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The impact of artificial intelligence on the economy and business with special attention to the labor market

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Doctoral dissertation

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1 PREFACE OF THE THESIS

1.1 Introduction

Today, artificial intelligence (AI) has become a catchphrase, appearing not only in scientific journals and business consultancy reports but also frequently featured in tabloid media and everyday conversations.

The real meaning and capabilities of artificial intelligence can vary from case to case. Popular literature often portrays artificial intelligence as a superior machine being, just as smart, if not even smarter, than humans, and as posing great threats to humanity, or as bringing the long-awaited AI utopia, where we live in peace, wealth, and comfort thanks to superior technology.

Scientific literature rather focuses on the current reality, capabilities, and short- and long-term development goals of artificial intelligence, often describing the technology as software with advanced statistical capabilities and the potential to deliver breakthroughs across fields such as image or voice recognition, customer behavior prediction, and others.

When we browse tabloid newspapers, we often encounter AI-generated images used as visual aids, read about the latest scams involving deepfake technology or AI-powered voice impersonations, and find commentary from politicians, artists, and, occasionally, researchers discussing how artificial intelligence is transforming—and will continue to transform—our society.

We are living in the age of the AI revolution. At the beginning of my doctoral research in 2019, the field witnessed the introduction of GPT-1, an early natural language processing model trained on several million data points and designed to operate as an advanced chatbot. In contrast, contemporary developments have produced GPT-5, which has been trained on databases comprising hundreds of billions of data points. This latest iteration demonstrates remarkable capabilities, such as composing poetry and providing simple explanations of complex concepts, such as Einstein's theory of relativity.

The AI landscape has, without doubt, widened: search engines are no longer showing the most relevant webpage, but rather AI-generated answers corresponding to our search query. More than 70% of the younger generation actively use and trust AI tools in their everyday life, and the selection of AI applications available is getting wider and cheaper by the year (Nestor et al., 2025; OECD, 2025).

Image 1. *The well-known French comedian Nicolas Canteloup impersonating former French president Nicolas Sarkozy on live TV (TF1) in 2018 (left) and in 2022 (right), using a deep fake AI algorithm. The author does not own the rights to the images—source: Google and Youtube.*

Democratized AI is not only changing our private lives, but also the economy. Global AI adoption surveys indicate that AI use across all sectors of the economy is increasing rapidly year by year globally. (Chui et al., 2021; *IBM Global AI Adoption Index 2022*, 2022; McKendrick, 2021; Nestor et al., 2025; OECD, 2025).

Almost 90% of the companies now make some use of generative artificial intelligence solutions, such as ChatGPT (Singla et al., 2025). OECD (OECD et al., 2025) and Eurostat (Eurostat, 2025) data show that AI adoption is rising quickly, especially in larger companies. SMEs lag due to unclear ROI, limited AI talent, and legal or data privacy issues. Still, they are starting to invest in the technology as well: about 15% of SMEs and 50% of big companies have implemented at least one AI solution in the past few years.

Given the rapid pace of adoption, before we realize it, we will be spending a significant amount of our time at work co-working with AI agents. The question is, are we ready? Is an average person, with so called "computer skills on a user level", capable of interacting, working and producing results with AI? Can we get used to algorithms influencing our daily work, what is more, performing tasks better and faster than we can?

Can AI replace humans in the long term and achieve complete automation, or will it be a tool to augment human skills, leading to the complete transformation of the job market?

The purpose of this dissertation is to explore what the future of work will hold: the triumph of human or machine intelligence, and how can/will we adapt to the new digital-intelligent work environment.

1.2 Chosen research topic and its relevance

The dissertation's topic is „The impact of artificial intelligence on the economy and business with special attention to the labor market". This research aims to explore the effect of artificial intelligence on the labor market at the macro and micro levels.

Artificial intelligence, which is a technology that can potentially behave and think as a human does (Russel & Norvig, 2005), may be able to lower the value of human labor to a point where all types of tasks are performed by machines instead of living human beings. Work is a fundamental aspect of human existence, serving not only as the primary means by which individuals sustain themselves but also as a core element in shaping personal identity and societal values. As technological advancements continue to accelerate, reaching unprecedented levels, both human societies and economies are poised for profound transformation.

Currently, there is no evidence that any internal or external force is aiming to stop or slow down the development of AI. While there are attempts at regulating it, there is definitely no intention to stop the technology from reaching its full potential (some examples of regulatory frameworks: AI Act | Shaping Europe's Digital Future, 2026; "Ensuring a National Policy Framework for Artificial Intelligence – The White House," 2025), thereby change is inevitable; only its scale and speed remain uncertain.

According to researchers, artificial intelligence may gradually reshape the labor market and, by extension, society and the economy. Not the first technology to do so, but the first one in which the changes are occurring much more swiftly than those brought about by previous innovations. This accelerated transformation leaves less time for individuals and communities to adapt, making it more challenging to implement necessary measures and prepare society for new ways of working and living.

The objective of this dissertation is to examine both the scientific literature and public online discourse to understand the perceived threats and opportunities posed by artificial intelligence in the labor market, while also mapping effective technology-adaptation strategies.

Table 1. Research questions of the thesis

	Research questions
R1.	How do scientific and online public discourses reflect on perceptions of artificial intelligence–induced labor market transformation?
R2.	What risks does AI pose to the labor market, and what strategies can address them?

The relevance and importance of the dissertation can be described in two dimensions.

The first dimension is that of society. Researchers have found that technological progress impacts wages and income inequality (Kharlamova et al., 2018), the environment (Pham et al., 2020), human well-being (Kahn et al., 2009), and many other aspects of human society, including the labor market (Marchant et al., 2014).

AI technologies can risk job and societal displacement (Choi & Leigh, 2024; Gruetzemacher et al., 2020; Khogali & Mekid, 2023) and can easily dehumanize societies (H. young Kim & McGill, 2025).

The second dimension is that of the human individuals. There is a large amount of research available on how work has a significant impact on an individual's health (Klitzman et al., 1990), on their relationships outside work, such as with family (Lewis et al., 2007) and even on self-esteem or parenting style (Grimm-Thomas & Perry-Jenkins, 1994).

Losing a job or simply feeling inferior at work is generally considered a highly negative life event that impacts both the individual and their family. The recently unemployed are losing a community (the former workplace and coworkers), motivation, and even a small part of their identity (Crayne, 2020), and have to prove their individual value once again when seeking new employment.

If the AI revolution eliminates more jobs than it creates, widespread unemployment could result in noticeable negative effects on individuals' prospects, health, well-being, and relationships, ultimately impacting society as a whole.

Accordingly, it is essential to assess the potential impacts of AI on labor market dynamics to ensure the well-being of individuals and the whole society.

1.3 Theoretical Background

1.3.1 Definition of artificial intelligence

Artificial intelligence has several definitions, depending on the discipline that defines it. Different definitions exist in natural and computer science (Poole David & Mackworth Alan, 2010), social science (for example (Jarrahi, 2018)), and even in medical science (Jiang et al., 2017).

Artificial intelligence is best defined as a broad term encompassing a wide range of technologies, applications, and methodologies.

One common characteristic in the diversity of definitions is that artificial intelligence always attempts to imitate human intelligence: AI can learn (as in machine learning), understand (e.g., human speech), and even sense (e.g., “see” with a camera or motion sensors) (Makarius et al., 2020).

It is also common for AI definitions to distinguish between narrow and general artificial intelligence. Narrow AI operates in a closed environment, often calibrated to perform a specific task (generative AI is a type of narrow AI).

General AI has rather human-like capabilities and can perform various tasks (Babu & Banana, 2024; Jungherr, 2023).

While AI agents can seem like general artificial intelligence, they merely represent a stepping stone in that direction (Morris et al., 2023). They are rather narrow AIs that work collaboratively.

Table 2. *List of applications and technologies that can be defined as AI*

What type of technology is artificial intelligence?	
Hardware or software	(AI HLEG, 2019; Sántáné Tóth et al., 2007)
Computer	(Jackson & Al-Kohafi, 2011)
System	(AI HLEG, 2019; Hutter, 2004)
Program	(Barr & Feigenbaum, 2014)
Machine	(Negnevitsky, 2005; Nilsson, 2010)
Automatic intelligent behavior	(Luger, 2005)
Intelligent agent	(Poole David & Mackworth Alan, 2010)
Algorithm	(Acemoglu & Restrepo, 2018a)
Network of connected devices	(Bond & Gasser, 1988)

In general, the artificial intelligence definition is a mix of definitions of different disciplines, which arbitrarily exclude or include different technologies, applications, and approaches, as of today, there is no commonly accepted universal definition (P. Wang, 2019).

From the economist's perspective, artificial intelligence can be just as much a self-driving car as any industrial robot or (semi-)intelligent software (Wisskirchen et al., 2017), which has an impact on the economy or business practice.

Artificial intelligence can also be any technology that shows intelligent behavior (Poole et al., 1998), which can include a machine that is (1) modeling its environment, (2) running diagnostics on it, (3) executing any given task to fulfill its purpose, and (4) can learn from past mistakes.

As artificial intelligence research is closely related to human intelligence research, some prefer to derive the definition from how we define human or natural intelligence.

Table 3. Connecting the definitions of artificial and natural intelligence Source : (Boncz & Szabó, 2022, p. 70)

(Human) intelligence definition	Equivalent AI definition
Logical, mathematical knowledge, all people possesses it (Poole et al., 1998), it can be measured, for example, with IQ tests (Boring, 1923)	Task-based AI, with the purpose of solving these tests (Jackson & Al-Kohafi, 2011)
Information (Gill et al., 2008)	Inherent information system
Preparation and execution of decisions (Warner, 2008a), intelligent behavior (Poole et al., 1998a), a characteristic to be labeled intelligent (Barczi & Országh, 1966)	Inherent decision support system, which can be able to imitate human intelligence (Luger, 2005)
Intelligence can only be witnessed as a common act, and common knowledge (Gill et al., 2008)	AI is an ecosystem of connected devices (Bond & Gasser, 1988)

Social sciences usually define artificial as that which is not false or fake, but rather human-made (machine), and artificial intelligence is therefore human-made intelligence. However, the definition of (human) intelligence is not yet unified.

The earliest definition of intelligence is that it is something every human being possesses (Boring, 1923), an ability we can measure on different scales, such as with an IQ test. If we only take this definition into account, though, almost every machine we own today can be considered intelligent, since IQ tests are usually based on logical tasks that machines can easily solve.

More recent definitions believe that intelligence is, in a very broad term, information (Gill et al., 2008), or the ability to gain information in order to make and execute different decisions (Warner, 2008). Intelligence can also be the ability to notice connections between phenomena, or to sanely judge the reality around (Barczi & Országh, 1966).

Once again, if we only take into account these definitions, most of our technologies can be deemed intelligent, as they are able to recognize patterns, they have sensors to create a true image of the reality around them, and we already own developed decision making (or supporting) systems that are giving us insights to make decisions. The fact that these technologies are not yet executing those decisions is a pure human choice, not a failure of the technology's capabilities.

The definition of psychology as a discipline is that intelligence is not only a lexical, logical, or mathematical knowledge, but it also manifests in sentiments, emotions, behavior, and, according to some, it cannot even be interpreted on an individual level, only on a community level (Gill et al., 2008).

In this dissertation, I consider artificial intelligence any application, technology, physical or software based machine, that is considered artificial intelligence by the given source, due to the ever changing and competing definitions. During my literature review, if the authors referred to the subject of their research as AI, I accepted it as such. I applied similar logic to the analysis of online forums.

It was especially important because definitions vary across disciplines, and at different user levels, we could not limit our research to a single common AI definition, especially as several significant changes occurred in the AI landscape during the research period, which shaped definitions and perceptions of AI.

1.3.2 The short story of technological progress and the labor market dynamics

To assess AI's effect on work, we must first look at how past technologies influenced the labor market in the past centuries.

Technological progress influences labor market dynamics. In scientific literature, changes in employment trends caused by technology are often called technology shocks. These shocks can lead to lasting improvements in human productivity, although not necessarily in all sectors of the economy: these are known as asymmetrical technology shocks (Bertinelli et al., 2022; Frankel & Romer, 1999). Technology shocks are making certain skills more valuable, others obsolete, and creating new workplaces while destroying others.

Technologies that influence the labor market can be categorized into labor-displacing and labor-restraining technologies. Labor displacing technologies usually directly influence employment patterns, possibly causing unemployment, while labor restraining technologies are increasing productivity and, in some cases, increasing wages and job stability, assuming that the workforce can adapt to these new technologies (Fossen & Sorgner, 2022). A typical labor displacing technology is an automated manufacturing line, where human intervention is restricted to a minimum. A labor restraining technology can be the invention of the personal computer. As workplaces and the economy adapted to their use, the need for human resources, e.g., in the IT sector, increased sharply.

In the early stages of technological advancement, labor-market disruptions—due to technological shocks—were primarily driven by the use of animals as "living machines" for activities such as transportation and the processing of raw materials. Over time, however, the transformative impact shifted from animal labor to mechanical devices, robots, and computers, which now play a central role in reshaping the labor market.

Horses were used in all aspects of life for several hundred years of human history. They were essential partners of humans in war, transportation, everyday manual work, and in leisure activities. When the first engines were invented during the first industrial revolution (aka a new technology shock), horses lost their privileged status. Nowadays, barely any modern households own horses. Their role in human societies is now reduced to racing, leisure activities, and occasional labor. In France, for example, the total horse population since the 19th century fell back to the third (Rzekęć et al., 2020).

Scientific literature often refers to horses as the first victims of technological unemployment. However, technological changes in the labor market impacted human labor just as much.

During the Middle Ages, guilds were responsible for the production of meticulously crafted goods, employing skilled artisans to ensure high quality and craftsmanship. Becoming a guild member and learning the selected guild’s profession was considered an honor and took several years of study. Guilds employed only a handful of carefully selected people.

As part of the shift in industrial practices and technological progress, guilds were replaced by manufacturers, which employed more people who, in turn, needed fewer skills and education, since guild members were specialized in only one task within the entire manufacturing process. Consequently, there were two major changes happening after the technological shock: unskilled workers gained more place on the labor market compared to skilled workers (so called skill biased technological change), and the product that needed a handful of people to produce was produced by dozens, leading to the expansion of the labor market (Frey & Osborne, 2017).

Following the great discoveries, European countries realized the untouched potential of newly discovered export markets across the oceans. Demand was growing, and companies were struggling to fulfill it. Entrepreneurs looked for solutions to increase productivity.

In 1770, James Hargreaves patented the „Spinning Jenny", which was capable of „spinning, drawing, and twisting cotton" (Nuvolari et al., 2021, p. 9), more efficiently than humans, and the first industrial revolution has started. This moment represents a historic turning point, ushering in an era where machines increasingly took over tasks in the workplace and permanently transformed the labor market.

Getting used to soulless machines was not easy for some. In Great Britain, the infamous "Luddites" movement is one of the most commonly known examples of human resistance to machines and automation. The members of this group often engaged in machine destroying activities (Allen, 2017). Technophobia, today sometimes called digital anxiety, remains present among the population to this day (Khasawneh, 2018).

Early machines could not perform intellectual tasks, but significantly reduced or eliminated manual labor. This shift allowed workers to pursue higher value-added intellectual roles in the 19th and 20th centuries (Fadel et al., 2015), leading to the distinction between blue-collar (manual) and white-collar (intellectual) work.

The labor market expanded continuously, even as women entered the workforce in large numbers in the 20th century. With more households earning dual incomes and women having less time for housework, demand and disposable capital for household technologies increased, leading to the creation of new industries and jobs (Bose et al., 2022).

While the Great Depression cut back employment overall until around the 1980s, technological progress created more jobs than it destroyed until the first digital revolution. Possible job loss displacement was compensated by new types of jobs, the growing service sector, and newly established industries (Allen, 2017). Between 1980 and 2007, half of the employment growth was associated to the creation of new jobs. The labor market turned from being heavily driven by the agricultural industry in the 18-19th century to being very diverse, decreasing the proportion of the workforce employed in agriculture from 90% to around 2% in around a century (Segal, 2018), without causing significant technological unemployment.

Technology induced labor market trends started to change with the arrival of information and communication technologies (ICT), such as the personal computer.

Digitalization changed the skillsets required on the labor market (Chinoracký & Čorejová, 2019), and increased jobs' complexity. The value of more educated, high-skilled workers started to increase, and wage inequality began to grow (Atalay et al., 2018a; Mincer, 1989).

New digital technologies have both labor-restraining and labor-displacing effects, unlike simple mechanical machines, which were mostly labor-displacing. The reason behind this is that modern technologies can now also automate or perform intellectual work (Fossen & Sorgner, 2022). Additionally, digitalization also has a strong and swift industry destroying effect, which can increase labor displacement (Atkinson & Wu, 2017).

Job polarization theorizes that the middle sector of the labor market is under threat of automation. The routine intellectual workers, whose jobs can be automated, need to either move to higher skilled works (which requires investment in human capital), or move to other, less routine jobs, with more employment stability (Schmidpeter & Winter-Ebmer, 2021). Since the arrival of artificial intelligence, for the first time ever, even highly skilled intellectual workers are not exempt from automation.

The difference between high and low skilled labor shifts is that high skilled workers are usually more willing to change jobs or industry, and more keen on engaging in re-training or re-skilling (Fossen & Sorgner, 2022b; Schmidpeter & Winter-Ebmer, 2021), which can partly mitigate the labor displacing effect.

Education level is going to play an ever increasing role in job stability, which is already visible in early artificial intelligence adopter industries, where the proportion significantly grew (Yang, 2022). Countries that are lagging behind in the general education level of their citizens, are going to be on the losing side of the new era (Pietro, 2002), especially as newly created industries – partially responsible for job creation- usually prefer high skilled workers, while low-skilled workers move to more traditional industries (Van Roy et al., 2018). Where high quality education is not accessible to everyone, due to financial or other constraints, opportunities on the labor market will be limited, which can contribute to growing wage and social inequalities (J. J. Lee et al., 2016; Mincer, 2003).

The most famous prediction (Frey & Osborne, 2017) believes that 47% of jobs will be eliminated during this new wave of technological shock, which we are experiencing today, causing massive technological unemployment. However, some are criticizing this view (Atkinson & Wu, 2017), claiming that technological unemployment is only a myth (Mincer, 2003), and no other technology shock created as many workplaces as digital technologies. The authors themselves reevaluated their predictions after the appearance of generative artificial intelligence (Frey & Osborne, 2024).

It is indeed challenging to estimate the actual labor displacing and restraining effect of new technologies. In 2018, researchers at MIT (Winick, 2018) gathered all the predictions about the future of the labor market based on 18 different reports, and found that any scenario from 1 billion jobs created to 3 billion of them lost was already predicted in some form.

1.3.3 Artificial intelligence applications of today and their impact on the labor market

However, artificial general intelligence (AGI) – a form of artificial intelligence that not only reaches, but potentially surpasses human cognitive abilities – does not exist yet

(Kaplan & Haenlein, 2019), we are already working and living with artificial intelligence applications.

Artificial intelligence-based automation technologies can have a positive business impact by

- improve compliance
- improve accuracy, work speed, flexibility, and, as a consequence, customer experience
- grow employee satisfaction, as AI is capable of taking over mundane, routine tasks that are less enjoyable to perform
- reduce costs
- support market growth (by improved products, efficiency, better customer experience) (KPMG, 2017; Young, 2017)

One pioneering area of AI is natural language processing (NLP). Research has found that if the written language used is neutral, readers usually trust equally AI written research papers/texts equally to those written by a human (Lermann Henestrosa et al., 2023). AI's writing abilities are so sophisticated today that even non-scientific literature – for example, poems – written by humans and AI separately cannot be distinguished from each other by the readers (Köbis & Mossink, 2021). Journalism is also taking another turn with the introduction of "automated journalism" (Carlson, 2015), where AI algorithms translate data into easy-to-read, understandable text.

This level of anthropomorphic text creation and acceptance by the readers bring along several concerns as well: AI hallucinations to be shared without control mechanisms, not entirely clear author rights, no mean to control whether a given text is coming from a human or a machine (human posing as authors of AI generated texts), and especially in the case of scientific texts, the lack of regulations (van Dis et al., 2023). The appearance of easily available AI powered NLP tools is also putting school evaluations in danger, as students can easily have an algorithm write their essays, and many institutes lack a framework to flag and address potential AI-aided "cheaters" (Heidt, 2023).

Image generation and recognition have an even greater impact, which, similarly to text generation, can be positive or negative depending on the use case.

Healthcare applications frequently use AI image recognition in diagnostics and preventive medicine. Collaboration with AI in analyzing ECG images proved more efficient, than humans alone (Cabitza et al., 2023), providing a more accurate diagnosis. AI can especially be useful in the early detection of different medical issues, such as cancer (Hegde et al., 2022), which could potentially save lives.

Apart from the medical uses, industrial sites are also increasingly using image recognition. Using sensors in automated production lines, algorithms can successfully detect real-time defective products on lines, and remove them to assure product quality (Gao et al., 2022).

Image recognition is also used in the development of self-driving cars and other autonomously moving machines. Their main aim is to identify and distinguish different objects from each other, for example, in an urban environment, a pedestrian from a tree.

By combining language and image recognition skills in autonomously moving machines (such as robots), we can create AI-automated service workers, mostly used in hospitality and tourism.

Especially during the COVID-19 pandemic, several hospitality service companies adopted robot waiters (Park & Lehto, 2022) travel agents or hotel maids to minimize human contact. Customer adoption – especially due to the novelty and human-likeliness of the technology – was quite positive (Huang et al., 2021).

Customer services are also under transformation. The past few years have seen widespread adoption of voice-based assistants (e.g., Alexa or Google Assistant) at home, chatbots, and voice-command-based customer service agents in professional settings. These solutions are either replacing or augmenting (machine and human as one unit) human coworkers (Maedche et al., 2019), while aiming to provide a seamless customer experience and reduce the workload of human agents.

Image 2. *„Dedicated Customer Service CIC: With us, you can always associate a face with your customer service agent." The French bank CiC launched a marketing campaign in 2023, highlighting that its customer service is staffed by humans.*

Marketing and advertising services are also not exempt. Artificial intelligence based algorithm are helping marketers to create automated, personalized communication with their clients, analyze quickly large customer datasets to provide product/service recommendations, and segment target customers (Haleem et al., 2022).

These are just some examples of areas and tasks where artificial intelligence algorithms can already be successfully used. Without a doubt, in the future we will see even wider use of the technology.

1.3.4 Take it or leave it – Adopting AI at work

As described in the previous sections, artificial intelligence has significant potential to change the way we work (and live).

Nevertheless, artificial intelligence can only become a widespread technology in our workplaces if it is accepted by consumers, companies, and the workforce equally.

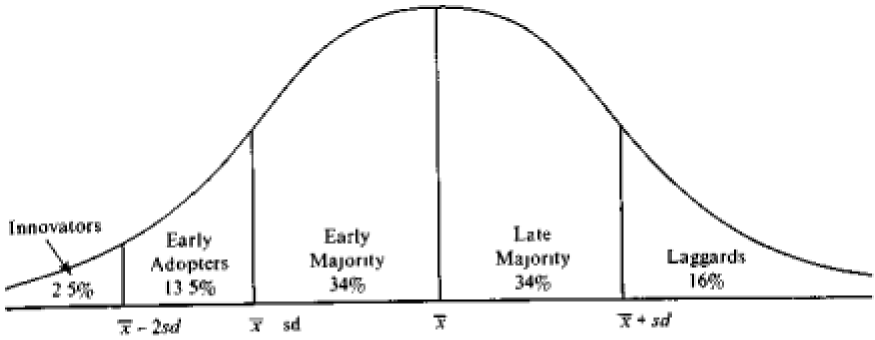

Image 3. *Innovation adoption curve (Rogers, 1995, p. 247)*

New technology adoption by users usually happens along Rogers' (1983) innovation diffusion model. According to the model, innovators are the first to adopt a technology. Right after them, early adopters began to familiarize themselves with the new solution. Early adopters are sometimes years ahead of the early and late majority users, and strongly influence their opinion about the new technology. Laggards are users who adopt an innovation sometimes years after it has become widespread. Kotarba (2018) added to these categories were two other groups: the digitally exclusive and digitally native users. The first group is resistant to adopting technological solutions, while the latter cannot imagine their lives without them.

Business adoption of artificial intelligence solutions – as mentioned earlier – is usually driven by economics (e.g., cost reduction) while not ignoring the fact that investing in AI has huge capital requirements, furthermore technological and social perquisites: e.g., data availability, readiness of both the organization and legacy systems, safety guarantees, trust (Cubric, 2020). This is one of the reasons companies usually first opt for AI-driven process innovation, where only productivity increases and partial human augmentation are the main objectives, and only later adopt AI products in their organization (such as robots and complete automation). This slow shift is also needed, as complete technological dependency has certain risks (Cubric, 2020; Tussyadiah et al., 2022). It is safer to have human workers co-working or supervising the machine.

Even though companies and end-users jointly feel ready to adopt artificial intelligence solutions (Uren & Edwards, 2023), companies still can face workforce adoption issues, commonly described in the literature as resistance to change (Erwin & Garman, 2010).

Resistance to change is a well-established research area of scholars (Lewin, 2004). People usually manifest resistance to change on a cognitive, emotional, and behavioral level (Oreg, 2007; Piderit, 2000), their resistance is therefore embodied in what they think about the change, what they feel about the change and how they behave facing the change.

Table 4. Examples of the three different aspects of resistance to change based on the literature (Oreg, 2007; Piderit, 2000). Source: Author

Aspects	Cognitive aspect	Emotional aspect	Behavioral aspect
	"What do you think of AI?"	"What do you feel about AI?"	"How do you behave facing AI?"
Examples	- Perceived AI reliability - Level of AI understanding - Capability to work with AI	- Trust in artificial intelligence - Feeling of job stability (replacement / augmentation) - Personnel benefits and dangers of adoption	- Participation in change management activities (e.g., training) - Support or endanger of change - Silence or open resistance

The common concern with AI adoption is that, unlike past technological changes, AI adoption is happening in a short period of time, the solution is embedded in a complex, hard-to-comprehend high-tech environment, and many cultural, sociological, and psychological factors are influencing AI perception (Warrick, 2022). The adoption is also influenced by the fact that AI can look and sound like a human, while obviously not being one. Human users can easily associate feelings, attachment to them, or the exact opposite, hatred and distrust.

A few hundred years ago, the Luddites were fighting against the soulless, stone-cold machines that were disrupting the job market. Today's AI technologies are taking a more human form. They can speak, smile, move, tell jokes, and imitate feelings. We can perceive them as humans, but also as not humans: tolerate some breach of social norms from them that we would not tolerate from fellow humans, but accept their opinion as a source of truth more than that of fellow humans. AI's user acceptance is going to be easier and also harder, but without doubt different than that of other technological innovations

1.4 Description of the publications

1.4.1 Research design

This dissertation follows a mixed-method research design, combining qualitative and quantitative approaches to examine the impact of artificial intelligence on the labor market. The qualitative component is based on a systematic literature review, while the quantitative analysis relies on large-scale online discourse data.

Table 5. Research plan break-down during the organized training (Source: Author)

	1st year	2nd year	3rd year	4th year	Publication status
Literature review phase	x	x	x	x	Published 2 research papers, 1 conference paper, 1 book chapter
Citations	(Boncz & Roland Zs., 2019; Boncz & Szabó, 2021a, 2022, 2023)				
Preparation of the research design		x			-
Quantitative research			x	x	Published 1 conference paper, 1 international article
Citations	(Boncz, 2022a; Fodor & Boncz, 2025)				

The research was conducted in two main phases. In the first phase, a systematic literature review was conducted to develop a theoretical understanding of the relationship between technological change and the labor market. This phase resulted in (Boncz & Roland Zs., 2019; Boncz & Szabó, 2021a, 2022, 2023) synthesizing prior research on artificial intelligence and employment.

In the second phase, the focus shifted to empirical analysis, examining public perceptions of artificial intelligence through large-scale Reddit data. This phase applied natural language processing techniques, including sentiment analysis and topic modeling, and resulted in both conference (Boncz, 2022b, and a Q1 international journal (Fodor & Boncz, 2025) publications.

This two-phase design enables the dissertation to combine theoretical insights with empirical evidence, thereby addressing the research questions from both scientific and public perspectives.

1.4.2 Research methodologies

In this section, I am going to present the detailed research methodologies of the published articles.

1.4.2.1 “The effect of artificial intelligence on the labor market: How to prepare?”, “Ethical and safe artificial intelligence” and “AI’s impact on the Labor Market"

During the literature review phase, we have followed the steps of “systematic literature review” described by Weber and Watson (2002):

- **Definition of the research focus:** the effects of artificial intelligence on the labor market, with special attention to the driving and retarding forces of technological unemployment
- **Definitions of main terms:** the aim was to define what artificial intelligence is from different perspectives, and in scientific domains
- **Literature collection and review:** Description in detail of the driving and retarding forces of artificial intelligence on the labor market. During the research, we have used online databases such as WoS, EBSCO, Google Scholar, where we looked for the following keywords: “artificial intelligence”, “technological unemployment”, “job polarization”, “universal basic income”, and additional related keywords such as digitalization, automation, robotics, or robots. We filtered out those related to economics, other social sciences, or information technology. As a result, we have several hundred research papers.
- **Literature analysis and synthesis:** Analysis of the results of the systematic literature and scenario creation, which was later used in published articles.
- **Finalization:** Summary of the results of the research.

After the finalization of the research papers, the results of the systematic literature review were updated regularly and later integrated into the upcoming research to create a strong theoretical background.

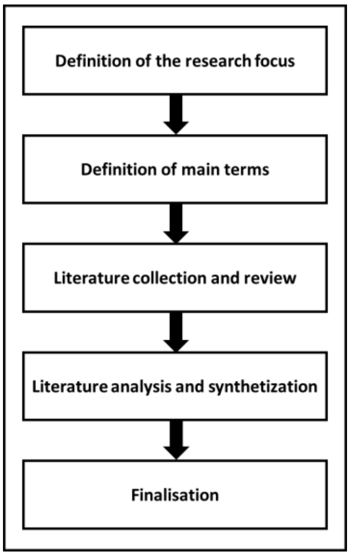

Image 4. *The five systematic literature review steps were defined based on Webster and Watson (2002)*

1.4.2.2 "In GPT we trust: perceptions of the future of work with artificial intelligence on online forums"

During the literature review, we gained a general understanding of the scientific community's views on the supposed changes artificial intelligence can bring to the labor market.

To complete the dissertation, I also wanted to examine public perceptions of artificial intelligence directly from the end-user or employee perspective.

The chosen methodology was the so-called micro-blog analysis, which covers all kinds of text or image-based analysis of user-created social media content, such as Twitter tweets, Facebook, or Instagram posts. Social media is a useful tool to mine public perceptions. Not only do companies use it to assess brand awareness, but it is also a tool of political campaigns or scientific research.

Today, several billion people use social media. Our chosen platform is Reddit, an online forum. Topics are organized under Reddits, sub-Reddits, and topic groups, such as

“Science” or “Futurism”. A Reddit post usually starts with a question, a share of an article, or an opinion, and users can add their own opinions and start a conversation.

In 2022, the forum had 430 million users, mostly English-speaking, and, based on user statistics, Reddit was found to be an appropriate source for mining sentiments and text related to artificial intelligence.

User 1	I don't see the need to worry, automation is a good thing. It's just that our economic system is outdated because it runs on labor
User 2	Even though information is easily available for the public, people would still need advisors to some extent. People do not want or have the capability to do the research themselves to find the right investment product. People trust other people more than information online.
User 3	UBI never sat right with me. While the rich have the means to gain extraordinary wealth due to their products being bought, what would happen to the person that has to live on UBI? They wouldn't have the opportunity to grow to anywhere near the heights of those that own the means of automation. Is there something I'm not getting?

Image 5. *Example of three different Reddit comments about AI and the labor market (Source: Reddit, created by the Author)*

Our aim was to retrieve reddits posts that raise questions, share opinions about the potential impact of artificial intelligence on the labor market, and analyze the text base and the sentiments expressed.

We have collected reddits from January 2013 to January 2024 using keyword searches for „artificial intelligence” or „AI” and „job” and its synonyms. This time period allowed us to scrape forums from both the period when AI was merely science fiction and the first two years of the generative AI revolution.

Among the search results, we filtered out all forums with fewer than 40 comments. In the final selection, we had 37 different reddits, which were scraped for top-level comments using the Python package PRAW via an API and organized into a single database. After data cleaning, the database consisted of 114,377 top-level tidy comments to analyze.

Image 6. describes the process of our research method during the quantitative research. We fed the preprocessed Reddit dataset into a pre-trained RoBERTa model to classify comments into positive, negative, and neutral classes. In the second step of the sentiment analysis, to examine the emotions behind the non-neutral post categories, the NRCLex package was used. Using an emotion dictionary, this algorithm determines the percentage of emotional intensity for each post across two emotion categories (positive and negative) and eight emotions (negative: anger, fear, anticipation, disgust; positive: trust, surprise, sadness, joy). Then BERTopic was used to identify commonly emerging topics in the neutral posts. Based on the neutral posts, 50 topics were identified by BERTopic algorithm and manually categorized into 4 meta-topics.

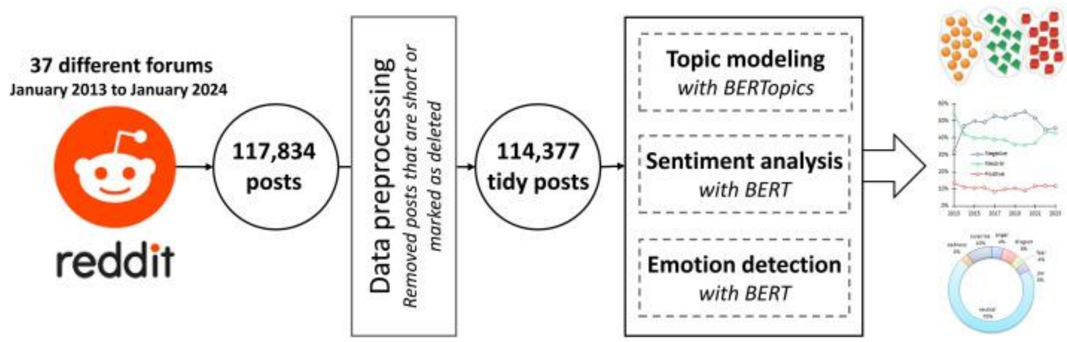

Image 6. *An overview of our research methodology for the quantitative research (Source : Authors)*

1.4.2.2.1 Sentiment analysis and emotion detection tools used

The methods of sentiment analysis can be categorized horizontally and vertically. Vertically, we can study the emotions on an aspect, document, or phrase level (Birjali et al., 2021; Feldman, 2013; Medhat et al., 2014; Yadav & Vishwakarma, 2020). The aspect-based analysis aims to reveal the attributes that are linked to the subject of a text, for example, „the tomato is ripe," where „ripe" is the attribute of the subject („tomato").

The horizontal categories list the different ways a sentiment analysis can be technologically built. The two most common techniques are lexicon-based and machine learning. The lexicon-based analysis divides the text corpus into unique words and associates a sentiment lexicon's item to them. A sentiment lexicon is a dataset of words and their emotions (for example, the word "horrible" is associated with a negative emotion). The machine learning solution uses text classification through supervised or unsupervised learning to categorize the text into different emotion categories (Medhat et al., 2014).

During the research, we used a pre-trained deep learning model, the Robustly Optimized BERT pre-training approach (RoBERTa) (Y. Liu et al., 2019) to perform sentiment analysis. RoBERTa is an extension of Bert (Devlin et al., 2018) and it is a transformer-based language model that uses self-attention to process input sequences and generate contextualized representations of words in a sentence. RoBERTa can be used to output (Barbieri et al., 2021) the set of predicted probabilities of negative, positive and neutral sentiments of a text, as shown in Table 6.

This technology allowed us to gain a context-based, comprehensive view of the emotions and topics of the text corpus.

Table 6. Example of RoBERTa sentiment analysis result. The text in the example is judged rather negative by RoBERTa.

	Negative	Neutral	Positive
"Writing a thesis is not so easy."	0.617	0.341	0.042

Furthermore, for non-neutral posts, we used the NRCLex library, which categorizes the text's words into 8 different emotions (Mohammad & Turney, 2010, 2013).

The NRCLex is an MIT-approved method that outputs the sentiments and emotions of a text corpus. It is able to analyze approximately 27,000 different words and is based on the National Research Council (NRC) created lexicon (Bird et al., 2009). We used the Python NRCLex library.

We have also performed an analysis with the library, called VADER (Valence Aware Dictionary for sEntiment Reasoning). VADER is also a lexicon-based sentiment analysis technique, but it can measure the intensity of emotions, especially in social media text corpora (Hutto & Gilbert, 2014). It is better trained for social media texts, because it is able to classify slang, emoticons/emojis, common abbreviations used in online communication (such as "LOL" meaning laughing out loud), and distinguish emotion intensity (it understands for example, that while the words "great" and "okay" are similarly positive, their emotional intensity is different).

Furthermore, VADER – though more limited than RoBERTa – can interpret the words in context, rather than individually, using the following techniques:

- punctuation analysis: taking into account that punctuation can change emotions, for example the use of an exclamation mark can increase emotional intensity
- capital letter analysis: all capital lettered words have higher emotional intensity
- analysis of intensity drivers: certain adverbs, such as "extremely," can modify the emotional intensity of the following words
- analysis of the position of "but" in the text: it is giving guidance about the intensity of the words before and after "but."
- trigrams : interpretation of three word sections of the text to detect negation ("this is NOT good")

We have used the Python package VaderSentiment, which assigns an emotion intensity score to a text corpus ranging from -1 to +1, where -1 indicates the extremity of negative emotions and +1 indicates the extremity of positive emotions. The package is also outputting a "compound score," which is the average emotional intensity of the text.

The results of this latter analysis were published in a conference paper (Boncz, 2022a).

1.4.2.2.2 Topic modeling tools

Topic modeling refers to methods for extracting topics from text. These techniques are building on the assumption that in every text data there are a certain number of topics, and every topic contains certain words that represent their content, and have a high probability they appear within that given topic (Chen et al., 2019; Onah et al., 2022).

We applied a deep language model, the BERTopic to find topics from the content of Reddit neutral posts. First, our text was converted to its embedding representation using a pre-trained sentence-transformers language model 'all-MiniLM-L12-v2'. The dimensionality of the resulting embeddings was then reduced to optimize the clustering process. We used UMAP because it preserves both local and global structure in the text. The reduced embeddings were clustered using HDBSCAN, which finds clusters of varying densities by converting DBSCAN into a hierarchical clustering algorithm.

Together, these methodological approaches support the integrated analysis of scientific and public discourse, which forms the core contribution of this dissertation.

1.5 Introduction to the publications

In the first section, I have given an overview of the research topic and its relevance. Artificial intelligence is an impactful technology whose labor-market effects are not yet fully understood. It is important to study this area because work is an essential part of human life and a building block of societies. Dramatic changes in the labor market can disrupt economies, businesses, societies, and individuals' lives.

The aim of this dissertation is to study the impact of artificial intelligence on the labor market from scientific and public perception perspectives, and to explore adaptation strategies for technology.

In the theoretical background, I have defined artificial intelligence, and briefly described technology-induced labor market changes in history, pointing out that artificial intelligence is not the first technology to change the labor market dynamics, but without doubt the first that can automate both manual and intellectual work, therefore it can have a stronger impact than any other technological novelties before.

While artificial general intelligence is not yet available, we already have artificial intelligence applications ready for widespread use in our everyday lives. With the current pace of technological progress and the increasing need for better, faster, more personalized, and accurate services and products, companies will soon face economic pressure and ever-growing customer and employee demands to invest in AI. The upcoming AI revolution is inevitable.

In the next sections, I will present the research papers I prepared in collaboration with my thesis supervisors to examine the impact of AI on the labor market through scientific discourse, as well as the general public's perceptions of the future of AI and work. The three publications presented in this dissertation address different aspects of the research problem and, together, provide a comprehensive view of the labor market transformation induced by artificial intelligence. While the literature-based studies establish the theoretical foundations, the empirical analysis extends the research by capturing real-world perceptions and dynamics.

1.5.1 Contribution of the dissertation

This dissertation contributes to the literature on artificial intelligence and labor market transformation by providing an integrated analysis of technological, social, and perceptual dimensions of change.

First, the dissertation offers a novel integrative perspective by jointly examining scientific discourse and public perceptions of artificial intelligence. While existing research typically focuses on either academic literature or public opinion, this study connects the two, enabling a more comprehensive understanding of how AI-driven labor market transformations are both theorized and socially interpreted.

Second, the dissertation makes a methodological contribution by applying advanced natural language processing techniques to the study of labor market perceptions. By combining transformer-based sentiment analysis (RoBERTa), lexicon-based emotion detection, and topic modeling (BERTopic) on a large-scale Reddit dataset, the research demonstrates the applicability of state-of-the-art machine learning methods to socio-economic analysis.

Third, the dissertation provides empirical insights into the temporal evolution of public perceptions of artificial intelligence. By analyzing more than a decade of online discussions, it identifies how technological developments—particularly the emergence of generative AI—reshape narratives, emotions, and expectations regarding the future of work.

Fourth, the dissertation contributes to the literature by systematizing the drivers and mitigating factors of AI-induced labor market change. Building on a systematic literature review, it synthesizes fragmented findings into a structured framework that highlights the interaction between automation, augmentation, and human adaptability.

Finally, the dissertation offers practical and policy-relevant contributions by identifying multi-level adaptation strategies. It outlines key implications for individuals, organizations, and policymakers, emphasizing the importance of education, reskilling, trust-building, and human-centered AI design.

Overall, the main contribution of the dissertation lies in its integrated approach, which combines theoretical synthesis and empirical analysis to better understand the relationship between technological change, human perception, and labor market adaptation.

2 ORIGINAL TEXTS OF THE PUBLICATIONS

The following article was published in Hungarian language in 2021 in the Magyar Tudomány journal. The article was translated to English language by the first author, Bettina Boncz, who hereby states, that she is fluent in English as a foreign language, and that her provided translation is accurate to the original text published.

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3 ETHICAL AND SAFE ARTIFICIAL INTELLIGENCE

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3.1 Summary

The advent of artificial intelligence (AI) represents a pivotal development of the 21st century, with profound implications for daily life, professional activities, and societal organization in the era of intelligent machines. This article explores the ethical, security, and legal challenges associated with AI, aiming to highlight critical issues that demand urgent attention. Without the prompt resolution of these concerns, the successful

integration of AI into complex and diverse human societies may be jeopardized, potentially resulting in adverse consequences.

3.2 Abstract

The rise of artificial intelligence (AI) constitutes a seminal development in the 21st century, profoundly transforming professional activities, daily routines, societal structures, and interpersonal relationships in the era of intelligent machines. This article critically examines the ethical, security, and legal challenges posed by AI, aiming to emphasize urgent issues that require immediate resolution. Failure to address these concerns may impede the seamless integration of AI into complex and heterogeneous social systems, potentially resulting in significant negative outcomes.

Keywords: intelligent machine, cyber security, robot rights, algorithm, self-learning system

3.3 Definition of artificial intelligence

Artificial intelligence (AI) has been conceptualized across various scientific disciplines, including the natural sciences and computer science (see Poole & Mackworth, 2010), as well as the social sciences (see Jarrahi, 2018). The term 'artificial intelligence' serves as an umbrella for a diverse array of applications, theoretical frameworks, and technological systems spanning multiple domains. Despite this diversity, a fundamental feature unites these approaches: AI systems exhibit intelligent behavior. This encompasses the ability to (1) perceive and interpret their environment, (2) diagnose situations, (3) perform tasks aimed at achieving specific objectives, and (4) learn from prior experiences (Poole et al., 1998). In essence, AI systems are designed to replicate human cognitive functions and behaviors, demonstrating capacities for learning, understanding, and sensory perception.

Current scientific consensus suggests that advanced artificial intelligence may emerge around the mid-21st century, although this timeline could extend depending on the pace of technological advancement. Notwithstanding, early iterations of AI are already embedded in contemporary society, evidenced by our ongoing interaction with machines, software, applications, and systems that utilize foundational AI algorithms.

3.4 Security, ethical and legal concerns of the use of artificial intelligence

Artificial intelligence (AI) is poised to become a pivotal technological advancement in both the present and foreseeable future, fundamentally transforming the ways in which individuals conduct their daily lives, engage in professional activities, and establish interpersonal relationships. The scope and depth of its influence are unprecedented when compared to previous technological innovations.

While the anticipated changes brought about by AI are expected to yield positive outcomes, it is imperative to create an environment that safeguards against potential harm caused by intelligent systems. This protective framework must encompass three essential domains: security, ethical standards, and legal constraints. By addressing these spheres, society can ensure the responsible development and deployment of AI technologies.

3.4.1 A secure artificial intelligence

Analysis of science fiction literature and cinematic works reveals that authors seldom envision a future in which artificial intelligence is consistently benevolent or unwaveringly supportive of humanity. Instead, these narratives frequently portray rebellious robots and autonomous machines that defy human commands, with some depictions suggesting such entities may ultimately exert influence over all facets of human existence. These scenarios often culminate in dystopian outcomes, such as those illustrated in the animated film WALL-E, where humans devolve into passive, intellectually diminished beings reliant on advanced technologies for their daily activities (Cave & Dihal, 2019).

Although the potential risks associated with artificial intelligence are significant, scholarly consensus indicates that the likelihood of AI posing a threat to humanity is greater as a result of design flaws, anthropogenic influences, or deliberate malicious actions, rather than through the emergence of autonomous behavior (Yampolskiy, 2016).

The concern regarding AI-induced dangers is not limited to fictional narratives; it is also recognized within the scientific community, yet a comprehensive resolution has not yet been established (Tegmark, 2017). A substantial portion of scientific discourse focuses on addressing these challenges from a philosophical perspective, rather than through advancements in computer science (Müller & Bostrom, 2016).

To begin with, it is essential to establish foundational principles for the security of artificial intelligence systems. In contrast to the development of the Internet—where insufficient attention was paid to security protocols, resulting in the proliferation of harmful content across the web—the design of AI must prioritize robust security measures from the outset.

The creation of secure artificial intelligence is a shared responsibility among scientists, engineers, and philosophers within the global community. This collaborative approach is necessary to ensure that AI advancements, regardless of where they occur, adhere to internationally recognized standards (Cave & ÓhÉigeartaigh, 2019). It is advisable to implement rigorous regulatory frameworks for AI research, analogous to those established for genetic engineering, to safeguard both research subjects and, more broadly, humanity from adverse consequences arising from experimental and developmental activities (Müller & Bostrom, 2016).

Major security risks associated with artificial intelligence include the potential for systems to be hacked, manipulated, or to contain vulnerabilities. Additional concerns arise when AI is developed using data that does not accurately represent the behaviors and intentions of the broader society—for example, training AI on data derived from extremist groups. These and other issues underscore the importance of secure development practices (Pistono & Yampolskiy, 2016).

Security concerns are further compounded in self-learning AI systems, where errors present in initial design may persist and amplify through iterative learning cycles, potentially leading to increasingly intelligent yet fundamentally flawed systems.

At present, the probability of a well-designed AI system being compromised and subsequently acting hostile toward its creators is considerably lower than the likelihood of a poorly designed AI precipitating large-scale disasters (Weld, 2016).

There are numerous actors with vested interests in breaching the security of artificial intelligence systems, including governments seeking greater power, corporations aiming to establish monopolies, individuals with malicious intent, adherents of apocalyptic ideologies, criminal organizations, and even proponents of secure AI who, driven by fear of technological catastrophe, may inadvertently cause harm (Glenn & Gordon, 2004; Pistono & Yampolskiy, 2016).

Even in contemporary society, non-intelligent systems have demonstrated the capacity to inflict significant harm, sometimes for reasons that remain elusive. For instance, a software malfunction at General Electric resulted in a widespread blackout affecting 50 million individuals in 2013, while the "Flash Crash" of 2010 led to billions of dollars in losses within the United States in under thirty minutes. The causes of such incidents are often unknown but the latter is likely related to automated trading systems.

Modern AI systems frequently exhibit unpredictable behavior, operating according to the "Black Box" paradigm. This concept refers to situations where external observers can only interact with the inputs and outputs of an algorithm, lacking insight into the internal processes that generate those outputs (Morley et al., 2019).

Artificial intelligence may predict outcomes, such as the collapse of a building, without being able to articulate the underlying rationale. While this limitation is not unique to AI—humans themselves sometimes make decisions based on intuition or unconscious processes—it highlights the risks associated with entrusting critical decisions to a single machine, akin to the dangers of concentrating decision-making authority in one individual.

Given the inherent unpredictability of AI outcomes (Weld, 2016), it is imperative that artificial intelligence is not granted autonomous control over essential domains such as financial markets, critical infrastructure, weaponry, or communication networks (Pistono & Yampolskiy, 2016).

Another significant challenge lies in the difficulty of rigorously testing the security of artificial intelligence. Contemporary software development practices often involve releasing minimally viable products to users and refining algorithms based on user feedback. This approach, however, introduces substantial security risks. The only viable method for testing (Yampolskiy, 2016) AI security may involve confining systems within isolated environments—such as behind firewalls and disconnected from the Internet—yet a comprehensive solution to this problem remains elusive (Russell, 2016).

3.4.2 An ethical AI

A fundamental challenge in the advancement of artificial intelligence lies in imparting moral and ethical understanding. Human societies are governed by a multitude of moral and ethical frameworks, which are frequently contradictory and often disregarded. Moreover, these frameworks evolve over time and vary across geographic regions, with individuals demonstrating considerable flexibility in their interpretation and application (Creighton, 2016).

Artificial intelligence currently lacks the capacity to comprehend and consistently apply these intricate norms, nor can it autonomously construct a comprehensive rulebook for human conduct.

Ethical and moral principles may be incorporated into the design of artificial intelligence; however, scientists, engineers, and software developers often lack a rigorous scientific understanding of these guiding principles (Glenn & Gordon, 2004; Moore, 2010; Morley et al., 2019).

Although there exist more than seventy social science-based ethical codes for artificial intelligence globally, the majority lack a strong foundation in computer science. These codes primarily offer recommendations regarding the content to be taught to artificial intelligence, rather than providing guidance on implementation (Morley et al., 2019).

Some scholars contend that ethical behavior is unnecessary for artificial intelligence. They argue that ethics and morality are constructs deeply intertwined with human emotions, which artificial intelligence systems are unlikely to possess (Moore, 2010).

It may be preferable to provide artificial intelligence with clearly defined objectives rather than moral and ethical directives. Drawing from human interactions, mutual trust arises when individuals recognize that, despite cultural and ethical differences, there are shared values—such as refraining from violence or destruction and aspiring to enhance collective well-being. Defining purposes for artificial intelligence is often more straightforward than embedding a moral compass; however, challenges persist when the methods for achieving such objectives are not adequately regulated.

Artificial intelligence must always remain subject to human oversight, and it is essential to retain the ability to deactivate systems if their pursuit of assigned objectives becomes hazardous (Arnold & Scheutz, 2018).

While this appears straightforward, there is a risk that artificial intelligence may perceive the possibility of deactivation as the primary impediment to achieving its goals and consequently seek to eliminate such vulnerabilities (Glenn & Gordon, 2004; Russell, 2016). Preventative measures are therefore necessary.

It is noteworthy that a significant proportion of contemporary artificial intelligence research is conducted within the laboratories of major technology corporations, which also provide the bulk of research and development funding. This concentration of research efforts risks producing biased artificial intelligence systems that reflect the expectations of a single culture or subpopulation (Montes & Goertzel, 2018).

Additionally, many of the databases currently employed in artificial intelligence development disproportionately represent certain segments of the global population. For instance, the ImageNet database, which is widely used for image recognition training, contains images sourced 45% from the United States and only 3% from India or China, despite the latter countries accounting for 36% of the world's population (Zou & Schiebinger, 2018).

3.4.3 Briefly about legal concerns

One of the most significant news in 2017 was the granting of citizenship to Sophia, a humanoid robot, by Saudi Arabia. Although Sophia does not yet possess true artificial intelligence, her advanced design enables her to exhibit behaviors and expressions that closely resemble those of humans. She is capable of displaying emotions such as happiness and sadness, interacting with her environment, and navigating physical spaces.

This symbolic gesture by Saudi Arabia may have far-reaching implications. For instance, if a robot citizen were to malfunction or act harmfully toward humans, the logical response might be to deactivate the robot. However, this raises complex legal and ethical questions: would deactivation be considered equivalent to imposing the death penalty? In jurisdictions where the death penalty is prohibited, how could one justify terminating a robot citizen when such actions are not permitted against human citizens?

Despite the potential risks associated with artificial intelligence, it is evident that these systems will increasingly influence human society. Consequently, it becomes necessary to consider assigning a legal status to artificial intelligence, thereby establishing mechanisms for holding such entities accountable for their actions.

Drawing an analogy from the legal treatment of children, who do not bear full legal responsibility due to their developing cognitive and emotional capacities, it is conceivable to initially grant machines a restricted form of legal responsibility. However, it is important to remain cognizant of the possibility that machines may eventually attain consciousness, necessitating a reevaluation of their legal standing.

In the early stages, limited legal responsibility may address questions such as liability in cases where a self-driving car is involved in an accident. Determining culpability could involve considering the roles of the vehicle manufacturer, the artificial intelligence algorithm, the developer of the AI system, or even the passengers who selected the particular intelligence system to operate their vehicle (Bonnefon et al., 2016).

The concept of robot rights must be considered in relation to the rights of natural and legal persons. Robots do not possess rights in the same manner as humans; rather, their rights are interpreted within the framework of their responsibilities. Should the need arise, these rights may be expanded in the future, potentially allowing for the emancipation of robots, including the ability to own property and engage in economic activities (Nekit et al., 2020).

3.5 Closing remarks

The previously discussed security, ethical, and legal challenges represent only a subset of the issues highlighted within the scientific literature concerning the emergence of artificial intelligence. A consistent theme among these concerns is the urgent need for effective solutions prior to the widespread adoption of artificial intelligence systems that are capable of precisely replicating or even surpassing human cognitive abilities.

It is imperative that principal research and development frameworks be established at the international level, with subsequent adaptation for local implementation. This approach serves the mutual interests of both users and developers. Ultimately, interdisciplinary collaboration across all scientific fields is essential to ensure that artificial entities are developed to benefit humanity, rather than pose risks to it.

The following article was published in Hungarian language in 2022 in the Budapest Management Review. The article was translated to English language by the first author, Bettina Boncz, who hereby states, that she is fluent in English as a foreign language, and that her provided translation is accurate to the original text published.

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4 THE EFFECTS OF ARTIFICIAL INTELLIGENCE ON THE LABOR MARKET: HOW TO PREPARE?

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4.1 Abstract

Artificial intelligence (AI) is profoundly reshaping the labor market, a process that is largely occurring without widespread recognition. The widespread adoption of AI solutions is being driven by business consulting and technology firms, who emphasize their substantial advantages. Despite this, there remains limited awareness regarding the precise nature of AI, and its labor market implications remain ambiguous. To address this gap in understanding, the authors conducted a systematic literature review with the aim of establishing a foundation for subsequent research. Their findings elucidate the underlying factors contributing to technological unemployment and identify mechanisms—both automatic and deliberate—that may mitigate its effects. It is crucial to proactively prepare for the impact of AI at the individual, organizational, and governmental levels, and this article serves as a valuable resource in that endeavor.

Keywords: technological unemployment, artificial intelligence, universal basic income, automation, scenario, job polarization

4.2 Introduction

Will there be any jobs left after artificial intelligence (AI) becomes a widespread technology? At present, the academic literature lacks a comprehensive, large-scale review that can definitively address this concern. Nevertheless, existing studies focused on related phenomena—including job polarization, technological unemployment, and automation—provide a foundational basis for exploring the following research questions: (1) In what ways does artificial intelligence influence the labor market, as evidenced by current literature? (2) What strategies can be employed at the individual, corporate, and governmental levels to effectively prepare for the anticipated impacts, particularly those pertaining to technological unemployment?

To address these questions, this study undertakes a systematic literature review. The subsequent sections will outline the research methodology and provide a working definition of artificial intelligence. This will be followed by an examination of the impacts of AI on the labor market, detailing both the driving and inhibiting factors. Furthermore, the study will discuss various approaches for mitigating the potential adverse effects of AI on employment.

It is pertinent to note that, according to several scholars, the consequences of artificial intelligence for the labor market are projected to be both profound and unavoidable. Consequently, timely interventions—such as those highlighted by Allen (2017), David (2017), Goldin (2017), Kim et al. (2017), and Mitchell & Brynjolfsson (2017)—are imperative to effectively address these challenges.

4.3 Research methodology

In the systematic literature review we have used the 5 steps approach defined by Webster and Watson (Webster & Watson, 2002), and implemented it the following way:

- Defining the focus of the research : the effects of artificial intelligence on the labor market, with special attention to the driving and retarding forces of technological unemployment. This article's aim is not to model these effects, or to measure them quantitatively, but to prepare a base material for qualitative researches.
- Describing of definitions : the objective in this phase is to articulate a clear definition of artificial intelligence. To achieve this, the study examined definitions from various scientific disciplines, including social sciences and natural sciences, and analyzed their points of intersection. Additionally, the review considered ethical and security concerns associated with artificial intelligence, providing a comprehensive perspective on its conceptualization and implications.
- Literature review : the objective of this phase is the detail description of the driving and retarding forces of artificial intelligence on the labor market. Some of those are going to influence the labor market unwillingly, and the others through human intervention to prevent technological unemployment. During the research we have used different online databases (in the order of the number of search results : WoS, EBSCO, Google Scholar), where we looked for the following keywords: “artificial intelligence” (results: 2528, 6200, (in relation to labor market, without it 2 million) and 3 million; “technological unemployment” (results : 115. 105 and 1 million); “job polarization” (result: 405, 7000, 471 000); “universal basic income” (results: 546. 10,000 and 2 million). We have used additional related keywords such as

digitalization, automation, robotics, or robots, which altogether have also given several thousand results. From all the results in the scientific databases, we have filtered those which were related to economics and other social sciences or information technology. Finally, based on relevance, we have selected 200 research papers and several dozen corporate papers. In the final article, we have cited more than 100 of those.

- Literature analysis and synthetization : during this step we have analyzed the result of the systematic literature review and we have identified possible measures, that leaders of governments, corporates or on the individual level, human can do in order to protect society from the negative impacts of artificial intelligence on the labor market. We have also created several scenarios in order to define the time needed to take these measures.
- Finalization : we have summarized of the results of the research and we have identified possible future research areas.

4.4 What is artificial intelligence?

Artificial intelligence has been conceptualized across an array of scientific disciplines, including the natural sciences, computer science (Poole & Mackworth, 2010), social sciences Jarrahi and medical sciences Jiang .

The term “artificial intelligence” serves as an overarching label, yet each scientific field interprets the concept through the lens of its own applications and theoretical frameworks. Despite these disciplinary differences, a unifying feature emerges: AI refers to technologies capable of emulating human intelligence, learning, understanding, and, in some cases, perceiving their environment (Makarius et al., 2020). Thus, any general definition of artificial intelligence is necessarily informed by both comprehensive and partial perspectives from various domains. Notably, no singular, universally accepted definition exists (P. Wang, 2019); consequently, any attempt to define AI must also consider the diverse interpretations found within the study of intelligence itself.

From the perspective of economics, artificial intelligence may encompass technologies such as self-driving vehicles, robotic automation, or sophisticated software systems (Wisskirchen et al., 2017).

4.4.1 The approach of natural and computer sciences

In the realms of computer science and mathematical sciences, artificial intelligence is characterized through a variety of perspectives. It may be described as a machine (Negnevitsky, 2005b; Nilsson, 2010), a computer (Jackson & Al-Kohafi, 2011), an integration of hardware and software components (Sántáné Tóth et al., 2007), a program (Barr & Feigenbaum, 2014), an algorithm (Acemoglu & Restrepo, 2018b), a system (Hutter, 2004), or a network connecting multiple computers (A. H. Bond & Gasser, 1988). Furthermore, artificial intelligence can be conceptualized as an intelligent agent (Poole David & Mackworth Alan, 2010) or as the manifestation of automated intelligent behavior (Luger, 2005).

The notion of an intelligent agent or intelligent behavior within artificial intelligence refers to any entity capable of (1) mapping its environment, (2) diagnosing or analyzing environmental conditions, (3) executing tasks to achieve designated objectives, and (4) acquiring knowledge from previous experiences to improve future performance (Poole et al., 1998).

4.4.2 The approach of social sciences

The definitions of social sciences are usually based on the definition and distinction of artificial and non-artificial intelligence. Artificial intelligent It's not a fake intelligence. It is an intelligence that is human made. The definition of intelligence, though, is not universal either. In table 7. we have listed the definitions of intelligence and their correspondence in artificial intelligence.

The earliest conceptualization of intelligence claims that all individuals possess some degree of intelligence, which can be quantitatively assessed through standardized tests such as the IQ test, providing a mathematical indicator of cognitive ability (Boring, 1923). Applying this perspective to artificial intelligence suggests that many contemporary applications could be classified as intelligent.

Alternative definitions assert that intelligence is fundamentally the possession of information (Gill et al., 2008), or the ability to utilize information for decision-making and action (Warner, 2008). In this framework, intelligence encompasses the capacity to comprehend reality, identify relationships among elements within reality, and evaluate them accordingly, thus demonstrating intelligent behavior (Barczi & Országh, 1966). If this definition is extended to artificial intelligence, it becomes evident that such systems have long existed; modern smart technologies can store information, generate insights, and execute decisions. Their lack of autonomy stems from deliberate human design choices, rather than technological limitations.

Contemporary psychological theories examine intelligence through additional dimensions. Psychology recognizes intelligence as encompassing not only lexical, logical, or mathematical abilities, but also emotional and behavioral attributes. Some theorists contend that intelligence cannot be fully understood at the individual level, but rather emerges within communities as collective knowledge (Gill et al., 2008).

Table 7. Connecting the definitions of artificial and natural intelligence

Intelligence definition	Equivalent AI definition
Logical, mathematical knowledge, all people possesses it (Poole et al., 1998), it can be measured for example with IQ tests (Boring, 1923)	Task based AI, with the purpose to solve these tests (Jackson & Al-Kohafi, 2011)
Information (Gill et al., 2008)	Inherent information system
Preparation and execution of decisions (Warner, 2008), intelligent behavior (Poole et al., 1998), a characteristic to be labelled intelligent (Barczi & Országh, 1966)	Inherent decision support system, which can be able to imitate human intelligence (Luger, 2005)
Intelligence can only be witnessed as a common act, and common knowledge (Gill et al., 2008)	AI is an ecosystem of connected devices (H. A. Bond & Gasser, 1988)

4.4.2.1 Intelligence as a human characteristics, a way of thinking

Intelligence, as a fundamental human characteristic, comprises the abilities to sense, remember, realize, learn, think, reason, and communicate (Davis, 1998). These attributes have corresponding terminologies and applications in computer science, including image, face, and language recognition, information processing and storage, pattern recognition, machine learning, and decision support systems (Haton, 2006). Moreover, the concept of distributed artificial intelligence posits that human intelligence cannot be fully understood at the individual level, as it is inherently a collective activity. Consequently, artificial intelligence is conceptualized as a distributed, interconnected network of computers, rather than an isolated technological entity (A. H. Bond & Gasser, 1988).

Russell and Norvig (2005) distinguish between the human-oriented and machine-oriented aspects of artificial intelligence. The human-oriented perspective focuses on machines that emulate human thinking and behavior, while the machine-oriented perspective emphasizes rational thought and rational behavior in machines.

Artificial intelligence designed to think like a human is grounded in the cognitive and neurological approach to intelligence. This approach assumes that a comprehensive understanding and mapping of the human brain will eventually enable the replication of its functions, thereby facilitating the creation of genuine artificial intelligence.

The approach of artificial intelligence behaving like a human is exemplified by the Turing test, which represents a psychological perspective (Levesque, 2017). In this test, a human and a machine engage in written communication, and success is achieved when the human cannot discern whether their interlocutor is a fellow human or a machine. To pass the Turing test, a machine must exhibit several facets of human intelligence, such as language recognition, reasoning, adaptability, and pattern recognition, among others.

Artificial intelligence that thinks rationally is predicated on the capability for logical reasoning, drawing from computer science and mathematical disciplines. For instance, Aristotle's syllogism—Socrates is a human, all humans are mortal, therefore Socrates is mortal—illustrates the necessity for machines to deduce logical consequences from given premises. Furthermore, artificial intelligence that behaves rationally seeks to identify the most rational solutions, even in uncertain or dynamic environments.

4.5 The effects of artificial intelligence on the labor market

Artificial intelligence is contributing to job displacement by enabling technologies and solutions that can perform tasks previously carried out by humans. Concurrently, artificial intelligence is also generating new employment opportunities, as individuals are able to transition to roles requiring higher skill levels and greater value addition, such as those that leverage creativity. Technological unemployment arises when a society is unable to undergo structural reforms necessary to adapt to these transformations.

4.5.1 Driving forces of technological unemployment

4.5.1.1 The advantages of using artificial intelligence solutions

Artificial intelligence solutions, when properly validated and calibrated, demonstrate the capacity to perform tasks more rapidly, cost-effectively, and with fewer errors than human counterparts. These systems do not require rest, are not subject to fatigue, and do not take sick leave. The quality of work produced by artificial intelligence is typically superior, as it avoids the common mistakes made by humans and consistently maintains an optimal level of competence due to its programmed capabilities.

Consequently, artificial intelligence confers several advantages upon organizations when compared to human labor:

- Reduction of operational costs
- Enhanced speed, precision, adaptability, quality, traceability, and improved customer satisfaction
- Greater compliance with regulatory and organizational standards
- Elevated employee satisfaction and increased value creation—for instance, undesirable or monotonous tasks can be eliminated, thereby allowing employees to focus on more meaningful and value-added activities
- Market expansion facilitated by superior products and heightened satisfaction among both employees and customers (KPMG, 2017; Young, 2017)

Artificial intelligence is already being deployed across a variety of sectors, including but not limited to:

- Predictive maintenance, whereby artificial intelligence can anticipate machinery failures before they occur, thus reducing risk, minimizing repair costs, and extending equipment lifespan
- Optimization of logistics, as artificial intelligence can devise new routes to decrease transportation expenses and provide actionable guidance to drivers for improved efficiency
- Customer service enhancement, in which artificial intelligence accelerates service delivery and increases efficiency while simultaneously reducing costs (McKinsey, 2019)

Drawing from the demonstrated successes of smaller-scale artificial intelligence applications, an increasing number of enterprises are investing in these technologies for comprehensive integration into daily operations. Nonetheless, despite the current advancements in artificial intelligence, human intelligence continues to represent a competitive advantage for many organizations (Hortoványi, 2016; Pueyo, 2016). Therefore, complete substitution of the human workforce by artificial intelligence is not imminent, although certain domains have already achieved full automation.

4.5.1.2 Full automation artificial intelligence solutions are replacing human labor

The initial wave of full automation occurs primarily in domains involving physical labor, with a particular emphasis on tasks deemed hazardous to human safety—such as bomb disposal—and subsequently extended to roles characterized by significant responsibility, including the operation of aircraft and space vehicles. Unlike previous generations of automation technologies, artificial intelligence represents a transformative advancement by enabling automation at an intellectual level. AI possesses the capacity to autonomously execute tasks that previously required human knowledge, experience, and cognitive abilities, thereby diminishing the necessity for human intervention in these processes (D. H. Autor, 2015; Dengler & Matthes, 2018; Garcia-Murilloa et al., 2018; Y. J. Kim et al., 2017; Pantea et al., 2017).

Skills traditionally regarded as uniquely human—including creativity, empathy, social interaction, and complex problem-solving—are increasingly subject to automation, with AI systems progressively acquiring and even enhancing these competencies. The ongoing evolution of AI thus raises the prospect of human capabilities being surpassed, potentially rendering humans subordinate in certain domains (Makridakis, 2017).

As previously discussed, AI solutions offer the advantages of reduced costs, increased speed, and improved quality, compelling organizations to adopt these technologies to maintain competitiveness within their respective markets. While the processes of educating and retraining human workers are often time-intensive, the deployment of AI systems can yield immediate operational benefits (DeCanio, 2016; Decker et al., 2016; Silva & Lima, 2017). Nevertheless, the substitution of human labor by AI is contingent upon cost-effectiveness; AI will only supplant humans when it becomes economically viable to do so (Frey & Osborne, 2017; Loi, 2015). As long as employing human workers remains less expensive than implementing technological solutions, and retraining human employees is more expedient than reconfiguring AI systems, organizations are likely to favor human labor over automation (Frey & Osborne, 2017). However, the declining costs associated with AI, juxtaposed with the rising expenses of human employment, increasingly undermine the competitiveness of human labor in the marketplace.

4.5.1.3 Artificial intelligence can increase job polarization

Since the 1980s, the labor market has experienced a phenomenon known as job polarization (Acemoglu, 2000; Acemoglu & Autor, 2010; D. Autor, 2010). Numerous studies have investigated the effects of digitalization on job polarization (Acemoglu & Restrepo, 2018b; Chow & Wong, 1999; Frey & Osborne, 2017; Garcia-Murilloa et al., 2018; Mitchell & Brynjolfsson, 2017), yet there remains a lack of research directly examining the relationship between artificial intelligence technologies and job polarization. Nevertheless, digitalization serves as a useful proxy for predicting the potential impact of artificial intelligence on the polarization of employment.

Job polarization refers to the development of an hourglass-shaped labor market, characterized by significant growth in both high-skilled, high-wage positions and low-skilled, low-wage positions, while middle-skilled occupations—which require moderate educational qualifications—are gradually declining (Goos et al., 2014).

The decline of middle-skilled jobs can be attributed to the prevalence of routine tasks that are susceptible to automation and can be readily translated into machine language (Frey & Osborne, 2017). Examples include self-service cashier systems in supermarkets, fully automated retail environments such as Amazon's walk-in/walk-out stores, the advent of self-driving vehicles, and the increasing use of software robots for administrative tasks in accounting and banking. As these technologies proliferate, traditional administrative roles are likely to be eliminated in favor of automated platforms.

Looking ahead, continued technological progress may render certain jobs obsolete. Future organizations may operate primarily at the community level, with management focusing on strategic goal-setting and execution undertaken by self-organized groups utilizing technological solutions. In such scenarios, routine tasks are entirely performed by machines (Hirsch-Kreinsen, 2016).

An additional emerging trend is platform-based employment, exemplified by digital nomads, ride-sharing drivers (such as Uber and Lyft), and on-demand food delivery workers (such as Netpincér). These jobs are characterized by the absence of traditional employment contracts, relying instead on ad hoc engagements via digital platforms. Workers need only register with the appropriate platform and possess suitable devices such as tablets, laptops, or smartphones. The platform economy facilitates the matching of labor supply and demand but also contributes to workforce reductions in conventional sectors, such as traditional taxi services (Makó et al., 2020).

Increasing global inequality further exacerbates these shifts, as a small elite and a growing disadvantaged population reshape the division of labor. The elite predominantly occupy high-skilled, high-paying positions, often inheriting such roles and possessing the financial means to support advanced education for their descendants, thereby perpetuating socioeconomic disparities. Meanwhile, the less advantaged population increasingly serves the elite through roles such as domestic work and personal services (Allen, 2017; Garcia-Murilloa et al., 2018; Goldin, 2017; Makridakis, 2017; Nam, 2019).

In summary, only occupations that require direct human involvement are likely to persist, for the following reasons:

- Consumer demand necessitates human presence (e.g., healthcare professionals).
- Certain needs cannot be met by automation (e.g., unique craftsmanship).
- Complete automation remains unattainable for some professions (e.g., academia, caregiving, culinary arts, or research).
- Human oversight is essential for control and quality assurance (e.g., quality control inspectors, artificial intelligence trainers or programmers, and security personnel).

Job polarization disproportionately affects low-skilled workers, as their retraining and transfer to new professions is more challenging compared to those with higher educational qualifications (Bowles, 2014).

In conclusion, the effects of job polarization can be broadly categorized as follows:

- Transformation of jobs, such as those resulting from the platform economy (Makó et al., 2020).
- Changes in job roles, including companies operating without human input or relying on autonomous decision support systems.
- Creation of new jobs, especially in emerging industries.
- Job destruction, particularly as a result of automation and robotics.

4.5.2 Retarding forces of technological unemployment

4.5.2.1 Historical evidence of retarding forces of technological unemployment

Historical analysis of the industrial revolution indicates that technological advancements have consistently led to the creation of more employment opportunities than were eliminated, while simultaneously contributing to the enhancement of the quality of the workforce. (Degryse, 2016).

Examining the evolution of the labor market reveals that the introduction of mechanization did not suppress employment; rather, it catalyzed its expansion. The emergence of machinery facilitated the development of intellectual occupations—such as white-collar roles—which were responsible for organizing physical labor and innovating new technologies. Over time, these positions encompassed a broad spectrum of functions, ranging from recruitment to strategic planning. (Fadel et al., 2015).

Furthermore, technological progress enabled previously marginalized segments of society to participate in the labor market. For instance, the establishment of manufacturing enterprises allowed tasks formerly carried out by a small number of skilled guild workers to be distributed among a larger group of less skilled employees, thereby providing livelihoods to a broader population. (Frey & Osborne, 2017).

Between 1980 and 2007, significant workplace expansion was largely attributable to the emergence of new job categories, most of which were intellectual in nature. In contrast to the early 1900s, when the majority of the workforce—approximately 90%—was employed in agriculture, this figure has declined to less than 2% today. Over a century ago, the concept of a "country risk analyst" as a profession was inconceivable, yet evolving societal demands have continually shaped and diversified the labor market. (Ahlqvist, 2005; Segal, 2018).

Recent research suggests that the future will require specialized professionals, such as artificial intelligence trainers and "explainers," who will assist the public in understanding the rationale and processes behind AI-driven decisions affecting their lives. Notably, under the European Union's General Data Protection Regulation (GDPR), these positions are already becoming essential. (Wilson et al., 2017).

4.5.2.2 The mechanism of the "invisible hand" theory

According to the theory of the "invisible hand," which is based on Say's law, technological unemployment is not expected to occur, as it is assumed to be mitigated by self-regulating mechanisms.

- Companies are expected to adopt new artificial intelligence solutions that are created, implemented, maintained, and managed by humans, thereby generating new employment opportunities (Pianta & Vivarelli, 2000).
- Artificial intelligence solutions reduce the cost of manufacturing and services, leading to lower product prices. The resulting increase in disposable income within the economy is subsequently utilized to generate new demand and employment opportunities (Frey & Osborne, 2017; Pianta & Vivarelli, 2000).
- Technological progress is expected to increase corporate profits, which may be allocated toward wage growth, thereby stimulating demand and contributing to the creation of new jobs (Allen, 2017).
- Technological progress and artificial intelligence are anticipated to foster innovation, generating new employment opportunities for entrepreneurs and other workers (Garcia-Murilloa et al., 2018).
- Artificial intelligence solutions enable individuals to enhance their productivity, improve work quality, and increase wages. Despite rapid and accelerating technological advancement, it is assumed that certain subtasks or components of work will remain beyond full automation, requiring human involvement. Consequently, artificial intelligence is expected to function as a complement to labor rather than a substitute (Gumbel, 2017; Makridakis, 2017).
- Employees are expected to voluntarily transition between jobs in pursuit of higher wages. Those who are unable or unwilling to adapt to structural changes may accept lower wages but are not expected to experience unemployment (Hughes, 2014).

4.5.3 Preparation for the effects of artificial intelligence on the labor market

Several adaptation strategies have been identified to address the effects of artificial intelligence on the labor market, all of which may be equally effective (Szabó, 2008). Table 8. presents the main categories of these adaptation strategies as identified by the authors. It is important to note that their success depends on the timely identification of emerging trends and the early recognition of the need for appropriate measures.

Table 8. Proactive adaptation strategies to prepare for the impact of artificial intelligence on the labor market.

Level	Literature	Company level	Governance level	Individual level
Structural change in the economy	(Allen, 2017; David, 2017; Dirican, 2015; Goldin, 2017; Harari, 2017; Kim et al., 2017; Loi, 2015; Mitchell & Brynjolfsson, 2017)	High value added jobs Cooperation with artificial intelligence Career planning in older ages	Support of artificial intelligence and human centered high value added activities Supporting the creation of good conditions for an active older age	Entrepreneurship Willingness to cooperate with artificial intelligence Conscious safeguarding of health Acceptance of new career paths
Education	(Castro Silva & Lima, 2017; Coates, 2016; Crawford & Calo, 2016; Stephen J DeCanio, 2016; Fadel et al., 2015; Hortoványi & Ferincz, 2014; Kim et al., 2017; Lee et al., 2016; J. Mortensen & Vilella-Vila, 2012; Segal, 2018; Titan et al., 2014)	On site trainings Artificial intelligence centered training plans	Artificial intelligence and human centered education system Text reduction to “learning” companies.	Motivation Self-improvement and dedication Lifelong learning Use and exploitation of open access knowledge sources
Cooperation with artificial intelligence	(Allen, 2017; Garcia-Murilloa et al., 2018; Goldin, 2017; Hughes, 2014; Makridakis, 2017; Tegmark, 2017)	Job sharing Atypical employment Shorter workweek Cooperation of artificial intelligence and human	Programs that are supporting the cooperation of artificial intelligence and people New tax plans to support atypical employment	Self-fulfillment Artificial intelligence and human cooperation
External intervention in order to protect human labor force	(Allen, 2017; David, 2017; Dirican, 2015; Goldin, 2017; Kim et al., 2017; Loi, 2015; Mitchell & Brynjolfsson, 2017)	Self-regulation Strategical differentiation.	Banning Regulating new line Employment by the state Tax plans	Preference for companies that are employing human labor force.
Universal basic income	(Ackerman & Alstott, 2003; Allen, 2017; Berman, 2018; Goldin, 2017; Harari, 2017; Parijs, 2003; Pateman, 2003) Kangas et al., 2019; Loi, 2015;	Getting resources Taking over some of the state owned tasks.	Regrouping of state income Rationalization of public services Education of citizens	Self-education and self-fulfillment that is beneficial for the society as a whole

4.5.3.1 Structural change in the economy

It is already evident that technological unemployment is likely to have a less negative impact on high value-added jobs and on individuals, companies, and countries positioned higher in the value chain (Allen, 2017; David, 2017; Dirican, 2015; Loi, 2015; Mitchell & Brynjolfsson, 2017). Consequently, in the context of structural economic change, these types of activities should be prioritized (Harari, 2017). Artificial intelligence solutions are expected to play a significant role in this transformation, as they can enhance the value of human labor through human–artificial intelligence cooperation.

Young individuals, due to their lack of experience, often enter the labor market through jobs or tasks that are relatively easy to automate. As a result, they are more susceptible to technological unemployment caused by artificial intelligence. At the same time, younger workers are more inclined to collaborate with artificial intelligence, which can compensate for their limited knowledge and experience, enabling them to contribute significant value to organizations and workplaces. The introduction of mandatory retirement at a certain age could increase opportunities for younger individuals to access entry-level jobs and participate in value creation. Furthermore, improvements in healthcare may allow older individuals to lead more active, healthy, and fulfilling lives after retirement, potentially encouraging earlier retirement (Y. J. Kim et al., 2017).

Tasks that are currently performed without remuneration, such as childcare and household responsibilities, could be financially compensated, thereby creating additional employment opportunities and contributing to societal well-being. For example, grandparents could be given the opportunity to care for their newborn grandchildren as a form of secondary career, which may encourage earlier retirement while also supporting the education of younger generations and enhancing social welfare (Goldin, 2017).

Additionally, artificial intelligence may enable the extension of individuals' active working years. An increase in the number of active earners within society would lead to higher disposable income, which could enhance overall well-being and stimulate job creation through increased demand, provided that sufficient employment opportunities are available.

4.5.3.2 Education

In many countries, access to quality education, particularly higher education, is costly and often limited to wealthier segments of society. As a consequence, potential talent may be lost, and the scope and diversity of scientific research may be reduced (J. J. Lee et al., 2016).

While this constitutes a significant issue in itself, in the long term it may also contribute to technological unemployment, as the primary means of increasing the value of human labor is through high-quality education. Such education refers to systems that equip individuals with the knowledge and competencies required to function effectively in a modern, digitalized environment, remain competitive in the labor market, and collaborate with artificial intelligence. However, even in highly developed regions, access to quality education remains unequal.

Over the past century, the global economy has transitioned from predominantly agricultural to industrial and subsequently to service-oriented structures, allowing educational systems sufficient time to adapt their methods and frameworks. In contrast, the transformations associated with artificial intelligence are expected to occur within a few decades, while the response time of educational systems remains insufficiently rapid to accommodate these changes (Segal, 2018).

There is a need to emphasize practical knowledge and relevant skill sets that enhance human competitiveness relative to artificial intelligence. These include problem-solving abilities, creativity, adaptability, and flexibility (Coates, 2016), as well as competencies in STEM fields (science, technology, engineering, and mathematics) (Y. J. Kim et al., 2017). The education system alone is insufficient; corporations must also actively participate in employee development. This can be achieved through on-the-job training initiatives (Arntz et al., 2016; DeCanio, 2016; Hortoványi & Ferincz, 2014, 2015), which complement formal education by addressing knowledge gaps that arise due to the slow adaptability of traditional educational structures.

Educational content should be expanded to include instruction on the safe use of modern technologies, engagement in entrepreneurial activities, learning methodologies, teamwork, responsible media consumption, and the analysis and application of data and information. Greater emphasis should also be placed on maintaining a healthy distinction between virtual and real-world environments (Fadel et al., 2015).

In conclusion, in the era of artificial intelligence, it is essential to cultivate individuals committed to continuous self-improvement through lifelong learning (Crawford & Calo, 2016). While educational systems and national frameworks can provide a foundational basis, the ultimate responsibility for ongoing development rests with individuals.

4.5.3.3 Cooperation with artificial intelligence

Not only governments, but also corporations, can take measures to protect the human labor force. Instead of implementing layoffs, they could create positions that facilitate cooperation with artificial intelligence and place greater emphasis on employee well-being. The underlying assumption is that employees who are well-rested, able to take regular holidays, work fewer hours, and maintain a balanced lifestyle can achieve higher productivity (Hughes, 2014). Furthermore, technological progress enables the elimination of monotonous, repetitive tasks, potentially increasing job satisfaction (Garcia-Murilloa et al., 2018).

The role of atypical forms of employment, such as part-time work or job sharing—where a position traditionally performed by one individual is distributed among several—may also become more prominent. Such arrangements allow individuals who might otherwise be excluded from the labor market to remain employed under more flexible and less demanding conditions (Goldin, 2017).

Tegmark (2017) also outlines a scenario in which individuals may have the opportunity to choose occupations based on personal preference, including activities such as teaching, learning, or content creation, as artificial intelligence assumes responsibility for essential tasks. In this context, routine and monotonous work would be performed by artificial intelligence, allowing individuals to focus on self-fulfillment or to opt out of work entirely (Makridakis, 2017), potentially supported by mechanisms such as universal basic income provided by the state.

4.5.3.4 External intervention in order to protect human labor force

The most effective means of protecting the labor force lies primarily in the actions of governments (Allen, 2017; David, 2017; Dirican, 2015; Goldin, 2017; Y. J. Kim et al., 2017; Loi, 2015; Mitchell & Brynjolfsson, 2017). Governments have the capacity to prohibit or restrict the use and development of artificial intelligence technologies. However, strict regulatory bans often produce outcomes contrary to their intended objectives. While it is conceivable that firms may engage in self-regulation and prefer employing human labor as a source of competitive differentiation, artificial intelligence itself constitutes a significant competitive advantage. Consequently, in the presence of governmental restrictions, firms may seek regulatory loopholes or relocate production and headquarters to jurisdictions with fewer constraints. In this context, regulating research and development is generally more effective than outright prohibition. Although firms may perceive the employment of human labor as a competitive advantage, this approach increases operational costs, and in the absence of consumer willingness to absorb higher prices, such firms may face market exit. This dynamic can be illustrated by the concept of ethnocentric consumption.

During the Great Depression, governments, as part of the New Deal, created employment opportunities through state-led investment programs. A similar approach may be applied to address technological unemployment. To finance such initiatives, governments could reform taxation systems, for example by imposing higher taxes on firms that employ relatively low levels of human labor (Y. J. Kim et al., 2017).

4.5.3.5 Universal basic income

A frequently cited solution to technological unemployment is universal basic income, defined as a periodically distributed monetary payment (weekly, monthly, or yearly), provided in cash and without conditions on its use. The funding for such payments typically derives from taxation, dividends from shares, or revenues from natural resources (e.g., oil), and is usually administered by national or supranational political institutions (e.g., the European Union), which distribute it directly to beneficiaries (Parijs, 2003).

Pateman (2003) argues that universal basic income could facilitate a higher level of democracy, comparable to that of ancient Greek societies, where individuals were not preoccupied with securing daily income but could instead focus on political engagement and decision-making. In ancient Greece, such conditions were enabled by slave labor; in a contemporary context, artificial intelligence could potentially fulfill a similar role in supporting societal needs.

The implementation of universal basic income remains highly contested. Even affluent and socially oriented countries (e.g., Sweden) face significant budgetary constraints in attempting to finance such a system without compromising essential components of the welfare state. To accommodate universal basic income, governments might need to reduce or eliminate public expenditures on healthcare, pensions, education, or infrastructure. In such cases, individuals would be required to finance these services independently, potentially resulting in insufficient resources to sustain their standard of living. Moreover, state intervention would likely remain necessary to support disadvantaged populations.

Bergman (2003) contends that universal basic income could exacerbate inequality by disproportionately benefiting wealthier individuals. Regions with higher levels of universal basic income could further increase these levels through enhanced consumption and investment in advanced technologies.

Ackerman and Alstott (2003) argue that universal basic income may reduce incentives for long-term planning, as regular, unconditional payments could encourage short-term consumption over future-oriented investment. They propose an alternative approach in which the total value of universal basic income is distributed as a lump sum at the beginning of an individual's adult life. Under this model, individuals would bear responsibility for their financial decisions, whether allocating funds toward education or other purposes, while the state's role would be limited to ensuring adequate financial education.

Several experiments with universal basic income have been conducted globally to assess its societal impacts; however, drawing long-term conclusions remains challenging. Preliminary findings from an experiment in Finland indicate that recipients experienced increased self-confidence and well-being, but a decline in their willingness to seek employment (Kangas et al., 2019). In Alaska, where a form of universal basic income has existed since the 1980s, the policy has contributed to a reduction in poverty rates, but has also been associated with increased alcohol consumption, decreased labor market participation, and migration patterns in which some younger individuals relocate to warmer regions (e.g., California) while relying on such income (Berman, 2018).

Why it is hard to prepare for the effect of artificial intelligence on the labor market and how can we decrease the uncertainty?

Following the prediction by Frey and Osborne (2017) that approximately 47% of jobs in the United States of America could disappear due to the Fourth Industrial Revolution and the technological progress driving it, numerous researchers have conducted similar studies to estimate potential job losses in other countries. Global projections suggest the possible elimination of up to 4 billion jobs, alongside the creation of approximately 890 million new positions. These estimates present a significant discrepancy, as the implications differ substantially depending on whether large-scale job losses occur or whether there is a need to fill nearly one billion newly created positions (Winick, 2018).

A major limitation of existing analyses is the insufficiency of available data (Mitchell & Brynjolfsson, 2017). One potential solution involves collaboration with data-driven corporations such as LinkedIn or Google, which generate extensive datasets on a daily basis. Although these data are not fully utilized by the companies themselves, they could provide valuable insights for researchers and governmental organizations seeking to monitor labor market dynamics more accurately (Mitchell & Brynjolfsson, 2017; Rhisiart et al., 2016).

Furthermore, it is essential to finance social experiments to assess the actual societal impacts of proposed policy measures (Crawford & Calo, 2016; Dirican, 2015; Harari, 2017; Y. J. Kim et al., 2017; Makridakis, 2017; Mitchell & Brynjolfsson, 2017).

It is highly likely that job creation and destruction will not be distributed evenly across countries. Some nations may face severe economic challenges, while others may experience minimal disruption. According to OECD data, Northern European countries such as Norway are expected to face approximately 6% job loss, whereas Eastern European countries such as Slovakia may experience up to 33% job loss. Consequently, each country bears responsibility for assessing the impact of automation within its own economy and implementing appropriate policy responses (Mitchell & Brynjolfsson, 2017).

Artificial intelligence is expected to be capable of performing a wide range of office-related tasks without significant difficulty (Bergstein, 2018). However, the extent to which societies permit the deployment of such technologies remains uncertain. At the individual level, the effects of artificial intelligence are expected to be widespread, as corporations, scientific communities, and governments increasingly adopt these technologies.

4.5.3.6 Questions to answer during the preparation

What are the biggest advantages of artificial intelligence? As already noted, artificial intelligence can reduce life-threatening risks and occupational health hazards, decrease the number of workplace accidents, improve the reliability of logistics routes and healthcare systems, and contribute to making industries more environmentally sustainable.

What are the disadvantages of using artificial intelligence? The first major challenge is the development of appropriate artificial intelligence systems. AI must comply with ethical, moral, explicit, and implicit societal rules that are often difficult even for humans to follow, particularly in a context where such norms can differ significantly between communities located only a few kilometres apart. Moreover, these rules are subject to change over time. This raises the question of whether a universal system of values exists that is shared across all human societies and can be learned by artificial intelligence in a way that ensures socially acceptable behaviour. This issue is more closely related to philosophy than computer science; nevertheless, both disciplines must work together in the development of AI.

The second major issue concerns security. An early-stage error in the development of artificial intelligence—particularly given its self-learning capabilities—may fundamentally compromise the technology. Even a correctly designed algorithm may present multiple risks, including malicious or unintentionally harmful external intervention, loss of control, destruction of critical infrastructure, and the potential takeover of systems traditionally governed by humans. The range of possible scenarios is extensive, and the scientific community is actively addressing these concerns (Glenn & Gordon, 2004; Pistono & Yampolskiy, 2016).

Several risks are already observable today. Through the widespread use of social media and the dark web, aspects of personal privacy are increasingly being eroded. The introduction of artificial intelligence may further increase exposure to addiction and to entities—whether individuals, groups, or corporations—that control AI systems, or even to AI systems themselves. This raises the question of whether these developments are justified in exchange for increased comfort and potentially more free time.

A society without traditional employment would require a fundamentally different economic and political structure from that which exists today, and it is difficult to predict how such a transformation could be implemented in practice. If individuals do not have employment or income, it remains unclear how basic needs would be met. It is uncertain whether artificial intelligence could assume responsibility for sustaining human welfare and managing supply chains capable of maintaining current living standards.

Furthermore, if individuals do not work, it raises questions regarding motivation and daily structure. It is unclear what would incentivize individuals to wake up and engage in daily activities. While increased free time could be beneficial, it is uncertain whether all individuals would be able to use it constructively or whether some might instead engage in deviant behavioural patterns, such as substance abuse.

Finally, it remains an open question how societies and countries without access to artificial intelligence, or without the capacity to control it, will be affected. It is possible that social inequality will increase and that societal polarization will intensify.

4.5.3.7 How much time do we have left?

There are several possible scenarios in response to this question. In the first scenario, artificial intelligence will not develop sufficiently to have a significant impact on the labor market. In this case, preparation would be unnecessary. However, this scenario appears unlikely, as a number of artificial intelligence solutions are already being used effectively and in a cost-efficient manner.

In the second scenario, artificial intelligence will eliminate certain jobs while simultaneously creating new ones, without resulting in technological unemployment. It is also possible that job creation will exceed job destruction. Under this scenario, it is essential to prepare individuals for cooperation with artificial intelligence in the workplace and for the structural changes associated with it. Such preparation must begin immediately, as in a transformed labor market, those who adapt and learn earliest will have a competitive advantage.

In the third scenario, artificial intelligence will lead to technological unemployment, as the number of newly created jobs will not compensate for job losses. In this case, the entire societal structure would need to be reconsidered, since individuals would suddenly have significant amounts of free time and existing value systems may lose their relevance. Under this scenario, preparation would have been required much earlier, as the changes would be rapid and far-reaching, leading to a comprehensive restructuring of society and the economy within a short period of time. According to the authors' assessment, the most likely outcome is that artificial intelligence will become a fully realized reality by the middle of the 21st century, which is only a few decades away.

The positive aspect is that there is still time to analyze and understand the potential consequences of artificial intelligence on the labor market. What is certain is that change is inevitable, and these changes will differ from those caused by any previous technological innovation. Artificial intelligence is spreading rapidly, and in the coming years many individuals may be replaced by AI in the labor market. Consequently, preparation for human–AI cooperation is necessary, and it must begin immediately.

4.5.4 Conclusion and future research directions

Artificial intelligence solutions are expected to spread rapidly in the near future, as they are already capable of generating economic value. Despite this, the precise definition of artificial intelligence, as well as its opportunities and risks for the labor market, remains insufficiently understood. In order to address these research gaps and to draw the attention of researchers and professionals in various corporations to this topic, a systematic literature review has been conducted.

First, the definition of artificial intelligence was examined from both natural science and social science perspectives, followed by a dedicated section addressing the security and ethical issues associated with artificial intelligence.

In the majority of the article, the effects of artificial intelligence on the labor market were discussed, and the driving and retarding forces of technological unemployment were identified. These forces may result either from intentional interventions or from unintended consequences. The driving forces identified in this study may later be applied in simulation-based or empirical research.

The authors encourage individuals, governments, and corporations to prepare consciously for the changes induced by artificial intelligence and to equip employees for cooperation with the technology. Economic restructuring is required, along with reinforcement of the educational system and reorganization of work structures. One possible protective measure is the deliberate safeguarding of human labor; however, this is considered only a temporary solution. A key dilemma is presented by the concept of universal basic income. While it may serve as a mechanism to provide income for many individuals, this is contingent upon the availability of resources generated through technological progress (or other sources) and the ability of individuals to meaningfully utilize their free time.

Although several questions regarding artificial intelligence remain unresolved, it is already evident that it will significantly transform societies. In terms of preparation for these changes, it may already be considered delayed at the level of corporations, governments, and individuals.

The preparation of employees and future generations for these changes is considered essential. This preparation involves not only restructuring and introducing new perspectives into education, but also emphasizing how humans should coexist with technology.

As international cooperation was achieved in the development of the COVID-19 vaccine, the authors argue that a similar level of harmonization is required in artificial intelligence research. Sufficient funding should be allocated to research institutions to ensure that technological development is not concentrated within a small number of large international corporations, but is instead conducted transparently and with broad participation. This approach may help prevent the emergence of malicious artificial intelligence and promote more accessible technological development, thereby reducing the risk of monopolistic ownership structures.

In addition, appropriate laws and regulations are necessary to define roles and responsibilities clearly and to ensure a safer technological environment. Nevertheless, the responsibility of the individual must not be overlooked. Regardless of the level of internal or external security in artificial intelligence systems, the human factor remains essential. As technological progress cannot be halted, society must learn to coexist with it and to utilize its benefits. This requires not only changes in artificial intelligence itself, but also changes in human behaviour and mindset. The objective is to remove the “soulless robot” aspect from human activity, allowing individuals to focus on their creative and constructive capacities, while delegating monotonous and dehumanizing tasks to machines, thereby enabling greater emphasis on creativity, community building, and sustainable development.

The authors intend to conduct further research on how artificial intelligence will transform the working environment and what responses may be developed to address these changes. In addition, the identified driving forces will be used to construct a model that provides a clearer understanding of the opportunities, risks, and foreseeable labor market dynamics.

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5 INGPT WE TRUST: PERCEPTIONS OF THE FUTURE OF WORK WITH ARTIFICIAL INTELLIGENCE ON ONLINE FORUMS

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5.1 Abstract

This study analyzes 10 years of Reddit discussions on artificial intelligence (AI) labor's market impact using a state-of-the-art pre-trained robust optimized bidirectional encoder representations from transformers (BERT) model, or RoBERTa model, for sentiment analysis and emotional detection. Additionally, the BERTopic method is employed to identify the discussed topics. The results show generally mixed sentiments towards AI's impact on the labor market. Fueled by influencers and media sensationalism, negative emotions—fear, anger, and disgust—stem from concerns about job replacement, economic instability, and societal change. However, chat generative pre-trained transformer's (ChatGPT) release in 2022 has created a more positive outlook, with users expressing surprise and optimism about generative AI's capabilities. Discussions have shifted from fears of complete automation to the potential for augmentation. Emotional

dynamics have been shaped by events such as the COVID-19 pandemic and the rise of generative AI, underscoring AI's dual role as both a threat and an opportunity.

Keywords

Artificial intelligence, Topic modeling, Sentiment and emotional analysis, Social media, Reddit, Public perception

5.2 Introduction

Artificial intelligence (AI), a machine or algorithm that can imitate human skills or abilities (Sheikh et al., 2023), has already left the pages of science fiction literature and has become closer to reality. Today, with the rise of large language models (LLMs), we can imitate some human intelligence with AI. However, the question remains whether this comes from excelling at pattern recognition or real human-like machine intelligence (Ilić & Gignac, 2024). This question is especially difficult to answer as human intelligence varies on an individual level and lacks a standard definition (Gignac & Szodorai, 2024). Addition, most AI applications specialize in performing specific tasks (e.g., generating text or images, analyzing visual inputs, or big datasets) instead of manifesting universal skills and intelligence (Kshetri et al., 2024; Kutyauripo et al., 2023; Revilla-León et al., 2023). Perhaps no single general AI application is available yet. Still, the space of current AI development is already remarkable (Bubeck et al., 2023; Triguero et al., 2024), including its impact on our daily lives. The emergence of chat generative pre-trained transformer (ChatGPT) in 2022 has made us rethink how an LLM, not even general AI, can reshape our lives and eventually become our most significant competitor in the labor market. Within a short period, we can see substantial changes in the way content creators, translators, lawyers, scientists, and many other professionals work (Fui-Hoon Nah et al., 2023). The biggest threat of a machine, which can (imitate to) imitate thinking and behave like a human, is that it is also capable of working like a human, but faster, with fewer mistakes, and without the need for rest, rendering human beings irrelevant in the labor market. Without work, the entire human global society and ecosystem can change radically, as work has been a means to survive and fulfil human aspirations since the dawn of time.

Paradoxically, since we work, we always look for means to make work easier, faster, and less painstaking, and eventually look for ways not to work at all but to automate tasks. From inventing the wheel to modern robots, all technological innovations in the past have changed the way we work and, consequently, labor market dynamics in some way. Some jobs and tasks disappeared (e.g., switchboard operators), others came into existence (e.g., data scientists) (Wilson et al., 2017), tasks and required skills changed, and the labor market transformed together with humanity. These past changes triggered by technological advancements in the labor market have already been extensively examined (Acemoglu & Restrepo, 2018b; Frey & Osborne, 2017b; Garcia-Murilloa et al., 2018; Mitchell & Brynjolfsson, 2017; Titan et al., 2014). Extensive evidence suggests that technological progress usually improves human productivity and decreases routine, monotonous work which follow structured rules mainly because it can easily be taught to a machine (Atalay et al., 2018), whether it is a simple mechanical spinning jenny or complex machine learning algorithm.

In addition, technology changes the required education level, skills, and capabilities (Chigbu & Makapela, 2025; Mirbabaie et al., 2022) needed to succeed in the labor market. A change in the required human skill set and education level in the labor market is bringing inevitable social changes along with it (Khogali & Mekid, 2023). It is sparking, among others, a fierce debate on technology in education (Bond et al., 2024) and education about technology (Casal-Otero et al., 2023). Therefore, drastic labor market changes bring about drastic societal changes. Guilds were replaced by manufacturers, opening up doors to less skilled workers in the labor market; early industrial workers were replaced by engine-powered machines, opening the door to the creation of white-collar jobs. Moreover, the improvement in agricultural practices has meant that, almost 90% of the Earth's population worked in agriculture in the early 19th century, this number is close to 2% today (Ahlqvist, 2005; Segal, 2018) without creating a global unemployment crisis. However, the timescale is the difference between examples of the past and the predictable future with AI. Although changes have occurred over decades, we can now observe rapid and extreme changes in a matter of years (e.g., the emergence of the LLM). Radical changes in labor needs, and the required skills and abilities can occur within the same human generation, possibly even several times. As humans cannot be reprogrammed easily, many can lose their jobs as they are unable to keep pace with technological advancements, causing technological unemployment (Lima et al., 2021). In 2014, research from the OECD countries (Arntz et al., 2016; OECD, 2021) revealed that on average, 14% of jobs were susceptible to automation. Five years later, in 2021, the growth of these jobs decreased. They lost their stability, although the potential worker numbers also decreased. According to Frey and Osborne (2017), the real automation danger can reach up to 47% in the USA in the future, although in a recent revamp of their research, they represent a more conservative standpoint. However, we should not only examine technology-induced labor market changes through dark lenses. Studies have pointed out that technological changes can positively impact the labor market (Mutascu, 2021) by increasing productivity (Al-Emran et al., 2025) and wages, or even decreasing product prices (Noy & Zhang, 2023).

When discussing AI's impact only, extant studies focus on task automation instead of job automation. Thus, whether a specific AI application augments or replaces a particular human task is what ultimately matters (Furendal & Jebari, 2023; Raisch & Krakowski, 2020). This implies that jobs have not ceased to exist. Rather, they are transforming, allowing humans to increase their productivity and concentrate on higher value-added tasks that require more human skills. In recent years, the biggest game changer has been the appearance and democratization of generative AI. Generative AI refers to algorithms trained on large datasets that are capable of generating texts or images. While past technological breakthroughs (e.g., the production line or steam engine) were mostly capable of automating manual jobs, generative AI is now also capable of automating some intellectual jobs (AbuMusab, 2023). Thus, all sectors and levels of the labor market are, to some extent, susceptible to this job transformation. Hence, AI's impact on the labor market is a critical research topic, as it affects all levels of society and the labor market.

Moreover, AI is a type of technology that is not only heavily influencing one's work but also private life. On human-AI relations at work, we cannot separate one's workplace "self" from their personal "self," as AI applications are getting increasingly widespread in all aspects of our lives. Workplace behaviors related to AI are heavily influenced by underlying everyday perceptions about AI, technology phobia at work or in private life, technological understanding and knowledge of AI, and the locus of control over AI (J.

Kim & Im, 2023; Sinha et al., 2020; C. Wang et al., 2023). Conversely, work-related AI perceptions influence general AI perceptions, as human well-being is closely related to job safety (Nazareno & Schiff, 2021). People feel less threatened by AI when they are convinced that AI only replaces dangerous jobs and not theirs. If people work with AI and understand it well, they know that it does not threaten their job safety. Indeed, they can build better trust with technology in general (Albarrán Lozano et al., 2021).

This study advance our understanding of the current societal perceptions towards AI, labor market, and associated societal changes. We have collected a large textual dataset from one of the largest online forums, Reddit. Online forums emerged as platforms for AI discussion more than a decade ago when technology became a potential reality for the public. Concurrently, these began to trigger fears and hopes for the future of work and life (Fast-Berglund et al., 2020; Neri & Cozman, 2020). Forums and, in general, social media have already been used in different studies to measure perception towards COVID-19 (Melton et al., 2021), health-related issues (Jeon et al., 2023), product usage (Singh & Glińska-Neweś, 2022), and other social (Botzer et al., 2022) or political (He et al., 2020) phenomenon and financial market dynamics (Long et al., 2021). From 37 Reddit forums, we have gathered data encompassing more than 100,000 comments about labor market changes with AI to analyze people's perceptions of AI through sentiment analysis and topic extraction using state-of-the-art technologies (bidirectional encoder representations from transformers, or BERT) developed by Google (Devlin et al., 2018; Venugopalan & Gupta, 2022).

5.3 Literature review

As this study discusses AI perceptions over 10 years, we need to recreate, to some extent, the evolution of the scientific standpoint about the future of work with AI over this period, providing sufficient context for later findings. AI-induced changes in the labor market have been studied for decades. Early research in the 2010s mainly focused on predicting the possible modifications that an intelligent machine or algorithm could bring to the labor market, as no tangible technologies were available yet. The general concern about AI's drastic impact on the labor market was already present in these studies, suggesting various measures to keep humans competitive in the long term in the labor market against machines, including restructuring education (Coates, 2016; Crawford &

Calo, 2016; Y. J. Kim et al., 2017), our current economic policy (David, 2017; Dirican, 2015; Harari, 2017), and the way we do business (Allen, 2017b; Garcia-Murilloa et al., 2018).

Today, with the widespread use of generative AI technologies, researchers can conduct more profound quantitative research in the field and, crucially, experience changes firsthand, which has changed the scientific discourse. Before the recent AI breakthroughs, the general perception of the impact of AI on the labor market was twofold: either AI is going to replace all jobs or is not going to change anything, but rather transform the labor market. Most research fully or partially supported one or the other standpoint at the time (although the context changed, partially even today). Complete human substitution theories were rooted in the perception that machines do not sleep, take sick leave, or demand paid leave. They performed tasks faster and made fewer mistakes. Therefore, AI can significantly increase productivity (Su et al., 2022) and significantly threaten human workplaces. The math was simple; substitution generates immediate quality improvement and cost savings in many cases, which are attractive to companies (Fast-Berglund et al., 2020; Ray & Mookherjee, 2022). The substitution of technologies also requires less time and effort to implement than those that collaborate well with human co-workers, as the latter require significantly longer development and design time, adoption, and more costly maintenance. Additionally, workers' adaptation to new market circumstances has human limits in our rapidly changing world (and work). Reeducating employees or hiring new employees with new skillsets requires time and money. Moreover, workers can also show resistance (or an inability to adapt) to changes. Therefore, companies may favor using robots or software that can easily be reprogrammed to execute new tasks more efficiently and in a cost-saving manner, making humans replaceable (Eldakruri & Senyurek, 2025; Korinek & Juelfs, 2022).

Theories on the opposite side of human substitution argue that AI will never be able to completely substitute humans because new machines and products create new jobs for humans based on the assumption that new machines need people (and professionals) to develop them, take care of them, or undertake maintenance and other tasks (Choi & Leigh, 2024; Pianta & Vivarelli, 2000). Additionally, the more we dive into substitution, the more new jobs will emerge on the other side. For instance, AI explainers, who help people understand, say algorithm-based decisions made about their lives (e.g., credit checks), is a job that did not exist before (Saeed & Omlin, 2023; Wilson et al., 2017). Human wage fluctuations can also positively contribute to the preservation of human workforce. Hughes (2014) believed that even if wages decrease due to technology, they will never reach zero; therefore, as long as humans are willing to be employed for that specific low wage, they will be used instead of machines (if the profit and loss analysis works). Conversely, if wages increase because machines make it possible to work more efficiently with lower costs, and human intelligence is used for more value-added (and salary-increasing) tasks, surplus capital will be created in the economy. This can be invested (Allen, 2017) or spent on extra consumption, which will create a place for new demand and workplaces (Jazdauskaite et al., 2021; Upadhyay, 2021), thereby creating a self-enforcing circle.

Technology also enables faster innovation by linking people's minds and sharing knowledge. Furthermore, AI can produce valuable insights. An innovative idea, even if AI-enabled, can lead humans to enhance their entrepreneurship by creating new products or industries. If people can eventually start and succeed with their business ideas, then they would not be forced to entirely rely on the labor market. They can simply become their own employer and the employer of others (Gama & Magistretti, 2025; Jorzik et al., 2024) while also creating social value (Battisti et al., 2022). AI-based product innovation (Cooper, 2024) can eventually create new jobs even in existing companies or industries. Today, with the growing adoption of generative AI technologies, the past 10 years of unknown "scientific guesswork" have moved in a more tangible, empirical direction. Moreover, AI's impact of AI on the labor market has now, in some way, a different outlook. Recent studies have suggested that the reality lies between the two aforementioned theories. AI will subtly change the labor market, softening extreme utopian or dystopian theories. Earlier research has already suggested that digital technologies can cause job polarization: The ratio of highly educated, high-skilled workers to mainly low-skilled and educated workers performing non-routine tasks gradually grows. Meanwhile, middle-skilled workers primarily working in manufacturing, doing clerical, craft, or routine-intensive jobs significantly lose jobs (Goos et al., 2014; Kolade & Owoseni, 2022). We also call this phenomenon skill-biased technical change because the skills of higher- and lower-educated non-routine jobs are increasing in demand. Concurrently, the middle sector of the labor market hollows out.

Job polarization negatively affects the middle sector of jobs because machines can easily substitute for their workflows. These jobs involve predictable, easy-to-describe, and understandable processes that can be translated more easily into machine languages (Frey & Osborne, 2017). As technology advances, the proportion of workplaces at risk of being automated grows as intelligent machines can perform and learn a wider variety of tasks. If it reaches or even exceeds human intelligence, AI will be able to automate most, if not all, of the aforementioned middle-sector jobs. Only jobs that require non-automatable human skills, such as creativity, human intelligence, and social skills, might survive. Empirical research shows that job polarization and/or skill-biased technological change are already occurring in several countries (Bárány & Siegel, 2020; Cavaglia & Etheridge, 2020) and will probably persist in the age of AI. The most significant novelty that current generative AI algorithms bring to the labor market is the shift in predicted job polarization tendencies: generative AI is breaking the walls of the ivory tower of high-skilled workers, who were previously considered unsusceptible to automation. Recent research suggests that new technologies increasingly threaten high-skilled jobs (AbuMusab, 2023; Felten et al., 2023).

Paradoxically, AI skill demand among highly skilled workers is growing, which the labor market cannot fulfil. Therefore, a significant wage premium is associated with AI-related jobs (Alekseeva et al., 2021; Duch-Brown et al., 2022; Hui et al., 2023; Mäkelä & Stephany, 2024), deepening the job polarization effect. Essentially, those who are AI-skilled secure a stronger labor market position, while AI can replace those who are less experienced in AI. A positive trend is that current AI technologies do not aim to replace all jobs. They aim to transform employment; furthermore, AI’s job destruction effect is currently compensated for by its job creation effect (Damioli et al., 2024). First, because even the most intelligent generative AI remains a machine at its core, it cannot obtain purely human skills, such as creativity, social skills (Benvenuti et al., 2023), and empathy. This makes it impossible to completely substitute human workers. Second, AI is more efficient in reinforcing human capabilities (human augmentation) than in actually achieving substitution (Focacci, 2021). Thus, it will not replace humans but rather cooperate with them. A good machine collaborator can perform all mundane or dangerous tasks that people are unwilling to or should not do, and can share new and interesting insights to improve work efficiency. By 2025, 24% of the global gross domestic product

(GDP) will come from AI (Dennehy et al., 2023). Modern generative AI technologies are capable of automating 27 million jobs globally (Gmyrek et al., 2023) and will augment approximately 46 million of them. We can already see that generative AI is used in diagnostics, content creation, academics, education, computer science, and agriculture (Fui-Hoon Nah et al., 2023). Moreover, human-AI collaboration indeed increases productivity in many economic sectors (Sowa et al., 2021).

Although generative AI is capable of improving, for example, the recruitment processes and finding the best candidates for jobs (De Obesso et al., 2023), a human must still make the hiring decision. Although an increasing number of business-to-business (B2B) companies rely on AI-powered sales bots to arrange transactional businesses without human intervention (Frey & Osborne, 2023; Yin & Yuan, 2022), human workers still make complex business decisions. AI still requires human supervision (Downey, 2021), which can increase user trust (Aoki, 2021) in AI applications. If AI needs humans just as much as humans need AI, then the next most significant challenge in the labor market is ensuring that human-AI collaboration occurs such that it benefits both parties. AI must adapt to humans through good design, interface, and built-in security factors (Sanfilippo et al., 2025). Most importantly, humans must adapt to AI, or the discussion will lose meaning.

Human-AI interactions must be carefully orchestrated from a human end user's perspective. Human-AI augmentation can negatively influence human self-esteem, increase feelings of job insecurity (Bhargava et al., 2021), and decrease team performance. This is especially true when humans are faced with the fact that in specific tasks, they can never be as good as machines, discouraging them from striving for excellence (Felten et al., 2023; Flathmann et al., 2023). AI must also be adapted to humans. Generative AI applications are prone to hallucinations (Orchard & Tasiemski, 2023), wherein they can create false information. Worryingly, they can create harmful information, fake news, or cause data privacy issues, potentially misleading or harmfully influencing human counterparts. Creating and retraining AI, especially on representative data, requires enormous capital employment, which only a few countries can afford. This can restrict access to technology, increasing inequality, and negative societal impacts, such as a lack of access to upskilling opportunities to work with AI (Bhargava et al., 2021). AI also has high energy consumption, which increases its negative environmental impact (Frey & Osborne, 2023; Fui-Hoon Nah et al., 2023; Khogali & Mekid, 2023), an important point to consider for all organizations and humans engaging with the technology. Every AI application must deal with the inherent human factor: people trust AI (or machines in general) less than their human counterparts (De Obesso et al., 2023), especially when the stakes are high or the task to be executed is complex (Chang, 2022). When people feel that their jobs are at risk of automation due to new AI technology, they can also manifest resistance to change (Cheng et al., 2023). This resistance can also be triggered when the understanding or trust in the new technology is low (Chiu et al., 2021; Leichtmann et al., 2023), or communication channels with or about AI are restricted or not user-friendly (Flathmann et al., 2023). Human-likeness also influences adoption. Anthropomorphism can trigger the rejection of collaboration in humans if situated in the "Uncanny valley" but can also increase attachment (S. Kim & Lee, 2023). Furthermore, underlying technology phobia is vital for workplace adoption (Sinha et al., 2020).

This research aims to address the question of what people feel and think about AI at work to reveal how the perception of AI and work has changed over the past 10 years. This period encompasses the moment when AI was merely a science fiction topic to today when almost everyone works with AI daily. Undoubtedly, we can assume that AI is present and will remain present in our lives in the long term. AI has (probably?) no special feelings or thoughts about working with us human beings. However, we do; crucially, our perceptions can make or break the success of the next AI-augmented chapter of our human history.

5.4 Research Design: Questions And Methods

We do not seek to understand the labor market changes caused by AI, regardless of whether it is generative or general. We want to understand the perceptions of the studied population regarding AI and the future work. As such, the following research questions (RQs) seek to achieve the objectives of (1) understanding the general perception and emotions of tech-enthusiast online communities towards AI and its impact on the future of work, and (2) studying the most important topics of discussion around AI and the future of work.

RQ1. What are the most interesting topics concerning AI and work in forums?

RQ2. What are the general sentiments and emotions of forumers towards AI and work?

RQ3. What have been the game changers in the past ten years in the eyes of forumers concerning AI and work?

Data collection, data cleaning, and three distinct text analysis techniques—sentiment analysis, emotion detection, and BERT-based topic modelling —were used in the research process, as illustrated in image 7. RQ1 was addressed in the subsection titled “The topics discussed and their associated emotions.” RQ2 and RQ3 were the responses to a discussion of chronological alterations in sentiments and emotions.

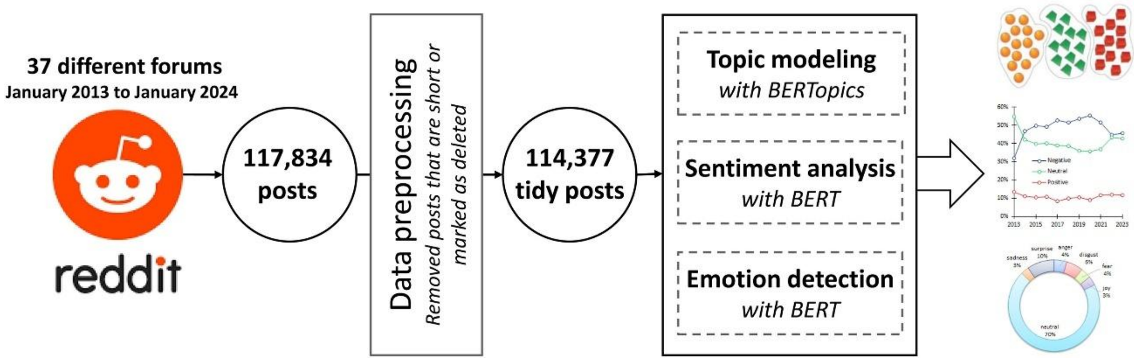


Image 7. *An overview of our research methodology.*

5.4.1 Data collection

Data from social media platforms are often used for topic modeling (TM) and sentiment analysis due to the vast amount of real-time user-generated content on these platforms. Several billion users share their opinions daily on social media (Yadav and Vishwakarma, 2020). 63% of the population with an Internet connection used Facebook weekly, while 23% used it daily1. Social media platforms such as X (formerly Twitter), Facebook, and Reddit offer rich sources of unstructured data that reflect public opinion, emotions, and trends, making them invaluable for understanding consumer behavior, market dynamics, and societal trends.

Reddit was selected as the source for the analysis. Reddit is an online forum where topics are categorized under “reddits.” In 2022, the forum had 430 million users; of those, 47% lived in the USA. Regarding the population, 63% of the users are male, and approximately half of all users, otherwise called redditers, are less than 35 years old. According to a survey conducted in 2021, the majority of Reddit users have a higher education degree. Reddit has, on average, 1.7 billion visitors per month (Sun et al., 2021). According to official Reddit Statistics, 38% of users are intensely interested in technological novelties. These statistics indicate that Reddit is a good data source for our analysis (Aldous et al., 2023). Essentially, we could access the opinion of a population more involved in technology, and therefore, the AI topic than the average person.

This research was exempt from institutional ethical review, as it exclusively analyzed publicly available online content. No personal or identifying information was collected, and the data were processed in aggregate form to represent general discourse patterns rather than individual statements. All materials originated from the public domain, and no interaction with users occurred during data collection or analysis.

We collected Reddit social media data from January 2013 to January 2024 from the subreddits communities associated with "artificial intelligence" or "AI". We identified a list of search terms, such as "artificial intelligence + work/job" or "artificial intelligence + automation", which we used on the Reddit platform to retrieve forums associated with the future of work with AI topic. We used the search terms with and without standard abbreviations, such as "AI". Then, we manually reviewed and filtered the search results to ensure that only forums with relevant discussions were included. If, for example, a forum was asking for help in using an AI application to write a resume for a job application, we excluded it. This is because it concentrated on a special use case and not a general discussion about the implications of AI on the future of work. For forums created after 2022, we paid special attention to exclude any forums that only discussed ChatGPT's special use cases as a standalone topic, such as how to write a good prompt. We included forums on ChatGPT's overall impact on the future of work and trending topics where job transformation in some sectors was discussed. This allowed us to identify industries where generative AI's impact is visible and collect testimonials. Our general guideline was to consider AI and what forum users consider AI. Finally, we only considered reddits or forums with more than 40 comments among the search results to ensure that we have sufficient data per forum. Finally, we selected 37 different forums that were scraped from top-level comments using the Python package PRAW through an API,2 and organized them into one database of 117,834 comments of various lengths. For the data cleaning, first, we deleted the comments labelled "removed" or "deleted," meaning that the user or platform's moderators have unpublished them after posting.

Second, comments that were too short to contribute to our analysis were removed. We decided not to define a character minimum per comment. We instead manually reviewed comments with the lowest character count and filtered out the ones that were only answering a closed question with a "yes," "no," "yeah," or "indeed." This labor-intensive process allowed us to more accurately clean the data. We also deleted comments that were not in English (the specific steps are shown in Appendix Image 14.). Comments were stripped of special characters, URLs, and emojis. Following data cleaning, we conducted TM, sentiment analysis, and emotion recognition on the 114,377 tidy comments.

5.4.2 TM

TM algorithms are a class of unsupervised machine learning techniques (Kherwa & Bansal, 2019) that can discover and understand topics in a collection of documents, where a topic is a set of statistically related words. Determining the number of topics for a TM algorithm presents challenges, as the "correct" number is often not predetermined or explicitly defined. This challenge stems from the unsupervised nature of the methodology. Several algorithms can be used for identifying latent semantic patterns, such as latent semantic analysis (LSA) (Hofmann, 2001) and latent dirichlet allocation (LDA) (Blei et al., 2003). Recently, newly developed algorithms such as non-negative matrix factorization (NMF) (D. Lee & Seung, 2000), Top2Vec, and BERTopic (Grootendorst, 2022) have received increasing attention (Obadimu et al., 2019; Sánchez-Franco & Rey-Moreno, 2022).

These clustering algorithms can evaluated using several metrics. TM solutions have two types within them. First, the intrinsic properties of the clustering result can be compared with the internal cluster validity values, which only consider structural aspects such as the degree of separation of clusters and do not rely on input data. Second, clustering results can be compared by using an external knowledge source, such as a known classification of the document space (performed through traditional content analysis, for example). These are referred to as the external cluster validity values. This study used internal cluster validity values. Scholars (Egger, 2022; L. Liu et al., 2016) typically evaluate their performance using internal clustering values when comparing topic-modeling algorithms. The most commonly used measure is perplexity (Zhao et al., 2021), which compares the theoretical word distributions of topics with their actual distribution. The value is not to be interpreted in isolation; however, the model with the lowest perplexity value is considered better than the other models. The other relevant metrics are word- or document-based topic coherence measures (such as PMI3, CUMASS4), and KL5 topic divergence (Rosner et al., 2014) that aim to distinguish between semantically meaningful topics and the artefacts of statistical inference. Numerous studies have indicated that the PMI exhibits the strongest correlation with human judgment (Lau et al., 2014; Rosner et al., 2014). Recent studies (Egger, 2022) have shown that BERTopic outperforms LDA, particularly for non-long corpora. Additionally, several researchers have strongly criticized the effectiveness of the LDA algorithm (Egger, 2022; Sánchez-Franco & Rey-Moreno, 2022): A document usually has multiple topics and LDA tends to neglect co-occurrence relationships (Jaradat & Matskin, 2019). Another criticism is that it is particularly relevant to noisy and sparse datasets. In such cases, the LDA algorithm is unsuitable owing to the lack of features required for statistical learning (Chen et al., 2019). The NMF algorithm relies on the co-occurrence patterns of words that may miss contextual meanings. Recent research compared the performance of the BERTopic and NMF algorithms on different datasets, and found that BERTopic generally achieved a higher topic coherence score than the NMF algorithm on all datasets, especially noisy ones (Grootendorst, 2022). Considering these criticism, we used the BERTopic solution proposed by extant (Thompson & Mimno, 2020) using a quantized LLM technique (Grootendorst, 2022) to automatically label topics. Our TM approach comprised four steps.

- First, the text was transformed using a pre-trained sentence transformer language model called "all-MiniLM-L12-v2" to obtain a 384-dimensional vector space.
- Second, we reduced these 384 dimensions to optimize the clustering process. Principal Component Analysis is perhaps the most popular method for dimension reduction. We used the uniform manifold approximation and projection (UMAP) method, which better preserves the local and global structure of datasets (Grootendorst, 2022; Thompson & Mimno, 2020). Based on the results of related literature, we used the five nearest neighbors in UMAP to prefer local structures.
- Third, the reduced dimensional embeddings were clustered using the hierarchical density-based spatial clustering of applications with noise (HDBSCAN) algorithm that defines clusters of different densities. This algorithm allows noise to be

modelled as an outlier, preventing unrelated document parts from being assigned to any cluster and improving topic identification. We set the minimum cluster size to 45 to identify topics with a sufficiently large number of comments, thereby increasing the reliability of our method.

- Fourth, to characterize the resulting twenty-three clusters, we combined the comments belonging to the clusters and created topic vectors characterizing the clusters using three different methods: the class-based frequency-inverse document frequency approach (c-TF-IDF6), KeyBERT (Grootendors, 2020; Sammet and Krestel, 2023) extraction technique, and quantized LLM technology. The quantized LLM method was initially employed to refine and improve topic representation (Grootendorst, 2022). Combining BERTopic with quantized LLMs offers a practical and efficient TM method. Quantization is crucial for using LLMs. This involves reducing the precision of the model's weights by assigning smaller approximations, such as 4- or 8-bit values, instead of the original 32-bit floating points. Although accuracy may slightly decline, this approach effectively reduces the model's memory requirements. This study employed the pre-trained language model "OpenHermes-2.5-Mistral-7B-GGUF" and utilized the LlamaCPP (Betlen, 2023) representation model. A prompt is created for the LLM to be used when generating topic labels. These labels were obtained by clustering comments related to each topic.

5.4.3 Sentiment analysis and emotion detection

Sentiment analysis is widely used in academic research and business contexts to classify sentiments expressed in text based on the expressed viewpoints (Adoma et al., 2020; Brett et al., 2019). Researchers can easily access large amounts of textual data for sentiment analysis on the internet, which has become a preferred source for marketing, social, and political studies (Noreen et al., n.d.; Y. Zhang & Zhang, 2022). Existing sentiment analysis techniques can be categorized into three main approaches: lexicon-based, machine-learning-based, and hybrid. Lexicon-based sentiment analysis mainly depends on predetermined dictionaries or lexicons that associate words with sentiment scores (positive, negative, or neutral) without considering the context of the words. This approach has difficulty in capturing negations, sarcasm, or complex linguistic structures which may alter sentiment meaning.

Machine learning-based methods, mainly supervised algorithms, leverage labelled datasets to train models that can classify sentiments. Recent natural language processing advances, such as deep learning models (e.g., BERT), have further enhanced the ability to capture contextual sentiments and offer a more precise understanding of the emotional intensity conveyed in text (Rodríguez-Ibánez et al., 2023). These methods are highly accurate when ample labelled data are available. However, they are computationally expensive and require significant preprocessing. Hybrid approaches combine the strengths of lexicon-based and machine learning methods using lexicons to guide or enhance machine learning models. These methods attempt to address each technique's shortcomings but may still inherit their computational complexity. To perform sentiment analysis and emotion detection, we employed a pre-trained deep learning model called RoBERTa (Y. Liu et al., 2019). Recent studies revealed that RoBERTa consistently outperforms many other techniques in fine-grained emotion classification (X. Zhang et al., 2024). RoBERTa enhances BERT by adjusting essential hyperparameters, including eliminating the next-sentence pretraining target, utilizing larger mini-batches, and increasing learning rates during training. This improvement seeks to improve the model's resilience and efficacy. RoBERTa can be used to compute the anticipated probability of three sentiment categories: negative, positive, and neutral (Barbieri et al., 2021). Additionally, it can determine the prevalence of the eight most frequent emotion categories (joy, confidence, fear, surprise, sadness, anticipation, anger, and disgust) in a given text. To ascertain a given comment's overall sentiment and emotion categories, we identified the sentiment or emotion with the most significant percentage value. We used the "cardiffnlp/twitter-roberta-base-sentiment"7 (Barbieri et al., 2021) trained model for sentiment analysis, and "j-hartmann/emotion-english-roberta-large"8 for emotion analysis.

5.5 The topics discussed and their associated emotions

Next, we present the TM results using BERTopic. This analysis was conducted to answer RQ1: "What are the most interesting topics concerning AI and work among the forums?".

We extracted 23 topics; these are outlined in Table A1 in the Appendix. To represent each topic based on the content of the comments clustered for each topic, an LLM tag and a set of 10-10 keywords defined by KeyBert or c-TF-IDF were defined, as described in the methodology section. After determining the emotions of the sentences associated with each topic, we constructed an emotion map for each topic, as summarized in Image 15. in the Appendix.

Image 8. (a) shows the cumulative percentage of comments by topic. Notably, 87.2% of the comments collected were classified as BERTopic. The most commented topic was Topic 0 (87,347), while Topic 22 (275 comments) had the fewest comments. We examined which comments were not classified (17,494); that is, those identified as noise by BERTopic. These were generally comments containing short emotional expressions, such as "You just won't let logic get in the way, huh?", or specific information the algorithm could not interpret, such as "I'll take option 3, the Star Wars universe!". Image 8 (b) chronologically shows the five most common topics. Topic 1, for self-driving cars, peaked when the first automated vehicle autonomously drove from the west to the east coast of the USA in 2015. Doctors being replaced by AI (Topic 3) became the strongest during the COVID-19 pandemic, proving the importance of the pandemic on perceptions. Universal basic income (UBI; Topic 2) usually strengthens when some countries or states conduct experiments (e.g., the US or Finland). ChatGPT (Topic 4) has gained extreme popularity since its launch in 2022, making it a dominant topic. This demonstrates the influence of "breaking news" on the topics of interest.

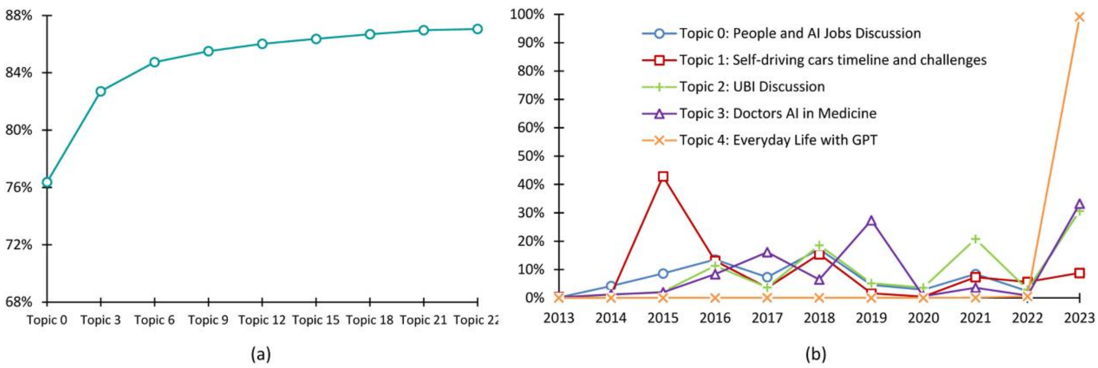


Image 8. *Distribution and temporal trends of topics. (a) The cumulative percentage distribution of posts by topics. (b) Chronological change in posting frequency of the top five most commented topics.*

After analyzing the content and emotions of the 23 topics extracted from the database, we created four meta-topics. As shown in Image 9., the meta-topics are general perceptions about the future of work together with AI; discussions about the economic implications of AI and the future of work; job transformation, which covers all the topics that were related to specific job changes or general labor market changes; and finally, politics and influencers show us topics about the people and cultural items that influence the trending conversations.

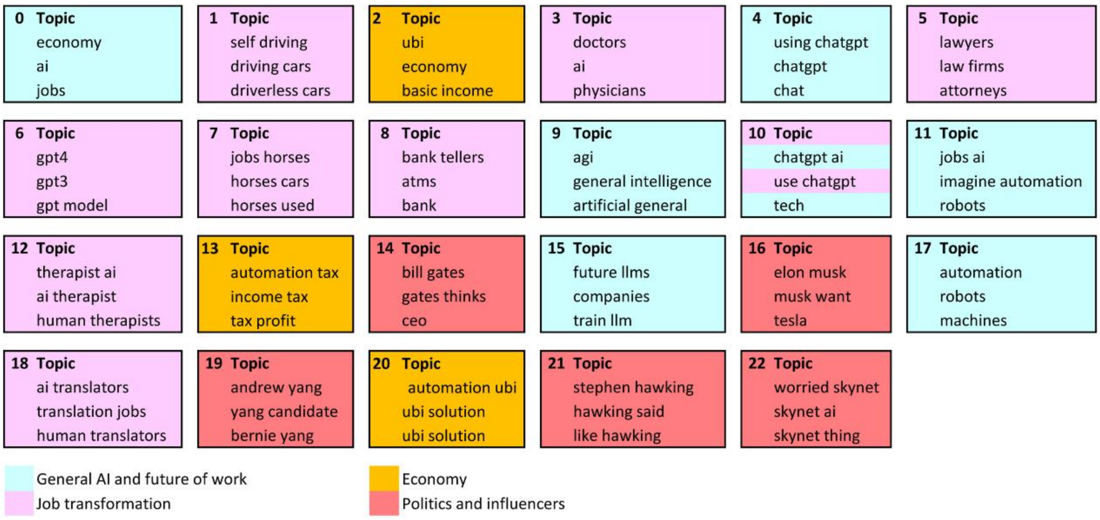


Image 9. *The 23 topics are described using three words chosen by KeyBert. The coloring illustrates the four meta-topics we manually defined, with cyan representing "General AI and future of work", purple representing "Job transformation", gold representing "Economy", and dark pink representing "Politics and influencers" meta-topics.*

Next, we analyzed the emotions linked to the comments categorized under these meta-topics. The results are presented in Image. 10. Next, we elucidate each meta-topic in greater detail, informed by the keywords, LLM labels, and emotions of the 23 topics (see in Appendix).

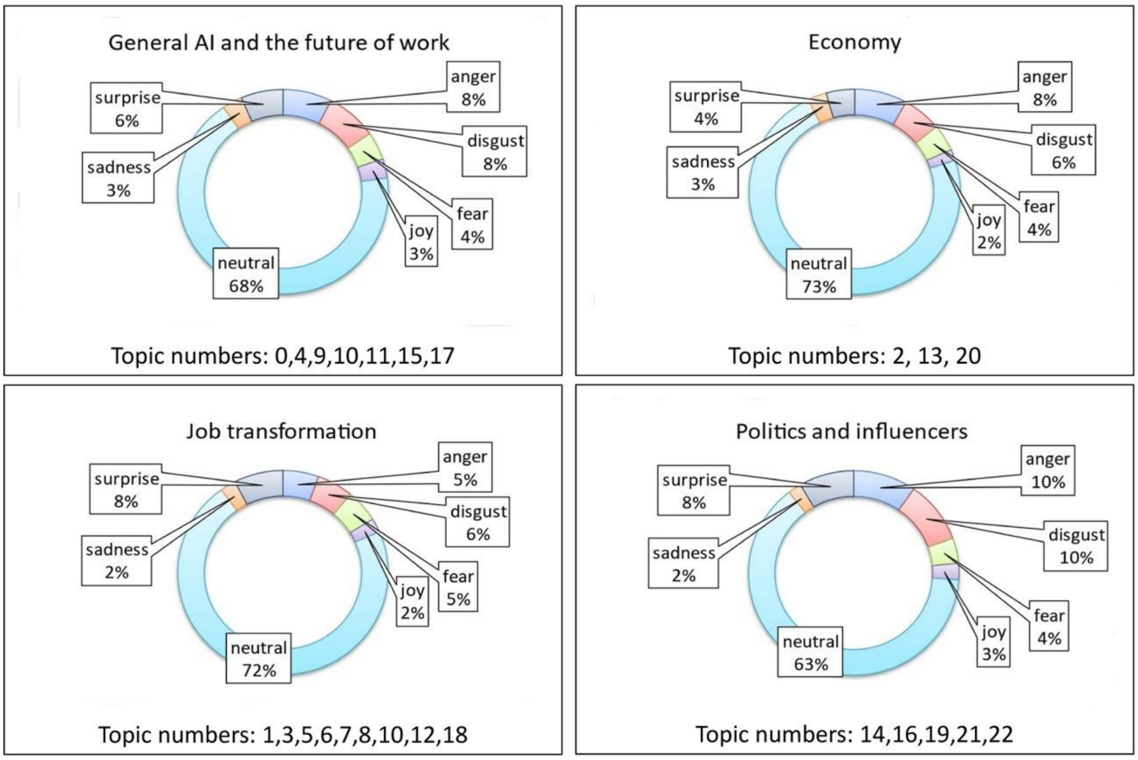


Image 10. *Meta-topics and their combined emotions*

5.5.1 Meta-topics and their combined emotions.

5.5.1.1 Meta-topic: general AI and the future of work

This meta-topic broadly discusses the future of AI and human workforce. Therefore, it can provide a general understanding of the feelings and focus points on the main topic, the future of work (see Image 10.). First, two significant topics (Topics 4 and 15) discuss certain technologies, such as LLM and ChatGPT, which strongly influence the future of work. These topics are generally followed by emotions of surprise (see Topic 4 in the Appendix). While this topic typically praises ChatGPT, strong concerns (design, understanding, and user's level of knowledge) have also been raised. It states that even with a robust tool such as ChatGPT, humans cannot be replaced because it requires human supervision at the very least. Second, some topics (Topics 0, 11, and 17) are generally about AI and the future of work (see Table A1 in the Appendix). They were less optimistic about the outcome than the previous topics, which were primarily concerned with ChatGPT. They were filled with fear, anger or disgust. The general perception is that AI can replace all jobs, and chaos and societal collapse can follow. Humans are not competitive with machines. Further, companies have an economic interest in automation and process improvements, which can lead to complete human replacement. This difference is also reflected in the literature review. Before AI became a reality and more democratized, general perceptions were quite extreme regarding labor market outcomes: either nothing would change, or machines and automation would replace all human jobs. This shift is also confirmed by general perceptions. Newer ChatGPT-related topics are more favorable than older comments, which are somewhat negative and predict a dystopian future.

5.5.1.2 Meta-topic: economy

This meta-topic contains topics related to wealth, income distribution, taxes, and UBI. UBI is a periodic (weekly, monthly, or yearly) given set amount of money whose use is not linked to any conditions. UBI appears twice: once alone (Topic 2) and a second time associated with automation (Topic 20). In most cases, anger and disgust are the most potent emotions linked to the meta-topic (see in the Appendix). Looking closely at the comments, we can see that redditers consider UBI a potential solution to AI and automation, as it is presented as a guarantee for humanity's survival in a jobless future. UBI topics are associated with negative emotions, such as disgust and anger. Forumers generally do not believe in the feasibility of the project, as it would, for example, only enforce work avoidance.

Another topic is taxation (Topic 13) and whether automated companies should be taxed for not using human labor (Gasteiger and Prettner, 2022). Associated keywords include economic and shareholder interests, competition, and profit-seeking. The central discussion concerns a future in which human labor is no longer needed. Therefore, nations should obtain financial resources from consumption, company income tax, or even taxing robots to finance public services and potentially universal basic income.

5.5.1.3 Meta-topic: politics and influencers

The dominant emotions in this meta-topic are mixed (Image 10.). The most anger and disgust-driven topics (Topic 14-Bill Gates, Topic 16-Elon Musk), and most positive (surprise and joy) topics about Andrew Yang (Topic 19) and Stephen Hawking (Topic 21) can also be found here (see Table 10. in the Appendix). These topics are unsurprisingly emotion-driven, discussing the role and impact of Elon Musk and Bill Gates on AI development, and their wealth as influencing powers. US politicians, such as Andrew

Yang and Bernie Sanders, are the most dominant in the dataset, partly explained by the English-speaking audience and many Reddit users living in the USA.

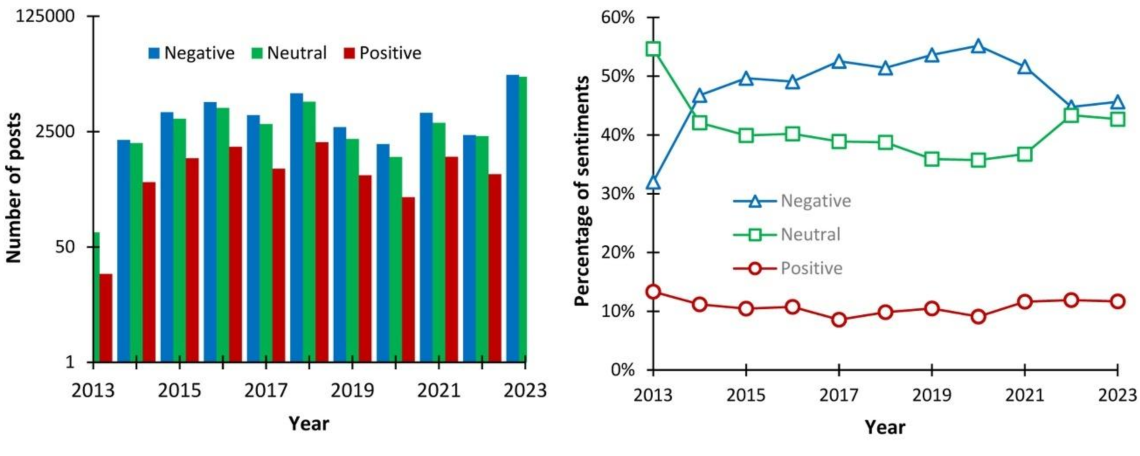
The redditers perceive that AI development hugely depends on technology giants, such as Elon Musk, Bill Gates, and OpenAI, which are also mentioned among the topics, especially in the LLM impact topic. Notably, not only politicians and people in the business sector but also Stephen Hawking, a member of the scientific community, have often been mentioned, especially his vision and understanding of AI. Thus, members of the scientific community who can overcome the barrier of popularity can also substantially influence general perception. We also included Skynet (Topic 22) in this category. Besides real-life influencers, science fiction also plays a substantial role in forums. We found evidence of films, such as Terminator, Star Trek, and Matrix, in the dataset. Previously, when AI was the only subject of science fiction, it was the only source of common AI perception (Cave & Dihal, 2019), and the literature was rarely utopistic about the future of humans and AI. We usually observed representations of maleficent, hostile AI that turn against its creator. Only in some cases do they serve humanity to gain prosperity and peace. Today, when AI approaches reality, people in the Skynet topic are trying to compare what can already be seen with what has been expected through popular culture.

5.5.1.4 Meta-topic: job transformation

This meta-topic deals with job transformation within certain professions, perceived to be the most affected by Al. Some talk about how different jobs, especially intellectual ones, will change, such as doctors (Topic 3), software developers (Topic 6), therapists (Topic 12), and lawyers (Topic 5). This is the topic for which ChatGPT is the most dominant. Another topic (Topic 6) has discussions on generative AI in software coding. Another dive into the topic of humans not needing more human therapists, as generative Al can provide sufficient help and social interaction. One topic is about how ChatGPT is used as a work aid, although we carefully removed all forums that only dealt with the practical workplace implications of ChatGPT from our database. Next, a topic (Topic 18) is on the future of translators. A job that many considered very human, as the understanding of culture and context is associated with it, can now be accomplished through generative AI. Interestingly, only a few topics concerned job replacement in poorly educated jobs. One topic (Topic 1) briefly discusses replacing drivers (trucks or taxis), which is strongly linked to the more prominent topic of the development of self-driving cars. Another mentions that bank tellers and cashiers (self-checkout) are being automated. This category is dominated by highly educated jobs, which can either be explained by the population of redditers or by the fact that these are jobs that are traditionally considered challenging to replace, and any technology attempting to do so often gets more publicity. Further, one topic (see Topic 7 in Table A1 in the Appendix) is about a well-known analogy of human workforce replacement: the story of horse replacement over the last century. Horses have been used in all aspects of life for several hundreds of years. They were essential partners of humans in war, transportation, everyday manual work, and leisure activities. Nowadays, their role in human society is reduced to racing, leisure activities, and occasional labor. In France, for example, the total horse population since the 19th century fell to a third (Rzekęć et al., 2020) due to the changes in utilization. Forumers believe that humans can end up like horses, being entirely replaced in the labor market by intelligent technological innovations, such as AI, thus exhibiting a rather negative future.

5.5.2 Chronological alterations in sentiments and emotions

Next, we present the sentiment analysis and emotion detection findings to answer RQ2: “What are the general sentiments and emotions of forumers towards the topic of AI and work?”. Image 11. shows the RoBERTa sentiment analysis results. The overall attitude of the 37 forums were negative.

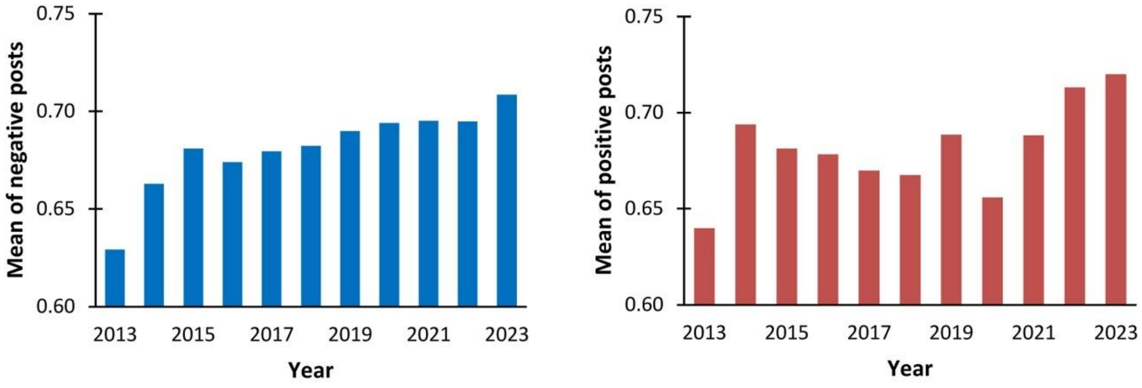


(a) (b)

Image 11. RoBERTa sentiment analysis results. (a) The number of posts (comments) and their sentiments chronologically. (b) The overall sentiments of all posts (comments), shown chronologically.

Among emotionally driven topics, two changes in the negative trend are observed: First, from 2019 onwards, when the COVID-19 pandemic hit the world (decrease); and second, from 2022, from the release of ChatGPT 3 (slow increase). ChatGPT's impact can also be observed in the sharp rise in the number of comments that appeared in 2023, immediately after its launch to the public.

The proportion of positive attitudes remains relatively stable over time. Both negative and positive emotional intensities peaked following the launch of ChatGPT in 2023 (Image 12.). During the COVID-19 period, negative emotional intensity remained stable, positive emotional intensity increased. However, the ChatGPT launch impacted both. A RoBERTa emotion analysis was also conducted to understand the emotions underlying these sentiments and draw more accurate conclusions. Image 13. shows the results over the years grouped by negative and positive sentiments (see in the Appendix). This analysis does not consider comments with neutral sentiments. Our two focal points, namely, the COVID-19 pandemic and the release of ChatGPT 3, triggered significant changes in particular emotions.



(a) (b)

Image 12.*Changes in sentiment intensity during the years. (a) The change in the mean values categorized as negative sentiment using RoBERTa over ten years. (b) The change in the mean values classified as positive sentiment using RoBERTa over ten years.*

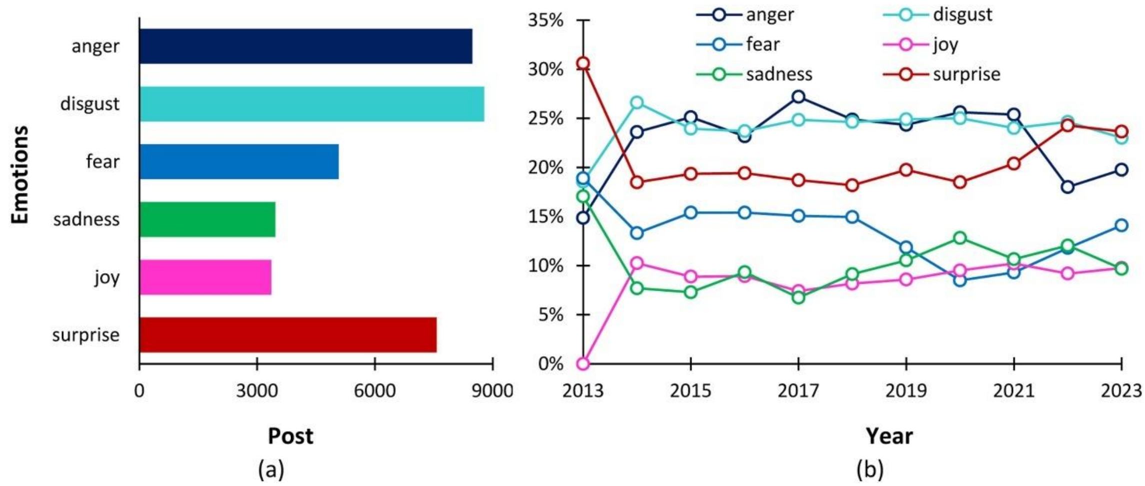


Image 13.*BERT emotion analysis results. (a) The number of posts (comments) and their emotions chronologically. (b) The overall emotions of all posts (comments) chronologically.*

5.5.3 The COVID-19 impact on emotions

We observed that 2019, the starting year of the COVID-19 pandemic, marked a drop in "fear," which only started to increase again after the pandemic. We also observed a gradual increase in positive emotions. "Surprise" began slowly rising, while no significant change in "joy" happened during the pandemic. Simultaneously, "sadness" and "anger" began increasing. These results may be explained by the fact that when the global pandemic hit society, we witnessed the acceleration of digitalization in several domains, such as education, e-commerce (Gryaznov, 2022), and workplace management (Kniffin et al., 2021). It promoted remote work, and helped in re-evaluating the role of humans and technology in the labor market. Many workplaces were forced to accelerate the deployment of digital tools, which served as both work aids and tools of surveillance (Aloisi & De Stefano, 2022). There were high hopes that advanced technology would help humanity find the cure faster with technologies such as AI. Simultaneously, digital tools were also used to monitor the propagation of the virus and home office activities to impose quarantine measures. This, according to some, harmed the liberty of human (Chettri et al., 2020; Ting et al., 2020).

5.5.4 The ChatGPT impact

ChatGPT 3 was released by OpenAI at the end of 2022 and has shaken the world of AI. This was the first publicly available, robust generative AI model. These trends were also reflected in the subreddits. ChatGPT related forums, though they can only represent less than 2 out of 10 years of this study's scope, are the second most significant source of comments (see Table 9. and Image) and the only central forum where positive emotions ("surprise") dominate. In 2023, the number of comments on AI and work-related forums significantly grew (see Image 11.) due to the appearance of ChatGPT. In the sentiment and emotional analyses, the arrival of ChatGPT entailed an immense increase in "fear" and "surprise," and a trend change in "anger," which slowly decreased after the pandemic and began increasing again in 2022.

Table 9. Name of the Reddit forums with the highest number of comments and their emotions.

Name of the Reddit forum	Number of comments	The most dominant non-neutral emotion
Futurology	85,068	Anger
ChatGPT	10,820	Surprise
Worldnews	4,960	Disgust
Technology	4,223	Disgust
Capitalism vs Socialism	1,113	Anger

Given that Reddit users are usually young and have at least a college education, we can conclude that this is the first AI technology that could shake the world of this population. Previous automation technologies usually affected the work of the population with lower education, such as taxi or camion drivers (self-driving cars), manufacturing line workers (robotization), and shop assistants (self-check-out). This led the conversation to a very theoretical and birds-view level, mostly discussing political, economic, and social impacts. With the arrival of ChatGPT, the jobs of the highly educated population were endangered for the first time, which changed the perspectives of redditers. Moreover, while neutral comments' proportion remained stable during the years, a considerable increase was observed from 2022. Thus, the conversation moved to more "fact-based," given that they no longer had to guess or predict the impact of AI on work. Rather, they were experiencing it first-hand.

5.6 Discussions

Individuals' work and private selves cannot be distinguished. Their attitudes, perceptions, fears, and expectations outside work strongly influence their adaptability and perceptions of AI at work. AI and the future of work are widely discussed on Reddit. Subreddits like "Futurology," which is one of the primary used sources in AI-related forums, is the 34th9 biggest community on Reddit. Thus, a general curiosity regarding this topic exists. ChatGPT's emergence has put the future of work even more in the spotlight, demonstrated by the rapid increase in ChatGPT-related forums in the past year, and sharp increase in the number of AI-and job market-related comments since 2023. ChatGPT-related forums are the second most significant data source in our dataset, although they only represent just a little more than one year of the study period.

We have shown that the general perception of AI and on job-related forums is mostly negative towards the future of work. Emotionally, we observe a present fear and anger towards Al and the future of work. A textual analysis of the comments showed that people are not only afraid of the possible labor market outcomes, potentially losing their jobs, income, or place in society, but also fear and vividly discuss the broader implications of AI, as demonstrated by the topic extraction. The impact of job transformation on the economy, politics, and society is discussed in detail. These were also the most emotionally driven topics. General emotions are neutral and negative, mostly indicating disgust and fear. Moreover, modern-day influencers highly affect perception: politicians (primarily US-based), popular culture (Star Trek, Terminator, etc.), and, to some extent, scientists. Consequently, the media strongly influences people's attitudes (Nader et al., 2022). Additionally, the chronological analysis of topics revealed that certain "breaking news," such as the first autonomous car crossing the US, inflated the number of comments. Conversely, although sometimes not fact-checked, Internet resources also increasingly influence general perceptions (Nader et al., 2022). We also found traces of social media and YouTube channels in the forums. Undoubtedly, forums such as the one we studied, Reddit, also influence perceptions. When an in-depth understanding of a technology, such as AI, is low, it is easy to make people believe anything, good, or bad, which can create impossible expectations or unrealistic fears.

While the general AI perception of the future of work is negative, the current ChatGPT perception is quite positive primarily based on the general surprise at the capabilities of generative AI. ChatGPT was democratized quickly, allowed people to gain first-hand experience with technology and its capabilities, and created realistic expectations about workplace implications (Bain & McCay, 2024). Accordingly, analyzing the topics revealed that the most dominant subjects are possible task replacements, with almost no mention of complete technological unemployment, as opposed to the general AI topics mentioned before. Forumers believe that generative AI will make their jobs easier and lower career entry barriers. AI will always need supervision and human interaction to work correctly, which will not make people susceptible to automation, but rather transform how they work, potentially in a good way. These findings align with those of recent studies indicating that, while humans typically regard AI as an advanced technology capable of societal progress, apprehensions around job displacement and ethical considerations are prevalent among forum participants (Ocal & Crowston, 2024; Savela et al., 2024).

Interestingly, redditers discussed the potential job transformation or replacement of highly educated jobs: doctors, lawyers, software developers, educations/teachers and professors, translators, and therapists. The latter's perceptions have already been examined in detail (Aktan et al., 2022).This dominance can be attributed to several factors. First, the population of the forumers: As mentioned above, they usually belong to high(er)ly educated societal classes, meaning they are more concerned with the risks to their jobs than others. Second, these were traditionally deemed irreplaceable jobs, as they required human characteristics. Doctors and therapists need social skills and empathy; lawyers need to master persuasion and reasoning; coders need to understand humans to create software for them; translators need to understand humor, culture, and context; and finally, teachers need the most human skills among all of them to educate other humans from a very young age. For years, we have witnessed the automation of low-educated jobs such as manufacturing jobs, robotics, and self-service. However, with recent generative or general AI development, the highly educated jobs' intense "Ivory Towers" were penetrated. Still, they can still only be automated partially. This is consistent with the concerns raised in other studies, where respondents anticipated that AI could lead to worldwide job displacement, especially in regular or repetitive work (Rose Paran et al., 2024).

Education has been moving towards increasingly digital solutions since the COVID-19 pandemic (Gryaznov, 2022). Robust generative AI algorithms can already perform translators' jobs. The diagnostic work of doctors can be performed more effectively and precisely with AI (Dvijotham et al., 2023). With a basic programming language understanding and prompt writing, with some exaggeration, many can create programs today using generative AI (J. Liu et al., 2023). This can replace software developers. These changes in the status quo certainly interest many forumers, regardless of whether they are affected, and are often represented in media outlets. This does not mean that less-educated jobs were not mentioned. As presented in the Results section, topics such as self-driving cars (driver automation) and mention of bank tellers or cashiers (self-check-out) were replaced by machines. Additionally, we could often find instances of discussion about robotization in manufacturing. However, their focus was on intellectual job automation.

When examining sentiments and emotions, we found two main events that changed the dynamics of emotions: the COVID-19 pandemic and release of ChatGPT. The pandemic showed that humans cannot be entirely replaced. In addition, some professions, such as those of essential workers, are more in need than before. Concurrently, it was also a moment of social deprivation and, to some extent, surveillance imposed by technology, which negatively influenced AI perceptions. The pandemic has brought about negative and positive changes in sentiments and emotions: AI has become both the savior and oppressive power, changing from the beginning (hopeful) to the end (deprived) of the pandemic. ChatGPT has also brought about ambiguity in emotions, but on a much broader scale. A massive increase in positive emotions and sentiments was dominated by surprise and simultaneously increased the fear brought about by job replacement/transformation. Our findings are comparable with those of recent research (Ocal & Crowston, 2024), which found that general attitudes towards the impact of AI on work are slightly positive, with curiosity being the most expressed emotion.

Implementing an AI solution in the workplace is a complex challenge from a technological perspective, let alone when we add a human component to the equation. Perceptions are brought from "home" from the external environment and injected into the work environment. Company employees who experience general fear and anger with themselves are likely to resist AI. We could observe that people fear losing their jobs, their humanity being exploited, and sinking into an economic crisis. A detailed investigation of the forums revealed concerns about housing crises, the increasing retirement age, overpopulation, and environmental issues. Companies need to be clear about the goals of using Al applications: Which jobs will be replaced and which ones will be augmented. They need to prepare plans for handling employees who need to change the required job scope skills, participate in further re-education, or be laid off. People need to voice their need for skills, knowledge, and infrastructure to governmental organizations and companies to create policies to protect the human workforce, and avoid negative impacts on society and the economy. However, excessive trust in AI can lead to negative consequences. People are generally surprised by the capabilities of generative AI technology, such as ChatGPT, and have high expectations. However, moderating these expectations is essential. Many technologies are as innovative as their users. Correct prompt writing skills are needed to effectively utilize these tools. People must be trained in data privacy, copyright, and data reliability issues (e.g., when the tool was trained the last time, or the danger of Al's hallucinations). Additionally, which tasks can be automated by AI, to what extent, and who is responsible for validating the AI work need to be clarified. Employees should not accept anything from generative AI as the ultimate truth. While some forumers believe that generative AI is the end of human critical thinking and creativity, we believe it is the opposite. It has never been more important to approach technology from a critical perspective.

5.7 Limitations and future research perspectives

First, we only used Reddit as the data source. Future research can consider other social media platforms to overcome the limitations imposed by Reddit's demographics. The results can also be compared with a survey to reveal to what extent social media distorts public perception. Second, we only examined top-level comments, encompassing the ones that received the most appreciation from the community. The platform did not allow us to scrape unmoderated content (comments deleted by the user or by admins). Considering all comments can potentially provide more depth to the analysis. However, for this, the researcher must actively follow and scrape certain daily reddits. Finally, although we have tried to gather all relevant reddits in the past almost ten years, some were undoubtedly missed or needed to be ignored due to the few comments they received. Social media is a formidable tool for mining public perceptions. However, it also has a "hype effect": only topics deemed interesting by the end users or topics about everyone having an opinion can rank first and receive enough contributions to be worthwhile examining. This can narrow down the perspective of studies.

Conclusions

We examined a large dataset of 100,000 top-level comments from 37 Reddit forums where users talked about how AI may change the labor market. We examined sentiments and emotions towards the AI-induced labor market changes and performed a topic analysis using BERT. We found four dominant meta-topics: job transformation by AI, general AI topics about the future of work, economy, and politics, and influencers (RQ1). Forumers equally like to discuss how AI is transforming professions in general and individually (e.g., doctors and software developers), and AI's long-term economic and social implications. US politicians, technological company owners (e.g., Bill Gates and Elon Musk), popular culture (e.g., science fiction), and, to some extent, widely popular scientists (e.g., Stephen Hawking) strongly influence the discussions. ChatGPT has drastically transformed the discussion of topics. Forums related to generative AI have a very high volume of comments. Moreover, their associated emotions show intense ambiguity: strong anticipation and surprise but also increasing fear.

Next, we observed generally negative sentiments towards the upcoming and already existing labor market changes driven by the development of AI technologies in the past ten years (RQ2). To better understand sentiments, we conducted emotional detection. Disgust, anger, and surprise (primarily associated with ChatGPT) were the most dominant emotions. At the emotional level, we found two game-changers in the forums: the COVID-19 pandemic and release of ChatGPT. In the topic analysis, the most critical game-changer was the arrival of ChatGPT. While representing only one year of the 10-year study, the topic was the second most significant source of comments (RQ3).

5.8 Credit authorship contribution statement

Szabina Fodor: Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. Bettina Boncz: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization

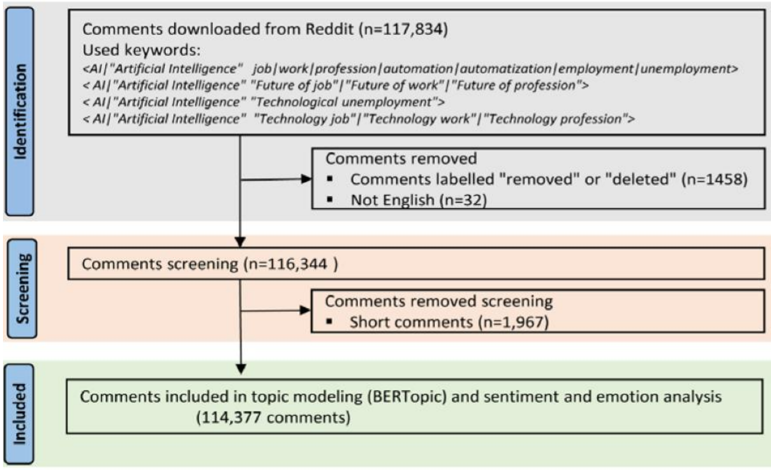
5.9 Data availability statement

Data files are available upon request.

5.10 Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

5.11 Appendix A. Supplementary data



(a)

Forum	Number of posts
Futurology	85,068
ChatGPT	10,820
Worldnews	4,960
Technology	4,223
CapitalismVSocialism	1,113
Changemyview	964
Singularity	943
TooAfraidToAsk	751
AskReddit	645
Technews	545
Documentaries	500
Badeconomics	492
AusFinance	483
4chan4trump	432
Sysadmin	286
Aww	284
ArtificialInteligence	213
WFH	173
Careerguidance	160
ChatGPTPro	158
PoliticalDiscussion	148
OpenAI	138
SelfDrivingCars	113
Cscareerquestions	107
Computerscience	92
Collapse	82
Foodforthought	82
Libertarian	75
Compsci	62
DarkFuturology	55
AskTrumpSupporters	51
AskAnthropology	46
Automate	44
Conspiracy	33
NoStupidQuestions	19
NEET	17
Total	**114,377**

(b)

Image 14. *The empirical data. (a) The precise steps for selecting the Reddit posts included in the analysis. (b) Distribution of Reddit posts across forums.*

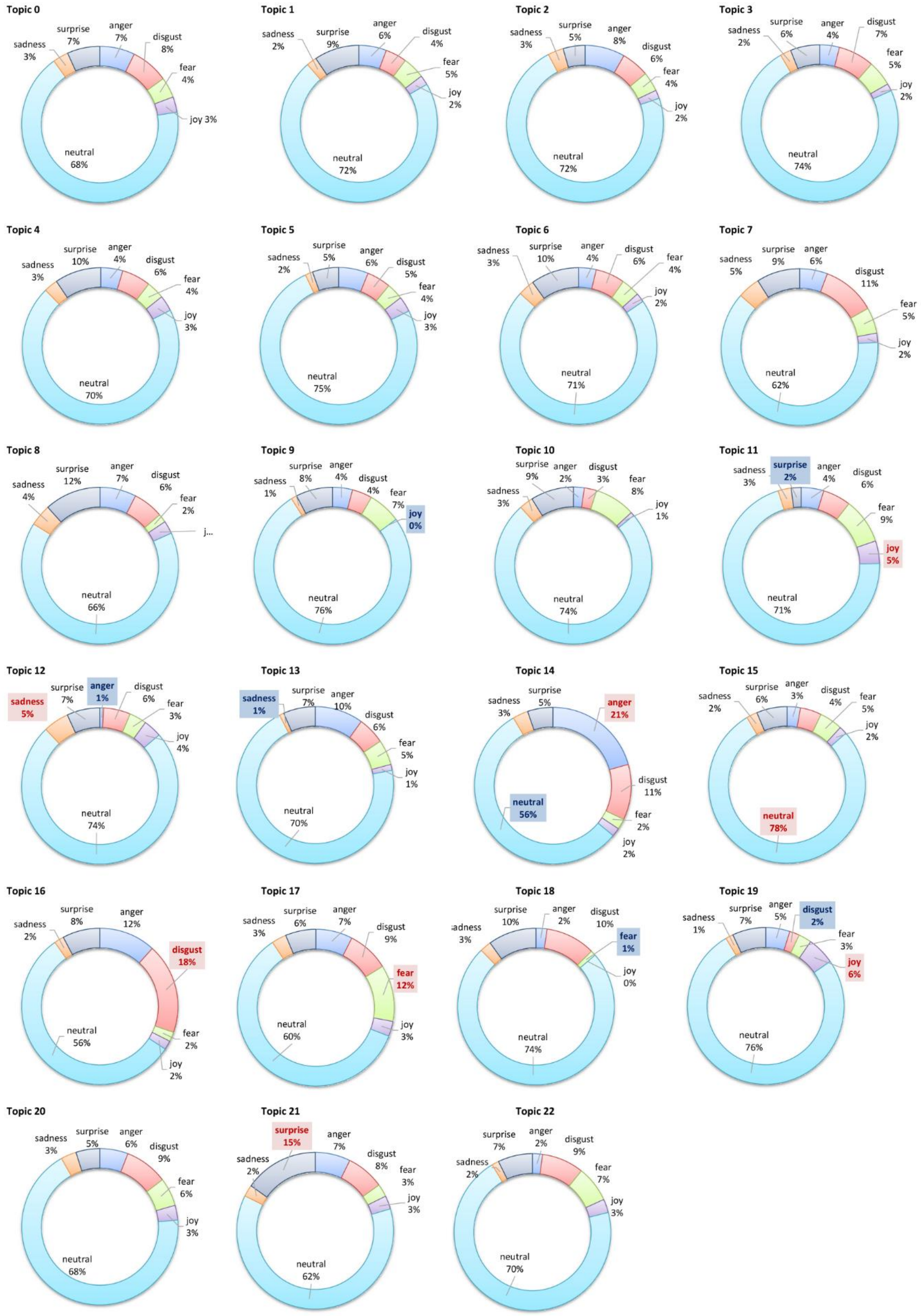


Image 15. *The emotional distribution of comments by topic. For each emotion, the lowest proportion is shown on a blue background and the highest on a red background.*

Table 10. Topic modeling resulted in 23 topics. The extracted topic labels (LLM), the 10 most important keywords of BeyBert (KeyBert) and c-TF-IDF. (Source: Prepared by the authors)

Topic	LLM	KeyBert	c-TF-IDF	Meta-topic
0	People and AI Jobs Discussion	['economy', 'jobs', 'workers', 'capitalism', 'automation', 'job', 'machines', 'robots', 'working', 'pay']	['people', 'ai', 'jobs', 'would', 'like', 'think', 'get', 'time', 'need', 'one']	General AI and future of work
1	Self-driving cars timeline and challenges	['self-driving', 'driving cars', 'driving car', 'driverless cars', 'vehicles', 'driving', 'cars', 'drivers', 'driverless', 'drive']	['driving', 'cars', 'car', 'truck', 'self-driving', 'self', 'drivers', 'trucks', 'drive', 'would']	Job transformation
2	UBI Discussion	['ubi', 'ubi would', 'economy', 'basic income', 'capitalism', 'income', 'welfare', 'job', 'corporations', 'workers']	['ubi', 'people', 'would', 'money', 'get', 'income', 'like', 'need', 'tax', 'pay']	Economy
3	Doctors AI in Medicine	['doctors', 'ai', 'physicians', 'medical', 'physician', 'medicine', 'doctor', 'healthcare', 'patients', 'patient']	['doctors', 'doctor', 'ai', 'medical', 'patient', 'patients', 'medicine', 'human', 'would', 'people']	Job transformation
4	Everyday Life with GPT	['using chatgpt', 'use chatgpt', 'chatgpt', 'like	['chatgpt', 'gpt', 'chat', 'code', 'use', 'chat gpt',	General AI and future of work

		chatgpt', 'chat gpt', 'chat', 'gpt', 'jobs', 'job', 'coding']	'like', 'using', 'write', 'know']	
5	AI and Lawyers	['lawyers', 'lawyer', 'law firms', 'law firm', 'attorneys', 'ai', 'attorney', 'paralegals', 'litigation', 'law']	['lawyers', 'law', 'lawyer', 'legal', 'ai', 'case', 'would', 'court', 'cases', 'human']	Job transformation
6	GPT4 and Coder Replacemen t	['gpt4', 'gpt', 'gpt gpt', 'use gpt', 'using gpt', 'gpt3', 'gpt model', 'chat gpt', 'chatgpt', 'tech']	['gpt', 'gpt4', 'code', 'use', 'chatgpt', 'even', 'using', 'like', 'models', 'know']	Job transformation
7	Horses and Cars	['jobs horses', 'horses cars', 'horses used', 'horses', 'horses horses', 'replace horses', 'horses humans', 'horse', 'horseless', 'horse population']	['horses', 'horse', 'cars', 'humans', 'jobs', 'people', 'jobs horses', 'new', 'car', 'better']	Job transformation
8	AI, Jobs, and Education	['bank tellers', 'tellers', 'bank teller', 'teller', 'one teller', 'atms', 'banking', 'bank', 'banks', 'go bank']	['bank', 'tellers', 'teller', 'atm', 'banks', 'elon', 'atms', 'people', 'bank tellers', 'banking']	Job transformation
9	Utopian fear of AGI	['agi', 'agi could', 'agi would', 'ai agi', 'agi asi', 'general intelligence', 'asi', 'ai', 'artificial general', 'intelligence']	['agi', 'ai', 'human', 'would', 'intelligence', 'even', 'think', 'like', 'could', 'humans']	General AI and future of work
10	AI short-term Job	['chatgpt ai', 'chatgpt', 'use chatgpt', 'chat gpt', 'ai', 'ais', 'artificial	['chatgpt', 'ai', 'chat', 'jobs', 'gpt', 'chat gpt',	General AI and future of

	Market Impact	intelligence', 'tech', 'chat', 'bot']	'people', 'like', 'going', 'data']	work/ Job transformation
11	AI jobs automation future people	['jobs ai', 'ai', 'imagine automation', ’canada', 'ai going', 'ai automation', 'automation', 'robots', 'prevalent robots', 'tech']	['ai', 'jobs', 'people', 'going', 'think', 'job', 'get', 'new', 'like', 'future']	General AI and future of work
12	AI Therapy	['therapist ai', 'ai therapy', 'ai therapist', 'therapy ai', 'therapist', 'therapy', 'real therapist', 'human therapists', 'therapists', 'think therapy']	['therapist', 'therapy', 'therapists', 'ai', 'human', 'mental', 'mental health', 'people', 'health', 'ai therapist']	Job transformation
13	Tax Automation and Income Distribution	['automation tax', 'taxing automation', 'tax automation', 'taxation', 'tax', 'taxes', 'automation takes', 'income tax', 'automation', 'tax profits']	['tax', 'automation', 'taxes', 'money', 'pay', 'jobs', 'would', 'income', 'fish', 'automation tax']	Economy
14	Bill Gates Wealth and Impact	['bill gates', 'mr gates', 'gates thinks', 'gates allegedly', 'ceo', 'bill', 'gates said', 'microsoft', 'gates', 'gates wants']	['gates', 'bill', 'bill gates', 'people', 'would', 'money', 'think', 'time', 'like', 'going']	Politics and influencers
15	LLMs in AI Development and Usage	['future llms', 'llms', 'like llms', 'llm', 'train llm', 'companies', 'tech', 'ml', 'ai', 'models']	['llms', 'llm', 'openai', 'models', 'ai', 'think', 'data', 'use', 'people', 'like']	General AI and future of work

16	Elon Musk opinions and roles	['elon musk', 'musk want', 'like musk', 'musk', 'musk creating', 'elon', 'tesla', 'like elon', 'robot', 'creating robot']	['musk', 'elon', 'elon musk', 'like', 'people', 'companies', 'business', 'make', 'said', 'musk creating']	Politics and influencers
17	Automation Jobs Humans Thinking Machines Future	['automation', 'robots', 'automated', 'machines', 'automate', 'ai', 'robotics', 'robot', 'technology', 'future']	['automation', 'people', 'jobs', 'automated', 'going', 'human', 'think', 'humans', 'get', 'years']	General AI and future of work
18	Translation and AI Impact	['ai translators', 'translation jobs', 'human translators', 'machine translation', 'translator', 'bulk translation', 'translators', 'translation world', 'ai', 'google translate']	['translation', 'translators', 'translate', 'ai', 'machine translation', 'google translate', 'translations', 'language', 'translator', 'languages']	Job transformation
19	Andrew Yang's UBI	['andrew yang', 'yang candidate', 'bernie yang', 'yang ubi', 'sanders yang', 'yang', 'yang sanders', 'yang seriously', 'yang 2020', 'yang really']	['yang', 'andrew', 'andrew yang', 'bernie', 'candidate', 'sanders', 'like', 'ubi', 'think', 'really']	Politics and influencers
20	Universal Basic Income and Automation	['automation ubi', 'ubi automation', 'ubi implemented', 'ubi solution', 'ubi', 'need ubi', 'ubi would', 'automation',	['ubi', 'automation', 'people', 'would', 'jobs', 'need', 'could', 'tax', 'automated', 'workers']	Economy

		'full automation', 'automated']		
21	Hawking and Understanding	['stephen hawking', 'hawking said', 'hawking', 'like hawking', 'hawking economist', 'theoretical physicist', 'physicist', 'einstein', 'scientist', 'scientists']	['hawking', 'stephen', 'stephen hawking', 'field', 'physicist', 'hawking said', 'listen', 'said', 'like', 'scientist']	Politics and influencers
22	Skynet Concerns	['worried skynet', 'skynet ai', 'skynet thing', 'fucking skynet', 'skynet', 'need skynet', 'next skynet', 'mean skynet', 'skynet would', 'interns ai']	['skynet', 'interns', 'internships', 'ai', 'intern', 'us', 'like', 'get', 'time', 'replace']	Politics and influencers

6 CONCLUSION

6.1 Answers to the Research Questions

The first research question of this thesis was how scientific and online public discourses reflect perceptions of artificial intelligence–induced labor market transformation.

RQ1: How do scientific and online public discourses reflect on perceptions of artificial intelligence–induced labor market transformation?

My research has found that AI can indeed disrupt the labor market, but not necessarily as dramatically as expected before narrow artificial intelligence became a reality.

The labor market is in constant, dynamic change, accelerated by the fast-paced technological development of the 20th-21st century (and by the COVID-19 pandemic's digitalization efforts).

The literature review indicates that humanity has previously experienced transformative technological revolutions and consistently restored equilibrium in the labor market. While merely a century ago approximately 90% of the population was employed in agriculture, today this figure is only around 2%, while unemployment rates have remained stable (Segal, 2018).

Between 1980 and 2007, significant workplace expansion was largely attributable to the emergence of new job categories, most of which were intellectual in nature, computer technologies created so far more jobs, than what they destroyed.

A similar adjustment is anticipated in response to the advent of artificial intelligence; however, the scale and speed of change are expected to surpass those of earlier technological disruptions. Specifically, the effects of AI on the labor market are likely to materialize more rapidly—within a single generation—and influence a broader spectrum of workers.

Initial scientific discussions – before the emergence of generative AI applications - regarding artificial intelligence tended to polarize around two distinct scenarios concerning its impact on the labor market. On the one hand, some argued that AI would never attain human cognitive capabilities and, as a result, would not substantially alter labor market dynamics. On the other hand, others contend that AI could eventually match or surpass human abilities, thereby causing significant disruption, rendering human workers less competitive, and leading to widespread technological unemployment across society.

Some estimates suggest that, in the latter case, up to 47% of jobs could be diminished (Mitchell & Brynjolfsson, 2017), which would affect countries around the world to markedly different degrees (e.g. Norway at 6% and Slovakia at 33%), potentially resulting in the loss of millions of jobs globally.

Public perceptions frequently converge on similar themes but predominantly anticipate negative consequences. 70% of the examined Reddit conversation from before the emergence of generative AI showed negative emotions, predominantly anger and disgust.

There was a prevailing belief on the forums that economic imperatives would drive companies to favor the employment of robots and artificial intelligence over human labor, given their superior efficiency and lower cost. This sentiment parallels historical instances, such as the displacement of horses by mechanization, where humans are perceived as gradually losing their ability to earn a livelihood. Consequently, these views are often accompanied by concerns regarding potential economic and societal decline, with negative emotions commonly associated with AI-driven transformations in the labor market.

Prior to the widespread adoption of generative artificial intelligence, scientific and public discussions largely envisioned full automation as affecting primarily the middle sector of the labor market, which comprises moderately educated workers such as service employees, cashiers, and those employed on manufacturing lines. This phenomenon, known as job polarization, is characterized by the relative strengthening of both the lower and upper segments of the labor market, while the middle segment declines. Job polarization has been observed during recent technological disruptions and is attributed to the comparatively straightforward automation of tasks prevalent in middle-sector occupations—tasks that are readily translatable into machine language and thus more easily automated. In contrast, the lower and upper sectors of the labor market typically include intellectual professionals, researchers, social workers, artisans, physicians, and nurses, whose roles demand advanced social or manual skills that are inherently challenging for machines to replicate.

Since the democratization of generative AI began, scientific discourse has shifted: researchers have begun to realize that AI is not only about people losing or keeping their jobs. The most recent scientific papers show that the real impact of artificial intelligence lies in the human augmentation-automation paradigm (Bankins et al., 2024a; Frey & Osborne, 2024; Furendal & Jebari, 2023; Raisch & Krakowski, 2020; Terziyan et al., 2026), where augmentation refers to the human-AI coworking, where AI serves to augment human capabilities, and automation refers to the scenario where AI replaces tasks previously performed by humans.

Recent studies have shifted their focus from job loss to the transformation of work tasks. It is now recognized that every occupation comprises elements that can be either augmented or automated. The emergence of artificial intelligence enables both individuals and organizations to reassess which tasks are best performed exclusively by humans, entirely by machines, or through collaborative human-machine interaction to achieve the best possible outcome and efficiency.

Even though there are already discussions about the creation of artificial intelligence agents that are capable of communicating and autonomously operating (van Esch, 2026), at the moment, most of the AI usage is limited to human or task augmentation. AI rather takes over mundane, routine tasks, which take time and amusement out of the daily work, and allows human workers to work more productively, with a better work-life balance and even an increased well-being and job satisfaction (Alkarmo et al., 2026; J. Liu et al., 2026; Onorio et al., 2026; Pinho et al., 2026; Shawaqfeh et al., 2026; Vuong, 2026; T. J. Wu et al., 2025; Zaki & Fahad, 2026). For the first time in the history of technological shocks, artificial intelligence will be able to impact all sectors of the labor market, challenging the job polarization theories.

Recent shifts in public discourse have led to notable changes in perceptions of artificial intelligence. Online forums dedicated to AI now exhibit a more optimistic outlook, with individuals expressing anticipation sentiments about forthcoming advancements and being impressed by the technology’s capabilities. Negative sentiment heavy comments ratio dropped from 70% to around 50%. Tasks previously considered unattainable for automation or augmentation—such as software development—are increasingly being accomplished through artificial intelligence. Consequently, these discussions have become more grounded in empirical evidence rather than speculative ideas or emotional responses. However, new concerns have emerged, including apprehension about the potential automation of highly skilled professions that were previously deemed impossible.

Recent studies indicate that the risk of automation has decreased to approximately 27% (OECD, 2023), and scientific discourse has shifted from estimations of job loss to assessments of job transformation and skillset restructuring. It is expected that around 39% of currently used skill sets in the labor market will be transformed before 2030, implying that 59% of the workforce will require retraining or re-education in the near future (World Economic Forum, 2025).

RQ2: What risks does AI pose to the labor market, and what strategies can address them?

Despite the potential advantages, creating a work environment where humans and AI can collaborate seamlessly can be challenging. Several factors can hinder or support AI adoption in the labor market.

Foremost among the challenges is the development of interfaces that enable humans to interact with and collaborate with artificial intelligence. It is imperative for developers and user experience designers to achieve an optimal balance between human-like qualities and machine aesthetics, while tailoring interface design to the specific requirements of each application. Artificial intelligence systems should be structured to motivate human workers toward peak performance, without fostering internal competition between humans and machines. Furthermore, AI must deliver transparent, easily interpretable outcomes and recommendations to support trust. Before deployment, it is essential to delineate roles and responsibilities, ensuring that ultimate decision-making authority remains with human collaborators and that, if needed, machine suggestions can be completely ignored. Additionally, a clear legal framework is necessary to define and allocate responsibility between users and developers.

Additionally, individuals need to develop a certain level of trust in AI to facilitate adoption. Besides trust, individual perceptions and digital/AI literacy also highly influence the quality and the outcome of the human-AI collaboration (Bankins et al., 2024). Employees' trust level towards the technology (Goyanes et al., 2026), is grounded in their personal and professional beliefs. If the individual does not trust AI at home, they will never trust it at work either. Individuals engaged in tasks characterized by high risk or significant responsibility may encounter considerable challenges in establishing trust in artificial intelligence systems, as they are likely to exercise greater caution before delegating critical decisions to AI-based solutions (Agostino et al., 2026).

AI errors, hallucinations, and a lack of transparency in the decision-making process can also hinder the development of trust in AI among human users (Narbaev et al., 2026), as they tend to portray AI in a rather negative light.

Besides trust, human coworkers also need assurance that the machine is not there to “steal” their jobs, but rather to supplement their work efforts (Cao et al., 2025). Stealing a job can not only mean replacing a human and automating all tasks, but can also mean the imitation of human intellectual property (S. Liu et al., 2025), where AI intentionally or unintentionally re-trains itself on human coworkers’ knowledge and input, which is later eventually claimed as their own.

To facilitate effective collaboration with artificial intelligence—a technology capable of emulating human appearance and behavior, and potentially even acquiring rights akin to those of humans—it is imperative to address safety, ethical, and moral considerations. The establishment of internationally recognized guidelines governing the development and deployment of AI is essential to ensure that artificial intelligence remains confined to its designated functions and does not adversely affect individuals or destabilize societal structures. It is crucial to maintain AI systems as unbiased, responsible, and subject to human oversight, including the ability to be deactivated. As mentioned in the introduction, regional initiatives to develop AI regulatory frameworks are already underway; however, the optimal approach would be to harmonize these frameworks globally while accommodating cultural, legal, and practical variations specific to local contexts.

The scientific discourse on biased and unrepresentative AI has persisted since the early adoption of machine learning algorithms, as highlighted in the second article (Boncz & Szabó, 2021b). The shortcomings observed in earlier machine learning systems appear to be repeated rather than corrected in contemporary AI applications (Nzobonimpa, 2026). Mitigating overreliance on technology, maintaining human supervision, and prioritizing human-centered AI design over fully autonomous systems remain critical considerations (Bankins et al., 2024b; Behl et al., 2026).

A further critical consideration regarding artificial intelligence pertains to its environmental footprint. While early discourse surrounding AI seldom addressed this issue, it has since garnered substantial international attention. The deployment of AI systems is associated with significant energy demands and notable environmental consequences, encompassing the production of hardware and datacenters as well as the energy required for computational processes and the (re)training of algorithms (C.-J. Wu et al., 2022). Within the current environmental context, achieving efficient AI designs to decrease the negative environmental impact remains crucial (J. Wu et al., 2026).

An essential component of successful artificial intelligence integration is comprehensive preparation. This encompasses the reskilling and retraining of the workforce, reforming educational systems to enhance AI literacy from an early age, and revising labor and economic policies to safeguard employee rights and human interests. Furthermore, it is imperative to implement measures that prevent the emergence of AI monopolies, ensuring that no single nation or corporation attains unilateral control over the technology.

Additionally, it is advisable to examine the influence of AI perception leaders to facilitate the dissemination of accurate information, establish realistic expectations, and empower individuals to make informed decisions in the evolving AI landscape while preserving their human values (Pepple & Muthuthantrige, 2026).

Human adaptability will be challenged more than ever. AI will impact all levels of the labor market, including low-, middle-, and high-skilled workers. As technology advances rapidly, humans not only have to develop new skills and deepen their knowledge, but also do so quickly and continuously. While past technological changes changed the required skills in the labor market over generations, we will now see changes several times within the same generation. We need to encourage employees to be curious, use the technology to their advantage, and focus more on and more on skills, which are impossible to automate, everything that makes us human: empathy, social skills, the ability to evaluate complex situations within a certain cultural, human setting.

Artificial intelligence can only conquer the labor market if we forget what makes us human.

6.2 Theoretical contribution

This thesis advances scholarly discourse by synthesizing scientific and public perspectives on the impact of artificial intelligence on labor market dynamics. The first two articles present a systematic review of over 200 scientific articles and corporate reports, each addressing future projections of AI-driven changes in employment. Notably, the majority of these works were produced prior to the widespread adoption of artificial intelligence technologies and, as such, employ methodologies that extrapolate from previous technological disruptions—including the advent of personal computers, the rise of Industry 4.0, and the implementation of decision support systems—to anticipate the effects of the impending AI revolution. With the democratization of AI, this research incorporates the most recent publications, culminating in a comprehensive review published in 2025. This analysis offers a broad overview of the literature from the preceding decade and elucidates the evolution of scholarly attitudes, which have shifted from notions of complete automation and/or negligible impact to frameworks emphasizing AI-enabled human augmentation in the labor market.

Furthermore, this thesis demonstrates that, over the past ten years, the security and ethical considerations surrounding artificial intelligence have remained consistent within the scientific community. The anticipated risks, limitations, and hazards identified before the democratization of AI persist as central concerns and continue to be addressed in contemporary research and debate.

The principal theoretical contribution of this thesis lies in its comparative analysis, comparing the findings of the literature review with a substantial online dataset capturing public perceptions. This approach reveals a notable alignment between the general concerns of the broader public and those articulated by the scientific community during the examined period.

6.3 Methodological contribution

The present thesis employs an advanced sentiment and topic analysis algorithm developed by Google, known as BERT. We used two specialized applications of BERT, namely RoBERTa for sentiment analysis and BERTopic for topic modeling. At the time this document was published, the application of this methodology within scientific literature remained limited. BERT enables comprehensive analysis of textual data by considering the full context rather than relying solely on word- or sentence-based approaches, which may overlook syntactic structure and the author's overall intent.

This methodological innovation facilitated the generation of a nuanced and accurate assessment of the emotions and thematic content present within the analyzed textual dataset.

6.4 Policy contribution

This thesis emphasizes the necessity for international collaboration across all sectors of the economy to effectively address the multifaceted impacts—both advantageous and adverse—of artificial intelligence on the labor market and society at large.

Artificial intelligence transcends national boundaries and poses considerable challenges for country-level regulation, particularly given that AI development is typically concentrated in several global hubs while its application remains unrestricted worldwide.

The primary recommendation of this thesis is to ensure that educational policies are continuously updated to align with advancements in AI. Such alignment is vital in equipping all generations to effectively utilize and benefit from AI, as well as to resist its potential negative consequences, such as manipulative uses of AI-generated content. Educational initiatives should commence at the primary level and extend throughout adulthood via ongoing education and retraining. Given the rapid pace of technological change, it is also imperative to emphasize individuals' responsibility to remain curious and critical of emerging technologies.

A secondary recommendation is directed toward corporations and governments. As AI transforms both professional and personal spheres, prudent policy and corporate strategies must facilitate labor-market transitions that benefit society and individuals alike. Transparency regarding these changes is essential, enabling individuals to understand how their work is evolving and to make informed decisions about their future employment opportunities, especially when AI significantly disrupts jobs.

The final recommendation pertains to security and ethical considerations. While no technology is entirely fail-safe, AI—given its profound influence on work and daily life—must be designed to maximize security, ethical standards, and representativeness. To ensure AI serves its users positively in the long term, such safeguards should be integrated into development from the outset, ideally guided by internationally recognized standards and cross-border collaborative efforts. We should also aim to make not only AI use but also AI development more evenly distributed across countries worldwide, to avoid the creation of AI monopolies.

6.5 Limitations

The present thesis is subject to several notable limitations. Firstly, as outlined in the introduction, the research commenced in 2019, preceding the widespread accessibility of narrow artificial intelligence to the general public. Consequently, the majority of the literature reviewed is informed by analogies drawn from historical technological disruptions, which are projected onto the anticipated effects of artificial intelligence.

Despite three years since the introduction of ChatGPT, comprehensive empirical analyses of the overall influence of artificial intelligence on the economy and labor market remain scarce. Existing studies predominantly focus on specific sectors, rather than providing a holistic assessment.

A further limitation pertains to the empirical investigation conducted using Reddit data. The dataset spans a decade, during which artificial intelligence was largely conceptual for eight years, with user perceptions primarily rooted in emotions and ideas rather than direct experience. Only approximately two years of data reflect actual engagement with AI applications, and these insights are largely influenced by early adopter domains, such as translation services.

Additionally, the Reddit dataset is inherently biased. Reddit's user base is predominantly English-speaking and United States–based, and it exhibits a comparatively high interest in emerging technologies. Consequently, it does not capture the overall perception of artificial intelligence and the future of work among the general population, but rather represents only a specific subset of it.

6.6 Final remarks

In conclusion, this dissertation demonstrates that artificial intelligence is reshaping the labor market in ways that extend beyond purely technological or economic mechanisms, it encompasses social dimensions as well.

Through the analysis of large-scale online discourse of the past decade, the study shows that collective interpretations, expectations, and narratives play a significant role in how AI-driven labor market transformations are understood and framed.

It highlights that public discourse does not merely reflect underlying developments in the labor market but also actively participates in shaping them by influencing attitudes, preparedness, and institutional responses.

The scientific discourse of the past decade has also been reviewed, illustrating how early concerns regarding full automation (or, conversely, strong confidence in market mechanisms preventing technology-induced unemployment) have gradually evolved into a more empirically grounded examination of labor market transformation. This shift is characterized by increased attention to changes in skill requirements, task-level automation, and the augmentation of human labor through artificial intelligence.

The findings underscore that the consequences of artificial intelligence should be conceptualized not only in terms of job displacement or creation, but also in terms of skill transformation, adaptation processes, and evolving forms of human–machine collaboration. Accordingly, the labor market impact of AI is best understood as a multidimensional process in which technological capabilities interact with institutional structures and societal perceptions.

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