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Artificial Intelligence (AI) and Employee Adaptation: Development and Validation of a New Scale[1]

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Abstract

This study aimed to develop a valid and reliable measurement tool to measure employees' awareness perceptions of AI integration and employee adaptation. In the first stage of scale development, in-depth interviews were conducted and a suggestion pool of 40 items was created as a result of content analysis. In the second stage, a draft item was created and the scale was structured by consulting expert opinions in order to ensure semantic, face and content validity. In the last stage, the scale was evaluated and a draft scale of 30 items was created. The draft scale was applied to 281 people working in the information technologies, education and customer service sectors. As a result of the analyses, it was determined that the scale had a one-dimensional structure and consisted of 6 items. Confirmatory factor analysis showed that the scale had an acceptable level of fit. According to the CFA results, it was seen that the factor loadings of the remaining 6 items in the scale were higher than 0.40 and the t values of all items were significant. The Cronbach Alpha coefficient for the entire scale was found to be 0.94 and the item-total correlation for all items was found to be higher than 0.30 (between 0.76 and 0.89). According to the validity and reliability analysis findings, the AI Integration and Employee Adaptation Scale was found to be a reliable and valid scale with its 6 items and one-dimensional structure.

Keywords: AI Integration, Employee Adaptation, Scale Development, Validation Study.

JEL Codes: M00, M1, O3

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1. Introduction

The rapidly increasing use of AI technologies in the business world indicates that business processes, leadership approaches, and employee behaviors need to be transformed (Brock and Von Wangenhelm, 2019; Enholm et al., 2022; Yazıcı and Sivaslıoğlu, 2024). In addition to increasing the operational efficiency of organizations, AI creates a new dynamic in human-machine interaction (Yazıcı, 2023). However, one of the biggest challenges encountered during the integration of this technology is how employees adapt to this change (Makarius et al., 2020; Arslan et al., 2022). While employees' adaptation processes to change play an important role in the success of businesses, there are limited studies in the relevant literature on how to measure this adaptation. For this reason, this study aims to address a comprehensive scale development study to understand the relationship between AI integration and employee adaptation.

The successful implementation of AI technologies in organizations is not only limited to the correct use of technology, but also includes the adaptation process of employees to these new systems (Brougham and Haar, 2018). Employees' perceptions of AI technologies, the extent to which they adapt to these technologies, and whether they resist this change are important for organizations to be successful in the long term (Ahmed et al., 2019). In this context, it is necessary to examine the relationship between AI integration and employee adaptation in the business world and to develop a measurement tool that can objectively evaluate this process (Brynjolfson and McAfee, 2014; Sullivan and Wamba, 2024).

AI technologies, one of the biggest and most important innovations of the digital age, are rapidly integrating into every aspect of our lives (Makridakis, 2017). The integration of AI not only offers technological innovations, but also leads to significant changes in a wide range of areas from business processes to education, from health services to art (Dwivedi et al., 2023). There are various studies emphasizing the importance of this integration. In studies detailing the importance of AI applications in strategic decision-making processes and the advantages provided by AI in areas such as data analytics, customer relationship management and automation, the impact of technology in increasing sustainable competitive advantage and power has been seen (Bessen, 2019; Kumar et al., 2024).

One of the clearest examples of AI integration and employee adaptation within the organization is related to task automation (Raisch and Krakowski, 2021). Increases in automation and efficiency levels are one of the most important advantages that AI applications provide to organizations (Javaid et al., 2022). For example, chatbots used in customer relationship management provide 24/7 service, increasing customer satisfaction and reducing costs (Jenneboer et al., 2022). In addition, thanks to machine learning algorithms and data analytics, organizations can obtain meaningful information from large data sets and align it with their strategies (Grover et al., 2018).

Integration of AI in the creation and improvement of organizational culture is of great importance in terms of developing employee competencies and improving business processes (Trushkina et al., 2020). AI -supported training and development programs increase employee skills and prepare them for the future of business (Rožman et al., 2023). In addition, AI-supported performance evaluation systems identify employees' strengths and weaknesses more objectively and help prepare personalized development programs (Frey and Osborne, 2017).

The aim of this study is to develop a reliable and valid scale to measure employee adaptation in the AI integration process. The ability of employees to adapt to new technologies is seen as an important factor in maintaining the competitive advantage of businesses. However, existing scales are generally examined under general headings such as technological competence or employee satisfaction, and the effects of a specific technology such as AI on the workforce are not addressed in detail. In this context, the scale presented by this study will provide both managers and researchers with the opportunity to measure the extent to which employees adapt to the AI integration process.

When the literature investigating the effects of AI integration on the workforce is examined, it is seen that the majority of existing studies focus on the contributions of AI use to operational efficiency and decision-making processes (Murugesan et al., 2023; Cramarenco et al., 2023; Perifanis and Kitsios, 2023). Artificial intelligence has become an important tool that increases productivity in human resources processes and supports strategic decision -making processes. Especially in areas such as recruitment, talent management and employee performance evaluation, artificial intelligence -supported systems provide more accurate and neutral decisions thanks to its major data analytics (Gao and Feng, 2023). For example, while artificial intelligence-based recruitment platforms accelerate the process of identifying the most appropriate candidates by analyzing the resumes of the candidates, it offers a more fair election process by minimizing the prejudice (Delecraz et al., 2022). In addition, artificial intelligence systems that support employees' career development provide personal education proposals by evaluating individual competencies and optimize corporate learning processes (Parveen and Alkudsi, 2024). These developments allow the adoption of more data-oriented and proactive approaches in human resources management, while providing innovative solutions that increase employee satisfaction and organizational commitment.

However, the role of employees in these processes, their ability to adapt, and the effects of these processes on job performance have not been sufficiently examined in the literature. Although there is a theoretical basis that employee adaptation is an important factor in the success of AI integration, an original scale has not been developed to measure this adaptation. This situation reveals the original value of the study. In this context, the scale to be developed will not only fill a theoretical gap, but will also provide a usable tool in the human resources management processes of enterprises.

2. Conceptual Framework

2.1. AI Integration and Employee Adaptation

While technology and digitalization are causing radical changes in the business world, AI technologies are at the center of this transformation (Malenkov et al., 2021). AI helps businesses achieve their strategic goals by providing speed, efficiency and cost advantages in business processes (Abousaber and Abdalla, 2023). However, the success of AI integration is directly related not only to the technological infrastructure, but also to the ability of employees to adapt to these innovations and new business models (Morandini et al., 2023). AI integration is reshaping the core functions of human resources management as a dynamic process that transforms the workforce. Especially in critical areas such as recruitment, talent management, and employee development, AI-supported systems make processes more efficient and data-driven (Dawson and Agbozo, 2024). AI is applied in a wide range of areas from candidate analysis to performance evaluations in the recruitment process, strengthening the role of human resources as a strategic business partner. In addition, AI-based training platforms that support employee skill development help the workforce adapt to changing job demands by providing personalized learning experiences (Regier and Grace, 2023). In this context, AI integration not only transforms business processes but also increases the impact of human resources management on organizational efficiency and employee engagement.

As a process that transforms the workforce, AI integration necessitates restructuring the way employees do business, job descriptions and learning processes. At this point, the concept of employee adaptation is important (Pan et al., 2023). AI creates great impacts on the operational processes of businesses through applications such as data analytics, machine learning and automation (Russell and Norvig, 2016). While these technologies automate repetitive tasks in business processes, they also allow employees to focus on more strategic and creative work. For example, AI-supported decision support systems improve business processes by helping employees make faster and more informed decisions (Sahoo et al., 2021; Yu et al., 2023). However, this technological transformation leads to changes in employees' duties, creates the need to develop new competencies, and brings various difficulties in business processes.

The adaptation process of employees to AI technologies is directly related to their perceptions, competencies and motivations. Adaptation to technology refers to the level of resistance or acceptance that employees show towards new systems and ways of doing business (Venkatesh and Davis, 2000; Kulkov et al., 2024). The extent to which employees adopt AI applications in this process, how they perceive the opportunities offered by technology and how effectively they can use these technologies in business processes determine the adaptation level of organizations.

The relationship between AI integration and employee adaptation is one of the most important issues that organizations face in the digital transformation process (Kahai et al., 2017; Frick et al., 2021; Trenerry et al., 2021; Gupta et al., 2024; Ali et al., 2024). Employees' reactions to technological change, their motivation levels and their participation in this process are the determining factors for the success of organizations in AI integration (Makarius et al., 2020). Employees' adaptation to AI technologies includes both cognitive and emotional adaptation processes. While employees on a cognitive level try to understand the impact of new technologies on business processes, they may experience anxiety, uncertainty and resistance regarding this change on an emotional level (Pereira et al., 2023). At this point, leaders need to provide support to their employees, effectively carry out change management and facilitate the adaptation processes of employees to technology (Suseno et al., 2023).

2.2. AI and Digital Transformation

AI technologies have become an important component of digital transformation in recent years. Organizations are integrating AI into their business processes to optimize processes, increase efficiency, and improve customer service. According to PwC's 2020 report, the global AI market is expected to contribute $15.7 trillion by 2030 (PwC, 2020). This huge economic potential causes organizations to invest more in AI in their digital transformation strategies. This potential of AI shows that it has created a serious transformation, especially in sectors such as industrial production, finance, and healthcare.

The impact of AI on digital transformation is directly linked to the automation of business processes and data analytics. According to a study by McKinsey, 75% of organizations' customer operations, marketing and sales, software engineering, and R&D departments are using productive AI (McKinsey, 2023).

The digital transformation process requires organizations to reconsider not only technology but also their business models. Many organizations need to restructure their business processes to make them more flexible and agile when implementing AI-based solutions (Mihu et al., 2023). The role of AI in digital transformation also affects workforce dynamics. As traditional business processes become automated, the role of employees changes. In particular, routine and repetitive tasks are automated, while employees focus on more creative and strategic tasks (Davenport and Kirby, 2018). This creates the need for employees to acquire new skills and increases the demand for training programs. Therefore, the impact of AI on digital transformation covers both technological and human factors. The success of AI and digital transformation is not limited to investing in technology alone. Successful transformation is also related to the cultural adaptation of organizations. According to Gartner's 2023 report, 85% of AI projects fail to deliver the expected results due to organizational cultural change failure (Gartner, 2018). Therefore, during the digital transformation process, leaders need to develop strategies that will support employees' adaptation to this transformation while investing in technology.

2.3. Employee Adjustment and Adaptation Theories

While employee adaptation plays an important role in digital transformation processes, especially the integration of new technologies is directly related to how employees adapt to these technologies. According to Roger's theory of diffusion of innovations, while technological changes are integrated into the organization, employees adapt at different speeds depending on their level of openness to innovation (Gallivan, 2001). Lewin's theory of change is another important approach used to understand employee adaptation. According to this theory, organizational change occurs in three stages: dissolution, change and freezing (Lewin, 1951). During the integration of AI, employees need to get rid of old ways of doing business (dissolution) and adapt to the new technology (change). A successful adaptation process can be possible by making this change sustainable and permanent (refreezing).

Employees' capacity to adapt to technological change depends on various factors such as individual differences, organizational support, and training programs. According to Bandura and Adams's social learning theory, employees learn new technologies through observation and experience (Bandura and Adams, 1977). Especially during the integration of complex technologies such as AI, training and mentoring programs provided to employees accelerate adaptation. In a study conducted by IBM in 2024, 42% of employees stated that they adapted to AI technologies more quickly with appropriate training programs (IBM, 2024). Psychological factors such as motivation and job satisfaction are also of great importance in the adaptation process. Herzberg's dual factor theory suggests that increasing employees' motivation in the workplace will also make it easier for them to adapt to technological change (Herzberg, 1966). It has been observed that employees with high job satisfaction adapt to new technologies more quickly and experience less stress during this process (Judge and Bono, 2001). Therefore, taking into account motivation-enhancing factors in the adaptation process of employees can positively affect success.

2.4. Challenges Encountered in AI Integration

Although AI integration offers a great opportunity for organizations, it also brings with it various challenges. According to a published study, one of the most important challenges is employee resistance to adopting new technologies. The most important of these challenges is the resistance of employees to new technologies. The most important of these challenges is employee resistance to new technologies. According to a published study, 70% of AI projects fail due to employee resistance. This resistance stems from employee concerns about job security and lack of trust in the technology (Koo et al., 2021). Therefore, organizations need to develop proactive strategies to address these concerns during the AI integration process.

Another challenge of AI integration is the lack of necessary technical infrastructure. Many businesses must invest in data management, cloud computing, and other digital technologies before implementing AI-based solutions. However, 45% of small and medium-sized businesses state that they do not have the financial resources to invest in such technologies. This is seen as a significant obstacle that slows down the pace of AI integration. These challenges are especially pronounced in developing countries, and the digital transformation processes of organizations in these countries are slower (Kaur et al., 2023).

Another challenge experienced during AI integration is data privacy and security concerns. Organizations collect large amounts of data using AI-based systems, and it is important to process this data securely. According to McAfee's 2024 report, 67% of businesses experience data security concerns when implementing AI projects (McAfee, 2024). The integration of AI is a process that affects not only technical challenges but also organizational culture and leadership strategies. According to transformational leadership theory, successful leaders motivate employees by clearly communicating their vision and facilitate their adaptation to technological change processes (Bass and Bass Bernard, 1985). However, it is stated that many leaders have difficulty managing this process and therefore fail in AI integration (Avolio and Yammarino, 2013). The challenges encountered in AI integration require a continuous learning and development process. Studies show that for AI projects to be successful, organizations must constantly learn new skills and adapt to technology (Regona et al., 2022). However, it has been observed that organizations that invest in training and development programs are more successful in the AI integration process. Therefore, the long-term success of AI depends not only on technology, but also on investing in organizational learning and cultural change (Morandini et al., 2023).

3. Development Process and Method of AI Integration and Employee Adaptation Scale

3.1.Problem of the Study

The efficiency, cost reduction and innovation opportunities that AI technologies offer to businesses are some of the elements that enable businesses to gain competitive advantage (Lee et al., 2019). However, the effective use of these technologies depends not only on the development of the technological infrastructure, but also on the adaptation of business managers and employees to these new technologies (Sjödin et al., 2021).

In most cases where AI integration fails or remains limited, the problem lies not in the technology itself, but in how employees adapt to these innovations. Employees' resistance to AI -based business processes, their lack of sufficient knowledge and skills, or their negative perceptions of these technologies are among the main problems that make AI integration difficult in businesses (Venkatesh and Davis, 2000). In this context, evaluating the level of adaptation of employees to AI integration is important in terms of developing strategies that will increase the success of this process.

The main problem of this study is that the adaptation levels of employees are not measured sufficiently during the integration of AI technologies into business processes and the impact of this adaptation on business activities is ignored. The adaptation of employees to AI technologies directly affects not only their individual performance but also the overall efficiency of the business, the speed of business processes and competitiveness. However, the limited measurement tools in the literature regarding the relationship between AI integration and employee adaptation create a lack of awareness on this issue. The main questions of this study are as follows:

RQ1: To what extent do employees adapt to the integration of AI technologies into business processes?

RQ2: What are the perceptions and attitudes of employees towards the changes caused by AI integration in business processes?

RQ3: What are the difficulties faced by employees who cannot adapt to AI technologies and how do these difficulties affect business performance?

RQ4: What strategies can be developed to reduce employees' resistance to AI technologies and accelerate their adaptation processes to these technologies?

Within the framework of this problem, the "*AI Integration and Employee Adaptation Scale*" aims to measure the level of adaptation of employees to AI technologies and to evaluate the effects of this adaptation on business performance. The scale to be developed will contribute to the more effective management of AI integration processes in the business world and will allow us to understand the effects of these processes on employee adaptation in more detail.

3.2. Scale Development Process

The three-stage scale development process suggested by Schwab was applied. The stages in the scale development process are: 1) Creation of the suggestion pool, 2) Structuring the scale, 3) Evaluation of the scale (Schwab, 2013).

3.3. Creating the Proposal Pool

In the first stage, academicians who are experts in business management, computer engineering, management organization, strategic management and management information systems were consulted regarding AI and collaboration leadership. A focus group was formed with the participation of these academicians and also managers/employees from information technologies, education and customer service sectors. In the meeting held with this focus group of 22 people consisting of academicians and sector employees, the important issues in measuring AI and collaboration leadership, the criteria to be used and the language to be used in the scale items were tried to be determined. In addition, interviews, one of the qualitative data acquisition methods, were conducted with the focus group members. In the interviews, content analysis was applied to the data collected with the help of semi-structured questions and a 40-item proposition pool was obtained. The proposition pool provided a comprehensive framework for measuring AI integration and employee compliance. The items created focused on important areas such as AI -based systems, digital collaboration tools, leadership strategies and areas of use of innovative technologies. These areas generally focused on the basic areas covered by the concept of AI and collaboration leadership.

3.4. Creating the Proposal Pool: Expanded Details

The Item Creation Stage aimed to generate a comprehensive set of items that would effectively measure the integration of AI technologies and employee adaptation within business processes. This stage involved the collection of qualitative data through various methods, including expert consultations and interviews.

Below is an expanded explanation of the process:

Expert Consultations

A focus group consisting of 22 participants from diverse fields—academics in business management, computer engineering, management information systems, strategic management, and practitioners from sectors like information technologies, education, and customer service—were consulted to gather their insights on the key criteria and language for the scale items.

Thematic Categories for Scale Items: Based on the focus group discussions, four thematic categories were identified to structure the scale:

- **AI Systems:** How employees interact with and adapt to AI technologies used in the business.
- **Digital Collaboration Tools:** The role of AI-driven collaboration tools in the workplace.
- **Leadership Strategies:** How leadership styles and strategies can facilitate AI integration.
- **Innovative Technology Adoption:** The perception of AI technologies and their impact on business practices.

Interviews with Focus Group Members

In-depth, semi-structured interviews were conducted with focus group participants to gain a deeper understanding of their views on AI integration and employee adaptation. Some sample questions from the interviews included:

- *"What are the biggest challenges employees face in adapting to AI technologies in the workplace?"*
- *"How do you think AI-based tools will change the way employees collaborate and communicate?"*
- *"What role do leadership strategies play in easing employee resistance to AI technologies?"*
- *"Can you share examples of AI technologies you think employees would resist the most, and why?"*

Content Analysis and Coding Steps

The responses from the interviews were analyzed using content analysis to extract key themes, issues, and areas of concern regarding AI integration. The coding process followed these steps:

1. **Transcribing:** All interview data was transcribed for a detailed review.
2. **Initial Coding:** Responses were divided into units of meaning and categorized into thematic areas.
3. **Refining Codes:** Similar codes were grouped under broader categories to ensure alignment with the key themes (e.g., "resistance to AI", "employee training", "leadership support").
4. **Final Coding:** After discussions with experts, the refined categories led to the formulation of clear and concise items for the scale.

Example Items Generated

Based on the thematic categories, the following sample items were developed to be included in the proposition pool:

- *"I feel confident in using AI technologies to perform my daily tasks."* (AI Systems)
- *"The digital tools we use for collaboration help me work more efficiently with my colleagues."* (Digital Collaboration Tools)
- *"The leadership in my organization is actively involved in supporting AI adoption."* (Leadership Strategies)
- *"I believe AI will bring positive changes to the overall efficiency of my work."* (Innovative Technology Adoption)

These items focused on different aspects of AI integration, employee adaptation, and leadership, aiming to capture a broad spectrum of experiences and perceptions related to AI in the workplace.

Thematic Categories for Item Evaluation

The items were later classified into specific categories to guide the evaluation of employee adaptation to AI:

- **Technological Confidence:** Focuses on how confident employees feel in using AI tools and their ability to perform work tasks with the help of AI.
- **Collaboration & Communication:** Measures how AI tools influence collaboration among team members and communication within the workplace.
- **Leadership Influence:** Evaluates the role of leadership in facilitating the integration of AI and supporting employees in adapting to these changes.
- **Adoption and Change Perception:** Assesses

employee attitudes toward the broader organizational changes induced by AI adoption.

By adding these expanded details to the **Item Creation Stage**, we provide a clearer and more transparent view of the methodological process involved in the development of the **AI Integration and Employee Adaptation Scale**. This transparency enhances the credibility of the scale and helps ensure that it effectively measures the key aspects of employee adaptation to AI technologies in the business context.

3.5. Scale Configuration

A draft scale was created using a pool of 40 items. For this purpose, the opinions of six experts in the fields of Turkish language, business management, management information systems, strategic management, industrial engineering and computer engineering were consulted. Thus, the scope validity of the items in the pool of suggestions created in the first stage was tested. The purpose of testing the scope validity is to determine whether the items to be used for the features to be measured with the measurement tool are sufficient in terms of quantity and quality. Expert opinions are generally consulted to determine the scope validity. The experts consulted at this stage shaped the scale draft according to the standards of sensitivity of the scale, measurability, language integrity, scope and understandability. Thus, it was tried to ensure that the scale items addressed the basic issues related to AI and collaboration leadership, were compatible with different businesses and activities, and were based on concrete and measurable targets. In the applications to be carried out using the scale, it is important that the language of the scale items is clear, understandable and explicit so that the sample can easily understand the meaning of the items. According to the Lawshe method, the items with a scope validity rate of zero and below zero were eliminated from among the 32 items. The items created more than once on the same subject were deleted or combined. The meeting held to structure the scale was held in four stages. In the first session, the scale was reduced to 40 items, in the second session to 36 items, and in the third session to 32 items. In the fourth session, a 30-item draft scale form was obtained. The "AI Integration and Employee Adaptation Scale Draft Form" is presented in Table 1 below.

Table 1. AI Integration and Employee Compliance Scale Draft Form

	AI Integration and Employee Adaptation	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
1	Do you think you understand the basic concepts of AI technologies?					
2	Have you attended any workplace training programs on AI?					
3	How well do you understand the impact of AI technologies on your workplace?					
4	Do you know the specific tools and solutions that AI offers for your field of work?					
5	Do you think AI reduces your workload?					
6	Do you think you can produce more creative solutions with AI technologies?					
7	Do you think AI increases customer satisfaction?					
8	Do you think AI is effective in reducing errors?					
9	Do you feel any resistance to AI integration?					
10	Do you think AI technologies are changing the nature of your job?					
11	Have you received enough support to adapt to AI integration?					

12	How comfortable do you feel using AI technologies?	
13	Do you think AI integration has increased your job satisfaction?	
14	Do you think AI has made your job more meaningful?	
15	Do you think AI technologies are reducing your stress levels at work?	
16	Has working with AI boosted your workplace morale?	
17	Are you aware of the decisions taken in the AI integration process?	
18	Have sufficient educational materials been provided on AI technologies?	
19	Have regular briefings been held on AI integration?	
20	Have you received guidance on the use of AI technologies?	
21	Are you worried that AI will take your job?	
22	Do you think AI technologies are fair and transparent?	
23	Do you believe that AI is being used ethically and responsibly?	
24	Did you find management support sufficient during AI integration?	
25	Do you think AI technologies are improving teamwork in the workplace?	
26	Do you think AI is driving innovation in the workplace?	
27	Have you encountered any technical problems during the AI integration process?	
28	Do you think AI technologies make communication easier in the workplace?	
29	Do you think AI is effective in standardizing business processes?	
30	Do you feel like you can share your feedback about AI technologies in the workplace?	

3.6. Evaluation of the Scale

A pilot study was conducted with a sample of 281 professionals working in the fields of information technology, education, and customer service. The collected data were analyzed to assess the scale's validity and reliability. To evaluate validity, factor analysis was performed, revealing a unidimensional structure. Reliability was examined through Cronbach's Alpha coefficient, which indicated a high level of internal consistency. The Cronbach's Alpha value was determined to be 0.94, with item-total correlation values ranging from 0.75 to 0.91, all exceeding the 0.30 threshold.

Based on these findings, the AI Integration and Employee Adaptation Scale has been confirmed as both a reliable and valid measurement tool in its finalized six-item, single-factor form. This newly developed scale is expected to serve as a valuable instrument for assessing employees' perceptions of AI and their awareness of collaborative leadership across various industries.

This process was followed in the development of the

AI Integration and Employee Adaptation Scale, and by ensuring the validity and reliability of the scale, the final form was transformed into a one-dimensional and 6-item form.

3.7. Target Group and Sampling Method

In the study, both online and face-to-face surveys were conducted in the last quarter of 2023 using the random sampling method. To use the survey questions related to the collection of data, firstly, "Ethics Committee Permission" dated 04.12.2024 and numbered 360 was obtained from Mersin University Ethics Committee. A total of 23 of the survey forms applied to the participants were found to be filled out incorrectly or incompletely and were excluded from the evaluation for this reason. Thus, 281 survey forms were evaluated in the information technologies, education and customer service sectors. According to Bryman and Cramer (2012), it is stated that in studies conducted for scale development, it is sufficient for the number of participants to be reached to be 5 or 10 times more than the number of questions used in the scale. The number of questions used in the scale in this study is 15. Since 15x10=150, the number of participants to be reached within the scope of this study must be at least 150. Therefore, reaching 281 employees in the information technologies, education and customer service sectors indicates that the number of participants is sufficient. The universe of the study consists of information technologies, education and customer service employees. The distribution of information technologies, education and customer service employees in the study according to demographic variables is shown in Table 2 below.

Table 2. Shows the Distribution of Participants According to Their Demographic Characteristics

Demographic Variables	Groups	n	%
Gender	Female	61	21,7
	Male	220	78,3
Marital status	Married	106	37,7
	Single	175	62,3
Age	21-24 years	32	11,4
	25-29 years	70	24,9
	30-34 years	89	31,7
	35-40 years	29	10,3
	41-44 years	35	12,5
	45 years and older	26	9,3
Education	Primary education	40	14,2
	High school	39	13,9
	Graduate	136	48,4
	Postgraduate	66	23,5
Duration in this workplace	1-5 years	69	24,6
	6-10 years	114	40,6
	11-15 years	70	24,9
	16 years and more	28	10,0
Working time with current manager	1-5 years	86	30,6
	6-10 years	118	42,0
	11-15 years	63	22,4
	16 years and more	14	5,0

Of the 281 employees who participated in the study, 21.7% were female and 78.3% were male. 37.7% of the participants are married, 62.3% are single. 11.4% of the participants are 21-24 years old, 24.9% are 25-29 years old, 31.7% are 30-34 years old, 10.3% are 35-40 years old, 12.5% are 41-44 years old, 9.3% are 45 years old and above. 14.2% of the participants had primary education, 13.9% had high school education, 48.4% had undergraduate education, and 23.5% had graduate education. The working period of 24.6% of the participants is 1-5 years, 40.6% is 6-10 years, 24.9% is 11-15 years, 10% is 16 years and above. 30.6% of the participants have been working with their current manager for 1-5 years, 42% for 6-10 years, 22.4% for 11-15 years, and 5% for 16 years or more.

The descriptive statistics of the 30 items in the AI Integration and Employee Cohesion Scale item pool are given in Table 3. When the mean scores of the 30 items in the AI Integration and Employee Compatibility Scale are analysed, it is seen that the AI integration and employee compatibility with the highest scores are '3 - Understanding the effects of AI technologies on the workplace' (3,60±0,86), '8 - Thinking that AI is effective in reducing errors' (3,60±0,89), '14-Thinking that AI makes your job more meaningful' (3,60±0,86), "15-Do you think that

Table 3. Descriptive Statistics of AI Integration and Employee Adaptation Scale Items

Items	$\bar{X}$	SD	S.	K.
1- Do you think you understand the basic concepts of AI technologies?	3,40	0,79	0,48	0,47
2- Have you attended any workplace training programs on AI?	3,30	0,89	0,11	0,36
3- How well do you understand the effects of AI technologies on your workplace?	3,60	0,86	-0,61	0,89
4- Do you know the specific tools and solutions that AI offers for your field of work?	2,96	0,91	-0,42	0,75
5- Do you think that AI reduces your workload?	3,39	0,94	-0,32	0,27
6- Do you think that you can produce more creative solutions with AI technologies?	3,40	0,73	0,35	0,53
7- Do you think that AI increases customer satisfaction?	3,52	0,98	0,13	-0,24
8- Do you think AI is effective in reducing errors?	3,60	0,89	-0,57	0,62
9-Do you feel any resistance to AI integration?	2,98	1,16	-0,06	-0,70
10-Do you think AI technologies are changing the nature of your job?	3,53	0,98	-0,31	-0,21
11-Have you received enough support to adapt to AI integration?	3,40	0,73	0,35	0,53
12-How comfortable do you feel using AI technologies?	3,52	0,98	0,13	-0,24
13-Do you think AI integration increases your level of satisfaction in your job?	3,30	0,89	0,11	0,36
14-Do you think AI makes your job more meaningful?	3,60	0,86	-0,61	0,89
15-Do you think AI technologies reduce your stress level at work?	3,60	0,89	-0,57	0,62
16-Has working with AI increased your morale at work?	2,96	0,91	-0,42	0,75
17-Are you aware of the decisions made in the AI integration process?	3,30	0,89	0,11	0,36
18-Have sufficient educational materials been provided on AI technologies?	3,40	0,73	0,35	0,53
19-Have regular information meetings been held on AI integration?	2,96	0,91	-0,42	0,75
20-Have you received guidance on the use of AI technologies?	3,60	0,86	-0,61	0,89
21-Are you concerned that AI will take your job?	3,60	0,89	-0,57	0,62
22-Do you think AI technologies are fair and transparent?	3,41	0,77	0,55	0,36
23-Do you believe that AI is being used ethically and responsibly?	3,30	0,89	0,11	0,36
24-Did you find the support of management sufficient during the integration of AI?	3,40	0,73	0,35	0,53
25-Do you think that AI technologies improve teamwork in the workplace?	2,98	1,16	-0,06	-0,70
26-Do you think that AI increases innovation in the workplace?	2,96	0,91	-0,42	0,75
27-Did you encounter any technical problems during the integration of AI?	2,55	1,19	0,54	0,32
28-Do you think that AI technologies facilitate communication in the workplace?	3,41	1,20	-0,39	-0,56
29-Do you think that AI is effective in standardizing business processes?	3,53	0,98	-0,31	-0,21
30-Do you think that you can share your feedback about AI technologies in the workplace?	3,34	0,96	-0,60	0,50

S: Skewness K: Kurtosis

AI technologies reduce your stress level at work" (3,60±0,89), "20-Receiving guidance on the use of AI technologies" (3,60±0,86), "21-Being worried that AI will take your job away" (3,60±0,89); The lowest score of AI integration and employee harmony belongs to the statement '27-Have you encountered technical problems in the process of AI integration' (2,55±1,19).

4. Method

In this study, statistical analyses were conducted using SPSS 21.0 and AMOS 22.0 software. To assess the validity and reliability of the developed scale, multiple statistical techniques were employed, including exploratory factor analysis (EFA), confirmatory factor analysis (CFA), item-total correlation analysis, and Cronbach's Alpha reliability measurement.

Exploratory factor analysis (EFA) is a widely used multivariate statistical method that identifies underlying constructs by grouping interrelated variables into meaningful factors (Çokluk et al., 2010). The first step in EFA involves testing the suitability of the dataset using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Sphericity Test. A KMO value above 0.70 and a p-value below 0.05 in Bartlett's test indicate that the data is appropriate for factor analysis. Among the available factor extraction techniques, principal component analysis (PCA) is the most frequently used method. To enhance interpretability, the orthogonal rotation technique, particularly the varimax method, is often preferred.

Following varimax rotation, factor loadings of the items are examined to determine their alignment with respective factors. Items should ideally exhibit high loadings (above 0.40, though in some cases, 0.30 may be acceptable) on a single factor while showing minimal cross-loadings on others. If an item loads on multiple factors, the difference between the highest and second-highest loading should be at least 0.10 to ensure distinct factor separation.

To determine the optimal number of factors, several statistical criteria are considered, including eigenvalues, total variance explained, and the scree plot. The scree plot visually represents the number of significant factors by identifying the point at which the slope of the graph starts to flatten. In single-dimensional scales, a total variance above 30% is generally sufficient, while higher variance percentages are expected for multi-dimensional constructs (Çokluk et al., 2010).

Confirmatory factor analysis (CFA) is an advanced statistical technique designed to test the validity of a predefined theoretical structure by examining latent variables within a model. It assesses whether the hypothesized factor structure aligns with the observed data. CFA is a key component of structural equation modeling (SEM), where ensuring model fit is a crucial step. Several fit indices are commonly used to evaluate the adequacy of the model, including the ratio of the Chi-square statistic to degrees of freedom (χ^2/df), the significance of individual parameter estimates (t-values), residual-based indices (SRMR, GFI), comparative fit indices (NNFI, CFI), and the root mean square error of approximation (RMSEA) (Çokluk et al., 2010).

For reliability assessment, Cronbach's Alpha coefficient is widely used to measure internal consistency, ensuring that all items in a scale contribute meaningfully to the overall construct. A Cronbach's Alpha value of 0.70 or higher is typically considered acceptable. Another method for reliability evaluation, item-total correlation, determines how well each individual item correlates with the total scale score. Items with a correlation coefficient above 0.30 are generally regarded as effective in distinguishing different response patterns among participants (Büyüköztürk, 2011).

Descriptive statistics were also used to summarize the demographic characteristics of the participants, with frequency and percentage distributions presented in tabular form. To further examine the dataset, the mean, standard deviation, skewness, and kurtosis values of the scale scores were analyzed. The skewness and kurtosis coefficients provide insights into whether the data follows a normal distribution, with values within the ±1 range indicating an approximately normal distribution (Büyüköztürk, 2011).

Since the total scale score demonstrated a normal distribution, parametric tests were applied to examine group differences. An independent samples t-test was used to compare mean scores based on gender and marital status, while a one-way analysis of variance (ANOVA) was employed to assess differences across age groups, education levels, tenure at the organization, and duration of working with the current manager. The significance level was set at $p<0.05$ with a 95% confidence interval to ensure robust statistical interpretations.

4.1. Exploratory Factor Analysis

4.1.1. Validity and reliability findings of AI integration and employee adaptation scale

When the correlation between the items in the scale was examined before the validity and reliability analysis for the AI Integration and Employee Compliance Scale (Appendix-1), it was determined that the correlation coefficient between many items was equal to 1 or higher than 0.90. Items with correlation coefficients higher than 0.90 with more than one item were gradually removed and 11 items remained in the scale. Validity and reliability analyses continued with the remaining 11 items. The KMO value (0.839), which was examined for the suitability of the data obtained from 281 participants for the AI Integration and Employee Compatibility Scale in terms of explanatory factor analysis, was quite high and the Bartlett's Sphericity test statistic (Barlett's X2=2912.20; $p<0.05$) was statistically significant and it was understood that the research sample was sufficient. The scree plot analysis of the AI Integration and Employee Cohesion Scale, originally structured with five factors, revealed a shift towards a horizontal trajectory after the third point. This pattern suggests that the scale may be more appropriately represented with a two-dimensional structure (Figure 1).

Figure 1. AI Integration and Employee Compliance Scale Scree Plot

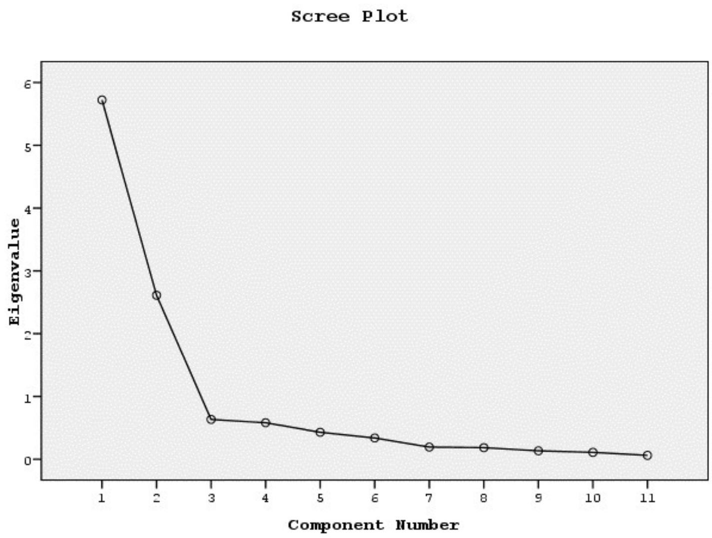


Table 4 presents the preliminary findings from the exploratory factor analysis performed on the AI Integration and Employee Adaptation Scale.

Table 4. AI Integration and Employee Compliance Scale Efa Findings-1

	Two Dimensions		One Dimensions		
Items	**Dimension**	**F2**	**11 items**	**10 items**	**6 items**
i1	**0,846**	0,179	0,831	0,704	0,758
i4	0,279	**0,845**	0,640	0,385	
i5	**0,903**	-0,105	0,848	0,737	0,816
i12	**0,871**	-0,043	0,791	0,647	0,741
i14	**0,894**	0,157	0,864	0,763	0,820
i17	**0,856**	0,256	0,877	0,774	0,806
i25	**0,584**	0,463	0,733	0,331	
i27	0,178	**0,917**	0,585	0,312	
i28	**0,844**	0,081	0,709	0,526	0,653
i29	0,168	**0,754**	0,203		
i30	-0,184	0,899	0,582	0,311	
Eigenvalues	5,723	2,612	5,723	5,690	4,650
Variance (%)	52,023	23,750	52,023	56,900	77,494
Total Variance	75,773		52,023	56,900	77,494
KMO	0,839				
Bartlett's Sphericity (X2)	2912,20				
df	55				
p	0,000				

In accordance with the 2 dimensions seen in the slope accumulation graph, it is seen that there are 2 factors with eigenvalues above 1. The variance explained by the first factor is quite high with 52,02%, while the contribution of the second factor to the variance is quite low (23,75%). When the item-factor relationship was analysed, it was determined that 7 items were in the first factor and 4 items were in the second factor. As a result of the EFA conducted with the unidimensional structure of the scale, it was determined that 1 item (i29) was eliminated in the first stage, 4 items (i4, i25, i27, i30) were eliminated in the second stage and 6 items remained in the scale. The variance explained by the six items was 77.49%. Although the total variance obtained in the structure of the scale consisting of two dimensions and 11 items is 75.77%, the fact that more total variance (77.49%) is obtained in the structure consisting of one dimension and 6 items shows that the unidimensional structure of the scale is more appropriate. In the confirmatory factor analysis, the structure consisting of 11 items and two dimensions as well as the structure consisting of one dimension and 6 items were checked and presented in Table 5.

Table 5. Model Fit Indices Obtained in Confirmatory Factor Analysis of AI Integration and Employee Fit Scale

Model Fit Indices	Reference Value1		Values obtained in this study			
	Good Fit1	Perfect Fit1	CFA 11 items 2 sub-scale	CFA 11 items 2 sub-scale*	CFA 8 items 2 sub-scale*	CFA 6 items 1 sub-scale
X2/df (p)	< 5	<3	15,162	14,974	13,016	2,443
SRMR	≤0,08	≤0,05	0,110	0,108	0,107	0,013
GFI	≥0,90	≥0,95	0,724	0,792	0,856	0,981
NNFI	≥0,90	≥0,95	0,743	0,747	0,789	0,986
CFI	≥0,90	≥0,95	0,806	0,843	0,887	0,993
RMSEA	≤0,10	≤0,08	0,225	0,223	0,207	0,072
Factor load	>0,40	>0,40	0,58 / 0,99	0,57 / 0,99	0,12 / 4,99	0,79 / 0,94
Covariance link count	-	-	-	6	4	2

1: (Çokluk et al., 2010) *: After appropriate covariance connections are made

The initial confirmatory factor analysis (CFA1) conducted for the two-dimensional structure identified through EFA revealed that the factor loadings were near 1, while the model fit indices were not within acceptable limits. Despite implementing six covariance connections based on modification recommendations, no significant improvement was observed in factor loadings or model fit indices. Consequently, items with extremely low factor loadings were removed from the scale. In the subsequent analysis, it was noted that certain items had excessively high factor loadings exceeding 1, and excluding these items caused the remaining factor loadings to surpass this threshold as well. Additionally, some items' factor loadings dropped below 0.40. Taking the EFA results into account, the scale was re-evaluated as a unidimensional structure with six items, which was found to be a more appropriate representation.

Table 6 presents the finalized factor loadings obtained from CFA, t-values of these factor loadings, as well as the item-total correlations and Cronbach's Alpha coefficients calculated for reliability assessment.

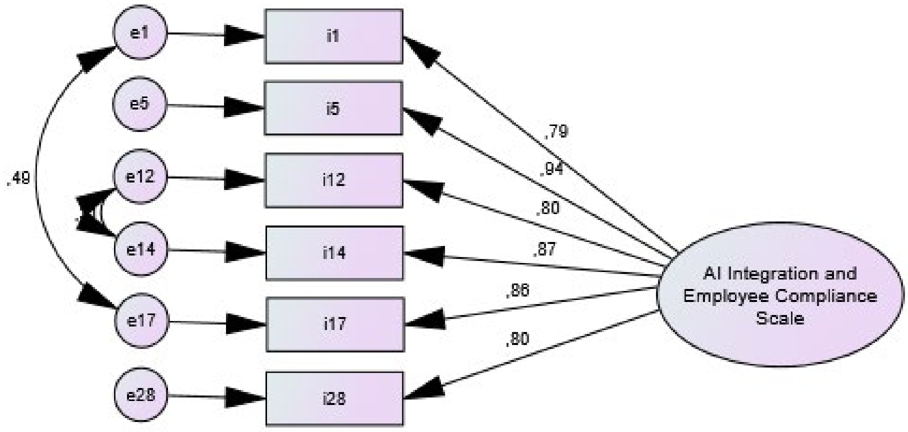
Table 5. Model Fit Indices Obtained in Confirmatory Factor Analysis of AI Integration and Employee Fit Scale

Item and Dimension	B	SE	Std. β	t	r	α
i1	1,000		0,79		0,795	0,94
i5	1,418	0,078	0,94	18,29**	0,888	
i12	1,264	0,085	0,80	14,90**	0,791	
i14	1,205	0,072	0,87	16,62**	0,860	
i17	1,225	0,054	0,86	22,72**	0,840	
i28	1,529	0,103	0,80	14,78**	0,756	

**p<0,01 r: Item total correlation

The CFA results indicate that the remaining six items within the single-factor structure exhibit factor loadings above 0.40, with all t-values reaching statistically significant levels. The overall reliability of the scale, as measured by Cronbach's Alpha, was calculated at 0.94, while item-total correlations ranged from 0.76 to 0.89, all exceeding the 0.30 threshold. Based on the validity and reliability analyses, the AI Integration and Employee Cohesion Scale demonstrates strong psychometric properties, confirming its reliability and validity as a six-item, unidimensional measurement tool.

Figure 2. AI Integration and Employee Fit Scale Cfa Diagram



5. Descriptive Findings

Table 7 shows the descriptive statistics of the AI Integration and Employee Adaptation Scale.

Table 7. Descriptive statistics of sub-dimensions and total scores of the AI integration and employee adaptation scale

				%95CI				
N	Min.	Max.	$\bar{X}$	SD	Lower	Upper	Skewness	Kurtosis
281	1	5	3,43	0,83	3,34	3,53	0,04	0,36

According to Table 7, the average score of the AI Integration and Employee Adaptation Scale was determined as 3.43±0.83. Considering that the lowest score on the scale is 1 and the highest score is 5, the participants' AI integration and adaptation is at a medium level.

6. Discussion

Studies on AI integration and employee adaptation reveal different approaches to how businesses manage the human factor in the digital transformation process. Studies in the literature focusing on the power of AI technologies to transform business processes generally emphasize the effects of these technologies on operational efficiency and cost advantages (Kraus et al., 2022). However, how employees adapt to these transformation processes and the processes of adapting to new skills have been addressed in a limited number of studies (Heim and Sardar-Drenda, 2021). The scale developed in this study fills this gap in the existing literature and provides an important tool for measuring the effects of AI integration on employees.

This research focuses on developing a specific measurement tool, unlike studies that address the professional and psychological adaptation processes of employees during the integration of AI technologies. For example, Bessen (2019) mentions employees' fear of losing their jobs and difficulties in adapting to changes in business models in his study on the integration of AI technologies into business processes. This study not only addresses these challenges but also contributes to the literature by providing a scale that measures how well employees adapt to AI integration.

Compared to other studies in the literature, another point where this research differs is that it approaches the adaptation processes of employees from a holistic perspective. While examining the effects of technological transformation on the workforce, Morandini et al. (2023) address the skill transformation created by the integration of AI, but do not focus on the psychological effects of this skill transformation on employees. The scale developed in this study provides a more comprehensive assessment by measuring both the professional skill acquisitions of employees and their psychological adaptation.

In the literature, the effects of AI integration on employees are mostly considered as an integrated process. In particular, the relationship between AI integration and the adaptation process of employees is evaluated based on a single basic factor (Burhan, 2025). Although employees' adaptation to AI includes many elements such as individual competence, learning process, and organizational dynamics, these elements are not considered as discrete categories but as an intertwined structure (Tang et al., 2023). Therefore, considering the scale in a one-dimensional structure is also compatible with the theoretical framework.

In addition, organizational behavior and technology acceptance models provide theoretical foundations supporting the one-dimensional structure. In particular, the Technology Acceptance Model (TAM) developed by Davis (1989) suggests that the process of employees' adaptation to new technologies is shaped by two basic factors such as perceived usefulness and ease of use. However, these two factors create a combined effect on the process of employees' adoption of technology, and this is generally evaluated as a holistic structure (Venkatesh et al., 2003). Similarly, Bandura's (1986) Social Cognitive Theory addresses the interactions of individuals with environmental factors within a single learning process. In this context, the evaluation of employee adaptation to AI integration under a single factor overlaps with theoretical models that include both technological acceptance and individual adaptation processes.

Finally, the factor analysis results also support this integrated structure presented in the theoretical framework. The high explanatory power of the single-factor structure and the homogeneous distribution of factor loadings indicate that the scale is based on a holistic conceptual framework. In addition, it is suggested that the one-dimensional structure increases the applicability of the scale and is more functional in terms of practical use (Briggs and Cheek, 1986). Therefore, the one-dimensional structure of the scale used in this study is supported by both theoretical and statistical findings.

Especially today, when AI technologies are rapidly integrated into the business world, the success of the employee adaptation process has become important for organizations to achieve long-term competitive advantage. However, existing studies in the literature generally use general methods to measure the adaptation processes of employees to technological innovations (Brynjolfsson and McAfee, 2014). This study aims to close this gap in the literature by addressing employee adaptation in the context of the integration of a specific technology such as AI.

This study provides an original contribution to the existing literature by developing a scale to measure employee adaptation in the AI integration process. Compared to previous studies on employee adaptation, this study provides findings that are valuable both theoretically and practically. In this context, the developed scale will provide businesses with an effective tool to assess employee adaptation levels in the AI integration process, allowing them to better manage their workforce management processes.

7. Conclusion

Within the scope of this study, a valid and reliable scale was developed to measure the adaptation levels of employees to AI technologies. The AI Integration and Employee Adaptation Scale was determined as a 6-item one-dimensional structure through a three-stage process. Confirmatory and exploratory factor analyses confirmed the validity and reliability of the scale, and the Cronbach Alpha value was calculated as 0.94 in reliability analyses. These results show that the scale has high reliability.

As a result of the analysis, it has been revealed that AI integration and employee adaptation directly affect the performance and efficiency of businesses. Employees' attitudes towards AI technologies and their adaptation to these technologies contribute to faster and more effective management of business processes. In order for AI integration to be successful in businesses, it is of great importance that employees have positive perceptions of these technologies and actively participate in technological transformation processes. The effective use of AI technologies increases employee satisfaction and positively contributes to the overall performance of businesses. Employees' adaptation to AI technologies and their effective use of these technologies in business processes is an important key to the success of businesses in digital transformation processes.

8. Limitations

This study, although providing important findings, has some limitations. First, the research data were collected from specific sectors, and the findings cannot be generalized to all industries. Considering the sectoral scope of the study, employee adaptation to AI integration may vary across different business lines. It is recommended that future research overcome this limitation with large-scale studies covering different sectors. Second, considering the geographical and cultural context of the study, the findings are based on the business culture in a specific country or region. Employee responses to AI integration may be shaped by cultural factors, organizational norms, and work values. Therefore, studies conducted in different cultural contexts will be useful in testing the universal validity of the AI adaptation process. Finally, the cross-sectional design of the study limits the ability to observe changes over time. Employee adaptation to AI is a dynamic process, and longitudinal studies are necessary to understand the long-term effects.

9. Recommendations

9.1. Theoretical Recommendations

This study contributes to the literature examining the effects of AI technologies on the workforce and presents an original scale that measures the adaptation process. While existing studies on technology integration generally focus on business processes, there are limited studies measuring how employees adapt to these technologies. In this context, the proposed scale provides the opportunity to analyze workforce adaptation within a conceptual framework. Future research can conduct comparative studies on employee adaptation in different sectors using this scale and reveal differences between sectors. In addition, testing the scale with larger and different samples can further strengthen the validity and reliability of the scale.

The developed scale aims to measure the adaptation process of employees to AI integration and includes the basic dimensions that determine this process. In the literature, employee adaptation is addressed in three basic dimensions: cognitive adaptation, emotional adaptation, and behavioral adaptation (Li and Yeo, 2024). In this framework, the items in the content of the scale are designed to reflect individuals' perceptions, emotional reactions, and behavioral tendencies regarding the new technology. For example, factors such as individuals' willingness to adopt AI-supported systems, the confidence they feel in working with these systems, and ease of use represent the sub-dimensions of the scale (Zheng and Montargot, 2022). The meaning of scale scores and their role in managerial decision-making processes are also very important. The adaptation levels shown by the results can guide strategic decisions regarding AI integration in the workplace. For example, low scale scores may indicate that employees are resistant to technology and that more training or support mechanisms are needed (Arora et al., 2024). On the other hand, high adaptation levels reveal that employees have successfully integrated AI into their work processes and that this can increase productivity (Bîzoi and Bîzoi, 2024). In this context, the scale provides information not only at the individual level but also at the organizational level.

9.2. Practical Recommendations

In practice, this scale can be an important tool for human resources management and workforce planning. In particular, businesses that integrate AI technologies in digital transformation processes can use this scale to evaluate how well their employees adapt to this process. Employee adaptation is a factor that directly affects the success of technological integration, and this scale can guide businesses in improving this process. Based on the scale results, managers can develop additional training programs for employees who have adaptation problems or create motivational strategies. In addition, employees who can adapt to AI integration can contribute more to the overall success of the organization, so the use of the scale can also be an effective tool in employee performance management.

In practice, the use of this scale can be an important tool in human resources management and organizational transformation processes. Organizations can develop targeted interventions to increase employees' adaptation to AI using the data obtained from the scale. For example, customized training programs or supportive leadership approaches can be created depending on individual differences (Stone et al., 2024). As a result, the developed scale not only provides a psychometrically strong assessment tool, but also provides managers with the opportunity to better understand and improve employee adaptation processes.

9.3. Future Recommendations

This study was applied to the information technology, education, and customer service sectors. However, as AI technologies increasingly spread to more sectors, more extensive studies can be conducted on how employee adaptation is shaped in different industries (e.g., healthcare, finance, manufacturing). In particular, industry-specific challenges and opportunities may reveal sectoral differences in how employees respond to AI integration. AI integration and employee adaptation can be greatly affected by cultural context. Future studies can examine how employees in different cultural environments adapt to this process. In particular, differences between collectivist and individualist cultures can provide important findings on how adaptation processes to AI technologies are affected. The scale used in this study provides an instantaneous assessment. Future studies can conduct long-term follow-up studies to examine how employees adapt to AI integration over time. Thus, changes and developments in employee adaptation levels can be better analyzed with the continuous development and change of AI technologies. Studies can be conducted to investigate the effects of employee adaptation to AI integration on job performance, employee commitment, and organizational success. Using the scale in this context can more comprehensively reveal the effects of AI integration in the workplace on employee behavior and outcomes.

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Appendix 1:

Artificial Intelligence Integration and Employee Adaptation Scale 6-Item Single-Dimension Application Survey

Items	
1	Do you think you understand the basic concepts of AI technologies?
2	Do you think AI reduces your workload?
3	How comfortable do you feel when using AI technologies?
4	Do you think AI makes your job more meaningful?
5	Are you aware of the decisions made during the AI integration process?
6	Do you think AI technologies make communication easier in the workplace?

Appendix 2:

Correlation Table

	i1	i2	i3	i4	i5	i6	i7	i8	i9	i10	i11	i12	i13	i14	i15	i16	i17	i18	i19	i20	i21	i22	i23	i24	i25	i26	i27	i28	i29	i30
1	1	0,83	0,71	-0,3	0,73	0,91	0,67	0,7	0,59	-0,01	0,91	0,67	0,83	0,71	0,7	-0,3	0,83	0,91	-0,3	0,71	0,7	0,97	0,83	0,91	0,59	-0,3	0,37	0,62	-0,01	-0,26
2	0,83	1	0,76	-0,33	0,82	0,82	0,67	0,75	0,55	-0,14	0,82	0,67	1	0,76	0,75	-0,33	1	0,82	-0,33	0,76	0,75	0,87	1	0,82	0,55	-0,33	0,43	0,66	-0,14	-0,36
3	0,71	0,76	1	-0,42	0,81	0,72	0,79	0,98	0,56	0,01	0,72	0,79	0,76	1	0,98	-0,42	0,76	0,72	-0,42	1	0,98	0,73	0,76	0,72	0,56	-0,42	0,25	0,71	0,01	-0,31
4	-0,3	-0,33	-0,42	1	-0,36	-0,2	-0,32	-0,41	-0,48	0,45	-0,2	-0,32	-0,33	-0,42	-0,41	1	-0,33	-0,2	1	-0,42	-0,41	-0,29	-0,33	-0,2	-0,48	1	-0,81	-0,22	0,45	0,83
5	0,73	0,82	0,81	-0,36	1	0,76	0,76	0,8	0,42	0,02	0,76	0,76	0,82	0,81	0,8	-0,36	0,82	0,76	-0,36	0,81	0,8	0,77	0,82	0,76	0,42	-0,36	0,26	0,76	0,02	-0,27
6	0,91	0,82	0,72	-0,2	0,76	1	0,73	0,72	0,57	0,14	1	0,73	0,82	0,72	0,72	-0,2	0,82	1	-0,2	0,72	0,72	0,94	0,82	1	0,57	-0,2	0,23	0,68	0,14	-0,17
7	0,67	0,67	0,79	-0,32	0,76	0,73	1	0,78	0,56	0,12	0,73	1	0,67	0,79	0,78	-0,32	0,67	0,73	-0,32	0,79	0,78	0,69	0,67	0,73	0,56	-0,32	0,13	0,64	0,12	-0,24
8	0,7	0,75	0,98	-0,41	0,8	0,72	0,78	1	0,56	-0,01	0,72	0,78	0,75	0,98	1	-0,41	0,75	0,72	-0,41	0,98	1	0,73	0,75	0,72	0,56	-0,41	0,25	0,69	-0,01	-0,31
9	0,59	0,55	0,56	-0,48	0,42	0,57	0,56	0,56	1	-0,19	0,57	0,56	0,55	0,56	0,56	-0,48	0,55	0,57	-0,48	0,56	0,56	0,62	0,55	0,57	1	-0,48	0,48	0,39	-0,19	-0,49
10	-0,01	-0,14	0,01	0,45	0,02	0,14	0,12	-0,01	-0,19	1	0,14	0,12	-0,14	0,01	-0,01	0,45	-0,14	0,14	0,45	0,01	-0,01	0	-0,14	0,14	-0,19	0,45	-0,58	0,17	1	0,52
11	0,91	0,82	0,72	-0,2	0,76	1	0,73	0,72	0,57	0,14	1	0,73	0,82	0,72	0,72	-0,2	0,82	1	-0,2	0,72	0,72	0,94	0,82	1	0,57	-0,2	0,23	0,68	0,14	-0,17
12	0,67	0,67	0,79	-0,32	0,76	0,73	1	0,78	0,56	0,12	0,73	1	0,67	0,79	0,78	-0,32	0,67	0,73	-0,32	0,79	0,78	0,69	0,67	0,73	0,56	-0,32	0,13	0,64	0,12	-0,24
13	0,83	1	0,76	-0,33	0,82	0,82	0,67	0,75	0,55	-0,14	0,82	0,67	1	0,76	0,75	-0,33	1	0,82	-0,33	0,76	0,75	0,87	1	0,82	0,55	-0,33	0,43	0,66	-0,14	-0,36
14	0,71	0,76	1	-0,42	0,81	0,72	0,79	0,98	0,56	0,01	0,72	0,79	0,76	1	0,98	-0,42	0,76	0,72	-0,42	1	0,98	0,73	0,76	0,72	0,56	-0,42	0,25	0,71	0,01	-0,31
15	0,7	0,75	0,98	-0,41	0,8	0,72	0,78	1	0,56	-0,01	0,72	0,78	0,75	0,98	1	-0,41	0,75	0,72	-0,41	0,98	1	0,73	0,75	0,72	0,56	-0,41	0,25	0,69	-0,01	-0,31
16	-0,3	-0,33	-0,42	1	-0,36	-0,2	-0,32	-0,41	-0,48	0,45	-0,2	-0,32	-0,33	-0,42	-0,41	1	-0,33	-0,2	1	-0,42	-0,41	-0,29	-0,33	-0,2	-0,48	1	-0,81	-0,22	0,45	0,83
17	0,83	1	0,76	-0,33	0,82	0,82	0,67	0,75	0,55	-0,14	0,82	0,67	1	0,76	0,75	-0,33	1	0,82	-0,33	0,76	0,75	0,87	1	0,82	0,55	-0,33	0,43	0,66	-0,14	-0,36
18	0,91	0,82	0,72	-0,2	0,76	1	0,73	0,72	0,57	0,14	1	0,73	0,82	0,72	0,72	-0,2	0,82	1	-0,2	0,72	0,72	0,94	0,82	1	0,57	-0,2	0,23	0,68	0,14	-0,17
19	-0,3	-0,33	-0,42	1	-0,36	-0,2	-0,32	-0,41	-0,48	0,45	-0,2	-0,32	-0,33	-0,42	-0,41	1	-0,33	-0,2	1	-0,42	-0,41	-0,29	-0,33	-0,2	-0,48	1	-0,81	-0,22	0,45	0,83
20	0,71	0,76	1	-0,42	0,81	0,72	0,79	0,98	0,56	0,01	0,72	0,79	0,76	1	0,98	-0,42	0,76	0,72	-0,42	1	0,98	0,73	0,76	0,72	0,56	-0,42	0,25	0,71	0,01	-0,31
21	0,7	0,75	0,98	-0,41	0,8	0,72	0,78	1	0,56	-0,01	0,72	0,78	0,75	0,98	1	-0,41	0,75	0,72	-0,41	0,98	1	0,73	0,75	0,72	0,56	-0,41	0,25	0,69	-0,01	-0,31
22	0,97	0,87	0,73	-0,29	0,77	0,94	0,69	0,73	0,62	0	0,94	0,69	0,87	0,73	0,73	-0,29	0,87	0,94	-0,29	0,73	0,73	1	0,87	0,94	0,62	-0,29	0,36	0,64	0	-0,26
23	0,83	1	0,76	-0,33	0,82	0,82	0,67	0,75	0,55	-0,14	0,82	0,67	1	0,76	0,75	-0,33	1	0,82	-0,33	0,76	0,75	0,87	1	0,82	0,55	-0,33	0,43	0,66	-0,14	-0,36
24	0,91	0,82	0,72	-0,2	0,76	1	0,73	0,72	0,57	0,14	1	0,73	0,82	0,72	0,72	-0,2	0,82	1	-0,2	0,72	0,72	0,94	0,82	1	0,57	-0,2	0,23	0,68	0,14	-0,17
25	0,59	0,55	0,56	-0,48	0,42	0,57	0,56	0,56	1	-0,19	0,57	0,56	0,55	0,56	0,56	-0,48	0,55	0,57	-0,48	0,56	0,56	0,62	0,55	0,57	1	-0,48	0,48	0,39	-0,19	-0,49
26	-0,3	-0,33	-0,42	1	-0,36	-0,2	-0,32	-0,41	-0,48	0,45	-0,2	-0,32	-0,33	-0,42	-0,41	1	-0,33	-0,2	1	-0,42	-0,41	-0,29	-0,33	-0,2	-0,48	1	-0,81	-0,22	0,45	0,83
27	0,37	0,43	0,25	-0,81	0,26	0,23	0,13	0,25	0,48	-0,58	0,23	0,13	0,43	0,25	0,25	-0,81	0,43	0,23	-0,81	0,25	0,25	0,36	0,43	0,23	0,48	-0,81	1	0,1	-0,58	-0,83
28	0,62	0,66	0,71	-0,22	0,76	0,68	0,64	0,69	0,39	0,17	0,68	0,64	0,66	0,71	0,69	-0,22	0,66	0,68	-0,22	0,71	0,69	0,64	0,66	0,68	0,39	-0,22	0,1	1	0,17	-0,08
29	-0,01	-0,14	0,01	0,45	0,02	0,14	0,12	-0,01	-0,19	1	0,14	0,12	-0,14	0,01	-0,01	0,45	-0,14	0,14	0,45	0,01	-0,01	0	-0,14	0,14	-0,19	0,45	-0,58	0,17	1	0,52
30	-0,26	-0,36	-0,31	0,83	-0,27	-0,17	-0,24	-0,31	-0,49	0,52	-0,17	-0,24	-0,36	-0,31	-0,31	0,83	-0,36	-0,17	0,83	-0,31	-0,31	-0,26	-0,36	-0,17	-0,49	0,83	-0,83	-0,08	0,52	1

Correlations

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).