Unveiling the impact of digital transformation: a study on key disciplines, technological unemployment, and neo-Luddism in the textile industry

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Abstract

Purpose – The primary aim of this study is to identify and analyze the key digital transformation areas and determine their impact on technological unemployment in the textile sector. In addition, this study explores whether digital transformation contributes to neo-Luddism or Robot Breaking.

Design/methodology/approach – The advent of digital transformation has raised significant concerns, particularly concerning technological unemployment. This study focuses on conducting an analytical hierarchical process (AHP) analysis to determine the impact of different disciplines within digital transformation on technological unemployment. The investigation specifically delves into the ongoing transition to Industry 4.0 within the textile industry. This study uses a mixed-method approach, consisting of a literature review, bibliometric analysis, eight expert phenomenological interviews, and AHP.

Findings – This study revealed that artificial intelligence, machine learning and deep learning are the most crucial disciplines that will affect the concept of neo-Luddism. The fact that technological unemployment in the textile sector is examined with AHP Analysis makes this study unique.

Originality/value – This study contributes to Industry 4.0 literature by examining the nexus of technological unemployment in textile manufacturing and the emergence of neo-Luddism.

Keywords Industry 4.0, Neo-Luddism, Technological unemployment, Digital transformation, Textile manufacturing, Analytical hierarchical process (AHP)

Paper type Research paper

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Introduction

The development of technology has accelerated, especially with the functioning of the internet on digital platforms. Digital transformation continues to change how people live, work and interact (Marzano, 2020). For this reason, it is essential that every sector, including the public and global representatives of the real sectors, produce and discuss policies (Garmann-Johnsen *et al.*, 2018). It is commonly believed that the first four phases of the Industrial Revolution were facilitated by the employment of steam engines, electricity, digitalization and information in all fields, particularly production (Hopkinson *et al.*, 2006). A profound digital transition occurred in the most recent process, generally recognized as the fourth industrial revolution. Based on Industry 3.0, this technique integrates with a process that evolves into a physically, digitally and biologically complex structure. Hence, the fourth industrial revolution is not merely a continuation of the third; it must be viewed as the emergence of a brand-new and distinct revolution with a focus on knowledge and social welfare. This is because the process is unique regarding speed, scale and systemic influence. Due to its breadth and depth, as well as its management and even governance philosophy, it permits a greater variety of analyses at the current level (Komlos, 1998). Technological and digital advancements attract an optimistic, pessimistic, biased and impartial audience (McKusick, 2007). Technology-induced change can be viewed as an external force over which humans have no influence. While this external power brings some negativities, especially the policies implemented by the public can stabilize the situation. In this respect, the technological unemployment discussed in this study reveals a differentiation between white- and blue-collar workers in the grip of digital transformation. This differentiation contains essential messages to policy practitioners, real sector representatives and white- and blue-collar workers (Lima, Barbosa, *et al.*, 2001).

In Industry 4.0, the understanding that emerged with technological and digital transformation is that the technologies that enable change are the components of the transformation. However, in this study, they are considered as the criteria that cause technological unemployment. In addressing the practical concerns surrounding Industry 4.0, numerous studies have examined the factors that facilitate or hinder its implementation from various perspectives. For instance, a Delphi-based study of AlMalki and Durugbo (2023) investigated the critical institutional factors that both promote and impede Industry 4.0 in the context of education reform. The study advocates gathering insights from diverse stakeholder groups, such as technologists, to address technological unemployment in future research on prospective economic systems (AlMalki and Durugbo, 2023). In addition, the study recommends conducting further research using various analytical methods, including qualitative cross- and within-case analyses (AlMalki and Durugbo, 2023).

Despite past research focusing on identifying the problems and challenges associated with Industry 4.0 in various contexts, there is a need to examine its implementation in other sectors, such as the textile industry, and to use alternative analytical methods. Further investigation into the impact of Industry 4.0 on technological unemployment is also warranted to enhance understanding of the concepts, challenges, problems and analysis techniques involved (Sahu *et al.*, 2023). This can be achieved by examining this relationship through various methods and techniques. Accordingly, this study incorporates analytical hierarchical process (AHP) analysis into the research framework to explore how the main disciplines of digital transformation will affect technological unemployment and their weights as the textile industry transitions to Industry 4.0. When searching on the Web of Science, selecting "all fields" and searching for the words "AHP," "Unemployment" and "Textile," one result is found. The result is obtained by running the structured query language at Web of Science: "((ALL = (textile)) AND ALL = (ahp)) AND ALL = (unemployment)." This result forced us to make a bibliometric analysis of technological unemployment, independent from the sectors using the

"((TS = (Technology) OR TS = (Digital)) AND TS = (Unemployment))" query statement. Furthermore, based on previous research, a bibliometric analysis of employment, technological and digital transformation, and Industry 4.0 is needed within the Web of Science framework to identify the most intensively and recently studied unemployment-related topics (Sahu *et al.*, 2023). This study bridges this gap in the Industry 4.0 literature and responds to the call of ref to further investigate the Industry 4.0 field from different perspectives and methods.

On the contrary, in the study, the opinions obtained from the eight participants in the phenomenon are used within the AHP. The results obtained with the AHP method are also parallel to those revealed by the bibliometric analysis. The fact that the obtained data are evaluated using two different methods and the results are compared with two different outputs indicates that the study uses a mixed methodology. At the beginning of the 19th century, Luddism movements were expressed as machine-breaking and may show themselves as neo-Luddism movements against robotic approaches if they reach an insurmountable point. The concern that people will become mechanized, robots will take over their jobs and all kinds of developing technology will replace them in working life brings along technological unemployment (Alonso, 2022). Moreover, it is foreseen that the situation will turn into structural chronic unemployment, increasing the effect of technological unemployment and expanding new technical and digital approaches (Minard, 2007).

In the past, advocates of Luddism, a workers' movement that arose due to technological advancements and mechanization to substitute machine power for human effort, argued that they would be unemployed. However, the evolving conditions, newly created jobs and economic changes have shown that these concerns are unfounded. Currently, similar worries exist for Industry 4.0. The exploration of Luddism involves various perspectives, ranging from a broad examination of technology's overall influence on societal intellect to in-depth discussions of key debates within the antitechnology movement (Carter and Yang, 2023). More specifically, there is a recognized need for comprehensive research on Luddism to unravel its multifaceted impact on different types of technology across various industries (Lubrano, 2023). Despite the importance of understanding Luddism's implications, there remains a significant gap in comprehending the intricate interplay between Luddism, technological progress and unemployment in the textile industry. This study faces the formidable challenge of deciphering the specific aspects of technological advancements that contribute to job-related difficulties.

This research focuses on the textile industry, which experienced the onset of the first industrial revolution, marked by the widespread use of steam engines. Following the literature review, a short bibliometric analysis was carried out, and then semistructured interviews were conducted by eight experienced experts in the textile industry; hence, the transformation components were weighted. In the discussion section, the effects of the findings on neo-Luddism are debated.

Literature review

This part will conduct a brief literature review on industrial 4.0 components and technological unemployment, followed by a bibliometric analysis of the same issue.

Industry 4.0 and employment issue

In the past century, the contribution of technique and technology to the industrial revolution has been outstanding, both the spread of the mass production approach brought by the previous century, the analysis of semiconductor technology after the two world wars, and the use of digital transformation, especially in the defense industry, in the life of human beings, social, economic, it has led to political, legal and environmental changes and even transformations (Barreto *et al.*, 2017).

Owing to technology and digital transformation, production efficiency will increase, industrial expansion will be promoted as economies advance, and businesses and regions will eventually become more competitive (Rüßmann *et al.*, 2022). However, some literature accepts that technological unemployment will increase beyond given efficiency, whereas others argue that reforms will occur in the unemployment structure. It is understood that there will be problems with employment. In that case, the answer to the question of which of these technology components will affect employment more effectively should be sought. In this case, it is necessary to express the subcomponents of digital and technological transformation. (Duman and Akdemir, 2021). The use of the components in the real economy will shape employment. It is a separate issue that affects blue-collar or white-collar workers more. However, from the perspective of entrepreneurs, because the weighted number of employment-oriented blue-collar workers in the textile sector is blue-collar, the participants in the analysis were informed that they should respond by thinking more about blue-collar workers. The reason for this is, for example, in the studies conducted in the province of Izmir, which has an essential place in Türkiye's textile sector, it is seen that 83 blue-collar workers are working against 17 white-collar workers (Karakitapoğlu *et al.*, 2017). Therefore, unemployment is thought to have a priority effect on the blue-collar. On the contrary, it is a sensitive situation that the primary source of Luddism uprisings is blue-collar, "working-class" workers (Navickas, 2005).

Data integrity, twinification (Digital Twin), artificial intelligence (AI), machine and deep learning, blockchain, virtual reality/augmented reality/mixed reality/extended reality, internet of things/internet of humans/internet of everything, three-dimensional printers and cybersecurity are accepted as the main components of technological and digital transformation. These criteria are taken from different studies on an Industry 4.0 basis and listed in Table 1.

Table 1 depicts the components of the Industry 4.0 discipline. The elements have impacts on the social and economic side. For instance, AI, in addition to the other parts of digital transformation and unemployment, is argued, and both positive and negative impacts have been analyzed. Although there are authors who state that unexpected scenarios can be

Table 1. Components of Industry 4.0

References	Criteria
Barreto *et al.* (2017); Sung (2018); Schroeder *et al.* (2016); Bagheri *et al.* (2018); Wanasinghe *et al.* (2020); Wanasinghe *et al.* (2020); Tao and Zhang (2017); Thomas *et al.* (2017)	Data integration (horizontal and vertical integration)
Bagheri *et al.* (2018), Wanasinghe *et al.* (2020), Tao and Zhang (2017), Thomas *et al.* (2017)	Twinification, digital twin
Hao *et al.* (2020), Lu (2019), Dubey *et al.* (2020)	Artificial intelligence
Diez-Olivan *et al.* (2019), Goh *et al.* (2021), Qin and Chiang (2019), Cioffi *et al.* (2020)	Mc and deep learning
Krishnan *et al.* (2022), Lohmer *et al.* (2022)	Blockchain
Damiani *et al.* (2018), Roldán *et al.* (2019), Havard *et al.* (2019)	VR/AR/MR/XR
Lin *et al.* (2019), Nedelkoski *et al.* (2019)	IoT, IoH, IoE
Chong *et al.* (2018), Fox and Subic (2019), Montes (2017)	3D printers
Moudoud *et al.* (2021), Yaacoub *et al.* (2022), Ervural and Ervural (2017)	Cyber security

Note: VR = Virtual Reality; AR = Augmented Reality; MR = Mixed Reality; XR = Extended Reality; IoT = Internet of Things; IoH = Internet of Humans; IoH = Internet of Everything; 3D = Three-Dimensional
Source: Created from (WoS, 2022) with different queries by the authors

encountered (Frank *et al.*, 2019), there are also studies stating that technological and digital transformation will provide advantages (Spyros, 2017), as well as research that draws more radical conclusions (McClure, 2018).

In the textile sector, some studies are optimistic that there will be no problems with new business areas and business transformation (James, 2019). On the contrary, employment in the textile industry has factors other than technology, implying that the priority may differ (MC, 2002).

Neo-Luddism and digital transformation

On the other hand, as Luddism was initially seen at the beginning of the 19th century, neo-Luddism could be generated with the new era of digital transformation (McKusick, 2007). The main idea behind neo-Luddism is almost the same as Luddism, but neo-Luddism includes also white-colored employers. This is because the new technology could be oriented and adapted to decision-making processes (Wu and Chen, 2017). Neo-Luddism is a contemporary movement opposing rapid technological development, citing concerns about job losses, growing inequality and environmental threats (Alonso, 2022). Advocates argue that technology concentrates power, exploits workers, and harms the environment. Examples include resistance to AI due to job displacement and opposition to technologies like self-driving cars over fears of congestion and pollution (Wu and Chen, 2017). Neo-Luddites foresee job losses through automation and AI, increased societal inequality and environmental harm from unchecked technological progress. (McKusick, 2007). This prompts reflection on the ethical use of technology for the collective good.

Methods and analysis

The study conducted a bibliometric analysis, then a phenomenological, semistructured interview was conducted with textile industry leaders (eight businesspeople with at least 15 years of experience in the sector), and AHP analysis was performed. The bibliometric analysis emphasizes the originality of the work. The data collected with the opinions of each participant using the phenomenological method were combined in the AHP analysis to weigh the digital transformation components that cause technological unemployment in the sector. While performing the AHP analysis, the mixed data were calculated using the geometric mean method and treated as input for AHP.

Bibliometric analysis

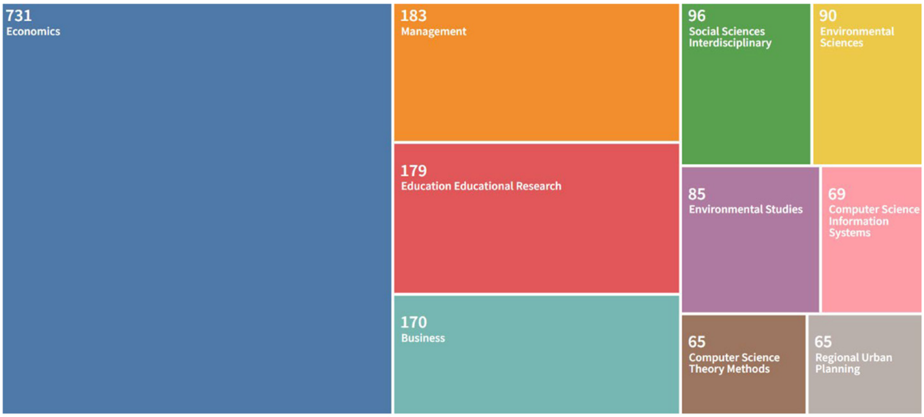
On the contrary, when a bibliometric analysis is made on the concepts of employment, technology and digital transformation, Industry 4.0 in a study conducted under Web of Science, a result, as in Figure 1, is obtained. Figure 1 shows that AI is the most intense and recently the most studied topic in unemployment-themed topics. This is in line with the result of this study. The *query* is as follows:

$$((TS = (Technology)\ OR\ TS{=}(Digital))\ AND\ TS = (Unemployment))$$

where TS refers to Topics, the query's output is 2,157 results (Web of Science, 2023). Figure 1 shows a general distribution of the query in terms of subjects.

According to the Tree Map Chart Analysis of the Web of Science, shown in Figure 1, over one-third of the 2,157 studies are about Economics.

A number of the studies related to the *query.* Web of Science displays that (Web of Science, 2023), the number of studies has increased during the last decade. Just 2022 has a bit less than 2021. In the previous five years, almost 200 studies were held yearly.



Source: Web of Science (2023)

Figure 1. Tree map of the Web of Science output on the *Query*

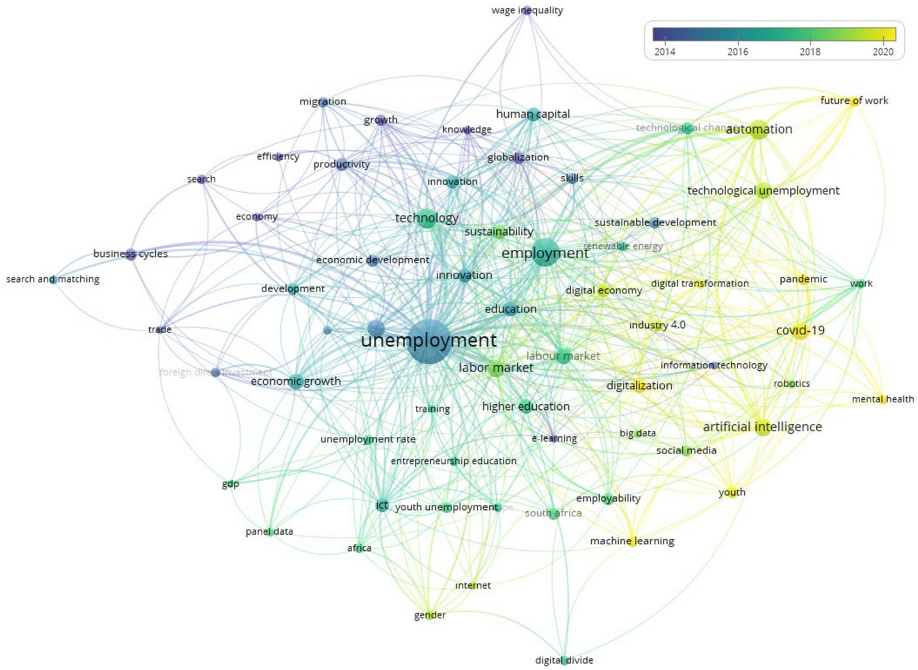
When the whole data is exported as a tab-delimited file and run in the VOSviewer program as the minimum number of keyword occurrences is 10, the program gives 5,620 keyword analyses, of which 66 met the threshold. Figure 2 shows the overlay visualization of the network graph. There are 533 links, and the total link strength is 1,068 under eight clusters.

According to Figure 2, AI and machine learning, the components of Industry 4.0, have been widely studied recently. Industry 4.0 itself has also been studied in the near past. However, the internet, social media and e-learning big data subjects are examined earlier than Industry 4.0, AI and machine learning.

When the bibliometric analysis is done on the keyword's technology or digitalization and unemployment terms, it is seen that technological unemployment has created a very intense field of study in recent times, and the keywords related to technological unemployment form a cluster (mainly at clusters 5 and 6). As listed below, no clusters include the textile sector but general concepts such as Industry 4.0, automation, and the future of work.

The cluster included the following keywords, given below:

- Cluster 1: ten items (Africa, digital device, employability, Europe, GDP, gender, information and communication technology, internet, machine learning, panel data).
- Cluster 2: ten items (business cycles, development, economy, efficiency, migration, productivity search, search and matching, trade, unemployment).
- Cluster 3: ten items (digital economy, entrepreneurship education, higher education, Industry 4.0, labor market, renewable energy, South Africa, sustainability, sustainable development, youth unemployment).
- Cluster 4: nine items (education, entrepreneurship, growth, human capital, innovation, knowledge, skills, technology, training).
- Cluster 5: eight items (AI, big data, digital transformation, digitalization, information technology, labor market, robotics, unemployment rate).
- *Cluster 6: seven items (automation, employment, future of work, globalization, technological change, technological unemployment, wage inequality).*



Source: : VOSviewer Output (2023)

Figure 2. Bibliometric analysis output as overlay visualization

- Cluster 7: six items (e-learning, economic development, economic growth, foreign direct investment, innovation, regional development).
- Cluster 8: six items (COVID-19, mental health, pandemic, social media, work, youth).

Source: VOSviewer Output, 2023.

As it is understood from the clusters, machine learning (Cluster 1) and AI (Cluster 5) are together with employability and unemployment rates, respectively. This depicts that Industry 4.0 components have been studied with the labor market widely but separately. In Cluster 3, without its components, Industry 4.0 has also been analyzed regarding youth unemployment, sustainability and the labor market.

When we were analyzed, according to the VOSviewer program, 2,157 studies were conducted by 5,003 authors. However, just 50 (minimum number of citations of an author = 0) have more than three documents, as only 5 have over five research. The analysis is ongoing with “minimum number of documents of an author = 3 and the minimum number of citations of an author = 10” settings related to 35 authors.

The bibliometric analysis on 35 authors of the *Query* depicts that (VOSviewer Output, 2023), a messy display of the authors results in fewer connections, yielding a total link strength of just 21.

In this bibliometric analysis, while the emphasis on technological unemployment comes to the fore in recent studies, the fact that the analyses on the textile sector were not included in the first nine clusters and 66 keywords can be considered an emphasis on the study's originality.

Analytical hierarchy process method process

The AHP method divides the problem into small parts and organizes the logical process by determining priorities for each hierarchy with a pairwise comparison method (Saaty, 2000). To carry out the AHP study, comparing the above criteria in pairs is necessary. It is open to criticism because it is obtained with subjective opinions. However, to reduce the dose of criticism, employers with a high technological tendency in their demographic structure and who are applying technology in their businesses were interviewed.

Comparisons will be requested from employers with a minimum of 15 years of experience. To carry out the AHP study, comparing the above criteria in pairs is necessary. It is open to criticism because it is obtained with subjective opinions. However, to reduce the dose of criticism, employers with a high technological tendency in their demographic structure and who are applying technology in their businesses were interviewed. Comparisons will be requested from employers with a minimum of 15 years of experience. The geometric mean of the views is calculated to obtain a quantitative value for each comparison result. The purpose of doing this is that AHP divides the problem into small parts and organizes the logical process by determining the priorities for each hierarchy with the pairwise comparison method (Saaty and Vargas, 2001)

While performing AHP Analysis, 8x9/2, i.e. 36 questions are asked for pairwise comparison of 9 criteria. The participant is asked which of the two criteria will have a more significant impact on unemployment in technological and digital transformation and then asked to determine the importance of the criteria between 1 and 9. Participants are asked to assess the degree of importance of each criterion on a scale of 1–9, as shown in the table. This process transforms the qualitative approaches of pairwise comparisons into quantitative values. A weight of 1 for a criterion indicates equal importance, whereas, for example, a weight of 3 signifies that the criterion is considered three times more critical (Saaty and Vargas, 2001).

The collected data from the participants for each pair needs a unique value. Because there are eight participants, the values are multiplied by each other and take the 11th root to get the result (geometric mean) of a compound pairwise. A phenomenological study is done within the AHP, and a bibliometric analysis is also carried out for some keywords.

Findings and discussion

The AHP Application is completed by performing the decision matrix, normalized matrix and finally, inconsistency analysis of the data obtained from the participants and getting the random and inconsistency indexes. In a nine-criteria application, the random index has a value of 1.452. The final table obtained by applying the AHP algorithm made by the authors is given in Table 2.

According to Table 2, the most important component of technological and digital transformation that causes unemployment is AI, with 23%. When the second one is considered, machine learning, deep learning and AI impact unemployment, with almost 40% in the textile sector.

The most negligible impact is seen in blockchain and cybersecurity. The two components do not need significant employment within the textile sector. When this study is renewed, for example, in the finance sector, it will undoubtedly change.

The participants may not understand the Internet of Things and object-oriented studies. It has a 6% impact on unemployment in the textile sector. Another issue that can be discussed is how, in general terms, the components are shaped by the participants' thoughts. So, for example, what do participants understand by twinning? Could the degree of importance change depend on whether we are talking about a twin of an object associated with AI or a

Table 2. Output of the AHP application

Number of criteria (*n*)	9	Consistency
Analysis is:	*Consistent*	*0.06*
Consistency index (CI)		*0.086*
Random index (RI)		*1.452*
Criteria	*Weight*	*Rank*
Cr1 – Data integrity	,09	5
Cr2 – Twinification	,07	6
Cr3 – Artificial intelligence	,23	1
Cr4 – M/C deep learning	,15	2
Cr5 – Blockchain	,04	9
Cr6 – VR/AR/MR/XR	,15	3
Cr7 – IoT, IoH, IoE	,06	7
Cr8 – 3D printers	,14	4
Cr9 – Cybersecurity	,06	8

Note: M/C = Machine
Source: Created by the authors

design twin of an existing object with a simulative approach? In this study, it is assumed that such differences do not exist. This can also be considered a limitation.

On the contrary, another issue that needs to be discussed is whether these components are independent. For example, AI cannot perform its functions without extensive data mining. Cybersecurity becomes more effective with the presence of other elements. The Internet of Things can be shaped by AI. It is debatable whether all these examples are suitable for AHP analysis. This study assumes that the criteria are considered separately, and their superiority over each other is evaluated accordingly. There were no objections from the participants in this context.

Another issue is that the identified digital transformation components are developing in a way that opens new business areas. When a component moves into the implementation phase in businesses, there may be a decrease in employment and support for the phenomenon of Luddism. However, new business areas will be established in the medium term (Tuna and Güz, 2020). This will create new employment areas. In this case, the expectation that the movement would not last long in this period is similar to the Luddism movements at the beginning of the 19th century.

General discussion

The activities of breaking machines (Luddism) during the industrial revolution may be done against robots (neo-Luddism) shortly, particularly by blue-collar employees. More unskilled workers are anticipated to be negatively impacted by Industry 4.0; it is stated that robots will take over jobs requiring muscle strength and dexterity, and in this case, it is stated that there may be a trend against robots that are built with AI and where components such as machine learning and deep learning are run. The approach is being expanded to encompass both blue-collar and white-collar employees. In addition, technological and digital transformation will play an active role in management and decision-making.

In this study, interviews were conducted with entrepreneurs (8 participants) who have at least 15 years of experience in the textile industry and who closely follow and use technology in their business. Technological and digital transformation, and therefore Industry 4.0

components, have been analyzed in terms of which weights can cause unemployment. According to the results of the analysis, AI (23%) and machine learning and deep learning (15%) were the two components with the highest impact. In the study, the least weighted components that will cause unemployment in the textile sector were blockchain (4%) and cybersecurity (6%). These two components can be considered areas that currently do not require employment in the textile sector. Although there is a finding that will support the study independently of the sector with bibliometric analysis, it is generally thought that making these components separate in each industry is beneficial.

According to Tunç and Öcal (2023) and Alonso's (2022) study, they addressed the issue of neo-Luddism conceptually but did not analyze the one in this study. Again, Wu and Chen (2017) only presented conceptual studies. In addition, McKusick (2007) focused on the social effects of the neo-Luddism concept, which is evaluated together with technological unemployment; such an analysis is not made on the textile sector. In this respect, it becomes clear that the concept of neo-Luddism in the period can be used because unemployment is integrated with the technological phenomenon and Luddism, and the issue should be addressed together with unemployment.

Theoretical implications

The study presents several theoretical implications regarding Industry 4.0 and textiles. Over the years, various industrial revolutions have reshaped institutions due to technological advances in all areas of life, including education. The fourth industrial revolution, introduced by Industry 4.0, uniquely threatens to disrupt existing organizations through virtualization, decentralization and digital transformation. This necessitates further research to analyze the main disciplines associated with digital transformation and understand their weight in influencing technological unemployment. These disciplines catalyze new institutional pressures, compelling organizations to accept significant change or reforms. To enhance research efforts to address the challenges of Industry 4.0 in the textile sector, this study focuses on the critical institutional factors. It examines whether digital transformation contributes to the new Neo-Luddism, known as Robot Breaking, in the era of the Fourth Industrial Revolution. In addition, the study has a distinctive feature in that it addresses and evaluates the components of the digital transformation issue, which is considered Industry 4.0, on a sectoral basis, with AHP analysis. In the literature, no other study in the textile sector evaluates unemployment with such a methodology.

Practical implications

This study applied to the textile industries; future studies can study other industries, such as transportation and logistics. In addition, it is recommended that policies be developed on neo-nudist movements. The results of the article confirmed several practical implications. For instance, policymakers should evaluate the impact of technological and digital transformation components on employment at the point of investment and support. Although, like Luddism, there will be temporary unemployment concerns for neo-Luddism, industrial policies should be produced to keep such an effect at a minimum level. These results on the real sector side are at a level that gives insight into human resources evaluation. This study is an essential input for the human resources departments of businesses. The results of this study have shown that AI in the real sector will gain more weight in business life in the coming periods. In this context, investments can be directed. The development of AI and its derivatives, such as generative AI, will play an essential role in the sector. As an important message to legislators, because it is seen that AI will make the most crucial change in the employment of the textile industry, issues such as employment training and orientation to new areas should addressed. In the era of advanced technology, robots and automation systems play a vital role in changing the textile industry. They contribute to automating labor-intensive tasks, indicating increased production speed and enhanced quality.

Moreover, these technologies are not only transforming the textile industry but also revolutionizing it by decreasing the dependence on human labor for repetitive and hazardous tasks. This, in turn, frees up workers to concentrate on creative and high-value-added activities. AI and data analytics are harnessing production data to identify weaknesses and enhance the quality of final products. Technology also reduces production costs by reducing energy and raw material consumption, improving profit margins. Finally, modern technology fosters the growth of innovative textile products with unique features like water and wrinkle resistance. This is making the industry more attractive in the market and reducing the sector's environmental impact by promoting energy efficiency and reducing the use of harmful chemicals.

Limitations and recommendations

This study applied to the textile industries; future studies can study other sectors, such as transportation and logistics. In addition, it is recommended that policies be developed on neo-nudist movements that may develop against AI and machine learning on the public side. In addition, because the study is a (phenomenological) study in line with the opinions of eight entrepreneurs, it is recommended to renew it using other methods. As a result, it is essential to repeat the study with the same process and different strategies for different sectors in the academy and make comparisons. In addition to the social and economic effects of AI on the textile industry, other effects should also be investigated, and subfields of the textile industry (e.g. garment, home textiles) should also be addressed with AHP studies. Our study used diverse research methods, including a literature review, bibliometric analysis, eight expert phenomenological interviews and AHP. This variety of approaches enhances the robustness of our findings and provides a solid foundation for future research. For instance, future studies could consider incorporating more expert analyses, phenomenological interviews and systematic reviews to further enrich our understanding of the topic. The interview sample was eight entrepreneurs, so future studies can expand the sample to compare with entrepreneurs from different industries.

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