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Article

Adapting to Technological Change: Cognitive and Emotional Response of Older Employees in the Industrial Sector

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Abstract: As automation and artificial intelligence (AI) continue to transform industrial processes, older employees often face challenges in adapting, mainly due to limited digital skills, increased cognitive demands, and psychological resistance. This study examines how employees over 50 adapt to digital transformation in two energy companies. One hundred employees participated in a three-month study, split into two groups: one received standard training, while the other underwent age-adapted training. Data collection involved LMS tracking, knowledge testing, forum analysis, surveys, and the Perceived Stress Scale (PSS). Results showed that the age-adapted group had higher knowledge retention (88% vs. 72%), lower stress levels (3.2 vs. 6.5), more engagement, and greater satisfaction with the learning process. They also demonstrated better confidence and smoother adaptation to automation tools. However, a follow-up after one year revealed a decline in long-term learning motivation. Around 30% of participants were reluctant to continue training, citing fatigue and interference with their primary work duties. The findings highlight the need for tailored training programs and psychological support for older workers. Age-sensitive strategies reduce stress, increase engagement, and improve knowledge retention, offering insights for inclusive automation strategies in age-diverse workforces.

Keywords: automation ; artificial Intelligence; older workers; adaptation; workplace stress; digital transformation; knowledge retention; training programs; employee engagement continuous learning

1. Introduction

Over the past few decades, automation and artificial intelligence (AI) have emerged as key drivers of efficiency in business processes, particularly in the energy sector [1]. These technological advancements significantly impact labor dynamics, industrial productivity, and broader economic development. As digital transformation progresses, it continues to reshape job roles and responsibilities—posing particular challenges for older employees with limited exposure to digital tools [2, 3]. Although automation offers many benefits, it also presents certain risks to job security and employment structures. However, these risks are often overstated. As noted in [4], automation typically impacts specific tasks rather than eliminating entire occupations. These technologies are primarily introduced to boost productivity and streamline management. Yet, successful adoption depends largely on user acceptance, shaped by factors such as perceived usefulness and social influence [5]. Nonetheless, the integration of AI and automation frequently encounters challenges—particularly among older workers who struggle to keep pace with rapid technological changes [6]. Older workers often face additional barriers to adopting new technologies due to psychological and physiological factors. This includes factors such as technology-related anxiety, lack of confidence, and cognitive overload [7]. According to a report by the U.S. Bureau of Labor Statistics, the integration of new technologies into the labor market has exposed key data collection gaps and

challenges related to workforce readiness (U.S. Department of Labor, 2024). Older individuals also experience barriers in adopting new technologies in their everyday lives [8, 9, 10].

Older employees often lack experience with digital and automation technologies because their careers developed in analog or manual environments where such tools were not essential [11, 12]. Today's energy and construction industries demand highly qualified professionals. Workers must also perform effectively under both physical and psychological pressure. These sectors often involve high-stress environments requiring a mix of technical skills and strict discipline. The introduction of automation and AI in such conditions may provoke resistance from employees, which is exacerbated by a lack of proper training and support. Engaging with modern technologies requires ongoing learning, which can strongly influence older workers' receptiveness to change [13]. Concerns persist among employees that artificial intelligence may replace human labor, despite evidence suggesting its primary function is to augment human productivity. Studies suggest that AI contributes to job growth by boosting productivity, creating new roles, and fostering virtual agglomerations [14].

Research indicates that effective employee adaptation to new technologies requires structured training along with psychological and organizational support mechanisms. Individual factors like age and experience play a crucial role in shaping attitudes toward technology, which in turn influence stress levels and productivity [5]. Studies on age-related adaptation across industries confirm the need for personalized training and psychological support to help older workers integrate into new workflows [15].

The combination of aging processes and the rapid development of new technologies creates additional challenges for older workers, increasing their vulnerability in the labor market. The lack of digital skills, adaptation mechanisms, and limited opportunities for retraining may lead to a decrease in their competitiveness. As a result, they may face labor market displacement, limited career advancement, and even early retirement. These findings underscore the need for realistic training strategies that align with the capacities and expectations of older employees [16].

The aim of this study is to evaluate how age-adapted training programs influence the adaptation of employees over 50 years old to automated technologies in energy enterprises. The research focuses on the psychological, cognitive, and behavioral aspects of technological change, comparing outcomes between standard and age-specific learning approaches. To achieve this, a quasi-experimental observational study was conducted at two energy enterprises, involving 100 employees divided into two groups: one receiving standard training and the other undergoing age-adapted training.

1.1. Preliminary Studies

Early research on automation in the workplace shows that introducing new technologies often encounters resistance, particularly due to differences in how workers of various age groups perceive change [17]. A key factor is the tendency among older workers to resist technological innovation. This resistance often arises from a lack of preparedness for fast-paced technological learning and from psychological barriers.

This pattern is evident not only in professional settings but also in daily life - for example, when using smartphones, online platforms, or AI-powered tools [18]. Despite their valuable experience, older workers may see new technologies as disruptive to their familiar routines, which can reduce efficiency and increase stress.

Studies show that the ability to adapt to new technologies varies by age and is influenced by several factors, such as how useful the technology is perceived to be, peer influence, and access to training. The Unified Theory of Acceptance and Use of Technology (UTAUT) helps explain why older workers often struggle with automation and highlights the need for additional support measures, such as personalized training and mentoring [5].

Training Methods for Automation in Enterprises Considering Age Groups.

In addition to structured training, informal social support can be critical. Studies have shown that the presence of "warm experts" — colleagues or family members who provide non-judgmental guidance — significantly helps older adults develop digital skills in both professional and everyday contexts [19].

Training strategies should address generational differences in digital literacy by offering flexible, socially supportive learning formats. This underscores the importance of mentoring and adaptive training programs tailored to employees' varying levels of technological expertise, helping them overcome barriers related to understanding and using complex technologies [20].

Practical experience shows that successful automation requires training programs that consider not only employees' technical skills but also their psychological readiness for change.

Research highlights that a clear and well-structured training and support strategy can significantly reduce resistance to automation, especially among older employees.

The Impact of Employees' Age on Adapting to Automated Processes in Enterprises.

Older workers may also experience decreased self-esteem and perceived exclusion when they are unable to keep pace with technological changes. Research highlights that these emotional responses — including disempowerment and decreased well-being — can significantly affect digital adoption among aging workers [21].

Automation impacts employees across age groups differently, with older workers often requiring more support to adapt to changing workflows. Workers' reactions to new technologies can vary significantly depending on their age, experience, and skill levels. Support for older employees during the implementation of mandatory business software should focus on reducing their negative attitudes toward changes brought by automation and minimizing their perception of the threat of job loss.

Young specialists generally adapt more quickly to changes and easily master new automated processes. They view innovations as opportunities for professional growth and expanding their skill set. Younger employees are often more flexible and willing to learn, which contributes to their successful integration into automated work processes.

Older workers may encounter unique challenges when learning new technologies, often due to lower digital fluency and cognitive workload [22]. This could be due to less experience with modern digital tools and a certain resistance to changes in established work processes.

It's important to note that automation of production processes and the introduction of digital technologies lead to changes in the qualification requirements for employees. While some routine tasks are automated, the demand for highly skilled specialists in information technology, data analysis, robotics, and artificial intelligence increases. This highlights the need for continuous learning and upskilling of employees of all age groups to successfully adapt to the changing work environment.

Retaining and developing the potential of older employees is a strategically important step for organizations aiming for sustainable growth. With their valuable professional knowledge and extensive experience, older workers represent a significant asset, and therefore, training in new technologies should be seen not as an alternative, but as a means to unlock their potential in the context of digital transformation [23, 24].

Thus, age plays a significant role in the perception and mastery of new automated processes in enterprises. To effectively integrate all employees into updated production processes, adaptive training programs should be developed and implemented, considering the age-related characteristics and needs of workers.

Although some studies suggest that age does not always correlate with core job performance, creativity, or training efficiency, it does have more pronounced effects on other dimensions of productivity, such as workplace behavior and safety [25]. The common element in these studies is the focus on employees' adaptation to technological changes, particularly in the context of automation. All emphasize the importance of training and preparing workers for the successful adoption of new processes and technologies in the workplace. Key aspects often discussed include age differences, the need for adaptive training programs, and the influence of personal factors such as the perception of new technologies and resistance to change.

One of the major gaps that many studies miss is the attention given to the psychological, social, and long-term aspects of employees' adaptation, as well as the contextual differences in work processes that can affect the success of automation implementation. Organizations must adapt to an aging workforce and apply strategies to effectively manage older workers [16]. Managers can use

various aspects of workforce management with older employees, including respecting their experience, building trust-based relationships, and using motivational and communication strategies that consider their longer professional careers [26]. Moreover, it's crucial to recognize the benefits and value of working with older employees, understanding why they are valuable assets to companies, given their experience and knowledge [27].

Although individual and qualitative factors are essential, most existing research on automation focuses predominantly on measurable outcomes like productivity or adoption rates, often overlooking employee perceptions and emotional responses. Research that considers emotional and psychological aspects (e.g., resistance to change, anxiety about job loss, or self-confidence) is becoming increasingly important in the context of a more holistic approach to automation implementation, but these aspects are still often overshadowed by quantitative data.

However, subjective aspects such as employees' perceptions of changes, motivation, and emotional and psychological barriers receive less attention. These elements, while influencing the success of technology adoption, are more difficult to quantify, which explains their limited attention in traditional studies. There is also a positive impact of technological changes on aging employees. New technologies streamline workflows, enhance flexibility at the workplace, and improve labor efficiency. Technological innovations have helped reduce physical strain and made tasks more accessible for aging employees [28].

1.2. Study Design

In this study, we conducted a field observational research to assess the adaptation of older employees (aged over 50) to the introduction of automation incorporating artificial intelligence (AI) in the workplace. During the familiarization stage, we observed high interest from older workers, which was previously noted in studies such as [22, 29]. There is also a stereotype that elderly workers struggle to adapt to new technologies; however, the results of this study show the opposite [25]. We used both objective and subjective methods of assessment to identify the factors influencing successful adaptation. The experimental tools for monitoring perceptions of changes in real-time included surveys, testing, mentorship, knowledge verification, and psychological support. The main focus during the experimental design stage was: (1) analyzing the processes of perception of changes and stress among employees, (2) collecting data in real work conditions to assess the impact of automation on production processes, (3) comparing results between employee groups with varying levels of preparedness and technology perception. The study revealed that employees who had not undergone specialized training faced difficulties in adaptation, while those who had received age-appropriate training showed improvements in technology perception and reduced stress. The study also showed that older employees' express interest in new technologies. Regarding continuous learning and development to ensure that employees possess the necessary skills to work in an automated environment, previous research from Kampala International University (Beatrice, 2024) emphasized the importance of upskilling and adaptability as essential elements of workforce transformation. The report noted that ongoing employee training is especially important for older workers, who may face additional barriers in adopting new technologies. The results can be used to develop recommendations for implementing automation and AI, considering the age-related and psychological characteristics of employees.

2. Materials and Methods

2.1. Field Data Collection

Data collection was conducted onsite across various work environments in a real working environment, with the time for data collection varying depending on the conditions at each site. From March to May, over a period of 3 months in 2022, a total of 100 employees aged over 50 years were selected at two energy companies involved in the automation process with the presence of AI. The inclusion criteria were as follows: (1) age over 50 years, (2) working in the specific industry for more than two years, (3) participation in the automation process. Participants were informed about the goals of the research and its procedure. They were provided with informational materials and video demonstrations to fully understand the research methodology. All participants signed written

informed consent to participate. The study was approved by the company's supervisory board. The research was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki of the World Medical Association (WMA). No significant differences in baseline data were observed depending on the season or location where the participant recruitment was carried out. Participants were divided into 2 groups of 50 people each. One group was trained in automation along with the entire staff, while the second group of 50 people was trained with consideration for age-related changes. The first group underwent training in automation as part of a general program developed for all employees of the enterprise, without considering age-specific characteristics. The second group, in turn, underwent adapted training specifically focused on age-related changes and the needs of older employees. This approach allowed the evaluation of how individualized training programs, taking age differences into account, could contribute to better mastery of new technologies and a reduction in stress levels among older workers. Following the three-month training and analysis of the results, additional sessions were conducted for the group that had not undergone specialized training to equalize the knowledge levels of the two groups. Then, exactly one year later, in March 2023, testing was carried out to assess the knowledge of both groups. It was also decided to proceed with further modernization of the enterprises with automated systems.

To measure the level of learning and mastery of automation among employees, several smart processes and methods were used, including:

1. Learning Management Systems (LMS): Platforms were used to track participants' progress, measure engagement, and test knowledge during the training process. These systems provide analytics based on test results, time spent on the platform, and participant activity.

2. Surveys and Questionnaires: Online surveys were used to measure the level of satisfaction with training and its perceived effectiveness. Surveys included both closed questions (e.g., confidence in applying new technologies) and open-ended questions to gather deeper insights into the participants' perceptions of the training.

The data analysis included statistical comparison of groups, but due to the limited sample size, formal statistical tests were not applied. The comparisons were made based on observed differences in key indicators.

2.2. Data Processing

After the ratification and collection of field data, the information processing included several stages aimed at analyzing the level of automation assimilation and its impact on older workers.

1. Data Processing and Analysis via Learning Management Systems (LMS):

The use of LMS (Learning Management System) allowed for systematic tracking of participants' progress. The following data were collected using this system:

Knowledge Tests: Participants took tests after each training module, which allowed for measuring how successfully they were absorbing new technological processes. These tests were analyzed to determine the level of knowledge assimilation.

Activity and Engagement: The LMS also tracked how much time participants spent on the platform, how actively they interacted with training content, and whether they accessed additional materials or resources.

Results Statistics: Analytics were gathered based on test results and assessments, which allowed researchers to identify groups that demonstrated the greatest successes or faced difficulties.

2. Surveys and Participant Questionnaires.

To complement the objective data from the LMS, subjective data were gathered through online surveys. These surveys included both closed and open-ended questions:

Closed Questions: For example, participants were asked about their confidence in applying new technologies in practice, how long it took them to master automated processes, and what level of difficulty they experienced.

Open-ended Questions: These were aimed at gaining a deeper understanding of the participants' perceptions, such as how they assessed the impact of automation on their work and stress levels, and their opinions about the training program. Open-ended answers provided valuable insights into personal feelings and trust in the technologies being implemented.

3. Processing and Analysis of Stress and Change Perception Data.

To assess stress levels and the perception of changes during automation, additional tools were used:

Stress and Adaptation Scale: Specialized questionnaires and scales were used to measure stress levels, anxiety, and perception of changes among participants. These data were used to compare between groups (the group with general training and the group with adapted training).

Analysis of Psychological Barriers: This included assessing how changes in technology are perceived, which affects older employees' acceptance of automation. This also enabled the analysis of the relationship between perceived stress and training outcomes.

4. Comparative Analysis Between Groups.

Based on the collected data, a comparative analysis was conducted between two groups:

The Adapted Training Group: Members of this group demonstrated a higher level of satisfaction with the training and lower levels of stress, indicating the importance of considering age-related differences in training.

The General Training Group: Members of this group showed lower levels of engagement, as well as higher stress levels and difficulties in mastering technologies.

The data from LMS and the results of the surveys were used to create a detailed report, which allowed for conclusions on how specific training methods could affect the adaptation of older workers to technological changes.

Processing the collected data not only allowed for quantitatively assessing the level of knowledge assimilation and employee engagement in automation processes but also qualitatively assessed the influence of age-related factors on adaptation. These data formed the basis for recommendations aimed at enhancing training programs and psychological support for older employees during the implementation of new technologies.

3. Results

Results after the three-month training conducted from March to May 2022.

Table 1. Comparative Evaluation of the Effectiveness of Different Approaches to Automation Training Among Employees Over 50 Years Old.

No.	Indicator	Adapted Training Group	General Training Group	Notes
1.	Knowledge Retention (%)	88%	72%	Evaluation based on test results and LMS activity.
2.	Stress Level (1-10 rating)	3.2	6.5	Stress measurement using stress scales.
3.	Engagement in Training (%)	90%	75%	Data on time spent on training materials (LMS).
4.	Satisfaction with Training (1-10 rating)	8.7	5.2	Participant evaluation via online surveys on satisfaction level.
5.	Difficulty Adopting Technology (rated 1-10)	2.1	6.8	Evaluation of difficulties in adopting automation and IT technologies.
6.	Progress in Adaptation (1-10 rating)	9.0	6.0	Subjective assessment of progress in adapting to new technologies.

1. Knowledge Retention (%) - Determined based on the results of testing and activity on the LMS platform.

Formula for calculation:

Knowledge Retention = (Average test score + Percentage of completed tasks + Average activity on LMS) / 3 (1)

Adapted Training Group: $(90+95+80) / 3 = 88\%$

General Training Group: $(75+75+65) / 3 = 72\%$

2. Stress Level (Rating 1-10).

Measured using the Perceived Stress Scale (PSS). The Perceived Stress Scale was developed by Sheldon Cohen in 1983 along with colleagues Tom Kamarck and Robin Mermelstein.

Participants answered questions, and then the average score was calculated.

Range of Calculation: 1 (low stress) – 10 (high stress).

Average Scores:

-Adapted Training Group: 3.2

-General Training Group: 6.5

3. Engagement in Training (%).

Determined based on LMS data:

-Percentage of completed modules;

-Time spent on the platform;

-Number of tasks completed.

Formula for calculation:

Engagement = (Average percentage of completed modules + Average activity on LMS) / 2 (2)

Adapted Training Group: $(95+85) / 2 = 90\%$

General Training Group: $(80+70) / 2 = 75\%$

4. Satisfaction with Training (Rating 1-10).

Evaluated through online surveys where participants expressed their degree of satisfaction (1 – completely dissatisfied, 10 – completely satisfied).

The final score was calculated as the average of the responses.

Average Scores:

-Adapted Training Group: 8.7

-General Training Group: 5.2

5. Difficulty Adopting Technology (rated 1-10).

Subjectively assessed through questionnaires, where participants indicated how difficult it was for them to learn new technologies (1 – easy, 10 – very difficult).

Average Scores:

-Adapted Training Group: 2.1

-General Training Group: 6.8

6. Progress in Adaptation (Rating 1-10).

Calculated based on participants' self-assessment and their supervisors' ratings.

It included the following parameters:

-Assessment of confidence in using the technologies;

-Percentage of successfully completed tasks using new tools;

-Final score – the average of these ratings.

Average Scores:

-Adapted Training Group: 9.0

-General Training Group: 6.0

The data shows that adapted training with the added improvements significantly increases employee engagement and satisfaction, reduces stress and difficulties in learning technologies, and accelerates the adaptation process.

Activity Assessment.

Table 2. Analysis of Employee Learning Activity Based on Training Approach.

Indicator	Adapted Training Group	General Training Group
Average time on platform (hours/week)	8 hrs	5 hrs
Frequency of visits (per week)	3 visits	2 visits
Test completion (in %)	95%	75%
Number of interactions on the forum	5 posts/comments	2 posts/comments
Quality of task completion (rating 1-10)	9.0	6.5

Based on this data, it can be concluded that the group that received enhanced, age-adapted training demonstrated significantly greater engagement in the learning process compared to the group that received general training.

Differences in General Patterns Between the Two Groups.

1. The adapted training group demonstrates consistent growth in key indicators, such as knowledge acquisition, engagement in learning, and adaptation progress. The curve shows a steadily increasing pattern, indicating better reception of training and reduced difficulty in mastering technologies.
2. The general training group shows a less pronounced dynamic and a decline at certain stages. For instance, the stress level remains high, engagement is lower, and difficulties in mastering technologies persist longer. The curve is flatter and more unstable, indicating difficulties in adaptation.

The overall pattern shows that personalized training, taking age-related factors into account, contributes to more effective knowledge acquisition and a reduction in stress levels compared to universal programs.

Research Results and Surveys After One Year of Work at Enterprises (March 2023).

The study revealed that older employees demonstrated a clear interest in learning new technologies, supporting previous findings [22]. If information about the benefits of automated systems is properly conveyed to older workers, explaining that these technologies are not created to replace human labor but to facilitate work processes and increase efficiency, it will help reduce their concerns. It is important to conduct special presentations where it is explained how automation and artificial intelligence can become useful tools to support them in performing tasks, rather than threatening their jobs. This approach will help build trust among senior employees towards new technologies and stimulate their willingness to adapt and learn.

However, one year after the initial three-month training, when the adaptive learning group rejoined the company as part of the initiative titled 'The Importance of Continuous Learning and Development,' new challenges emerged. Many older workers expressed reluctance toward continuous learning, preferring that technology training occur only once every few years. Specifically, 30% of the 100-person group refused to continue training on new automated processes after a year, citing that it interfered with their focus on production processes.

To understand the specific difficulties workers faced, surveys and tests were conducted before the training began, immediately after the three-month program, and a year later. The results showed that many participants experienced stress and difficulties mastering new technologies, despite positive test results that confirmed their knowledge. Presentations and training sessions conducted at the beginning and end of the training were aimed at clarifying the goals and benefits of the technologies. However, it is important to note that after a year of working with new processes, older employees expressed fatigue from continuous learning and focusing on new tools, which also became a significant barrier. The presentations and informational sessions helped reduce anxiety, but employees did not always see the specific benefits of continuous learning in the context of automation. While Beatrice (2024) emphasizes the importance of continuous learning and development to equip employees for working in automated environments, our findings reveal

significant motivational and practical barriers to long-term learning engagement among older workers. This suggests a need to complement theoretical approaches with realistic strategies tailored to older employees' capacities and expectations [14].

4. Discussion

This study developed and applied a framework for assessing stress and the difficulty of adapting workers over 50 years of age to the introduction of automation in the workplace. The assessment system included both objective and subjective indicators, such as stress levels, difficulties in mastering technologies, and progress in adaptation. The system was designed considering real work conditions, which allowed for an effective evaluation of how the introduction of new technologies impacts employees' psychological state and how successfully they cope with changes.

In the context of adapting workers over 50 years of age to the introduction of automation in the workplace, objective and subjective indicators may vary. Barriers to the implementation of the continuous learning theory were also identified. For example, motivational barriers— not all older workers see the need for continuous learning, especially if they do not feel the direct benefit of the technologies being implemented in their daily tasks, or they consider them unnecessary for performing their current duties. Psychological barriers, including fear of new technologies and lack of confidence in their abilities, may lead to resistance to change and reduce engagement in educational processes.

This study is limited by the relatively small sample size and the practice-focused design. As a result, the analysis was descriptive, and no formal statistical tests were applied. However, the comparative data still offer important insights into group differences in engagement and adaptation.

Table 3. Evaluation of Employees' Response to Training and Adaptation to Technologies.

Evaluation Period	Stress (on scale)	Knowledge Retention (from tests)	Reaction to Training	Comments/Challenges
Before training	High	Low	Positive expectations, but anxiety	Fear of new technologies among older worker
After 3 months of training	Medium	High	Positive reaction, interest in new knowledge	Some fatigue from the intensity of the program
One year after training	Medium-Low	Medium	30% refused to continue training, feeling it interferes with work	Resistance and low motivation among some older workers
Reaction to presentations and training sessions	Medium	(Indirectly positive effect, but not measured separately by tests)	Some workers found them useful, but resistance remained	While the informational presentations helped alleviate initial anxiety, they were insufficient in fully overcoming resistance to technological changes.

Objective Indicators:

1. Time Spent on Learning Platforms (LMS) — a quantitative measure showing how much time an employee devoted to learning. The more time spent, the higher the involvement in the process.

2. Frequency of Accessing Learning Materials (per week) — a quantitative indicator demonstrating how often an employee returns to learning and how actively they engage with the materials.

3. Test Results (in %) — an objective metric measuring how well the employee has mastered the new information and skills. This indicates the level of material comprehension.

4. Number of Interactions on Forums or Groups — a quantitative assessment of participants' activity, based on the number of posts or comments. This can indicate how engaged the employee is in collective discussions and knowledge sharing.

5. Quality of Task Completion (rating on a scale of 1-10) — the basis for an objective assessment of the completed work, including quality standards, even though the evaluation can be somewhat subjective depending on the trainer's or expert's expectations.

Subjective Indicators:

1. Stress Level (rating on a scale of 1-10) — a subjective assessment of the stress an employee feels during the adaptation to new technologies. The higher the score, the more stress is experienced during the change process.

2. Satisfaction with the Training (rating 1-10) — the employee's perception of the usefulness and effectiveness of the training. This indicates how comfortable they feel during the training process.

3. Difficulty in Learning Technologies (rating 1-10) — a subjective assessment of how difficult it is for an employee to master new technologies. The higher the rating, the more difficulties are encountered in the adaptation process.

4. Progress in Adaptation (rating 1-10) — a subjective assessment by the employee of how they feel about their progress in mastering new technologies. This is an important indicator of their perceived success in the learning process.

5. Conclusions

Digitalization can have both positive and negative effects on the perception of aging in the profession, including the opportunities for continued work and social activity of older employees [6]. The main issues include a lack of skills, the need for retraining, technological anxiety, cultural changes, and age discrimination [25, 30]. The importance of designing ethical and inclusive smart workplaces that prioritize the well-being of older employees during digital transformation has been emphasized in previous research [31]. The findings of this study support this perspective, showing that psychological support and ethically grounded training practices play a crucial role in reducing stress and improving technology acceptance among workers over 50. For older age groups, digital literacy can be an important factor in ensuring their employment [7]. Digital technologies can be a tool for strengthening their independence and participation in society, as well as for increasing feelings of helplessness [21].

The goal of this study was to create a real-time assessment system to measure the level of adaptation of employees over 50 years old to automation processes at the enterprise, using adapted training programs and applications for data collection, as well as to explore the readiness of older workers to adopt the concept of continuous learning in the context of the transition of modern enterprises to a new stage, where the ability to continuously acquire new information throughout their professional careers plays a key role.

To assess the impact of age on the perception and adoption of new technologies, 100 employees were involved in the study, divided into two groups. The long-term effect and continuity of training were also examined.

Informal learning elements play a key role in the process of older adults mastering digital technologies and how these elements affect their subjective impressions of training and using technologies in daily life [19]. Digital technologies have the potential to either empower or marginalize older adults, depending on how they are introduced and supported in the workplace [21]. The aging of the population and the workforce affects the vulnerability of older workers' jobs in the context of the introduction of new technologies. As automation and artificial intelligence continue to transform industries, older workers may face greater challenges in adapting to these advancements. The introduction of new technologies can result in increased job displacement risks,

especially for those with limited digital skills or those who have been in a particular job for a long time. At the same time, these technologies can also create new opportunities for older workers, particularly in roles that support technological integration and maintenance. Understanding the balance between these challenges and opportunities is essential for creating supportive work environments that help older employees remain productive and engaged in the workforce [32].

These findings underscore the importance of tailoring technological training and support systems to the cognitive and emotional needs of older employees, ensuring their inclusion and productivity in the evolving digital workplace.

Objective factors, such as engagement and test performance, directly depended on the individual features of the training and the adaptation of the training materials for older employees. Subjective factors, such as stress and the perception of difficulties, tended to decrease in the group that underwent adapted training compared to the group that followed the general program.

The findings underline the practical value of customizing training frameworks to align with age-related cognitive and emotional needs. It also revealed the attitude and perception of workers over 50 years old towards continuous learning, and that not all older employees are ready for it.

This study makes a significant contribution to understanding the process of adaptation of employees over 50 years old to the introduction of automation and new technologies in enterprises and continuous learning. It highlights the importance of considering age characteristics in educational and training programs, which not only contributes to more effective knowledge acquisition but also reduces stress levels and resistance to change. In particular, the results show that adapted courses and individualized approaches to training can significantly improve outcomes when training older employees, helping them adapt more quickly to changes in the technological process.

Future research may expand on this topic by considering the influence of other factors, such as cultural differences, digital literacy levels, and prior experience with new technologies, which will allow further optimization of educational programs and processes for implementing innovative technologies in enterprises.

Despite the significant advantages of this study over previous research, it is important to note its limitations:

- Use of real work conditions: One of the significant advantages of the study is the data collection in real work conditions rather than laboratory settings. This allowed for more accurate and reliable data reflecting the actual factors influencing employees' adaptation to new technologies and their perception of changes in the work process.

- Focus on the older generation of workers: One of the unique aspects of the study is its focus on the adaptation of older employees (over 50 years old) to automation and AI. Unlike most studies that often focus on younger generations, this study helps to understand how older workers perceive the introduction of new technologies, which is important for optimizing adaptation processes in workforces with diverse age structures.

- Adapted training: The study assessed the effectiveness of two types of training (general and adapted for older employees), which allows for conclusions about which approach is more effective for older workers. This is an important contribution to the development of training programs that account for the age characteristics and needs of workers.

- Long-term effect and the theory of continuous learning checked in real time, with real people.

The results of this study should be interpreted with some limitations. These include the restriction on diversity during data collection. We only collected data from employees over 50 years old working in two enterprises, which may limit the generalizability of the results to broader groups of workers or enterprises in other industries. It is important to note that the perception of automation and adaptation to new technologies may vary depending on the industry, corporate culture, and other factors, such as employees' personal experience and prior interactions with technologies.

Technological solutions play a key role in creating and maintaining a healthy, productive, and efficient work environment, especially in the context of an aging workforce. Innovations in automation, artificial intelligence, and digital platforms allow work processes to be adapted to the age characteristics of employees, reducing physical and cognitive load. Interactive training systems, personalized upskilling programs, and adaptive interfaces help older employees master new

technologies and remain in demand on the labor market. Additionally, digital tools can contribute to monitoring employees' health, preventing burnout, and creating inclusive working conditions, which ultimately improves the overall efficiency and resilience of organizations [33]. Future research is recommended to include a more diverse sample, including employees from different age groups and professional backgrounds, as well as across different time intervals. This will allow for a more comprehensive picture and provide practical recommendations for the implementation of technologies in enterprises. Furthermore, it is important to use a wider range of tools to assess the effectiveness of employees' adaptation to automation and AI, which will help improve the technology implementation process and reduce resistance to change among older workers.

Future research is needed to improve and consider a broader range of factors. The results of this study have identified several areas for further valuable research. First, the impact of personal characteristics of employees, such as education level, prior experience with technologies, and personal preferences regarding changes in the work process, should be considered. These factors can significantly influence the perception of automation and AI and employees' readiness to adapt to new conditions and continue lifelong learning.

It is important to expand the research to include a variety of industries and types of enterprises. While this study focuses on the energy sector, future research may include other industries, such as manufacturing, healthcare, or transportation, where the introduction of automation and AI may have different implications for employees, including older employees.

A more detailed study of the psychological aspects of adaptation is necessary, such as stress perception, resistance to change, and confidence in the ability to cope with new technologies. These factors may vary not only by age but also by other variables, such as personal motivation, social support, and stress levels.

Furthermore, future research could explore more long-term effects of automation, including stress resilience over time and its impact on the psycho-emotional state of older employees during the adaptation process. This will help to better understand the dynamics of changes and propose strategies for optimizing them. For example, research focusing on digital skills among older workers highlights the importance of developing these skills to reduce automation risks and improve adaptation [34]. Understanding how digital skills can alleviate stress and emotional challenges faced by older employees will help develop more effective support and training strategies for this group.

It can also be concluded that the aging workforce is becoming one of the reasons for the implementation of automation, especially through robotics, in various countries [35], [36]. Studies show that in highly developed markets, with a decrease in the number of young and middle-aged workers, the demand for automation is growing. This is observed in countries with an aging population, such as Japan and Germany, which apply robotics on a much larger scale compared to other countries. The introduction of artificial intelligence into work processes can influence employees' decisions to retire early. This is particularly noticeable among workers with higher education, for whom new technologies can serve as an incentive to continue working, while for employees without higher education, these changes have less impact [37]. Moreover, many companies are facing a shortage of labor due to the mass retirement of baby boomer generation workers, and they are using automation and artificial intelligence to increase productivity and optimize their work processes. Examples include companies like Amazon and Schneider Electric, which are actively implementing new technologies, including robots and AI, to improve workflows, while also training workers to interact with machines. Furthermore, despite initial concerns from workers, automation can create new and better jobs, not just replace them [2]. Recent studies also show that the implementation of artificial intelligence (AI) and industrial robots in enterprises can contribute to job creation rather than displacement [38].

Declarations

Ethics Statement: This study was approved by the supervisory board of the participating energy enterprises and was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki (World Medical Association). However, formal ethical approval from an institutional ethics committee was not required

for this study as it did not involve clinical research or sensitive personal data. All participants were informed about the study's objectives and procedures and provided written informed consent prior to participation.

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Consent to Participate: All participants were informed about the objectives and procedures of the study and provided written informed consent prior to their inclusion.

Data Availability: The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

References

1. Dong, X., & McIntyre, S. H. (2014). The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. *Quantitative Finance*, 14(11), 1629-1642. <https://doi.org/10.1080/14697688.2014.946440>
2. Semuels, A. (2024). How Automation Is Helping Companies Prepare for Labor Shortages. *TIME*, December 3. <https://cap.csail.mit.edu/members/research/how-automation-helping-companies-prepare-labor-shortages>
3. Alcover, C.-M., Guglielmi, D., Depolo, M., & Mazzetti, G. (2021). "Aging-and-Tech Job Vulnerability": A proposed framework on the dual impact of aging and AI, robotics, and automation among older workers. *Organizational Psychology Review*, 11(2), 2041386621992105. <https://doi.org/10.1177/2041386621992105>
4. Arntz, M., Gregory, T., & Zierahn, U. (2016). The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis. *OECD Social, Employment and Migration Working Papers*, No. 189. <https://doi.org/10.1787/5jrs5jmmxntm-en>
5. V. Venkates, M.G. Morris, G.B. Davis, F.D. Davis, User acceptance of information technology: Toward a unified view, *MIS Q.* 27 (3) (2003) 425–478. <https://doi.org/10.2307/30036540>
6. Kortmann, L., Henning, G., & Huxhold, O. (2023). Digitalization in occupations and self-perceptions of aging of older workers. *The Journal of Aging and Social Change*, 13(2), 129-156. <https://doi.org/10.18848/2576-5310/CGP/v13i02/129-156>
7. Charness, N., & Boot, W. R. (2009). Aging and Information Technology Use: Potential and Barriers. *Current Directions in Psychological Science*, 18(5), 253–258. Available at: <https://doi.org/10.1111/j.1467-8721.2009.01647.x>
8. Schroeder, T., Dodds, L., Georgiou, A., Gewald, H., & Siette, J. (2023). Older Adults and New Technology: Mapping Review of the Factors Associated With Older Adults' Intention to Adopt Digital Technologies. *JMIR Aging*, 6(3), e44564. <https://doi.org/10.2196/44564>
9. Fischl, C., Lindelöf, N., Lindgren, H., & Nilsson, I. (2020). Older adults' perceptions of contexts surrounding their social participation in a digitalized society—an exploration in rural communities in Northern Sweden. *European Journal of Ageing*, 17(3), 415-423. <https://doi.org/10.1007/s10433-020-00558-7>
10. Neves, B. B., & Amaro, F. (2012). Too old for technology? How the elderly of Lisbon use and perceive ICT. *The Journal of Community Informatics*, 8(1). Available at: https://www.researchgate.net/publication/265208632_Neves_B_B_Amaro_F_2012_Too_old_for_technology_How_the_elderly_of_Lisbon_use_and_perceive_ICT_The_Journal_of_Community_Informatics_81
11. Vaportzis, R., Clausen, M. G., & Gow, A. J. (2017). Older Adults' Perceptions of Technology and Barriers to Interacting with Tablet Computers: A Focus Group Study. *Frontiers in Psychology*, 8, 1687. Available at: <https://doi.org/10.3389/fpsyg.2017.01687>
12. Smith, A. (2014). Older Adults and Technology Use. Pew Research Center. Available at: <https://www.pewresearch.org/fact-tank/2014/04/03/older-adults-and-technology-use/>

13. A. Arbogast, P. Cummins, K. McGrew, Older workers and digitalization: Opportunities and challenges for lifelong learning, *Innov. Aging* 2 (suppl_1) (2018) 398–399. <https://doi.org/10.1093/geroni/igy023.1486>
14. Beatrice, S. (2024). Employee Training and Development in the Age of Automation. Kiu Publication Extension, Kampala International University, Uganda. Available at: https://www.researchgate.net/publication/383556098_Employee_Training_and_Development_in_the_Age_of_Automation
15. Zhang, M. (2023). Older People's Attitudes Towards Emerging Technologies: A Systematic Literature Review. *Public Understanding of Science*, 32(8), 9636625231171677. <https://doi.org/10.1177/09636625231171677>
16. Kappelli, P., Novelli, B. (2013). Managing the Older Worker: How to Prepare for the New Organizational Order. *NHRD Network Journal*, 6(4), 83-84. <https://doi.org/10.1177/0974173920130414>
17. E. Soja, P. Soja, Fostering ICT use by older workers: Lessons from perceptions of barriers to enterprise system adoption, *J. Enterp. Inf. Manag.* (2020) ahead-of-print. <https://doi.org/10.1108/JEIM-12-2018-0282>
18. Shandilya, E., & Fan, M. (2022). Understanding Older Adults' Perceptions and Challenges in Using AI-enabled Everyday Technologies. *arXiv preprint arXiv:2210.01369*. <https://doi.org/10.48550/arXiv.2210.01369>
19. Korpela, V., Pajula, L., & Hänninen, R. (2024). Investigating the multifaceted role of warm experts in enhancing and hindering older adults' digital skills in Finland. *International Journal of Lifelong Education*, 43(1), 1-14. <https://doi.org/10.1080/02601370.2024.2353176>
20. R.W. Berkowsky, J. Sharit, S.J. Czaja, Factors predicting decisions about technology adoption among older adults, *Innov. Aging* 1 (3) (2017). <https://doi.org/10.1093/geroni/igy002>
21. Hill, R., Betts, L. R., & Gardner, S. E. (2015). Older adults' experiences and perceptions of digital technology: (Dis)empowerment, wellbeing, and inclusion. *Computers in Human Behavior*, 48, 415-423. <https://doi.org/10.1016/j.chb.2015.01.062>
22. Hampel, K., & Kunze, F. (2023). The Older, the Less Digitally Fluent? The Role of Age Stereotypes and Supervisor Support. *Work, Aging and Retirement*, 9(4), 393–398. <https://doi.org/10.1093/workar/waad001>
23. Bain & Company. (n.d.). Better with age: The rising importance of older workers. Bain & Company. Retrieved from <https://www.bain.com/insights/better-with-age-the-rising-importance-of-older-workers/>
24. Chetty, K. (2023). AI Literacy for an Ageing Workforce: Leveraging the Experience of Older Workers. *OBM Geriatrics*, 07(03), 1-17. <https://doi.org/10.21926/obm.geriatr.2303243>
25. Aisa Rived, R. M., Cabeza, J., & Martin, J. (2023). Automation and Aging: The Impact on Older Workers in the Workforce. *Journal of the Economics of Ageing*. Available at: <https://ssrn.com/abstract=4392004> or <http://dx.doi.org/10.2139/ssrn.4392004>
26. Nedeljko, M., Gu, Y., & Bostan, C. M. (2023). The dual impact of technological tools on health and technostress among older workers: an integrative literature review. *Cognition, Technology & Work*, 26, 47-61. <https://doi.org/10.1007/s10111-023-00741-7>
27. Sundstrup, E., Meng, A., Ajslev, J. Z. N., Albertsen, K., Pedersen, F., & Andersen, L. L. (2022). New Technology and Loss of Paid Employment among Older Workers: Prospective Cohort Study. *International Journal of Environmental Research and Public Health*, 19(12), 7168. <https://doi.org/10.3390/ijerph19127168>
28. Alcover, C.-M., Guglielmi, D., Depolo, M., & Mazzetti, G. (2021). "Aging-and-Tech Job Vulnerability": A proposed framework on the dual impact of aging and AI, robotics, and automation among older workers. *Journal of Occupational and Organizational Psychology*, 94(3), 615-639. <https://doi.org/10.1177/2041386621992105>
29. Martínez-Alcalá, C. I., Rosales-Lagarde, A., Alonso-Lavernia, M. D. L. Á., Ramírez-Salvador, J. Á., Jiménez-Rodríguez, B., Cepeda-Rebollar, R. M., López-Noguerola, J. S., Bautista-Díaz, M. L., & Agis-Juárez, R. A. (2018). Digital Inclusion in Older Adults: A Comparison Between Face-to-Face and Blended Digital Literacy Workshops. *Frontiers in ICT*, 5, 21. Available at: <https://www.frontiersin.org/journals/ict/articles/10.3389/fict.2018.00021/full>
30. Allam, S. (2021). AI-Assisted Hiring Process and Older Workers: An Exploratory Study. *International Journal of Emerging Technologies and Innovative Research*, 8(1), 681-687. Available at: <https://www.jetir.org/papers/JETIR2101610.pdf>

31. Segkouli, S., Giakoumis, D., Votis, K., Triantafyllidis, A., Paliokas, I., & Tzovaras, D. (2021). Smart Workplaces for Older Adults: Coping 'Ethically' with Technology Pervasiveness. *Universal Access in the Information Society*, 22(1), 1–13. <https://doi.org/10.1007/s10209-021-00829-9>
32. Spijker, J. J. A., Barlin, H., Grad, D. A., Gu, Y., Klavina, A., Korkmaz Yaylagul, N., Kulla, G., Orhun, E., Ševčíková, A., Unim, B., & Tofan, C. M. (2024). The impact of digital technology on the physical health of older workers: Protocol for a scoping review. *JMIR Research Protocols*, 13, e59900. <https://doi.org/10.2196/59900>
33. Wissemann, A. K., Pit, S. W., Serafin, P., & Gebhardt, H. (2022). Strategic Guidance and Technological Solutions for Human Resources Management to Sustain an Aging Workforce: Review of International Standards, Research, and Use Cases. *Human Factors in Human Resources Management*, 9(3). <https://humanfactors.jmir.org/2022/3/e27250>
34. Yamashita, T., Narine, D., Chidebe, R. C. W., Kramer, J. W., Karam, R., Cummins, P. A., & Smith, T. J. (2024). Digital Skills, STEM Occupation, and Job Automation Risks Among the Older Workers in the United States. *The Gerontologist*, 10.1093/geront/gnae069. <https://doi.org/10.1093/geront/gnae069>
35. Aísa, R., Cabeza, J., & Martin, J. (2023). Automation and aging: The impact on older workers in the workforce. *The Journal of the Economics of Ageing*, 26(2), 100476. <https://doi.org/10.1016/j.jeoa.2023.100476>
36. Acemoglu, D., & Restrepo, P. (2018). Automation Can Be a Response to an Aging Workforce. NBER Working Paper No. 24421. <https://www.nber.org/digest/jul18/automation-can-be-response-aging-workforce>
37. Casas, P., & Román, C. (2024). The impact of artificial intelligence in the early retirement decision. *Empirica*, 51(3), 1-36. <https://doi.org/10.1007/s10663-024-09613-3>
38. Y. Shen, X. Zhang, The impact of artificial intelligence on employment: the role of virtual agglomeration, *Humanit. Soc. Sci. Commun.* 11(1) (2024). <https://doi.org/10.1057/s41599-024-02647-9>

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