today enable not only the registration and control of economic events, but also dynamic risk management, the creation of scenario simulations or automatic adaptation to regulatory changes. Thus, modern accounting is becoming a key element of the digital transformation of enterprises, and the competences of accountants must include knowledge not only of accounting standards, but also of the functioning of digital information ecosystems and ethical issues related to the design and supervision of automated decision-making systems.

4 Cyber-physical systems (CPS) are the connection of physical components (such as machines and devices) to digital information systems and communication networks. They enable bidirectional integration of the real and digital worlds, which allows for automatic data processing in accounting systems without human intervention (cf. Granlund, 2011; Brynjolfsson et al., 2014, pp. 111–114).

## 2.5. Toward Intelligence — Machine Learning and Artificial Intelligence in 21st-Century Accounting

### 2.5.1. The New Face of the Accounting Professional in the Digital Era

The history of the development of accounting technology, presented in the previous sections, shows a clear evolution of tools, methods and approaches—from the simplest manual solutions to advanced digital systems. Starting from the abacus, which is the symbolic beginning of technologies supporting calculations, through mythological and philosophical concepts of thinking machines, to the first mechanical and logical constructions, such as the Leibniz machine, one can see the long-term maturation process of the idea of automating the accounting information system—the basic management tool, the purpose of which is to generate, process and provide the most valuable resource of the modern economy: Information. The 19th and 20th centuries saw a rapid development of mechanical and electronic devices—from Burroughs machines to mainframes—that enabled large-scale automated data processing. Microcomputers, appearing in the 1980s, opened a new chapter in the availability of technology, allowing for the decentralization of accounting work and democratization of access to modern tools. Finally, the development of integrated ERP systems and the automation of processes with RPA have brought accounting into the era of full digitization, the key sign of which is the integration of financial processes with intelligent IT systems. All these changes have led to the transformation of not only work tools, but above all—the role of the accountant in the organization.

In the context of the fourth industrial revolution (Industry 4.0), which is transforming modern business models through the use of intelligent technologies, the role of the accountant is undergoing a significant transformation. The traditional image of an accountant as a contractor of record-keeping and reporting activities is replaced by a new identity—a financial data analyst, strategic advisor and information systems architect. As Brynjolfsson et al. (2014, pp. 57–61), the digital revolution is not only automating repetitive tasks, but also redefining the way organizations acquire, analyse, and use financial data.

In the digital age, accounting systems are becoming more and more integrated with artificial intelligence, machine learning, cloud databases, and predictive analytics. A key aspect of this transformation is the exponential growth of available digital data—a phenomenon referred to as big data (Appelbaum et al., 2017, pp. 9–10; Granlund, 2011, pp. 6–8). This allows accounting professionals to not only record economic events but also use data from multiple sources to forecast trends, analyse risks, perform scenario simulations, and support strategic decisions.

Especially in the area of management accounting, big data enables the implementation of new analytical methods that are cheaper, faster and more precise than traditional approaches. These techniques include, among others, dynamic budgeting models, which allow financial plans to be created taking into account market variables in real time, as well as advanced deviation analysis, which allows for quick identification of irregularities and their causes. Processing large volumes of data in real time allows for a more accurate assessment of the financial situation, faster response to changes in the environment and more effective resource management. In this context, technology not only supports but also redefines existing accounting roles and procedures, making the accounting specialist an active user and interpreter of data in the digital information ecosystem. According to research by Appelbaum et al. (2017, pp. 9–10), the use of business intelligence tools and ERP systems enables the transformation of the accountant's role into an advisor providing valuable information in real time. This is also confirmed by the observations of Granlund & Mouritsen (2003, p. 16), who emphasize that integrated systems require the active involvement of accountants in the analysis of business processes.

Digitization also forces a change in professional competences. As Granlund (2011, pp. 10–11) points out, a modern accountant should understand the architecture of IT systems, know the basics of data analysis and algorithmics, as well as be able to cooperate with IT, audit and risk management departments. New specializations are also emerging, such as financial analyst with automation competencies, algorithmic compliance accountant, or designer of control processes using RPA tools. The authors Appelbaum et al. (2017, pp. 9–10) also draw attention to the need for accountants to acquire communication skills with system designers and data analysts in order to jointly model and implement solutions that optimize financial activities.

This transformation is not only a technological modernization of the profession but requires a paradigm shift—a shift from perceiving accounting as an operational function to the role of a strategic information system. This change is evident in the way management reporting systems are designed, which use accounting data as a basis for creating scenario analyses, performance indicators, and predictive models (Scapens & Jazayeri, 2003, pp. 211–213).

Modern accounting is therefore becoming an integral element of the organizational data ecosystem, and the accountant is one of the key users and interpreters of this data. The ability to critically evaluate algorithms, validate data, and design automatic control rules is a competitive advantage for a specialist in this area.

It is also worth noting that the transformation of the role of an accounting specialist brings with it significant ethical challenges. Digitization, automation, and the implementation of artificial intelligence raise questions about accountability for decisions made by systems, transparency of algorithms, and protection of the privacy of financial data. As Granlund (2011, pp. 8–9) notes, the responsibility for the proper functioning of accounting information systems still rests with humans, who should maintain the ability to critically analyse and control the results generated by automatic mechanisms. In this context, professional ethics takes on a new dimension—it includes not only honesty and reliability in the classic sense, but also the ability to assess and mitigate risks related to data abuse, errors in code or lack of supervision over automated processes.

To sum up, the integration of AI and machine learning with accounting is one of the most important directions of its development in the 21st century. It's no longer just about operational support but about transforming accounting into a cognitive-decision-making system that reacts to data in real time and supports the organization in achieving its strategic goals. This requires not only investment in technology, but also a transformation of the accountants' competency model, adaptation of reporting standards and redefinition of audit processes (Abbas, 2025, pp. 15–17; Appelbaum et al., 2017, pp. 6–7).

### 2.5.2. Machine Learning and AI in 21st-Century Accounting

The technological progress of the last two decades has changed the way almost all sectors of the economy operate. In particular, accounting—as a discipline closely related to information, its processing and analysis—has undergone significant transformations. One of the most groundbreaking developments in this area is the integration of artificial intelligence (AI) and machine learning tools into accounting systems. As part of the fourth industrial revolution (Industry 4.0), these technologies are transforming an organization's information systems, enabling not only the automation of routine activities, but also the development of predictive systems that detect anomalies and support strategic decisions (Brynjolfsson et al., 2014, pp. 111–114).

Machine learning is a subset of artificial intelligence in which computer systems are able to learn from data—without the need for a human to program rules. These algorithms learn from patterns and trends, and then make predictions, classifications, or recommendations. In accounting systems, machine learning is used, among other things, to recognize invoices, categorize transactions, predict cash flows, and detect fraud. As Appelbaum et al. (2017, pp. 9–10) notes, the integration of such technologies allows you to significantly reduce the time of accounting processes, increase their accuracy and reduce operating costs.

Particularly noteworthy is the development of the so-called Large Language Models (LLM), such as GPT (Generative Pretrained Transformer), BERT (Bidirectional Encoder Representations from Transformers) developed by Google, LLaMA (Large Language Model Meta AI) developed by Meta or Claude created by Anthropic. All these models belong to the LLM category and use the transformer architecture for analysis and natural language generation, which allows them to be used in the automatic creation of accounting documents, the analysis of non-financial texts in integrated reports, as well as in voice communication with the end user. These models, based on the transformer architecture, allow you to process and generate natural text while maintaining context, logic, and consistency. In the context of accounting, they can be used to analyse financial reports, create comments on reports, interpret figures, and support the audit process. LLMs can also serve as a user interface to advanced analytics systems, allowing accounting professionals to communicate with the system in natural language—e.g., queries such as "Show me all invoices over $10,000 from the last 30 days", "Generate a revenue comparison for Q1 2024 and Q1 2023 in the business segments layout", "Identify unusual cost operations in the sales department from the last 60 days" or "Evaluate the compliance of invoices with contracts for contractor X from of the last quarter". Such features are already available, among others, in tools such as Microsoft Copilot for Finance, which integrates the language model with Dynamics 365 ERP systems and Excel spreadsheets, as well as SAP Joule, an intelligent business assistant that allows users to analyse financial data using natural language and generate forecasts and alerts. Another example is the BlackLine system with an AI component for automatic account reconciliation and variance analysis. These tools enable not only the automation of reporting, but also the quick identification of risks and the generation of a financial narrative to support management decisions.

As (Granlund, 2011) points out, the use of advanced analytical systems in accounting requires not only the implementation of technology, but also a change in the competence model of accounting specialists. They are expected to know the basics of programming, data analysis, algorithmic logic, as well as the ability to interpret the results generated by artificial intelligence models. This means that the future of the profession will be based not on manual accounting, but on supervision, validation and strategic interpretation of financial data.

The use of AI and machine learning in accounting also brings new ethical challenges. Automated decision-making systems, based on input data, can reinforce biases or lead to wrong decisions if not properly supervised. Therefore, as (Granlund, 2011, p. 8–9) notes, an important role of an accounting specialist is to critically evaluate the input data, supervise the modelling process and be able to explain the logic of the algorithm to the auditor or supervisory authorities. In this context, professional ethics include, among others, transparency of decision-making models, ensuring data integrity, and mitigating the risks associated with their misuse.

Modern accounting systems, equipped with AI components, enable full automation of the accounting cycle—from recognition of source documents, through assignment, to reporting. These tools also support audit activities by generating control trails, identifying unusual transactions and assessing the level of risk. As Appelbaum et al. (2017, pp. 9–10) emphasize, these systems are able to process data from thousands of documents in real time, which opens up new possibilities for financial management in large organizations.

From the perspective of Industry 4.0, AI technologies are not only innovation but are becoming an integral component of the modern accounting ecosystem. Integration with the Internet of Things (IoT), cloud computing, ERP systems, and predictive analytics tools allows you to create decision-making environments where the accountant acts as a technology partner rather than a passive user (Brynjolfsson et al., 2014, pp. 113–114).

The future of accounting systems in the context of AI is associated with the development of the so-called cognitive accounting, in which learning systems support the user in interpretative tasks, verify the compliance of operations with legal regulations and automatically identify financial risks. As Abbas (2025, pp. 4–5) notes, this means that the organizational structure of finance departments needs to be redesigned, with a greater emphasis on interdisciplinary teams that combine financial, IT, and legal expertise.

To sum up, AI and machine learning in accounting in the 21st century are not just a technological novelty, but a methodological revolution. They change the way we work, the required competences, the relationship between man and the system, and the limits of professional responsibility. Ultimately, however, it is the human being—as a designer, controller and interpreter—who remains the most important link in the digital accounting system.

Practical examples of LLM implementation in financial and accounting systems include:

- ***Microsoft Copilot for Finance****, which integrates the GPT language model with Dynamics 365 ERP systems and the Microsoft Excel package, enabling for instance generation of financial analyses, natural language response to user queries, and automatic report creation.*
- ***SAP Joule****, an AI-powered assistant that analyses business and financial data in real time, supporting enterprise decision-making processes.*
- ***BlackLine Accounting AI,*** *a platform for automating account reconciliation and variance analysis in real-time, especially used by global finance teams in data-intensive sectors.*

When comparing the functionalities of these tools, Microsoft Copilot for Finance stands out for its deep integration with the Microsoft ecosystem, which makes it especially attractive for companies already using Office 365 and Dynamics. Its advantage is the ability to directly interact with financial data via Excel and the automation of creating a financial narrative. SAP Joule, on the other hand, offers advanced predictive capabilities and integration with the SAP S/4HANA system, enabling real-time data analysis and the creation of recommendations to support management. BlackLine focuses primarily on month-end close automation and account reconciliation, supporting particularly large organizations operating in multiple markets. Each of these tools supports a different stage of the financial information life cycle—from collection and reconciliation, through analysis, to reporting and strategic recommendations.

Chapter 3

# Contemporary Applications of AI in Accounting — Directions and Processes

Jacek Kalinowski

## 3.1. Strategic and Managerial Directions of AI Applications

### 3.1.1. The Strategic Importance of Applying AI in Accounting

With the development of microcomputers (as described in Chapter 2) a digitization process of accounting has begun. It's rate grows exponentially—a direct consequence of the development of new technologies. Today we find that the complexity of business processes along with pressure on efficiency and transparency of accounting processes have made Artificial Intelligence (AI) an integral part of the modern accounting system. This technology automates repetitive tasks, supports predictive analytics, aids in detection of irregularities gives insight for strategic decision-making. In this chapter, we focus on the analysis of the current state of use of artificial intelligence in the analysed area, transferring the theoretical considerations and historical context contained in the earlier part of the work to specific applications. Descriptions of various AI technological solutions in accounting, financial and auditing processes are presented here, with particular emphasis on tools such as RPA (Robotic Process Automation), OCR (Optical Character Recognition), NLP (Natural Language Processing), as well as GenAI (generative artificial intelligence).

First, let's remind you once again what artificial intelligence is.[1] As Kaplan & Haenlein (2019) note, it is defined as a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation. In turn, it indicates that it is a mechanical simulation system that collects knowledge and information, which also processes the intelligence of the universe, including the collection, interpretation and dissemination of knowledge and information in the form of operational intelligence (Grewal, 2014). AI, therefore, is, in a nutshell, computer programs developed to perform tasks that would otherwise require human intelligence.

As pointed out in previous chapters, the development of digital technologies, such as big data or blockchain, has facilitated the collection and analysis of large amounts of data, which has opened the way for the integration of AI technologies with modern accounting practices. Dwivedi et al. (2021) emphasize that AI has the potential to transform many tasks and processes that have traditionally been performed by humans. In the context of accounting, Hamdan et al. (2021) see the development of AI as a key tool shaping the future. Analysing the literature on the subject, it can be seen that the main possibilities and importance of AI in accounting include the following areas:

- ***Automation and cost savings***: *AI offers opportunities to automate processes, which leads to cost savings. This technology has the potential to take over repetitive accounting tasks.*
- ***Data-driven decisions and predictive analytics***: *Enables automated, data-driven, and predictive analytics-driven decision-making, planning, and control in real time. Companies that have implemented AI solutions, such as robotics in taxes, have increased their productivity and effectiveness.*
- ***Human-machine collaboration***: *AI opens up opportunities for human-machine collaboration, which allows people to increase their own efficiency. This is crucial for management with the increasing complexity of business processes.*
- ***Risk management and fraud detection***: *AI is used to detect financial fraud and other applications such as forecasting defaults. It can improve the accuracy and efficiency of financial error detection.*
- ***Supporting management control processes***: *AI technologies can support integrated management control systems by leveraging big data. Digitalization, and with it - AI, is changing the overall role of accounting and finance.*
- ***Added value from big data***: *The rise of artificial intelligence and big data technology has changed the way companies create value together with their customers. By analysing massive data sets, it is possible to better understand the needs of your audience, and AI plays a key role in connecting this data to business activities. As a result, companies not only deliver value, but co-create it together with users.*

1 This issue is explained in more detail in Chapter 1.

### 3.1.2. Performance Under Control — Modern Controlling Supported by AI

Modern controlling is transforming under the influence of digitization, automation and the explosion of data. Artificial intelligence (AI) is entering this area as a next-generation analytical tool that not only processes data, but can also predict, diagnose and recommend actions. AI's ability to continuously analyse huge data sets and correlate them with operational, financial, and market results puts it at the centre of modern controlling solutions. This importance is growing especially in the era of pressure for operational efficiency and flexible decision-making. One of the most important areas where AI is revolutionizing is cost and performance indicator (KPI) analysis. Previous approaches, based on ex-post analyses and simple regression models, are giving way to machine learning models capable of detecting non-linear, multivariate relationships between costs and operating variables. For example, the use of decision trees and neural networks can identify cost patterns that indicate structural organizational problems. Richins et al. (2017, pp. 66–68) indicate that systems using AI in the budgeting process are able not only to detect deviations, but also to automatically classify them according to their causes and predict their occurrence well in advance.

The use of artificial intelligence also allows for dynamic adjustment of performance indicators. Instead of rigid benchmarks, KPIs can be adjusted in real time depending on seasonality, structural changes within the company, and external influences such as macroeconomic factors. As indicated by Jarrahi (2018, pp. 578–580), AI can play a role supporting humans in decision-making processes, which gives them a competitive advantage over others. This approach is referred to as human-AI symbiosis, and it allows controllers not only to interpret data, but also to design data acquisition and use based on suggestions generated by AI.

In addition to descriptive and diagnostic analytics, AI also enables the construction of a new generation of controlling tools, such as predictive and prescriptive dashboards. Predictive dashboards allow you to create KPI forecasting models and financial performance based on current and historical data and consider contextual data such as economic forecasts or consumer behaviour. Prescriptive dashboards, on the other hand, go a step further by offering specific suggestions for actions that can optimize the organization's performance. As shown in the paper Appelbaum et al. (2017, pp. 31–34), AI dashboards can use data about customers, market trends, and enterprise resources to build decision-making scenarios and recommendations for action.

Reinforcement learning algorithms are of particular importance here, as they learn by interacting with the environment, rewarding decisions that lead to the desired outcomes and eliminating inefficient ones. They are used to dynamically optimize decision-making processes in real time, e.g. in inventory management, resource allocation or price recommendations. In controlling, they allow you to design policies that adapt to changing market conditions. They also allow you to consider uncertainties and continuously update the probabilities of economic phenomena as new data become available. This makes it possible not only to predict future scenarios, but also to correct them on an ongoing basis.

In the literature, in the context of artificial intelligence (AI) in controlling and performance management, the Bayesian modelling technique based on Bayesian probability theory and using Bayesian Belief Networks (BBN)[2] is also mentioned. It is recognized as an important approach, especially because of its ability to deal with uncertainty and its ability to deliver interpretable results. However, although Bayesian models are inherently interpretable according to Lipton (2016), interpretations are often underspecified. In turn, Hamdan et al. (2021, pp. 12–13, 442, 451) point out that in the context of machine learning, the so-called naïve Bayes classifier is an example of supervised machine learning. However, Bertomeu et al. (2021, p. 507) add that it may have lower accuracy compared to other, more complex machine learning algorithms in some tasks, such as detecting erroneous financial statements. The Bayes model, as noted by Yi et al. (2023, p. 15), is also characterized by high insensitivity to missing data.

As indicated by Jarrahi (2018, pp. 578–580), the use of AI in operational performance management allows not only to identify areas of maladjustment, but also to adapt recommendations in response to changes in the business environment. For example, in a dynamically changing environment of raw material prices, a prescriptive dashboard can suggest a change in the purchasing policy or a modification of the pricing strategy in real time. Richins et al. (2017, pp. 66–68) show how this approach allows you to reduce the organization's response time to the market and increase the accuracy of strategic decisions.

In the area of analysis of variance, AI offers a radically higher level of accuracy and detail. Traditional analysis of variance is based on comparing budget with execution at the aggregate level, while AI allows you to go down to the level of individual transactions or business processes. The deep autoencoder models described Schreyer et al. (2017, pp. 3–5) by demonstrate the ability to detect subtle deviations from the norm that may indicate inefficiencies or financial irregularities.

The use of AI in benchmarking makes it possible to create dynamic performance comparisons between organizational units, as well as external comparisons, e.g. with other companies in the industry. With access to market data, public registers, and information from third-party data providers, AI systems can build comparative models that take into account contextual variables. As Appelbaum et al. (2017, pp. 31–32) point out, the combination of internal and external data by AI models allows for accurate detection of performance gaps and identification of best practices.

AI-assisted scenario analysis is based on the creation of predictive and simulation models that test various assumptions and predict their impact on future

2 Bayesian Neural Networks were explored in further detail in chapter 1.4.1.

outcomes. Generative models such as GAN (Generative Adversarial Networks)[3] and VAE (Variational Autoencoders)[4] can generate realistic operational scenarios that take into account the complexity and unpredictability of the economic environment. As shown in the paper Hemati et al. (2021, pp. 4–6), this approach allows not only to model uncertainty, but also to design adaptive decision-making policies. Generative models are widely used for unsupervised anomaly detection. In the financial context, especially in auditing, deep autoencoder neural networks are used to detect anomalous journal entries in large data sets (Schreyer et al., 2017, p. 5).

The practical application of this type of analysis is of key importance for the strategic planning of companies operating in the VUCA (Volatility, Uncertainty, Complexity, Ambiguity) conditions.[5] According to this concept, classical planning methods turn out to be insufficient, and their place is taken by adaptive analytical systems, capable of quickly responding to changing data and creating alternative scenarios. In this context, AI acts as a catalyst for transformation, enabling the creation of agile and resilient management strategies based on predictive and prescriptive decision-making models (cf. Jarrahi, 2018, pp. 579–581). AI models can support decision-making in the field of risk management, resource allocation, foreign expansion or supply chain optimization. In the context of dynamic tax or geopolitical changes, AI supports the analysis of the impact of various fiscal scenarios on the liquidity and profitability of the company.

AI applications in controlling are not limited to ex ante analyses. As (Schreyer et al., 2017, pp. 3–5) points out, deep learning techniques, including autoencoders, can be used to monitor accounting processes in real time and detect anomalies, allowing for immediate response to irregularities. Jarrahi (2018, pp. 578–580), on the other hand, emphasizes the role of artificial intelligence in improving performance management systems—thanks to the use of large data sets, it is possible to identify places of process overload ("bottlenecks") and propose data-driven optimization actions.

It is also worth noting that the implementation of AI solutions in controlling does not have to mean complete automation. As Jarrahi (2018, pp. 578–580) points out, the most effective approaches are based on a human-machine collaboration model, in which AI systems support users in data analysis and decision-making, but ultimately remain the responsibility of the human. Such symbiosis makes it

3 GANs are generative models that focus on creating new data. Traditionally, they work on the basis of a competition between two components: a generator that creates the data, and a discriminator that evaluates its authenticity. For more information, see [in:] (Annepaka & Pakray, 2025).

4 Variational Autoencoders (VAEs), referred to in sources as "Variational Autoencoder Neural Networks", are a special type of Autoencoder Networks (AENs). These are unsupervised machine learning models, mainly used to detect anomalies(Hemati et al., 2021).

5 This concept refers to the volatility, uncertainty, complexity, and ambiguity that characterize the modern business and macroeconomic environment. For more on this topic, see [in:] (What VUCA Really Means for You, n.d.).

possible to maintain flexibility, contextual interpretation and ethical control over the decision-making process, while using the computing power and predictive capabilities of artificial intelligence.

To sum up, AI in controlling and performance management is not just a technology, but a paradigm shift. Instead of analysing the past, controlling becomes a tool for forecasting, recommending, and automating decisions. The development of AI not only improves cost efficiency but also enables more accurate strategic decisions to be made in real time. These solutions also change the role of the controller: from a data analyst to a designer of data-driven decision-making systems.

### 3.1.3. Regulatory Intelligence — AI in Tax and Compliance

Artificial Intelligence (AI) is also playing an increasingly important role in the field of tax and compliance, offering new solutions to traditional accounting and financial problems. As Peng et al. (2023, pp. 2–3) emphasize, AI has the potential to profoundly affect traditional procedures and activities related to accounting functions, making them more effective and efficient. AI technologies, including machine learning and generative AI, automate routine tasks, streamline data analysis, and provide deeper insights, significantly improving the efficiency and accuracy of accounting and tax processes. The next part of this section describes the most important directions for the use of AI in tax and compliance, selected due to their practical importance for operational efficiency, risk mitigation and adaptation to the changing regulatory environment.

AI is used in the process of automatic classification of transactions in terms of tax, as well as in the calculation of tax liabilities. By using machine learning (ML) and natural language processing (NLP) algorithms, it is possible to automate routine tasks and report generation. Peng et al. (2023, pp. 2–3) indicate that AI is used to automate data entry and filtering, which contributes to the automation of business processes. This results in a fully automated data generation process, used by to prepare tax reports with high accuracy and in a timely manner (Hamdan et al., 2021, pp. 311–313). This is particularly important in the case of routine tax tasks, such as e.g. automatic assignment of VAT rates based on the content of invoices and source documents, recognition of transactions subject to the reporting obligation (e.g. WDT/WNT, MOSS, GTU), categorization of costs to appropriate tax groups, preliminary calculations of tax liabilities based on accounting data or handling classification according to national reporting requirements (e.g. SAF-T in Poland).

By using historical data and self-learning mechanisms, AI systems increase their accuracy and compliance with regulatory interpretations, minimizing errors and the need for manual corrections. This can be an effective support for taxpayers and tax advisors, although special caution should be exercised in this case. In the practice of using chatbots, the phenomenon of hallucinations often occurs, which was described in more detail in the previous section. These risks are also confirmed by tests carried out by the Washington Post editorial team in 2024. They showed that chatbots in popular tax services were useless or gave incorrect answers in as many as half of the cases (The Washington Post, 2024).

A separate area of application of AI is support for tax administrations. AI can automate repetitive tasks, such as responding to taxpayer complaints. As an example of such applications, Kuźniacki et al. (2022, p. 4) they cite the fact that 80% of annual complaints in the Dutch tax administration are handled automatically by NLP algorithms, which saves hundreds of days of work. Similarly, the Finnish tax administration uses AI to analyse and monitor email inboxes related to tax collection, saving almost two years of manual work. However, the most important application of AI in tax administrations is tax fraud detection, risk profiling, and audits. The same authors describe how the Norwegian tax authorities are using data analytics and machine learning to increase the efficiency of selecting cases for VAT audits, doubling the success rate of audits compared to manual processes. In Japan, an AI system analyses financial results and documents, as well as voice recordings of managers, which has led to a decrease in the number of companies suspected of tax evasion. In France, by contrast, almost a quarter of tax audits in 2019 were supported by AI systems for data mining, contributing to a 30% increase in collected taxes. French regulators have allowed publicly available data from social media and online platforms to be used to power AI algorithms to detect tax fraud. Another example is the UK, where HMRC has been using an AI system called Connect since 2010 to analyse data from social media and a number of other databases to detect fraud. Connect looks for correlations between declared income and lifestyle, helping to recover billions of pounds in taxes.

International organizations are also actively encouraging tax administrations around the world to implement AI systems, which is confirmed by the report OECD (2020). A 2021 OECD study found that nearly 75% of tax administrations surveyed use or implement advanced techniques to leverage data to reduce the need for human intervention (OECD, 2021).

Another area of application of AI is the automation of compliance processes. This increases the efficiency of business processes and automates tasks related to information gathering and document management. In the context of accounting processes, Peng et al. (2023, p. 5) emphasize that AI capabilities help organizations make better financial decisions while maintaining compliance with regulatory regulations. This is possible thanks to the analysis and ordering of financial data in real time, which supports the delivery of reliable and useful information to stakeholders just in time. In addition, AI's ability to recognize patterns and anomalies supports fraud detection and helps accountants take preventive actions to mitigate various operational risks.

When analysing the applications of AI in taxes and compliance, it is also worth quoting the results of a survey conducted in Poland on a group of 575 accountants in the period from 10.2023 to 07.2024, which were published in Honko & Hendryk (2024). When asked about the areas of application of AI in accounting, respondents indicated support for tax settlements in 28% of responses. This is relatively little compared to the use of AI in the preparation and circulation of documents (67% of responses) and in their accounting records (45% of responses). These results indicate that the expectations of professionals in the development of AI technology are primarily in the area of automation of routine and repetitive processes currently performed manually. More complex issues, requiring a thorough formal and legal analysis, in the opinion of accountants, will still remain the responsibility of professionals. The reason for this conclusion, which we believe can also be generalised to other tax systems, is the constantly changing regulatory requirements in the area of various taxes. They result in an increase in the number of complex regulations that may be mutually contradictory or subject to different interpretations. This, in turn, is a challenge for AI-enabled systems due to the need to update the databases on which the answers are based on an ongoing basis. Adding to this the previously described phenomenon of AI hallucinations, we have the problem of uncertainty about the reliability of the opinion or tax interpretation issued by AI. It can be based on data—legal regulations, court judgments, interpretations of tax authorities, but it can also be a hallucination.

The development of AI systems also poses challenges in terms of data confidentiality, legal liability, intellectual property rights and ethical standards. Therefore, it becomes necessary, as they emphasize, Odonkor et al. (2024, pp. 177–178) to develop appropriate policies, regulations and legal frameworks to prevent the misuse of AI and ensure transparency and accountability in the event of errors. This requires the cooperation of technologists, ethicists and decision-makers. Regulators should seek legal clarity on the implementation of algorithmic decisions and autonomous systems in existing legislation.

In summary, AI offers significant opportunities in automation, risk analysis, and tax compliance and compliance, but its full use requires overcoming challenges related to data privacy, ethics, and the need to adapt to a rapidly changing regulatory framework.

## 3.2. Automation and Optimization of Accounting Processes

### 3.2.1. Routine Automation — AI and RPA in Accounting Records

Automation of accounting processes is one of the most mature and most frequently implemented applications of artificial intelligence (AI) in the area of accounting. In the era of digital transformation of enterprises, tools based on AI and Robotic Process Automation (RPA) significantly affect the way daily accounting tasks are performed, reducing operating costs, minimizing the risk of errors and accelerating information processing.

A special case for the use of RPA in accounting, which has gained wide acceptance and application, is OCR (Optical Character Recognition) technology. OCR enables automatic recognition of text from paper documents and images, such as scanned invoices, receipts, or bank statements, transforming unstructured data into digital data that can be processed by accounting systems. This allows organizations to reduce manual data entry and increase the speed and accuracy of document processing.

As Pingili (2025, p. 104) and Moll & Yigitbasioglu (2019, p. 38) point out, OCR technology has undergone a significant evolution, from simple character recognition systems to advanced solutions using artificial neural networks (CNNs) and deep learning, which has increased the effectiveness of text recognition, even for low-quality or distorted documents.

In the context of keeping accounting records, modern OCR systems not only scan documents, but also classify their content and transfer them to the appropriate ERP systems. ABBYY FlexiCapture, Kofax ReadSoft, and Rossum use machine learning and artificial intelligence algorithms to analyse and process accounting documents. ABBYY FlexiCapture is based on Intelligent Document Recognition (IDR) technology, which enables document layout detection, classification, data extraction, and data validation and export to ERP systems (ABBYY, 2023, p. 15). Kofax ReadSoft, on the other hand, specializes in automatic recognition of invoice data and their matching to relevant records in accounting databases, integrating directly with SAP and Microsoft Dynamics (Kofax, 2022, p. 8). As a cloud solution, Rossum uses the so-called cognitive data capture, i.e. semantic processing of documents using deep neural networks (Rossum, 2023, p. 11), learning individual document schemes in real time. All these tools enable automatic detection of data fields, headers, dates, values and classification of content in accordance with accounting requirements, which speeds up and authenticates accounting processes.

As the PriceWaterhouseCoopers (2022, pp. 19–21) report emphasizes, the use of OCR allows to reduce the average time of handling one invoice by up to 65%, reduce input data errors by 80% and significantly improve the compliance of processes with internal policies and audit requirements. When combined with RPA, OCR enables the creation of automated workflows in which a document is automatically read, interpreted, decreed, and then sent for approval or further processing after scanning. These solutions, referred to as Intelligent Document Processing (IDP), are especially useful in large organizations that process thousands of documents every day. Research by Wright & Schaefer (2022) indicates that companies that implemented OCR and RPA in their accounting departments observed not only improved operational efficiency, but also better quality of financial data, which resulted in more accurate financial forecasts and better strategic decisions.

At the same time, the development of OCR technology supported by AI has led to increased availability of this type of tools also for the SME sector, where previously process automation was limited by implementation costs. Today, many solutions offer subscription (SaaS) models that lower the entry threshold and enable automation to be implemented in smaller organizations without the need to build their own IT teams.

However, it is important to note that the effectiveness of OCR is dependent on the quality of the input documents, as well as the system's ability to learn new formats and structures. That's why more and more companies are investing in OCR systems supported by supervised learning, where the user can manually mark up data on previously unknown documents, allowing the system to better adapt and learn.

In the Polish context, OCR technology is used in many financial and accounting systems used by small and medium-sized enterprises. An example is Comarch ERP Optima, which offers the function of automatic reading of data from invoices using the OCR AI service, which integrates document scanning with their automatic assignment and registration in the accounting system. The Symfonia system (formerly Sage Symfonia) also has the e-OCR function, which allows you to read invoices and save them in the VAT register. Third-party solutions such as SaldeoSMART, which can work with many ERP systems and offers invoice recognition in the cloud, with the ability to learn specific document schemes of a given company, are also gaining popularity. It is worth noting that the implementation of OCR in these systems effectively supports the automation of accounting processes and significantly reduces the time needed for manual accounting of documents.

To sum up, OCR technology is the foundation of modern automation of accounting processes using RPA. Its dynamic development and integration with AI make it not only a useful tool to support the daily work of accountants, but also a catalyst for the transformation of the finance function in organizations of all sizes.

Modern ERP (Enterprise Resource Planning) systems are increasingly integrating AI functionalities, enabling automatic processing of accounting documents, classification of invoices and accounting of business operations. As Moll & Yigitbasioglu (2019) point out, AI-based automation allows for the simplification of accounting procedures, the reduction of the number of human errors and the acceleration of the closing of reporting periods.

RPA is a technology that enables the creation of bots that perform repetitive tasks in an automated manner, mapping user actions in IT systems. The combination of RPA with AI (e.g., NLP—natural language processing or machine learning) increases the flexibility and intelligence of automation solutions. These systems are able not only to perform the task, but also to "understand" its context, e.g. by classifying the invoice as cost or investment based on the content of the description.

### 3.2.2. Reporting 2.0 — Algorithms in Financial Reporting

Artificial intelligence (AI) and digital technologies have the potential to profoundly transform accounting processes. AI applications are increasingly being used in the practice of financial reporting and reporting. These technologies streamline the processing of accounting information and turn it into ready-made reports.

Greenman et al. (2024, p. 192) emphasize that AI has ushered in a new era of efficiency and accuracy. What was once a time-consuming, manual practice has become a streamlined, automated operation. Machine learning (ML) algorithms are used to manage financial data, the essence of which we have already written about. They are capable of compiling vast amounts of financial information, analysing complex data sets at remarkable speed, and presenting results in a comprehensive and easy-to-understand format. This AI-powered approach drastically reduces the time it takes to create reports and significantly improves their quality, minimizing human error and ensuring data consistency. Generative AI, on the other hand, including large language models (LLMs) such as GPT or BloombergGPT, are used to search through information, which previously took people hours, and now allows you to analyse financial statements in a matter of seconds, which Calderon et al. (2023) also point out in their work. LLMs can generate text, respond to queries and translate languages by understanding complex speech patterns and responding rationally to them. Another key AI tool in financial reporting and reporting is natural language processing (NLP). It focuses on the replication of human natural language and communication methods. It is used to process unstructured textual information, systematically and automatically search and review documents, as well as to identify high-risk cases.

An essential element in making AI easier on financial reporting is standardized and accurate reporting procedures that ensure compliance with accounting regulations and standards, reducing the effort involved in manual reporting and improving the reliability of financial statements. This is explained in more detail by Peng et al. (2023, pp. 2–3) who also rightly note that the role of AI in accounting is significant and huge. Automated data entry is one of the main benefits of AI in accounting. This enables, among other things, real-time financial reporting, which was unattainable in the traditional, manual model of the accounting system. This is the result of automatic identification of transactions based on established criteria and previous data patterns, which simplifies the process of categorizing financial transactions and reduces time, while ensuring correct and reliable accounting entries.

One of the key areas that deserves special attention when analysing the role of artificial intelligence in financial reporting and reporting is the process of digital data standardization. Modern reporting is no longer based solely on static PDF or paper documents but is increasingly using modern markup languages to automatically analyse data. Technologies such as XBRL (eXtensible Business Reporting

Language) and XML (Extensible Markup Language) play a key role here—as Hasan (2022, pp. 445–446) emphasizes, they are the foundations for the electronic transmission of financial information over the Internet, in a structural, unambiguous and readable way for both humans and AI-based systems.

In parallel with the digitization of the data format, a technological environment is developing that enables data integration and automatic processing. The development of the Internet of Things (IoT) has led to a situation in which devices and IT systems collecting financial and operational data can be integrated within a single platform, which significantly improves not only the process of creating reports, but also their audit and analysis of compliance with regulations. As a consequence, the role of financial audit is also changing. Tools such as Electronic Data Interchange (EDI), Electronic File Transfer (EFT), as well as image processing technologies are increasingly being used to speed up and automate audit work. They not only enable faster access to source documentation, but also automatic data comparison and detection of irregularities. This transformation is also reflected in the growing use of CAATs (Computer-Assisted Audit Techniques), which have become a standard in many organizations. Their development has enabled the emergence of the concept of the so-called continuous auditing, i.e. constant monitoring and analysis of financial transactions in real time. This approach allows for faster detection of errors and abuses and provides supervisors and managers with more up-to-date and reliable information. Both digital data standardization and the aforementioned audit tools fit into the broader context of the digital transformation of accounting, in which artificial intelligence acts as a catalyst for change—enabling not only improved quality and transparency of reporting but also redefining the way of thinking about financial control and regulatory compliance processes.

In a separate, but equally important dimension, researchers such as Odonkor et al. (2024, p. 183) point out that the implementation of artificial intelligence in accounting practices translates into a significant improvement in the precision of financial statements. Thanks to the use of algorithms capable of analysing huge volumes of data, it is possible not only to speed up information processing, but also to significantly reduce the number of potential errors. The result is an increase in the reliability of the presented financial data and an increase in confidence as to their compliance with applicable legal and accounting standards. This accuracy is of fundamental importance both from the perspective of information responsibility towards stakeholders and in the context of mitigating financial and reputational risks and potential regulatory sanctions. AI-based systems can process huge amounts of data with high precision, reducing the likelihood of errors and increasing the reliability of financial statements. This accuracy is crucial for compliance with regulatory standards and can help companies avoid costly fines and reputational damage.

The culmination of the previously described observations is the increasingly visible role of AI as a tool supporting the pursuit of high-quality financial statements. This is also emphasised by Hamdan et al. (2021, p. 347), who note that artificial intelligence not only simplifies the process of presenting data and publishing it—especially in the digital environment such as business entity websites—but also contributes to better disclosure of information. It is worth noting that the impact of AI on the quality of financial statements can also be interpreted in the context of classic attributes of information from the accounting system, such as usability and decision-making usefulness, cost-benefit ratio, level of risk, or transparency and transparency. Each of these elements, combined with modern technologies, supports the construction of more reliable, complete and functional reports, tailored to the expectations of modern stakeholders.

## 3.3. Analytical Support and Human–Machine Collaboration

### 3.3.1. Prediction and Analytics — Forecasting with AI

Modern accounting, going beyond traditional reporting functions, more and more often plays the role of an active participant in the process of strategic management. In this context, predictive analytics and decision support systems are of key importance. As Appelbaum et al. (2017, p. 6) note, these are tools that use financial and non-financial data to identify patterns that can form the basis for making management decisions. These authors also emphasize the role of data integration from multiple sources and automation of the analytical process, which makes these systems an important support for management accounting. Granlund (2011, p. 7) points out that in the context of accounting, decision support systems are gaining particular importance through their connection with analytical and predictive tools, becoming a valued element of controlling and data-driven reporting. In this approach, they are an integral component of the ecosystem supported by artificial intelligence.

In order to fully understand the importance of these systems today, it is worth looking back at the evolution of accounting technology—starting with the first mechanical devices, such as the Burroughs machine from 1888, which was described in more detail in the previous chapter of the monograph It was this machine that was a breakthrough in the automation of accounting calculations—it allowed for mechanical summing up and printing of results, which significantly reduced working time and the risk of error (Encyclopædia Britannica, 2025). It was the first manifestation of the idea that technology can take over some of the cognitive-manual tasks of an accountant, freeing up his potential for analytical functions. However, the Burroughs machine was not only a mechanical tool—as Granlund (2011, p. 4) notes, its emergence initiated organizational changes and a redefinition of the role of the accountant. It became an impulse to think about automated accounting, which in the following decades took the form of mainframe computers and, finally, integrated systems. These systems, similar to the IBM System/360 of the 1960s, allowed for the collection and analysis of large financial data sets in real time, which already at that time enabled early forms of management decision support (Granlund, 2011, p. 5).

Modern systems based on artificial intelligence and predictive analytics can therefore be seen as a continuation of this evolution—they are the heirs of accounting machines and central computing units. But while Burroughs automated simple arithmetic operations and mainframes provided quick access to data, today's systems not only analyse data, but also make recommendations, predict future events, and support managers in making decisions in conditions of volatility and uncertainty.

Developing Business Intelligence tools and predictive machine learning algorithms, such as gradient boosting or neural networks, are a response to the needs that appeared already in the Burroughs era: the need for fast, accurate and adaptive financial information. Today's dashboards, risk management applications or advanced scoring models are in fact an extension of the same idea—that information should be available quickly, reliably and in a way that is understandable to decision-makers. In this sense, modern AI-based accounting is a logical step in a process that began more than a century ago in the mechanical studio of William S. Burroughs.

Predictive analytics itself—as defined by Appelbaum et al. (2017, p. 6)—is "the application of statistical models and machine learning algorithms to predict the probability of future events based on historical and current data". According to Moll & Yigitbasioglu (2019, p. 37), they are a key element of "analytics supporting real-time decision-making", based on data streams processed in an adaptive way. The purpose of predictive analytics is to predict financial phenomena such as revenues, costs, cash flows, and insolvency risk—all in order to enable more accurate and data-driven strategic decisions. Technologies used in this area range from classical regression models to more advanced machine learning (ML) and deep learning (DL) algorithms.

Machine learning (ML) is a field of artificial intelligence that enables computer systems to learn from data without having to program every rule of operation. According to the definition of Appelbaum et al. (2017, p. 6), it is the process of identifying patterns in data using statistical algorithms, which allows for the automation of forecasting and classification.

Deep learning (DL), a subfield of ML, is based on multi-layered artificial neural networks capable of modelling complex, non-linear relationships. As Moll & Yigitbasioglu (2019, pp. 36–37) point out, DL enables a significant increase in the accuracy of predictions thanks to the ability to automatically extract features from raw data, without the need for prior preparation or feature engineering.

These methods use, among others, decision trees that build hierarchical decision-making structures; Random forests, which aggregate multiple trees to improve accuracy. neural networks that simulate the structure of the biological brain;

and gradient boosting algorithms that learn subsequent base models correcting errors of the previous ones. Thanks to these tools, it is possible not only to accurately forecast numerical values, but also to classify customers, transactions or events with a potential risk nature.

Natural Language Processing (NLP) also plays a special role in the context of predictive analytics, which enables the transformation of non-numerical data—such as email content, auditors' comments, transaction descriptions or records of conversations with customers—into structures suitable for quantitative analysis. NLP allows not only for keyword extraction and document classification, but also for the recognition of intent, sentiment, and even emotion in textual messages (Moll & Yigitbasioglu, 2019, p. 37). As a result, it becomes a tool of strategic importance for risk forecasting, credibility of contractors or early detection of financial problems.

NLP's ability to convert text into predictive variables is applicable to various areas of accounting. An example may be the analysis of the sentiment of the management board's statements in annual reports and the interpretation of the content of bank transaction descriptions, where the analysis of financial statements may reveal hidden risks and dependencies (Appelbaum et al., 2017, p. 10). NLP is also sometimes used to classify and sort emails in terms of financial priority or risk, allowing for an automated response from decision support systems (Granlund, 2011, p. 7).

The practical applications of artificial intelligence in predictive analytics are varied. In addition to classic forecasting models used to estimate cash flows or revenues, AI also supports the assessment of contractors' insolvency based on dynamically updated financial and behavioural data (Pingili, 2025, p. 104; PriceWaterhouseCoopers, 2022, p. 21). Another example is the detection of anomalies in transactions using anomaly detection algorithms, which can identify operations that are unusual for a given business cycle. These algorithms can capture deviations from the norm in real time, analysing both financial and contextual data PriceWaterhouseCoopers (2022, p. 24). This makes this technology an important tool supporting not only internal control, but also automated audit systems.

AI-based systems are increasingly integrating the functionalities of dynamic "what-if" predictive models, which enable the analysis of the impact of various macroeconomic scenarios on the company's financial situation (Pingili, 2025, p. 107). These models, based on the analysis of input data and a set of decision-making rules, create structures that allow for systematic consideration of the possible consequences of actions, which makes them continuators of the tradition of logical reasoning in the spirit of Aristotelian syllogistics. According to the principles of syllogistic logic formulated by Aristotle, which we discussed in more detail in the previous chapter, correct reasoning is based on a structure of premises leading to an unambiguous conclusion. In the case of "what-if" models, this structure takes the form of "If A—then B" rules, which are reflected in practice in AI decision-making systems. Thanks to this structure, managers can create sets of premises (e.g. decrease in demand, increase in energy costs) and on their basis derive the expected effects (e.g. decrease in EBITDA, the need to renegotiate contracts). In this sense, modern predictive models are an extension of classical logical structures in practical applications. Their architecture not only reflects the basics of logical reasoning but also makes these operational principles operational in the digital environment. This is an example of the modern application of Aristotelian syllogistic logic in modern accounting technologies—from scenario analysis to strategic decision support.

It is worth noting that this logic has also had an impact on the development of expert and rule systems, from which modern AI decision engines are derived. The decision-making structures used in predictive algorithms reflect classical forms of deductive reasoning, which confirms that the foundations of Aristotle's logic still apply to the construction of accounting information systems. This allows managers to make decisions based on clear, structured analyses, minimizing subjectivity and increasing predictability in the face of uncertainty.

The next stage in the evolution of AI in accounting is the integration of predictive tools with managerial reporting. Intelligent dashboards are being created that present key performance indicators (KPIs) on an ongoing basis, warn of impending risks, and suggest corrective actions in a way tailored to the organization's profile (Appelbaum et al., 2017, p. 12; Granlund, 2011, p. 9). Using ML and NLP techniques, these dashboards analyse data not only numerically, but also qualitatively—interpreting, for example, entries in transaction comments or narratives accompanying accounting decisions.

To sum up, artificial intelligence not only supports financial analysis in a retrospective perspective but also enables accounting to actively participate in managing the future of the organization. The shift in emphasis from the record of economic facts to the prediction and recommendation of data-driven actions makes accounting one of the key strategic tools of management in conditions of uncertainty and volatility (VUCA) (Appelbaum et al., 2017, p. 13; Moll & Yigitbasioglu, 2019, p. 39).

### 3.3.2. Detecting the Undetectable — Fraud and Anomaly Detection Using AI

Modern accounting, developing towards intelligent decision support systems, increasingly uses advanced artificial intelligence tools to detect fraud and analyse anomalies in financial data. Thanks to the increasing computing capabilities and the development of machine learning techniques, it has become possible to identify irregularities in real time and predict fraud risks. The use of techniques such as anomaly detection, which support both internal and external audits, becomes particularly important PriceWaterhouseCoopers (2022, p. 24).

Anomaly detection is an analytical technique that involves identifying patterns of behaviour that deviate from the accepted norm or typical pattern of action. In accounting practice, this refers to transactions, financial events or accounting entries that do not fit the learned pattern or profile of the entity's business. As Pingili (2025, pp. 104–106) notes, such solutions are particularly effective in analysing large volumes of transactional data, where traditional control methods become insufficient. Anomaly detection detects subtle discrepancies (or as the name suggests—anomalies) which can indicate for instance an extortion attempt, clerical manipulation or a violation of the financial policy.

In internal auditing, these techniques support the identification of unusual events in the purchasing, remuneration or payment cycle. This allows auditors to focus on analysing the highest-risk cases instead of searching through the entire data set. In the context of an external audit, anomaly detection can serve as a complement to traditional control procedures, increasing the chances of detecting accounting fraud, e.g. by analysing unusual provision postings, year-end operations or revenue manipulation (Appelbaum et al., 2017, p. 9).

An important application of AI in accounting is also fraud detection. In this case, algorithms learn fraud patterns from historical data and use predictive models to identify high-risk behaviour. As Granlund (2011, p. 8) points out, it is important to combine numerical data (e.g. transaction amounts, deadlines, counterparties) with sparse data (e.g. transaction description, document source) in order to obtain a full picture of the context of the event.

One of the most promising directions is the integration of data from various sources—accounting, operational, behavioural—to detect unusual patterns of behaviour that may indicate fraud. This approach allows you to create so-called user or individual risk profiles, which are compared in real time with real actions. When the system detects a discrepancy—e.g. a sudden increase in the value of invoices from a given contractor or an unusual accounting time—it triggers an alert that can be investigated by the control team.

An important aspect in anomaly analysis and fraud detection is the possibility of using unsupervised and semi-supervised learning algorithms. Their importance is emphasized by, among others, Richins et al. (2017, pp. 71–72), who point out that the lack of labels in transactional data is one of the main challenges in AI-supported auditing. In such conditions, it is necessary to implement methods that can independently identify unusual behaviours without first defining fraud patterns. A similar approach is presented by Schreyer et al. (2017, pp. 3–4), who propose the use of autoencoders to detect anomalies in accounting data as an effective tool for early detection of irregularities in large volumes of data. Hemati et al. (2021, pp. 6–7) take this concept further to include continual learning mechanisms, which allow models to be updated as new data becomes available without the need for full retraining. In a review approach, Phua et al. (2010, pp. 6–8) emphasize the importance of unsupervised approaches in the context of fraud detection as a way to identify fraud patterns that were previously unknown or classified. As a result, these methods are becoming crucial in accounting and auditing environments, where data is incomplete, variable, and difficult to interpret unambiguously.

Typical algorithms used in these approaches are, among others, autoencoders, which are neural network structures that learn to compress and reconstruct data—if a given point deviates significantly from the scheme, the reconstruction turns out to be inaccurate, which is a signal of a potential anomaly (Moll & Yigitbasioglu, 2019, p. 38). Another example is Isolation Forest—an algorithm that is based on the principle that anomalies are easier to isolate in randomly built decision trees. It works quickly even on large data sets and is resistant to the “multidimensional void” effect typical of financial analysis. Local Outlier Factor (LOF), on the other hand, allows for the identification of outliers by comparing the density of the point with respect to its neighbours—this method is particularly useful in the analysis of accounting data with irregular distribution, e.g. seasonality or industry variability (Moll & Yigitbasioglu, 2019, p. 38).

In accounting practice, these approaches are used to catch rare but potentially significant events, such as unusual invoicing patterns, unauthorized transfers, redundant accounting corrections, or repeated documentation errors. Importantly, thanks to the possibilities of data mining and visualization of results (e.g. using Kohonen maps or t-SNE), it is possible to present the results of the analysis in an intuitive form for auditors and financial analysts, which strengthens the interpretability of the entire process. Kohonen Maps (SOM—Self-Organizing Maps) are self-learning neural networks that map multidimensional data onto a two-dimensional grid, preserving topological relationships between observations. This makes it possible to group similar cases and identify outliers, which is used in the analysis of accounting fraud and financial anomalies (Appelbaum et al., 2017, p. 35; Schreyer et al., 2017, p. 5). SOMs enable visual data exploration, which significantly supports the interpretation of results by auditors and risk specialists.

t-SNE (t-distributed Stochastic Neighbour Embedding) is a nonlinear dimensionality reduction technique that is used in the analysis of high-complexity datasets. It allows you to transform data with multiple characteristics into two-dimensional or three-dimensional space while maintaining the local data structure, which supports the visual identification of clusters and anomalies. Hemati et al. (2022, p. 6) indicate that t-SNE is used, among others, in the continuous analysis of financial operations in the unsupervised learning mode, where the visualization model supports the decision to further investigate potentially risky transactions.

In practice, the use of SOM and t-SNE not only increases the efficiency of anomaly detection but also strengthens the transparency and communicativeness of analysis results, which is crucial for the implementation of Explainable AI in accounting and auditing processes (Phua et al., 2010, p. 9). Both methods allow for effective detection of anomalies and understanding their context without the need for manual analysis of each case, which is especially important in environments with a large amount of accounting and transactional data (Moll & Yigitbasioglu, 2019, p. 39).

In internal audit systems, unsupervised learning is also used to group accounting operations into clusters—if a given transaction does not fit into any of the established groups, it may be classified as requiring further investigation.

Semi-supervised learning, on the other hand, is used in situations where an organization has a limited set of identified cases of abuse—algorithms such as semi-supervised SVM or transductive learning can detect new, similar patterns in unlabelled data on this basis (Granlund, 2011, p. 10).

It is also worth noting that algorithms of this type are often more resistant to attempts by perpetrators of abuse to circumvent the system. While supervised models can be manipulated by providing "false positive" data for training, non-labelled models learn the structure of the data itself, making them harder to fool. As a result, organizations using unsupervised learning gain a tool that enables more flexible and adaptive protection against previously unknown types of fraud.

However, the use of unsupervised and semi-supervised learning in accounting requires appropriate preparation of the data infrastructure: aggregation, standardization and quality assurance of source data. As Appelbaum et al. (2017, p. 30) point out, the success of implementing these techniques depends largely on the team's competence and the level of technological integration between ERP systems and the analytical layer. Thanks to these methods, accounting and auditing can transform from reactive processes into dynamic systems for monitoring and detecting risks, which is one of the pillars of modern management control.

Another important area is transaction risk assessment systems. ERP systems such as SAP, Comarch ERP, or Oracle Financials implement AI modules that analyse data in real time and assess the risk of each transaction. On this basis, high-risk transactions can be blocked automatically or forwarded for additional verification (Granlund, 2011, p. 9; PriceWaterhouseCoopers, 2022, p. 22).

In Poland, similar functions supporting the detection of irregularities and fraud are increasingly being built into financial and accounting systems, such as Comarch ERP Optima or enova365. These systems, according to manufacturers' documentation, enable the analysis of risk indicators, the handling of validation rules, and the verification of the completeness and consistency of data in real time, which significantly increases their usefulness in audit and control activities.

The development of AI fraud detection tools is also an important response to increasing regulatory requirements and stakeholder pressure on compliance and financial ethics. In the face of global crises of confidence in financial institutions and rising expectations for corporate responsibility, the implementation of advanced technologies to support financial transparency and integrity is becoming essential. AI-based systems can detect patterns hidden in huge volumes of data, which allows not only to reveal known types of fraud, but also to identify new, previously unclassified fraud patterns.

In this context, ethics becomes an integral part of the design and implementation of fraud detection algorithms. As Richins et al. (2017, p. 72) note, one of the challenges is to ensure that AI systems are not only effective, but also fair and transparent in their operations. The use of Explainable AI techniques involves the use of such methods of modelling and data analysis that allow a human to understand the mechanism of the algorithm. This means that fraud detection systems are not a black box, but offer clear, transparent explanations as to why a transaction is considered suspicious. These techniques—among others including LIME (Local Interpretable Model-agnostic Explanations), SHAP (SHapley Additive ex-Planations) or heatmap visualizations for autoencoders—allow accounting system users and auditors to track which data features had the greatest impact on classification. This approach is particularly relevant in the context of accounting and auditing, where there are high standards of transparency, compliance and the possibility of retrospective scrutiny of the decisions made by the system. As emphasized by Schreyer et al. (2017, p. 4) and Richins et al. (2017, p. 72), only such an approach can ensure that the use of AI in accounting complies with the principles of professional ethics, public trust, and transparency. Ensuring auditability of decisions made by algorithms is also essential to build trust with both system users and regulators. Schreyer et al. (2017, p. 4), on the other hand, point out that the use of advanced models, such as autoencoders, should be balanced with mechanisms for verifying the results to avoid false alarms and unfounded accusations.

The implementation of AI in audit and financial control also carries the risk of potential biases encoded in training data. Hemati et al. (2021, p. 6) highlight, misrepresentation of data can lead to unfair treatment of certain groups of entities or transactions. Therefore, a responsible approach to AI in accounting requires not only technical competence, but also ethical awareness and the use of validation procedures in line with the principles of corporate governance and compliance (Phua et al., 2010, p. 7).

The use of artificial intelligence in this area is changing the way we think about auditing—from reactive data research to proactive risk modelling. Modern algorithms are able to catch deviations that would not be noticed by a human or standard procedures. Moreover, by using Explainable AI methods, it is possible to provide a logical justification for detecting anomalies, which increases trust in these technologies (PriceWaterhouseCoopers, 2022, p. 25).

In conclusion, AI is changing the approach to detecting fraud in accounting. Thanks to anomaly detection, fraud detection techniques and contextual data integration, it is possible to create systems that not only monitor accounting correctness but actively support the protection of the organization's interests against the risk of fraud. The roles of the accountant, auditor and controller are transforming—from data analyst to co-designer of intelligent financial control and security systems.

### 3.3.3. Human–Machine Collaboration — Cognitive Interfaces in Accountants' Work

Modern accounting is increasingly based on advanced technological tools, including artificial intelligence systems, which redefine both the way accounting processes are organized and the place of humans in these structures. AI transforms a work model focused on manual and repetitive activities into a model focused on data interpretation, risk analysis, and management decision support. As Abbas (2025, p. 11) emphasizes, the implementation of AI in accounting is not only a matter of automation, but the transformation of the accountant's role into a strategic business partner that interacts with technology in a dynamic decision-making environment. The increasing human-computer interaction in recent years requires further exploration of the coexistence of humans and machines in the existing artificial intelligence environment. As Hamdan et al. (2021, p. 4) notes, the Fourth Industrial Revolution is redefining the boundaries between humans and technology, leading to an ever-deeper penetration of algorithmic systems into everyday decision-making processes in organizations. As a result, coexistence can no longer be perceived as a one-sided relationship—AI affects humans, but also requires their presence, interpretation and supervision. In this context, it becomes important not only to integrate various systems technologically, but also to integrate humans with algorithms socially and ethically. The ability to act cooperatively, understand decision-making models and consciously supervise them becomes the foundation of effective interaction. It is not only an engineering task, but also an organizational and cultural challenge. Human-machine interaction must be based on trust, communication, and the ability to recognize the boundaries of responsibility between the system and the human operator.

Dwivedi et al. (2021, pp. 8–9) emphasize that AI is changing the way organizations process information. Hasan (2022, pp. 443–444) notes a similar relationship, pointing out that machines are able to process large amounts of data and learn from experience, which relieves people of monotonous tasks. These findings lead to the definition of new, hybrid models of collaboration between accountants and artificial intelligence. They seem to be key elements leading to increased efficiency and value in accounting processes. Jarrahi (2018, p. 584) proposes the use of so-called dual experts, who are initially employed as specialists in a given field (e.g. accountants, controlling specialists) and then are trained in machine learning or other areas of artificial intelligence. Such people are later most likely to develop the most practical solutions to integrate AI with accounting.

As pointed out several times in the previous points, AI offers great potential in expanding and automating human tasks. Organizations can benefit from optimizing human-AI collaboration by developing "fusion skills" in employees to work effectively at the human-machine interface, which they also emphasize in their considerations Dwivedi et al. (2021, pp. 10–11). Today, the automation of accounting processes has become a basic manifestation of the practical application of AI in accounting, which they emphasized in the results of their research Honko & Hendryk (2024). In turn, in their article, Colombo & Beuren (2023) described that the culture of innovation, commitment to work and the use of interactive performance measurement systems (PMS) have a positive and significant impact on the automation of accounting processes in the surveyed shared service centre (SSC). In addition, the use of interactive PMS has a mediating effect in the relationship between the culture of innovation and work engagement. However, the paper Andreassen (2020) shows that in some companies, such as InsuranceCo, the role of the technical management accountant is to be an expert in digital planning and forecasting systems. This ensures the collection, processing and correct presentation of integrated information from sales systems and other professional systems, as well as assists in the implementation and monitoring of data consistency. These examples quite clearly indicate the current change in the competences and role of the accountant, shifting them in a more analytical and advisory direction.

Digital technologies and the resulting automation of basic accounting processes create new opportunities for multidisciplinary collaboration and redefine professional boundaries, which Abbas (2025) writes about in more detail in his work. Also Dwivedi et al. (2021, pp. 17–18) in their work, they rightly note that accountants will have to develop new skills and knowledge in the near future, including management roles. This is because AI contributes to increased productivity and streamlines processes by eliminating non-productive activities and removing monotonous, repetitive work. Accountants can thus become experts in digital planning and forecasting systems.

Acquiring new skills by accountants entails the need to modify the existing curricula in this area. A good example of this is experiential learning, which simulates the real-world workflow of accounting professionals involved in the analysis of financial and non-financial data. Stancheva-Todorova & Bogdanova (2021) in their paper, they published the results of a case study conducted in a group of accounting students, aimed at examining the practical application of AI and ML in investment analysis. They took on the role of members of the accounting team of furniture manufacturing company, ABC, Inc., whose management wants to improve its investment strategy by applying the latest developments in AI. The students' task was to develop and implement an integrated two-stage AI system based on ML to predict upward and downward movements in the stock prices of listed companies. The case study included seven tasks, ranging from data retrieval and cleansing, through the input of lagging values, automatic selection of features, the provision of predictions and error matrix, feature analysis, to consulting for the board. By using AI to support investment decision-making, students developed analytical thinking and interpretation skills, highlighting the importance of AI and machine learning competencies in modern accounting education. However, it should be remembered, as he rightly reminds us Jędrzejka (2019, pp. 159–160), that there is also a need to include the development of soft skills, technology and data management skills in the educational approach in accounting. All of this, therefore, requires significant investment in training and the development of new opportunities that AI creates for the accounting profession.

When describing the interactions between man and machine in the work of an accountant, it is impossible to ignore the ethical challenges in this area. From an accountant's perspective, technological transformation means not only the need to acquire new competences, but also the redefinition of one's own professional identity—from a data operator to a strategic partner and information value architect. Abbas (2025) stresses that AI poses new challenges for accountants, such as ensuring data privacy and security, confidentiality and ethical concerns. In turn, Hasan (2022, pp. 454–455) adds the risk that AI algorithms will be exploitative, deceptive, internally biased, or contain human logical errors or built-in biases. Prejudice is also noted by Dwivedi et al. (2021, p. 19), who emphasize, that it is well documented in many forms of AI, from racist financial algorithms to sexist chatbots. The problem of bias stems from the fact that algorithms are "opinions embedded in code", reflecting the preconceived judgments, morals, ethics, and biases of the creators. A major challenge, therefore, is the lack of understanding of how AI works by most people. It must also not be forgotten that when AI makes autonomous decisions, the issue of responsibility becomes very difficult to solve, especially when the decision-making algorithm is sometimes unknown even to the designer himself. Therefore, as Dwivedi et al. (2021, p. 31) rightly postulates, it is necessary to develop transparent and uniform standards (Global Alliance for AI Standardisation). Two potential novel human rights in light of AI/robotics-related advances namely the "right not to be measured, analysed or coached" should also be considered.

In conclusion, human-machine interaction in accounting is evolving toward hybrid models, where AI automates routine tasks and accountants move into analytical, advisory, and strategic roles. This transformation is associated with the need to improve and reskill competences. The key challenges are ethical issues and building trust in AI, so that the results of this cooperation are always transparent and understandable to humans.

Chapter 4

# AI in Practice — Case Studies from Leading Organizations Worldwide

Jacek Kalinowski

## 4.1. An Introduction to Inspiring Stories That Shape the Future of Accounting

This chapter presents case studies ranging from global technology and financial leaders to smaller, dynamic companies. The described cases include, among others:

- Implementation of RPA by a multinational manufacturing company in cooperation with Cognizant to automate invoice processing.
- End-to-end transformation of financial processes at Uber, including RPA and advanced automation using OCR and integration with ERP systems.
- The use of OCR in the educational company Aceable to process cost documents.
- IBM project involving the integration of AI and OCR in the handling of financial liabilities of a corporate client.
- Mastercard's implementation of a GenAI system for real-time fraud detection.
- EY's pilot use of AI in audit to detect irregularities that were not identified in conventional audits.
- Implementation of DARTbot by Deloitte as an intelligent assistant supporting auditors in the interpretation of accounting regulations.
- Bank of America's implementation of Erika's chatbot in customer service, using NLP and AI to support personal finance management.
- Unilever's use of AI in management accounting, cost planning and ESG targets.
- KPMG project transforming the financial reporting and audit process using AI and NLP.

Each case presents a different aspect of AI application: from automating operations, through decision support and prediction, to improving the quality of audit and regulatory compliance. In this part of the monograph, we have shown the diversity of contexts in which technology can be effectively implemented, and illustrate how AI contributes to the efficiency, transparency, and strategic value of the accounting function. Thus, it is a practical guide to the current possibilities and an inspiration for further research and implementation.

## 4.2. Strategic and Managerial Applications of AI

### 4.2.1. Unilever — AI in Cost Optimization, Management Transformation and ESG Goals[1]

Unilever is one of the largest and most recognizable FMCG (Fast Moving Consumer Goods) companies in the world. The company produces and sells a wide range of everyday consumer products—from cleaning products (e.g. Domestos, Cif), through cosmetics (Dove, Rexona), to food products (Hellmann's, Knorr, Lipton). The corporation operates in more than 190 countries, has a portfolio of over 400 brands and serves billions of consumers, employing nearly 150,000 employees. The scale of its operations is impressive—for example, as indicated in the Unilever (2025) on progress in sustainable sourcing of agricultural raw materials, the company's annual demand for vegetable oils—used in the production of margarine, sauces and snacks, among others—exceeds 1 million tonnes. This is an amount comparable to the year-round production of vegetable oils in countries such as Hungary, Romania or Ghana. Such huge volumes demonstrate the scale of Unilever's operations and the key importance of effective management of raw material costs in the context of the corporation's global operations.

With such a scale of operations, Unilever faces an ongoing need to make strategic decisions related to cost control, production optimisation and sustainable supply chain management. With multiple production sites spread across the globe, the company is constantly faced with challenges related to differences in the availability and cost of raw materials, currency fluctuations, and the impact of geopolitical and climatic factors. Any change in the prices of production components—such as vegetable oils, plastics or chemicals—can translate into multi-million-dollar changes in operating costs on a global scale.

To meet these challenges, Unilever decided to implement modern solutions in the field of artificial intelligence. Predictive systems based on machine learning were used, which allowed for the analysis of huge data sets—both internal (historical, cost, production data) and external (stock exchange quotations, meteorological reports, information on the condition of crops and geopolitical situation). The aim was to create a mechanism for forecasting changes in the prices of key components and their impact on the company's cost structure.

1 Based on: DigitalDefynd Team (2025).

A key element of this implementation was the close integration of the AI system with the management accounting subsystem, which is responsible for supporting planning, budgeting and controlling processes. As a result, the data generated by the predictive models was not only used for ex-post analyses but had a real impact on strategic and operational decisions in real time. The controlling department was not only able to plan expenses more accurately, but also dynamically adjust purchasing and production strategies to current forecasts.

The implemented system made it possible to identify the most profitable moments for the purchase of raw materials, renegotiate contracts with suppliers, as well as optimize the cost structure by region and product line. This approach has allowed for significant savings—according to the company's data, Unilever has saved more than €600 million in one operating cycle. Equally important, the implementation of AI contributed to reducing resource waste, better inventory management, and improving the energy efficiency of production plants—which had a direct impact on the achievement of ESG (Environmental, Social, Governance) goals.

From the point of view of management accounting, the AI system became an advanced component of the information subsystem, which not only provided up-to-date and precise cost data, but also generated scenario simulations, sensitivity analyses and recommendations for corrective actions. As a result, management could make more informed and faster decisions, and the entire accounting system became an active tool to support the strategic management of the organization.

The transformation at Unilever has also shown that the implementation of AI is not just a technological project, but a profound cultural transformation. Finance departments have been transformed into high-value-added analytical units, and controlling specialists have become key strategic partners for operations managers. In this way, Unilever created a new organizational model in which data and analytics became the basis of management, not just an element of reporting.

Unilever's case is a prime example of how advanced technologies can be integrated into management accounting and ESG strategy, leading to a comprehensive organisational transformation. It also shows that investments in AI—if properly planned and implemented—bring not only cost-effective, but also qualitative, social and environmental benefits.

### 4.2.2. KPMG — AI in Financial Reporting and Auditing[2]

As one of the key global players in audit, advisory and tax services, KPMG operates in more than 140 markets and employs approximately 270,000 people. It is one of the largest organizations in its industry, with a significant position in the international environment, known for its wide range of services, numerous consulting projects and large scale of operations. In the face of growing stakeholder

2 Based on: KPMG (2024a, 2024b).

expectations, changing regulations and pressure for digitization, KPMG is investing heavily in technologies, including advanced artificial intelligence (AI), to transform its processes and maintain its leadership position in the audit and reporting area.

In 2022–2024, KPMG completed a large-scale global project aimed at a thorough implementation of artificial intelligence technology in the areas of financial reporting and auditing of financial statements. The project was transformative and covered dozens of markets and thousands of customers operating in various industries—from finance and energy to the pharmaceutical industry and the public sector. A key element of this project was the introduction of integrated analytical platforms based on machine learning and natural language processing (NLP) mechanisms, capable of processing and analysing both numerical data and narrative descriptions contained in financial documentation.

To illustrate the scale—the implemented system was able to analyse data from thousands of pages of financial reports, management reports and notes of statutory auditors, which previously had to be reviewed manually by audit teams, during a single analytical session. The algorithms were tuned not only to meet the requirements of international accounting standards (IFRS) or national standards such as US GAAP, but also to take into account local regulatory, tax and industry conditions. This meant that whether the client was operating in Germany, India or Brazil, the AI solutions were able to support reporting processes in a way that was compliant with the regulations in force there, automatically identifying risks, inconsistencies and potential areas for additional control.

A key aspect was to transform the classic retrospective audit process into a predictive and advisory tool. Instead of analysing only historical data, audit teams have begun to use AI to detect patterns of risky financial behaviour, identify unusual trading patterns, and automatically classify and prioritize potential areas that require special attention. The system was able to process millions of records from financial documents, management reports, contracts, protocols, and correspondence—analysing them in the context of accounting standards and reporting logic.

A particular added value was the support in the process of data validation and their clear visualization, which allowed auditors not only to identify problems faster, but also to communicate risks to clients more effectively. AI has also been used to assess the efficiency of business units and identify areas where savings or optimisation are possible. Thanks to the integration of AI tools with management accounting subsystems, it was possible to generate real-time analyses to support strategic decisions of management.

Digital transformation has also affected KPMG's internal organizational culture. The company created new career paths—it hired AI specialists, data engineers, designers of reporting interfaces, and auditors with analytical and technological skills. Training and upskilling have become the foundation for the modernization of staff competences, and the finance and audit departments have been rebuilt for teamwork with the use of artificial intelligence.

From the customers' perspective, the implementation of AI in reporting and auditing has brought measurable benefits. Project lead times have been shortened, audits have been more accurate, and the risk of mistakes has been reduced. Clients received more in-depth analyses and recommendations tailored to their business profile. At the same time, KPMG strengthened its position as a strategic partner in the digital transformation of corporate finance, providing higher value-added services.

The described activities of KPMG are part of a broader paradigm of digital transformation of accounting systems and audit 4.0—an integrated approach that combines automation, predictive analytics and a data-driven approach. The use of AI in this case was not limited to technical improvement but became part of a new business and organizational model. This is an example of how accounting is transforming from a support function into a strategic tool supporting sustainable development, regulatory compliance and transparency of business activities in the 21st century.

### 4.2.3. Ernst & Young — AI in Audit and Fraud Detection[3]

As part of the pilot implementation of the artificial intelligence system, EY (Ernst & Young)—one of the four largest audit firms in the world, along with PwC, KPMG and Deloitte—tested the use of AI to detect fraud in audit processes. EY is a global organization with a presence in more than 150 countries, hundreds of thousands of employees and clients from all sectors of the economy. Financial audit is a key pillar of its business—it is a service that is fundamental to the reliability of the financial statements of companies around the world. The quality of audits is a strategic issue for EY, and any shortcomings in this area may lead to a loss of trust of the market, clients and financial supervisory authorities. Therefore, detecting fraud, both in customer financial data and in the audit process itself, is not only an operational priority, but also a reputational one. Fraud can be not only accounting, but also procedural—it can concern, for example, concealing information, circumventing approval procedures or non-standard treatment of financial risks. Failure to detect them during an audit means that the final financial statements may not reflect the actual situation of the company, which can lead to serious consequences for stakeholders—investors, employees, regulators.

As part of the test implementation, EY analysed ten completed financial audits conducted in various organizations. It is important that these audits were already finalized, i.e. accepted by the audit teams and considered completed in accordance with the applicable procedures. Under natural conditions, the audit process in these cases would be considered closed and properly executed. Meanwhile, an analysis carried out with the use of artificial intelligence revealed new, previously

3 Based on: Sighn (2023).

undetected irregularities. This significantly raises the rank of the entire implementation, showing that even completed and formally accepted audits can contain hidden anomalies that escaped human analysis.

In each of these cases, the AI system was tasked with identifying potential irregularities, procedural deviations, red flags, and unusual patterns of action that could suggest a risk of fraud or breaches of accounting principles. It was an attempt to use modern digital tools not only as support in the current work of auditors, but above all as a breakthrough in the standards of audit analysis—a new stage in the development of this discipline, in which the quality, depth and objectivity of the assessment of financial data reach an unprecedented level. The introduction of artificial intelligence into audit practice does not only mean technical modernization, but represents a fundamental paradigm shift in which data analysis is no longer just a verification tool and becomes an active factor uncovering hidden irregularities and potential risks that the human mind would not be able to identify in the conventional course of work.

The use of AI enabled a new dimension of control, the purpose of which was not only to confirm the correctness of procedures, but also to catch subtle anomalies and absurdities in the data that could indicate intentional actions aimed at manipulating financial results. This approach strengthened the audit process by building its second line of defence—independent, based on algorithmic analysis and real-time learning. As a result, it was possible to detect irregularities that, if left unnoticed, could damage EY's reputation as an institution that provides transparency and credibility in the global financial ecosystem.

The system, which was implemented as part of the EY pilot project, was based on machine learning algorithms, i.e. technology that allows computers to learn on their own from historical data without the need to manually program each case. In practice, this means that the algorithms analysed huge sets of financial data, including, among things, accounting entries, transaction history, document approval structures, changes in account balances, and relationships between different departments of companies.

The aim of the analysis was to identify patterns that have been associated with fraud in the past, such as false invoices, unjustified accounting adjustments, non-standard expense approval schemes or suspicious flows between departments. By using this technology, the system was able to "learn" the relationship between seemingly harmless actions and real incidents of irregularities.

After the training process was completed, the AI was able to analyse new data from ongoing audits and indicate areas where there are worrying signals (so-called red flags). The system generated risk reports for each of the analysed units, marking specific operations, documents or action schemes that deviated from the norm and could require in-depth control by the audit team. This type of intelligent data analysis allows auditors to focus their attention on key areas, thereby increasing the effectiveness and efficiency of the audit process.

In two out of ten cases, the system identified serious irregularities which, after independent verification by a team of auditors, turned out to be real cases of violations. Importantly, none of these situations had been previously identified in the standard audit process. This means that the AI system was not only accurate in its predictions (100% effectiveness in recognizing fraud), but also brought additional cognitive value, complementing the traditional methods of auditors' work.

This experience has shown that the use of AI can provide significant support in identifying anomalies that are difficult to detect and enables earlier detection of symptoms of abnormalities. As a consequence, this may contribute to increasing the effectiveness of audits, improving the quality of financial information and strengthening trust in reports prepared by independent statutory auditors. According to information provided by EY, the organization plans to further develop this solution and integrate it with global audit procedures.

## 4.3. Process Automation and Operational Optimization

### 4.3.1. Uber — Automation of Financial Processes[4]

Uber, founded in 2009 in San Francisco, is a global technology company that has revolutionized the way people get around cities and use logistics services. Originally a ride-hailing app, it now operates in more than 70 countries, also offering food delivery services (Uber Eats), freight transport, and micromobility solutions. The company listed on the NASDAQ stock exchange, employs thousands of employees and serves tens of millions of users per month, generating revenues counted in billions of dollars.

Due to the growing scale of operations and the need to optimize internal administrative operations, Uber has made a strategic decision to widely implement solutions based on Robotic Process Automation (RPA). This initiative was launched in 2021–2022 as part of a global digital transformation program. Its goal was not only to reduce operating costs and increase efficiency, but also to improve data consistency, accelerate decision-making processes and better manage risk in a dynamic, multinational business environment. As a result of the analysis, more than 100 business processes were identified, which were repetitive, time-consuming and prone to human error. Particular emphasis was placed on activities carried out in the finance, controlling, settlement, and management of accounts payable and receivables departments, which were considered to be key from the point of view of operational stability and regulatory compliance.

4 Based on: Impact Insights (2023).

As part of its digital transformation, Uber has implemented software robots (bots) that have taken over many routine tasks in the area of finance. The automation included, among others, invoice processing (Accounts Payable), reconciliation of payments between systems and validation of financial data. The verification of accounts has been automated taking into account compliance with the company's chart of accounts and accounting policy. Bots assign costs to the correct cost centres, allowing you to track costs across organizational units in real time. The systems also automatically detect budget overruns and deviations from the set limits. In addition, they monitor the compliance of transactions with the purchasing policy. Thanks to integration with controlling modules, it is possible to periodically generate budget execution reports, analyse deviations and forecast future costs. This information supports management at the operational and strategic levels. The bots also prepare reports in accordance with applicable accounting regulations and internal reporting standards.

Of particular importance was the implementation of RPA in the process of handling purchase and cost invoices, which before the transformation was characterized by a high degree of manual employee involvement, high susceptibility to errors and low scalability. Thanks to the implementation of bots, it has become possible to fully automate over 70% of cases—from the moment of receipt of a document in electronic or scanned form, through the acquisition and structuring of invoice data (using OCR and business rule algorithms), then validation with the order in the ERP system (three-way matching), to automatic posting of the transaction and sending it for archiving and reporting.

Integration of bots with the existing ERP architecture and workflow tools (among others SAP, Oracle and ServiceNow) allowed to achieve a high level of data consistency, full traceability of operations and shorten the cycle time of processing a single invoice from several days to several hours. Automation also ensured full logging of activity, which strengthened control supervision and auditability of processes, responding to increasingly stringent compliance and internal governance requirements.

According to information provided by Impact Networking—an American consulting and technology company[5]—the implementation of RPA in Uber's financial structures turned out to be a great success. In the case of cooperation with Uber, Impact Networking provided consulting, process analysis and support in the implementation of RPA technologies in areas such as invoice management, billing, internal audit and controlling. The results of this transformation have been

5 Impact Networking was founded in 1999 in Illinois and over the years has grown into one of the leading companies providing digital transformation services to medium and large organizations in the United States. It specializes in providing solutions in the field of document management, IT infrastructure, cybersecurity and business process automation. The company is known for its comprehensive approach to projects, combining technological, analytical and implementation competencies—and its approach focuses on measurable business results.

significant: savings estimated at about $10 million per year. They result from reducing workload, speeding up processes, improving timely payments, as well as reducing errors and increasing operational compliance with regulations. What's more, automation has helped make Uber's financial systems more flexible, allowing them to scale as the number of transactions and the company's global presence grow.

Uber's experience clearly shows that the implementation of Robotic Process Automation (RPA) in a large organization does not have to be treated as a local initiative limited to one department, e.g. accounting or controlling. Instead, it can be the pillar of a broad strategy to digitize and transform the entire financial ecosystem of the company. Automation of financial processes allows not only to improve operational efficiency, but also to increase the accuracy of reporting, improve compliance, better risk management and a more flexible approach to growing data volumes and changing regulations.

In the context of Uber's implementation, a comprehensive approach to RPA made it possible to build an integrated digital architecture in which many processes take place without human intervention, and data is processed, analysed, and aggregated in near real time. Such an environment creates conditions for the effective implementation of further technologies—among others artificial intelligence to forecast future directions of changes in the structure and level of operating costs, budget cycles and the impact of external factors such as changes in exchange rates, commodity prices or tax regulations, as well as advanced analytics to identify irregularities in transaction data. The success of this implementation is a strong impulse for Uber to further develop towards the so-called autonomous finance, i.e. an environment in which an increasing range of financial decisions are made by algorithms supporting managers in real time. In this way, the organization is in line with the global trend of redefining the role of finance departments—from transactional functions to analytical centres supporting strategic business decisions.

### 4.3.2. Cognizant — The Use of RPA in the Mass Processing of Invoices[6]

A multinational manufacturing concern, which is one of the leaders in its industry, faced the challenge of increasing the efficiency and compliance of the process of handling liabilities to suppliers. The company processed about 80,000 invoices per year, each of which required manual retrieval from the web application, reading data from eight different fields (supplier number, name, invoice number, currency, net amount, tax, order number, and invoice date), verifying the data in the SAP system, and manually filling in the information and submitting the document for approval. This process was time-consuming and error prone.

6 Based on: Cognizant (2020).

In order to automate this process, the company decided to cooperate with Cognizant—one of the largest providers of consulting and technology services in the world. Cognizant is an American company listed on the Nasdaq-100 index, employing over 350,000 employees in over 35 countries. The company specializes in digital transformation, including business process automation, ERP system integration, cloud computing, and AI-based solutions. Its clients include global corporations in the financial, manufacturing, healthcare, retail and technology industries. Cognizant has many years of experience in the design and implementation of RPA systems, offering comprehensive services from process analysis to their full automation and maintenance. For this reason, the choice of this company as an implementation partner was a strategic decision, providing access to the latest technologies and an experienced team of engineers and process analysts.

To meet these challenges, the company decided to implement an advanced Robotic Process Automation (RPA) solution developed by Cognizant. The designed bot works seven hours a day, seven days a week, automating the entire process: from invoice download and data extraction, through its validation in the SAP system, to generating a unique identifier and submitting the invoice for approval. Additionally, if the provider does not yet exist in the system, the bot automatically initiates its onboarding. If shortages are detected—such as the lack of an order number—an exception is generated for manual handling by the analyst.

The bot sends daily, detailed reports on processed and unprocessed invoices, which allows for full transparency and control over the process. The implementation brought impressive results: 100% compliance and accuracy in data processing, as well as a reduction in the average invoice handling time by 50%. In addition, the solution includes reusable components, which allows the company to easily extend automation to other financial processes of a similar nature. This case shows how an effectively designed RPA solution can transform a complex and error-prone accounting process into an automated, transparent, and scalable operating model.

### 4.3.3. IBM — AI and OCR in Invoicing

IBM, a global leader in information technology, has been involved in the development and implementation of AI-based solutions in the area of finance and accounting for years. As part of the project described by Tater et al. (2022), IBM's R&D team conducted a comprehensive digital transformation of the accounts payable process in 2021 using a combination of AI and OCR technologies.

A project carried out by IBM in 2021 involved the processing of large volumes of invoices—both in paper and electronic form—as part of cooperation with a global corporation whose identity was not disclosed due to confidentiality clauses. In this project, IBM did not act as a beneficiary, but as a contractor and supplier of a comprehensive technology solution. The company was responsible for the design, implementation and integration of artificial intelligence components and

OCR (Optical Character Recognition) systems, which were aimed at improving the process of processing accounting documents.

The main objective of the project was to automate the process of acquiring, classifying and processing invoice data and integrating them with ERP systems and the so-called financial workflow. Financial workflow should be understood as a set of automated and logically ordered activities within the document handling cycle—from its receipt, through validation, approval, posting, to archiving and reporting. This integration enabled the automatic allocation of costs to responsibility centres, the approval of transactions according to authorizations, and the control of compliance with budget and financial policies.

IBM, as an implementation partner, conducted a detailed analysis of the client's processes, prepared the architecture of the solution, adapted AI models to the specifics of the data, and then connected the OCR system with existing ERP systems. The implemented system allowed for the extraction of data from invoices, their unification and validation using rule classifiers[7] and machine learning algorithms.[8] The combination of these two approaches made it possible to achieve high flexibility and accuracy of the system while maintaining control over the business logic of document processing.

The implementation resulted in achieving an advanced level of automation in the area of invoice processing—as much as 76% of all documents were handled completely without human intervention. This means that the data extraction process, its validation and posting were carried out in a fully automated manner, without the need for the intervention of the financial department employees. In addition, this automation has been achieved with a very high level of data accuracy (the so-called precision), which means minimizing system errors.

The remaining 24% of documents that were characterized by poor image quality, incomplete information, non-standard format or the presence of data unusual for the system were automatically identified by algorithms as requiring additional verification. In such cases, the documents were transferred to a special user interface supported by artificial intelligence, which allowed operators to efficiently fill in the gaps, correct the data or confirm its correctness. This made it possible to maintain the consistency of the entire process without holding it back and to ensure operational continuity.

This project brought the client a number of tangible benefits: shortening the time of document processing, reducing operating costs, reducing the number of accounting errors and increasing the availability of data for reporting and management analysis. In addition, the entire process gained transparency and compliance

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7 Rule classifiers are sets of predefined logical rules and decision conditions that determine how data is processed based on its content—for example, assigning an invoice to the appropriate cost centre based on keywords in the description.

8 Machine learning algorithms learn from historical data and examples, allowing them to identify patterns and adapt the system to changing circumstances.

with internal control requirements, which was an important element in the context of audit and compliance with industry regulations.

The system also used components to automatically match invoice data to the relevant orders and cost centres (three-way matching), which significantly reduced the share of manual work. The processed data was directly sent for approval in workflow systems and archived with full auditability. This means that every operation related to a document—its entry into the system, reading data, approving, changing or deleting—was automatically recorded and stamped with a time stamp and an ID of the user or algorithm that performed it. This type of detailed event log (the so-called audit trail) made it possible to later verify the compliance of processes with the company's internal procedures and facilitated external and internal audits. This ensured full transparency, allowed for the detection of irregularities and built trust in the integrity of financial data processed in the system. The entire process was covered by monitoring the performance and quality of the data, which allowed for continuous improvement of the AI models.

Thanks to the implementation, an advanced level of automation has been achieved—as much as 76% of all financial documents have been processed completely without human intervention. This means that data extraction, validation, matching to orders and posting were fully automatic. The process was carried out based on established business rules and AI models, while maintaining a high level of data precision and consistency.

The business benefits of implementing the solution were multifaceted and went far beyond the obvious cost reduction and reduction in document processing time. The organization noted a significant improvement in compliance with legal regulations and internal corporate regulations, which translated into a reduction in audit risk and better preparation for external audits. Automating document processing has also dramatically reduced accounting errors, increasing trust in financial data across the organization. In addition, the implementation enabled much faster and easier access to financial data—both historical and current—which in turn strengthened the analytical capabilities of the controlling department and improved management reporting. The data processed by the AI system became the foundation for generating dynamic, precise reports, used to monitor budget execution, assess profitability and predict costs.

IBM's case study clearly demonstrates that the use of integrated technology solutions based on artificial intelligence and optical character recognition (OCR) in accounting not only increases operational efficiency, but also enables the construction of scalable, flexible financial systems that become an integral part of the management strategy at the enterprise level.

### 4.3.4. Aceable — OCR in Cost Invoices[9]

Aceable is an innovative education company based in Austin, Texas, specializing in providing online training and licensing courses, primarily for drivers, real estate agents, and insurance professionals. It has been in business since 2012 and is known for using technology to transform traditional learning processes. Its rapid growth and development of educational services on a national scale in the United States has led to an increase in external transactions and the need to process a large number of cost invoices.

The automation process was launched around 2021 when the company's finance department identified operational issues resulting from the manual processing of cost documents. In the model at that time, invoices were first physically scanned or received in PDF form, and then the employees of the accounting department manually transcribed data—such as the name of the supplier, invoice number, date of issue, net and gross amount, tax—into the financial and accounting system. Each document then had to be submitted to the appropriate person for approval, which generated additional delays.

This approach resulted in an average processing time of 2 to 4 business days per invoice, and even longer in the case of illegible documents or documents that do not comply with company policy. The process was also a source of errors, such as mistakes in amounts, incorrect vendor assignment, double posting, or lack of proper approval documentation. What's more, as the business scaled and the number of accounting documents grew, the process became more difficult to control and more taxing for the finance team.

To solve this problem, Aceable implemented an advanced OCR (Optical Character Recognition) system that completely changed the way invoices are processed. After implementation, the process has become almost fully automated and consists of several integrated stages. Paper documents are first digitized using a scanner, while PDF invoices are sent directly to the system. OCR automatically reads and structures the most important information: vendor name, invoice number and date, net and gross amounts, tax values, cost codes, and other metadata required by the financial system.

In the next step, the data is transferred to an integrated Accounts Payable (AP) workflow system, which automatically compares it with existing orders in the ERP system (three-way matching), verifies compliance with the purchasing policy and forwards it to the appropriate people for approval. If the data is consistent, the invoice is approved and submitted for payment and archiving. In case of discrepancies or deficiencies, the system generates exceptions and sends the document for manual review.

9 Based on: Henderson (2025).

The implementation of this technology has dramatically reduced the processing time of a single invoice from 2–4 days to just a dozen or so minutes. Automation made it possible to approve and settle liabilities faster, which had a positive effect on the company's financial liquidity. By eliminating manual data rewriting, the number of errors—such as incorrect amounts, incorrect account assignments or omissions of important information—has also been significantly reduced. This improved the quality of financial data and allowed for more precise cost management.

For the organization, the benefits were multidimensional. In addition to operational savings and better utilization of accounting resources, there has been an increase in transparency, compliance, and auditability of processes. The OCR system integrated with ERP has become the starting point for further automation and development of financial analytics. Importantly, the implementation of this technology has also contributed to the improvement of the company's external image. As a modern and innovative online learning platform, Aceable has proven that it can consistently innovate not only in terms of products, but also in organizational structures.

The use of modern technologies in the area of accounting has increased the trust of customers and business partners, strengthening Aceable's position as a leader in the digital education market. Thus, automation has affected not only operational efficiency, but also revenue growth and brand value. The Aceable case is a great example of how investments in modern accounting technologies can bring benefits beyond cost and operational efficiency.

## 4.4. Analytical Support and Human–Machine Collaboration

### 4.4.1. Mastercard — Fraud Detection with GenAI[10]

Mastercard, a global company headquartered in Purchase, New York, operates in more than 210 countries and territories, handling billions of payment transactions annually and employing more than 30,000 employees worldwide. As one of the market leaders in financial services and payment technologies, Mastercard consistently invests in digital innovations, including in the area of transaction security. In 2024, the company implemented an innovative fraud detection system based on generative artificial intelligence (GenAI). The goal of this implementation was to significantly increase the effectiveness of identifying unauthorized or suspicious transactions and to dramatically reduce the number of false positives, which in the past often led to unnecessary blocking of legitimate payments.

10 Based on: Mastercard (2024).

The challenge Mastercard faced before implementing GenAI was the limitations of its analytics solutions. These schemes have not kept pace with the changing methods of financial fraud. Criminals used increasingly advanced patterns that were difficult to detect by classic algorithms based on static decision-making rules. These types of traditional rule systems relied on a set of predetermined conditions (e.g., "if the transaction amount exceeds $10,000, mark as suspicious") and were unable to learn from new cases or adapt to context. As a result, their effectiveness in detecting new forms of fraud was limited.

Their lack of adaptability meant that these systems often generated false positives, blocking correct, legitimate transactions. This resulted not only in image and customer trust losses, but also in the need to involve employees in manual review and correction of a large number of requests. Worse, some sophisticated fraud schemes may have escaped the system's attention because they did not fit into a pre-established decision-making framework. Thus, Mastercard needed a more flexible and intelligent solution that could analyse data in a contextual way, identify patterns of user behaviour, and learn in real time.

In response to these needs, a modern system based on generative artificial intelligence (GenAI) was implemented in 2024. This tool allowed for the analysis of billions of transactions in real time, the identification of non-obvious patterns of behaviour, as well as the generation of accurate risk predictions. By combining historical data with the current transaction context, it has become possible not only to recognize known fraud patterns, but also to detect new, previously unobserved anomalies. The system automatically made decisions on how to flag or block suspicious transactions, reducing the need for human intervention. This state-of-the-art solution has not only increased operational security but also streamlined processes and improved customer experience.

According to data published by Mastercard, the implementation of this tool has doubled the fraud detection rate compared to previous analytical solutions. At the same time, the number of false positives, which led to unnecessary blocking of legitimate payments, decreased by 200%, which significantly improved the customer experience and reduced the number of complaints.

The implementation of GenAI not only increased Mastercard's transaction security and operational efficiency, but also significantly strengthened the company's image as an innovation leader in the financial sector. This example proves that the use of advanced analytics based on artificial intelligence can effectively support supervision and anti-fraud systems on a global scale, which is also applicable in accounting, especially in the areas of risk analysis and compliance.

### 4.4.2. Deloitte — DARTbot for Auditors[11]

Deloitte, one of the most recognizable companies in the global professional services sector, which is part of the so-called "Big Four", plays a key role in the area of audit, consulting and taxation. With hundreds of thousands of professionals in more than 150 countries, the organization serves companies with local, international and global reach. A financial audit—which is a pillar of its activity—is not only a source of revenue, but above all the foundation of credibility, reputation and trust from customers, investors and regulatory authorities. As a result, Deloitte is constantly looking for ways to improve the quality, efficiency and reliability of its inspection processes.

In 2023, the company began implementing an innovative tool called DARTbot (Deloitte Accounting Research Tool), based on artificial intelligence, which aims to support 18 thousand auditors in the United States. This initiative is part of a broad digital transformation agenda that aims to move from a traditional organization model to an organization 4.0 model that is data-driven, automated, flexible, and learning. DARTbot is an intelligent chatbot that uses generative language models (GenAI) and natural language processing (NLP) algorithms. This allows auditors to access information quickly and intuitively about US Accounting Standards (US GAAP), audit and reporting regulations, and professional practices. It is enough to ask a question in natural language to get an answer supported by the current interpretation of the regulations—eliminating the need to search through extensive and often scattered collections of knowledge. A chatbot acts as an intelligent advisor that instantly provides accurate answers, thus supporting data-driven decision-making.

DARTbot allows you to standardize the interpretation of regulations across the organization, which significantly reduces the risk of non-compliance and increases the consistency of the application of standards. By implementing this tool, Deloitte not only accelerated analytical processes, but also increased information security and the quality of audit documentation. In addition, this tool is constantly developing—it is updated with new regulations, interpretations and suggestions from users, which makes it flexible and adapted to the changing regulatory environment.

It is worth noting that the implementation of DARTbot is not only an operational improvement—it is a breakthrough in the way the company operates. Deloitte, by reaching for GenAI solutions, initiates a real revolution in the field of organizational culture. Chatbot not only increases the independence of auditors, but also promotes a culture of cooperation, knowledge exchange and continuous learning. Just as the fourth industrial revolution (Industry 4.0), described in the previous chapters of the monograph, led to a profound transformation of the production model, accelerating automation, integration of IT systems and introducing a new logic of business functioning, Deloitte's digital revolution transforms

11 Based on: Noto (2023).

the foundations of professional services provision. It is not only a technical improvement or a change of tools—it is a redefinition of the role of humans in the organization, the relationship between experts and technology, and the way in which knowledge is created and distributed. A new quality in the world of auditing means moving away from static, reactive processes in favour of dynamic, predictive, and data-driven processes, in which artificial intelligence not only supports, but co-creates the substantive value of consulting services. In this approach, Deloitte not only uses digital tools, but also becomes a model of an organization that actively shapes a new paradigm of operation in the information age.

With DARTbot, auditors can focus on tasks that require critical thinking, risk analysis, and strategic consulting—instead of wasting time searching for information. Not only is the way of working but also the expectations of auditors' competences are changing digital, analytical and communication skills are becoming increasingly important. The chatbot has therefore become a symbol of the transition to a new paradigm of organizational functioning—a paradigm in which technology does not replace humans but enhances their capabilities.

To sum up, the implementation of DARTbot by Deloitte is an example of the modern use of artificial intelligence in accounting and auditing. This proves that digitalization can not only increase efficiency, but also reformulate the way we work, the organizational structure, and the relationship between people and technology. DARTbot is not just a chatbot—it is a manifesto of digital transformation in professional consulting services.

### 4.4.3. Bank of America — Chatbot Erica[12]

Bank of America is one of the largest and most influential commercial banks in the world. Headquartered in Charlotte, North Carolina, USA, the institution serves more than 66 million individual and corporate clients worldwide with approximately 200,000 employees. The bank operates in more than 35 countries and has an impressive portfolio of financial services spanning retail, investment, corporate and wealth management banking. Thanks to its scale and importance, Bank of America plays a key role in the global economy, while being one of the most recognizable financial brands in the global market.

Against this background, the launch of Erika in 2018—a virtual assistant based on artificial intelligence—was an important and groundbreaking step in the institution's digitalization strategy. This project was not just the implementation of new technology, but an integral part of a broader digital transformation aimed at increasing the level of personalization and efficiency of the customer service while reducing operational costs. Erica, as an advanced tool using natural language processing (NLP) and machine learning (ML), is designed not only to respond to

12 Based on: Bank of America (2024).

basic customer inquiries, but also to provide valuable analysis, proactive financial recommendations, and support in planning and managing personal budgets.

This project stands out for its scale—Erica has processed over 2 billion customer interactions, making it one of the most advanced and widely used digital assistants in the global financial sector. Moreover, Erika's development was based on continuous improvement and learning from interactions with customers, which allowed her to better understand their needs and adapt to individual user profiles. The importance of this solution goes far beyond the operational aspect—Erica has become a strategic tool supporting the building of a modern image of Bank of America as an institution of the future, ready for the challenges of the digital era and able to shape new standards of customer experience.

Erica not only responds to inquiries about account balance or transaction history, but also advises on budget planning, reminds about upcoming payments, analyses spending patterns, monitors a client's FICO score,[13] and enables clients to make more informed financial decisions by providing personalized recommendations. A key aspect of its operation is real-time integration with banking systems, which enables immediate access to up-to-date data and dynamic response to user needs in an automated and proactive manner.

From the customers' perspective, this means a significant improvement in the comfort of using banking services—elimination of the need to contact the hotline in many cases, faster responses, greater control over one's own finances and improved budget planning. For the bank itself, the benefits are operational (reduction of customer service costs), strategic (increase in customer loyalty and satisfaction) and accounting.

Erica, being part of the bank's financial information system, plays the role of a modern interface for accessing accounting data of individual customers—it processes queries, aggregates data and enables its presentation in a way that is understandable to the user. Thanks to this, it fits into the idea of digital accounting, in which financial data is not only passively stored, but actively used to make decisions. In this approach, Erica becomes an element of the management accounting system—it supports end users in analysing their financial situation, and at the same time provides the bank with valuable data that can be used to model risks, predict customer behaviour and optimize financial product offers. As a result, Erica is not only an advanced customer support tool, but also an integral component of a modern financial institution's accounting system in the digital age.

13 The FICO® Score, developed by Fair Isaac Corporation, is a consumer credit risk scoring indicator commonly used by financial institutions in their lending, interest rate setting and loan portfolio management processes. The rating model is based on credit history data, such as on-time payments, debt levels, length of credit history, newly opened accounts, and types of loans held. According to a report by the U.S. Federal Reserve, the FICO Score plays a key role in the credit decision-making process, having a direct impact on the availability and cost of credit for consumers. For more on this topic, see [in:] Board of Governors of the Federal Reserve System (2007, p. 23).

Through advanced learning from historical data, Erica has become more effective at diagnosing problems and proposing solutions tailored to individual customer profiles over time. In practice, as many as 98% of interactions are successful without the need for the bank's employee, which translates not only into a reduction in operating costs, but also into a significant improvement in customer experience and shorter waiting times for service.

From Bank of America's point of view, Erica is a strategic element of digital transformation—she fits into the concept of organization 4.0, where automation, data analysis and personalization of financial services are becoming key competitive advantages. The implementation of this system has not only improved the bank's internal operations, but also significantly increased its prestige as an innovative, modern and customer-oriented institution.

Erica is an example of an AI application that not only optimizes accounting and operational processes but also plays a vital role in building customer relationships and strengthening the brand of a financial institution in the digital age. Its success sets new standards for the entire banking sector, proving that the implementation of AI can bring measurable benefits from both the point of view of efficiency and customer satisfaction.

# Key Findings and Summary

The integration of artificial intelligence (AI), and especially generative models in the field of accounting, appears to be one of the most important achievements of modern times. This monograph traces the historical, technological, and practical context of this phenomenon, showing a rich picture of opportunities and challenges. To summarize the main takeaways: AI is transforming accounting from both a technological and human perspective. On the one hand, AI technologies automate routine tasks, enable real-time data analysis, and unveil new predictive capabilities; On the other hand, they force a redefinition of the role of the accountant, raise important ethical questions, and require new competences and organizational practices. In the following pages, we have shown that the impact of AI on accounting is profound, albeit subtle,—it offers unprecedented opportunities while requiring careful risk management.

The aim of the monograph was to examine the impact of artificial intelligence and generative models on accounting, focusing on the assessment of opportunities and threats associated with their application in practice. To achieve this goal, we have asked five research questions. The content we presented allowed us to answer them.

The first question was: "What is the nature of artificial intelligence (especially generative AI) and how has it evolved, especially in the context of accounting?" We have shown that AI is data-driven learning that performs tasks that previously required human intelligence, such as language understanding, reasoning, and decision-making. The evolution of AI has included breakthrough moments, from early chatbots (ELIZA, PARRY) and neural networks, through deep learning and LLMs (GPT-3, GPT-4, GPT-5). For accounting, the development of NLP and language models that enable the creation of financial reports, narrative analysis and intelligent assistance in decision-making processes has been crucial.

The next question was how technological advances have historically affected accounting, and what does this mean in the context of AI development? The historical context we described in chapter two has shown that accounting has always used technology—from abacuses and punch cards to computers to ERP systems. Each wave of technology has increased efficiency and changed the work of accountants. AI is therefore a natural extension of this evolution, integrating into existing systems and bringing new possibilities for prediction and analysis. However, as history shows and what we want to emphasize very strongly, the implementation of AI tools in accounting also requires, or perhaps even primarily, the adaptation of ethical standards and employee education.

What are the main contemporary applications and processes in which AI is used in accounting and how do they change this function—this is the third research question we have posed. As we presented primarily in chapter three, AI currently automates transactional processes (e.g. invoice processing), supports financial and narrative reporting, detects fraud, supports controlling and forecasting. The accounting function is shifting from data collection and verification to interpretation, consulting, and strategic collaboration. AI allows accountants to focus on added value, while the human is still responsible for oversight, context, and ethical judgment.

The fourth research question was how leading organizations implement AI in accounting and what conclusions can be drawn from these implementations? The examples of Unilever, KPMG, EY, Uber, IBM, and others described in chapter four show that AI increases the efficiency, quality, and speed of accounting processes, but also requires investment in training, organizational change, and data management. The key conclusions from this part of the monograph are that implementations must be strategic, include change management and preparation of people, and ensure compliance with ethical and legal standards. Organizations that treated AI as part of the transformation, and not just as an IT installation, achieved the best results.

The last question focused on looking for the main opportunities and challenges that AI and generative models pose to accounting and how they can be managed. We have shown that AI offers accounting automation, better decisions through data analysis, enhanced fraud detection, and improved financial communication. However, there is no shortage of challenges. These include bias and lack of transparency in models, data quality issues, privacy issues, impact on jobs and competences, and regulatory gaps. Managing this requires simultaneous actions, such as investing in people and their skills, building trust in AI through transparency, ensuring data quality, developing ethical standards, and engaging in regulation. It is crucial to maintain a balance between innovation and responsibility.

The results of the research conducted in this monograph have significant practical implications for various stakeholders in the field of accounting—including, above all, accountants, accounting departments in corporations, educators, software developers and regulators. Analysing both the literature on the subject and adding our own practical experience, we have distinguished the eight most important areas presented further in the form of a table.

**Table 2.** Practical implications for various stakeholders in the field of accounting

| No. | Implication | Description |
|---|---|---|
| 1 | Redefining the role of accountants and the required competencies | AI is changing the role of accountants from "guardians of the books" to analysts and advisors. With AI taking over many of the mechanical tasks, accountants will increasingly oversee AI systems, interpret their results, and provide insightful analysis. In practice, this means the need to expand the competences of accountants with knowledge in the field of digital technologies, statistics, and data interpretation. Organizations should invest in training and development programs for their accounting teams: workshops on how to use AI tools in finance, courses in data analytics and basic programming (e.g., Python) can help build "hybrid accountant" competencies, combining accounting knowledge with technological proficiency. In professions related to accounting, new ones are appearing, which did not occur before. These are, for example, "AI auditor", "financial data analyst" or "digital transformation consultant". This indicates a diversification of career paths in accounting and a redefinition of the role of accountants in the digital age. |
| 2 | Process transformation and change management | AI integration requires organizations to rethink and redesign processes, as well as skilful change management. Companies should adapt their internal procedures to the new reality, ensuring that where processes are automated, human-in-the-loop supervision still remains over them. It is crucial to communicate that the implementation of AI is aimed at strengthening the role of the accountant, not marginalizing it. Involving employees already at the stage of selection and configuration of AI systems increases acceptance of change. Companies can appoint "change leaders" in finance teams—people who are enthusiastic about technology and promote its benefits to colleagues. Pilot projects are also a good practice to test solutions on a small scale and build trust before full implementation. |
| 3 | Data and data quality management | Since the effectiveness of AI is directly related to data quality, organizations should invest in robust data management practices. Before implementing AI, it is worth conducting a data audit: assess its consistency, completeness, and cleanliness. It also requires the integration of data from different systems (ERP, banking, sales) and the unification of formats and codes. Practical actions include, among others, introducing quality control at the data entry stage, implementing procedures for ongoing validation, and establishing principles of data ethics and data protection. Companies should also make sure that their data privacy and security policies meet the requirements of regulations such as the GDPR. |

**Tab. 2** (cont.)

| No. | Implication | Description |
|---|---|---|
| 4 | Quality control and validation of AI results | Organizations should develop new forms of quality control of AI-enabled results. Just as traditional accounting processes require verification and reconciliation, AI systems should also be regularly tested and calibrated. At the beginning, it is worth conducting parallel processes—compare AI results with those obtained traditionally, and in case of discrepancies, fine-tune the models. It is a good practice to maintain a "queue of exceptions"—cases that AI considers questionable and that are verified by a human. Companies should also document how algorithms are tested and approved—similar to how internal control is documented. |
| 5 | Ethical framework and corporate governance | The implementation of AI in accounting requires the development of appropriate ethical standards and corporate governance frameworks. Organizations should formulate rules for the use of AI, e.g.: "AI results must be validated by a human in the case of decisions of significant importance", "employees should understand the principle of operation of the AI tools used to the extent that the results can be justified". It is also worth including AI risk oversight in the responsibilities of audit committees or appointing dedicated data ethics and AI teams. |
| 6 | Implications for Software Vendors | Solution providers should design AI tools with transparency and user-friendliness in mind—e.g. by showing the degree of confidence score or explaining the logic of the decision ("qualified as a travel expense because it is consistent with previous records and the name of the contractor"). Systems that allow algorithms to be adapted to the data of a specific organization and co-created with accountants increase the chances of their success. |
| 7 | New services and advisory opportunities | Accounting firms can use AI to develop new services, such as consulting on the implementation of AI in finance, auditing algorithms or adapting internal controls to the new reality. It is worth building consulting competences in this area and creating specialized teams or laboratories of AI tools. |
| 8 | Lessons for regulators and educators | Educational institutions should update their study and certification curricula to include elements of data analytics and AI fundamentals. Regulators should consider introducing new guidelines and standards—e.g. on auditing algorithms or disclosing the role of AI in accounting processes in financial statements. |

**Source:** own study.

In summary, the practical implications boil down to readiness and proactive adaptation. Organizations that consciously integrate AI—by investing in people, processes, data, and ethics—can expect significant benefits: lower costs, better decisions, higher quality of service. Those that neglect these aspects risk inefficiencies, mistakes, and reputational damage. This is a breakthrough moment—it depends on our decisions whether AI will become an integral, valuable accounting tool or a source of chaos.

Although the monograph covered a wide spectrum of issues related to AI and generative models in accounting, we also identified a number of areas requiring further research, which is presented further in several points.

- Building trust and explainability of AI in accounting—Research should develop simple and understandable explanations of AI decisions to increase user trust.
- The impact of AI on the quality of financial information—How AI improves the quality and speed of financial information should be measured.
- Ethical framework and accountability—Research should define ethical principles and the division of responsibility between humans and AI systems.
- Integration of generative models into accounting systems—It is worth exploring how to safely and effectively implement an LLM in the daily work of accountants.
- AI vs. ESG reporting and regulation—You need to see how AI can support ESG reporting and compliance.
- Human-AI interaction and decision-making—Research should clarify when and why accountants trust or reject AI recommendations.
- Macroeconomic and sectoral effects—The impact of AI on companies' competitiveness, market structure and sector transparency should be assessed.

When analyzing the importance of AI in accounting, it is worth noting both the continuity and the disruptive nature of this phenomenon. Historically, accounting has always used the best tools available—from clay tablets in Mesopotamia, to abacuses and calculating machines, to spreadsheets. AI is the next step in this evolution, but also a qualitative leap—for the first time, a tool shows signs of "intelligence", learning, reasoning and making decisions similar to a human. AI fulfills a dream that has been present in accounting for centuries: freeing people from monotonous tasks and creating space for more creative, analytical work. Just as in the nineteenth century, the mechanization of accounting made it possible to handle huge volumes of transactions, today AI allows accountants to focus on strategy and consulting.

However, AI is also changing the way we understand professional judgment and accountability. The history of accounting shows that every new technology has raised fears—of losing jobs, of reducing quality, of being "dehumanized"—but it has usually turned out to strengthen the accounting profession. Today's concerns about AI are similar, but there is also the question of whether AI can really replace ethical, critical human judgment. Modern accounting is increasingly becoming continuous and proactive thanks to AI. It provides real-time insights and predictions to support management in a rapidly changing business environment. AI can help to improve market transparency, increase trust in reporting and better manage resources.

AI is part of the historical mission of accounting—to provide reliable and understandable economic information that enables stakeholders to make informed decisions. As previous technological breakthroughs have shown, the most important thing is not to lose the values of ethical and critical thinking—that AI serves accountants as a tool, not dominates them.

To sum up, AI in accounting is not only a technology, but also another chapter in the history of adapting the profession to the needs of its time. We are entering a new era—"accounting 4.0"—the shape of which depends on the decisions made today by accountants, educators, regulators and companies. If AI is used responsibly, the accounting profession will become even more relevant and valuable, combining technological proficiency with human wisdom. The challenges and opportunities of artificial intelligence and generative models in accounting are two sides of the same coin. Moving between them requires combining the lessons of history with bold innovation in the present. The analyses and reflections in this monograph suggest that through the prudent implementation of AI—with respect for ethics, education, and human judgment accounting can enter a new era of trust, transparency and strategic value. This conclusion is not the end, but the stopping point on a journey that integrates what we have learned and points to the directions we have yet to explore as we shape the future of accounting in the age of AI.

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*AI in Accounting. What the past and present mean for the future* is an interdisciplinary work that shows how artificial intelligence and generative models are transforming the world of accounting. The authors combine the historical background of technology with practical case studies from global companies. The book is particularly important **for accountants**, who face the challenges of automation and redefining their role in the digital age. As reviewer Prof. Stanisław Hońko noted, they are the very audience who should turn to this book.

At the same time, it serves as a **practical guide to AI tools**. The authors organize and systematize a wide range of technologies – from OCR and RPA, through chatbots and popular solutions such as ChatGPT or Microsoft Copilot, to large language models including GPT, Gemini, Perplexity, and DeepSeek. Such a broad spectrum can easily overwhelm, but this book provides a clear and structured introduction. Reviewer Prof. Karol Klimczak highlighted its logical structure and comprehensive scope, which make the work valuable for both scholars and practitioners.

For that reason, *AI in Accounting* is not only essential reading for accountants, controllers, and auditors, but also an accessible guide for anyone beginning their journey with AI – whether in finance, education, business, the arts, or any other field where artificial intelligence can become a source of support and inspiration.

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The book is also available as an e-book

ISBN 978-83-8331-879-0
9 788383 318790