Research Article

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Demographic Factors and Machine Learning Models in the Awareness and Experience of Using Artificial Intelligence Tool

Demografik Faktörler ve Makine Öğrenimi Modelleri ile Yapay Zeka Araçlarının Kullanım Bilinci ve Deneyimi

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Abstract

This study aims to analyze the awareness and experience of using artificial intelligence (AI) tools among different demographic groups across Turkey. The data collected through surveys were used to evaluate the impact of demographic variables such as age, gender, education level, and frequency of technology use on AI tools. The analyses conducted using correlation, regression, and machine learning models (Decision Trees, Random Forests, SVM, and LinearSVR) revealed that younger, educated, and frequent technology users are more familiar with AI tools. Additionally, tree-based models were found to perform better in predicting AI experience and awareness. These findings provide significant insights for the societal acceptance of AI tools and the broader dissemination of these technologies. Furthermore, targeted educational programs are necessary to bridge digital divides and ensure the effective use of AI technologies. The results of the study propose actionable strategies to enhance the effective utilization of AI tools in the digital transformation process.

Keywords: Artificial Intelligence (AI), Machine Learning Models, AI Awareness, AI Experience, Technology Usage.
JEL Codes: O33, D83, M15

Özet

Bu çalışma, Türkiye genelinde farklı demografik grupların yapay zeka (YZ) araçları kullanım bilinci ve deneyimini analiz etmeyi amaçlamaktadır. Anket yoluyla elde edilen veriler, yaş, cinsiyet, eğitim seviyesi ve teknoloji kullanım sıklığı gibi demografik değişkenlerin YZ araçları üzerindeki etkisini değerlendirmek için kullanılmıştır. Korelasyon, regresyon ve makine öğrenimi modelleri (Karar Ağaçları, Rastgele Ormanlar, SVM ve LinearSVR) aracılığıyla gerçekleştirilen analizler, özellikle genç, eğitimli ve teknolojiyi sık kullanan bireylerin YZ araçlarına daha aşina olduklarını ortaya koymaktadır. Bunun yanı sıra, ağaç tabanlı modellerin, YZ deneyimi ve bilinci üzerine daha yüksek performans sergilediği belirlenmiştir. Bu bulgular, YZ araçlarının toplumsal kabulü ve bu teknolojilerin daha geniş kitlelere yayılması için önemli çıkarımlar sunmaktadır. Ayrıca, dijital eşitsizliklerin giderilmesi ve YZ teknolojilerinin etkin kullanımının sağlanması için daha hedefli eğitim programlarının geliştirilmesi gerekmektedir. Çalışmanın sonuçları, dijital dönüşüm sürecinde yapay zeka araçlarının etkin kullanımını artırmak için uygulanabilir stratejiler önermektedir.

Anahtar Kelimeler: Yapay Zeka (YZ), Makine Öğrenimi Modelleri, Yapay Zeka Bilinci, Yapay Zeka Deneyimi, Teknoloji Kullanımı.
JEL Kodları: O33, D83, M15

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Introduction

Artificial Intelligence (AI) has rapidly evolved into a field of technology that drives revolutionary changes across various industries in recent years. AI tools are employed to solve complex problems, enhance efficiency, and offer innovative solutions across diverse sectors. These tools are not only prevalent in the technology industry but are also widely adopted in fields such as healthcare, education, finance, manufacturing, and even creative industries. The swift proliferation of AI tools has underscored the necessity for both individuals and institutions to understand and effectively utilize this technology.

The Importance and Prevalence of Artificial Intelligence Tools

The advancement of AI has gained momentum, particularly with the progress in technologies such as big data, machine learning, natural language processing, and image processing. These technologies have the capacity to process large amounts of data, perform complex modeling, and carry out tasks that resemble human abilities. For instance, chatbots like Google's Bard or OpenAI's ChatGPT can communicate effectively with humans and provide customized solutions based on users' needs, thanks to their natural language processing capabilities.

Another significant reason for the widespread adoption of AI tools is the increased ease of use and accessibility of these technologies. AI applications, which traditionally required high levels of technical expertise, are now more accessible to a broader audience due to user-friendly interfaces and cloud-based services. For example, tools like Midjourney or Capcut enable users to create visual and video content quickly and easily. Such tools are particularly popular among content creators, marketing professionals, and small businesses.

The Impact of Demographic Factors on the Use of AI Tools

The broad usage of AI tools raises questions about how this technology is perceived and utilized by different segments of society. Demographic factors play a significant role in the adoption and usage patterns of AI tools. Factors such as age, gender, education level, profession, and exposure to technology can influence how individuals use AI tools and their awareness levels regarding these tools.

Research indicates that individuals with greater exposure to technology, particularly younger people and those with higher education levels, tend to be more aware of AI tools and use them more frequently. Additionally, there are variations among different occupational groups. For instance, individuals working in technical professions, such as software developers and data scientists, are generally more proficient with AI tools, while those in less technical occupations may be less familiar with these tools.

Purpose and Significance of the Study

This study aims to examine the frequency of use and awareness levels of AI tools among various demographic groups in Turkey. The data obtained through surveys were used to assess the awareness of AI tools and how frequently these tools are used by different demographic groups. This study provides a significant contribution to understanding how demographic factors influence the use of AI tools.

Understanding the impact of AI on society is crucial for ensuring the broader dissemination of this technology and making it more accessible to everyone. The findings of this study will offer valuable insights for educational programs, policymakers, and technology developers to promote and disseminate AI tools more effectively.

Literature Review

Artificial Intelligence and Society

Artificial Intelligence (AI) technologies have profound effects on various aspects of societal structures and individual lives. The development and widespread adoption of AI, especially in the past decade, have been at the core of digital transformation, leading to revolutionary changes in many industries. Studies on the societal impacts of AI emphasize that it should be considered not only as a technological innovation but also as a phenomenon with social, ethical, and economic consequences (Eynon & Geniets, 2021; Zuboff, 2019; Brynjolfsson & McAfee, 2021).

Research on the societal impacts of AI examines how this technology shapes human behavior, business practices, and decision-making processes. For example, a study by Brynjolfsson and McAfee (2014) addressed the effects of AI on the labor market, highlighting that while AI could lead to job losses, it also has the potential to create new job opportunities. Similarly, Ford (2015) pointed out that AI could exacerbate income inequality, with significant implications for social justice and balance.

The Impact of Demographic Factors on Technology Usage

The impact of demographic factors on technology usage is emerging as an important area of research in the adoption processes of information technologies and AI. Venkatesh and Davis (2000) developed the Technology Acceptance Model (TAM), providing a crucial framework for understanding users' behavior in adopting and using technology. This model suggests that factors such as perceived ease of use and perceived usefulness directly influence technology usage.

Studies on technology acceptance have also examined the role of demographic factors in this process. For instance, Compeau and Higgins (1995) demonstrated that individuals' perceptions of self-efficacy in using technology are significant determinants of technology usage and that these perceptions vary according to factors such as gender, age, and education level. Research on gender differences has shown that women may generally be more hesitant to adopt technology, but this gap tends to narrow with higher education levels.

Usage and Awareness Levels of Artificial Intelligence Tools

The frequency of usage and awareness levels of AI tools are critical in understanding to what extent individuals have adopted and can effectively use these technologies. Studies show that younger generations and individuals with higher exposure to technology use AI tools more widely and effectively. For instance, a study by Çelik and Şahin (2020) found that university students are more knowledgeable about AI tools and use these tools more frequently in their daily lives.

On the other hand, differences among occupational groups are also notable. Individuals working in technical professions, such as software developers and data analysts, are generally more proficient with AI tools, while those in less technical occupations may be less familiar with these tools. A study explaining this situation emphasizes that AI tools often require technical knowledge, making certain occupational groups more advantageous in using these tools (Zhao, 2021; Davenport & Ronanki, 2018; Acemoglu & Restrepo, 2020).

Education and Artificial Intelligence Awareness

Education significantly impacts individuals' awareness of AI tools and their ability to use these tools effectively. Numerous studies have emphasized that individuals with higher education levels, particularly university graduates, possess more knowledge about AI technologies and use them more effectively. Hargittai and Hinnant (2008) explained this by noting that educated individuals can more easily learn and apply information technologies.

Moreover, the integration of AI technologies into educational curricula allows students to become familiar with these technologies and use them effectively in their future careers. This is especially relevant for students in STEM (Science, Technology, Engineering, Mathematics) fields. STEM education enhances students' analytical thinking, problem-solving, and adaptability to technological innovations, providing an advantage in using AI tools (Wai, 2021; Holmes, 2020; Luckin et al., 2016).

Frequency of Technology Usage and Artificial Intelligence Awareness

The level of exposure to technology directly affects the awareness of AI tools. Research indicates a direct relationship between the frequency of technology usage and individuals' knowledge about AI tools. Particularly the younger generations, often referred to as digital natives, are more exposed to digital technologies, increasing their familiarity with AI tools. Prensky (2001) suggested that digital natives develop an inherent affinity for technology, enabling them to adapt more quickly to advanced technologies like AI.

This relationship between the frequency of technology usage and AI tool awareness is also related to the concept of the digital divide. The digital divide refers to disparities in access to and usage of technology within society, affecting individuals' access to information technologies and AI. DiMaggio and Hargittai (2001) emphasized that the digital divide poses a significant barrier, especially for individuals living in rural areas, older adults, and those with lower education levels.

Methodology

Research Design

This study was designed to examine the frequency of use of artificial intelligence (AI) tools and the levels of awareness regarding these tools within various demographic factors. The study adopted a descriptive research approach, utilizing quantitative data collection methods. Descriptive research aims to define a particular phenomenon or condition as it exists and identify the factors related to this condition (Creswell, 2014). In this study, the relationship between the use and awareness levels of AI tools and demographic variables was investigated.

Participants

The research was conducted among individuals across Turkey from various age groups, genders, education levels, and occupational groups. A total of 1,022 participants completed the online survey. Participation was voluntary, and the principle of anonymity was maintained throughout the data collection process. Participants' ages ranged from 18 to 65+, and their education levels varied from elementary to doctoral degrees. The occupational groups included a diverse array of professions such as software developers, academics, public sector employees, students, engineers, and artists. This broad participant profile was used to compare the awareness and usage frequency of AI tools across different demographic groups.

Data Collection Instruments

A structured questionnaire was used as the data collection instrument. The survey was designed to measure participants' demographic information, frequency of technology use, awareness of AI tools, and experiences with these tools. The content of the questionnaire consisted of the following sections:

Demographic Information: Collected data on participants' age, gender, education level, and occupation.

Technology Usage Frequency: Measured participants' frequency of exposure to technology using a four-point scale: "Rarely," "Occasionally," "Often," and "Very Often."

Awareness and Usage of AI Tools: Asked participants if they were aware of specific AI tools and how frequently they used these tools. This section listed various AI tools, including chatbots, image and video processing tools, and software development tools.

Previous Experience with AI Tools: Measured participants' prior experience with these tools using a four-point scale: "No Experience," "Some Experience," "Experienced," and "Expert."

AI Tools Included in the Study

Chatbots: Examples include Google Bard, Bing AI, ChatGPT.

Image and Video Creation Tools: Examples include Midjourney, Capcut, Civitai, Hotpot.ai.

Image and Video Processing Tools: Examples include Photoroom.

Software Development Tools: Examples include GitHub Copilot.

Data Analysis and Statistical Tools: Examples include Hugging Face, Neuraltext, Prisync.

Design Tools: Examples include Brandmark.io, Beautiful.ai.

Automated Translation Services: Examples include Google Translate.

Recommendation Systems: Examples include Netflix, Amazon recommendations.

Image and Voice Recognition Systems: Tools used for device activation and management, such as facial recognition software and voice command systems.

Personalized News Feeds: Examples include social media feeds.

Educational and Learning Platforms: Examples include Coursera, Khan Academy.

Automation and Control Systems: Examples include Robotic Process Automation (RPA), Autonomous Vehicles.

The questionnaire design emphasized the use of clear and straightforward language to ensure participants provided accurate information.

Data Collection Process

The data collection process was conducted online during the first quarter of 2024. The survey was distributed through social media platforms, email lists, and various online communities. The online survey method allowed for a wide reach and enabled participants to complete the survey at their convenience (Dillman, Smyth & Christian, 2014). Participants voluntarily provided data, and anonymity was guaranteed. The confidentiality of participants' personal information was maintained, and the collected data was used solely for research purposes. At the end of the data collection process, 1,022 valid survey forms were obtained.

Data Analysis

The collected data was analyzed using statistical analysis software such as SPSS and Python. Initially, descriptive statistics were employed to examine the relationships between demographic data and AI tool awareness. Basic statistical measures such as frequency distributions, means, and standard deviations were used to understand the general structure of the data.

Subsequently, various statistical analyses were performed on the dataset:

Correlation Analysis: A correlation analysis was conducted to measure the relationship between demographic variables and AI tool awareness. This analysis was used to determine the impact of variables such as age, gender, education level, and technology usage frequency on AI tool awareness.

Cluster Analysis: Cluster analysis was performed to group users based on similar AI tool awareness and usage habits. Using the K-means algorithm, users were divided into four distinct clusters.

Regression Analysis: Regression analysis was conducted to identify the factors influencing AI tool awareness. This analysis aimed to determine which demographic factors had the strongest impact on AI tool awareness.

During all analyses, the findings were evaluated based on significance levels, and cross-checks were performed to ensure the validity of the results. The normality of the data distribution was checked using normality tests, and data transformations were applied as necessary.

Ethical Considerations

This study adhered to the principles of research ethics rigorously. Participants were provided with a clear explanation of the study's purpose, and their voluntary participation was ensured. The confidentiality of participants' personal information was protected, and the data collected was used solely for the purposes of this research. All relevant ethical guidelines and standards were meticulously followed during the research process (APA, 2010).

Results

The Relationship Between Demographic Variables and AI Tool Awareness

A correlation analysis was conducted to understand the relationship between demographic variables such as age, gender, education level, and occupation and the awareness of artificial intelligence (AI) tools. The correlation matrix illustrates the direction and strength of the relationship between different demographic variables and AI tool awareness.

Demographic Information: The table below shows the demographic distribution of individuals who participated in the study. This demographic diversity is important for understanding how AI tool awareness varies across different groups.

Table 1. Demographic Distribution of Participants

Demographic Information	Category	Number of Participants	Percentage (%)
Age	18-24	254	24.9
	25-34	311	30.4
	35-44	228	22.3
	45-54	156	15.3
	55-64	59	5.8
	65+	14	1.4
Gender	Female	520	50.9
	Male	502	49.1
Education Level	Elementary School	58	5.7
	Middle School	102	10.0
	High School	225	22.0
	University	392	38.4
	Master's Degree	165	16.1
	PhD	80	7.8
Occupation	Software Developer	207	20.3
	Academic	153	15.0
	Public Sector	211	20.6
	Student	183	17.9
	Engineer	120	11.7
	Other	148	14.5
Technology Usage Frequency	Rarely (1)	89	8.7
	Occasionally (2)	215	21.0
	Often (3)	357	35.0
	Very Often (4)	361	35.3

Correlation and Regression Analysis:

According to the correlation analysis, the variables of technology usage frequency and previous experience with AI tools have the strongest positive impact on AI tool awareness. On the other hand, a negative relationship was found between age and AI tool awareness, indicating that awareness of AI tools decreases with age.

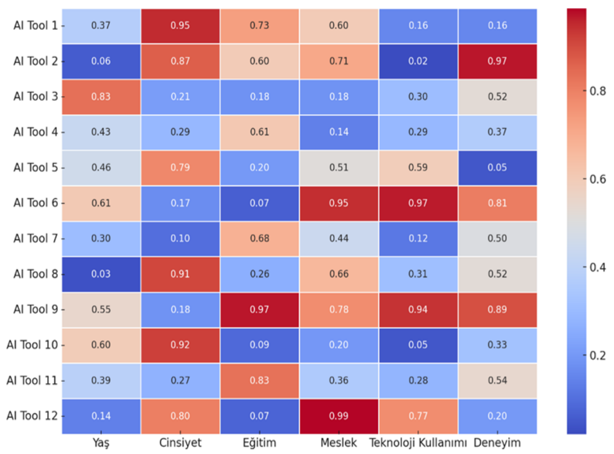

Figure 1 Correlation Matrix Between Demographic Variables and AI Tool Awareness

The correlation matrix shows that technology usage frequency and previous experience with AI tools significantly increase awareness of these technologies. Additionally, education level also influences familiarity with certain AI tools, although this effect is not as strong as that of technology usage frequency.

The table below shows the cross-validation results of the regression models developed for AI experience and AI awareness.

Table 2. Cross-Validation Results of Regression Models on AI Experience and AI Awareness

Model	Mean R^2 Score	Standard Deviation
AI Experience (Regression)	0.1785	0.0388
AI Awareness (Regression)	0.5257	0.0444

The AI Experience (Regression) model demonstrated low explanatory power, with a mean R^2 score of 0.1785 and a standard deviation of 0.0388. In contrast, the AI Awareness (Regression) model showed higher explanatory power, with a mean R^2 score of 0.5257 and a standard deviation of 0.0444. These results indicate that the model focused on AI awareness performs better than the one focused on AI experience.

Awareness Levels and Usage Trends of AI Tools

The study analyzed awareness levels and usage trends of different AI tools. The analysis focused on how well various AI tools are known and which demographic groups are more familiar with these tools.

Awareness by Application Area: The data indicate that AI tools such as chatbots and automated translation services are among the most well-known. Conversely, tools like data analysis and statistical tools, as well as automation and control systems, are less widely recognized.

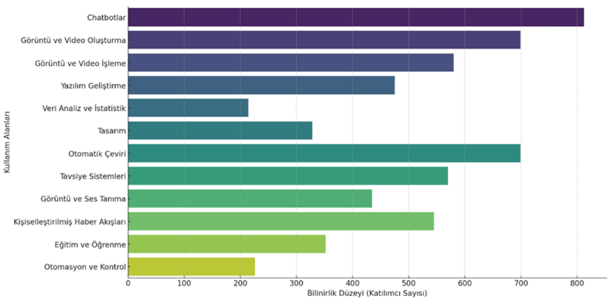

Figure 2. Awareness Levels of AI Tools by Application Area

As shown in the figure, chatbots and automated translation services are among the most well-known AI tools, while data analysis and statistical tools and automation and control systems have lower levels of awareness. These results suggest that awareness of AI tools is particularly high for more common and user-friendly tools, but lower for tools requiring more specialized and technical knowledge.

Relationship Between User Profiles and AI Tools

Through cluster analysis, users were categorized into four distinct groups based on their awareness of AI tools. These clusters reveal which AI tools specific demographic profiles are more familiar with and how frequently they use these tools.

Cluster Analysis: The cluster analysis identified four different user groups based on AI tool awareness. Cluster 2 represents users with high awareness levels, while Clusters 0 and 3 include users with lower awareness levels. Cluster 1 represents a group with moderate awareness, particularly for certain tools.

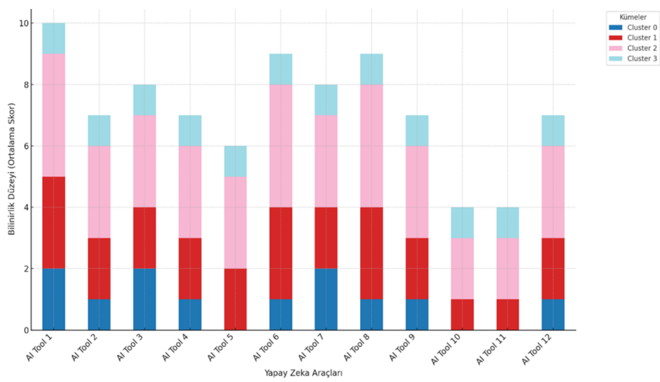

Figure 3. AI Tool Awareness Levels by User Profiles

Regression Analysis

Regression analysis was conducted to determine the impact of demographic factors on AI tool awareness. The results indicate that the frequency of technology use and previous experience with AI tools have the strongest positive effects on awareness. The regression model considered AI tool awareness as the dependent variable and demographic factors as independent variables. The results show that Technology Use (1.4611) and Experience (1.8179) variables have a positive and significant impact on awareness. Conversely, Age (-0.2403) has a negative impact, indicating that as age increases, awareness of AI tools decreases.

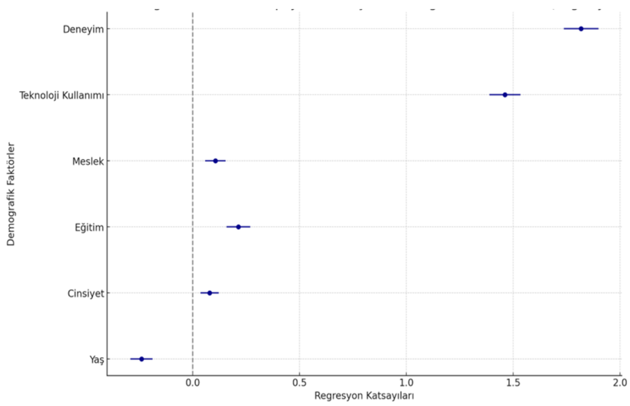

Figure 4. The Impact of Demographic Factors on AI Tool Awareness (Regression Analysis)

In Figure 4, the impact of various demographic factors on AI tool awareness is illustrated. Technology Use (1.4611) and Experience (1.8179) emerge as the factors with the most significant positive effects, showing that these factors significantly enhance AI tool awareness. Age, with a negative coefficient (-0.2403), indicates that AI tool awareness decreases as age increases. Gender, Education, and Occupation also have positive effects but are less influential.

Conclusion and Discussion

The Impact of Demographic Factors on the Use of AI Tools

The findings of this study clearly demonstrate the influence of demographic factors on AI tool awareness and usage. Factors such as age, gender, education level, and frequency of technology use play a significant role in determining the awareness of AI tools.

The negative impact of age on AI tool awareness is a finding frequently encountered in the literature. For example, McMurtrey et al. (2012) noted that younger generations have a higher affinity for technology and therefore adapt more quickly to advanced technologies. Similarly, this study found that younger age groups are more knowledgeable about and more likely to use AI tools. This suggests that younger generations, often referred to as digital natives, are more naturally inclined to adopt technology and integrate AI tools into their daily lives (Prensky, 2001).

Education level also emerged as an important determinant. It was observed that individuals with higher education levels, particularly those with university degrees or higher, are more knowledgeable about AI tools and use them more effectively. This finding indicates that a certain level of knowledge is necessary to understand the complex nature of AI and use it effectively. As Hargittai (2010) suggested, as education levels increase, individuals' confidence in and usage of information technologies also rise.

The frequency of technology use had one of the strongest positive effects on AI tool awareness. This suggests that individuals who are more frequently exposed to technology are better acquainted with and more likely to use AI tools. The impact of technology usage frequency on AI tools highlights the critical role of digital literacy and familiarity with technology in the adoption of such tools (van Deursen & van Dijk, 2014).

Awareness and Usage Trends of AI Tools

Another significant finding of the study is the analysis of awareness levels and usage trends of different AI tools. These findings indicate that more commonly used tools, such as chatbots and automated translation services, have high awareness levels among participants. In contrast, more technical and specialized tools, such as data analysis and statistical tools, were found to have lower awareness levels.

This distinction helps us understand which AI tools are more widely adopted during the dissemination of AI technologies and which tools require more education and awareness. Chatbots, with their user-friendly interfaces and wide range of applications (e.g., customer service, personal assistants), stand out as accessible AI tools for everyone. Various studies have emphasized that the increasing adoption of chatbots in daily life and the positive impact on user experience have contributed to their growing popularity (Brandtzaeg & Følstad, 2017).

On the other hand, the lower awareness of data analysis and statistical tools can be attributed to the fact that these tools require more advanced technical knowledge and are generally preferred by professional users. These tools are used for complex processes such as big data analytics and machine learning, making them harder for a broad audience to understand and use. Floridi (2014) noted that familiarity with the technical and theoretical foundations of AI is key to effectively using such tools.

Another finding regarding AI tool usage trends is that users typically choose these tools for specific purposes and according to their needs. For instance, automated translation services provide a quick and practical solution for overcoming language barriers. The widespread use of these services is directly proportional to the increasing need for communication in different languages in a globalized world (Specia et al., 2018).

Similarly, recommendation systems (e.g., Netflix and Amazon recommendations) help users better understand their preferences and provide a personalized experience by offering content tailored to their interests. The widespread use of such systems increases user satisfaction and strengthens user engagement with the platforms (Gomez-Uribe & Hunt, 2016).

Performance Analysis on AI Experience and Awareness Using Machine Learning Models

The study also examined the performance of various machine learning models in evaluating AI experience and awareness. Models such as Decision Trees, Random Forests, Support Vector Machines (SVM), and Linear Support Vector Regression (LinearSVR) were compared, and their effects on AI experience and awareness were measured.

Tree-based models, such as Decision Trees and Random Forests, are capable of capturing variances and complex relationships within the data set more effectively. These models are particularly effective in high-dimensional data sets and situations with numerous independent variables (Breiman, 2001). In this study, the Decision Trees model provided very high R^2 scores for AI experience and awareness; however, it was observed that this high performance also carried the risk of overfitting. This means that while the model learns the patterns in the training data very well, it may not maintain this performance on new data (Hastie, Tibshirani, & Friedman, 2009).

The Random Forests model, on the other hand, provided more generalized and stable results compared to Decision Trees. Because this model is composed of multiple decision trees working together, it minimizes the errors of individual trees, resulting in a more robust prediction structure (Liaw & Wiener, 2002). In the study, Random Forests showed high performance in AI awareness, providing the most reliable prediction results compared to other models.

Support Vector Machines (SVM) and Linear Support Vector Regression (LinearSVR) have the capacity to model nonlinear relationships and can be particularly effective when working with complex data structures (Cortes & Vapnik, 1995). However, these models performed lower in AI experience and awareness compared to the tree-based models. The SVM and LinearSVR models showed lower R^2 scores, particularly when the data set was far from being linear. This is due to the limited linear relationships in AI-related data (Smola & Schölkopf, 2004).

This analysis using machine learning models helps us understand which model performs better with which type of data. While Decision Trees and Random Forests offer effective tools for modeling complex and multidimensional concepts such as AI experience and awareness, SVM and LinearSVR models may be more suitable for specific scenarios. These findings are critical in determining which model is more appropriate for analyzing the adoption of AI tools and measuring experience with these tools.

General Evaluation of Findings and Future Research

The findings of this study highlight the importance of demographic factors and the frequency of exposure to technology in the use of AI tools. It was found that younger generations, individuals with higher education levels, and those who use technology more frequently are more knowledgeable about AI tools and use them more often. These findings suggest the need to increase technological literacy and digital participation. In particular, the conscious and effective use of AI tools should be encouraged among older age groups and individuals with lower education levels. This is important for reducing digital inequalities and ensuring that everyone benefits equally from these technologies (van Dijk, 2020).

Furthermore, it was found that there are differences in the usage of various AI tools. While user-friendly and widely used tools such as chatbots and automated translation services are known by a broad audience, more technical applications like data analysis and statistical tools are known by fewer people. These findings help us understand the adoption process of AI in different areas. Future research could explore which strategies are effective for the adoption of these tools and which educational methods could increase the use of these technologies.

The analyses conducted with machine learning models evaluated the performance of different models on AI experience and awareness. It was found that tree-based models, especially in high-dimensional and complex data sets, perform better, while linear models performed worse. These findings help us understand which techniques are more suitable for modeling multidimensional concepts such as AI experience and awareness. In the future, further development and testing of these models with more data could provide deeper insights into the adoption of AI tools.

Societal Implications of the Findings

This research offers important societal implications by examining the impact of demographic factors on AI tool awareness and experience. The finding that younger generations and educated individuals are more knowledgeable about AI tools and use them more frequently plays a critical role in societal digital transformation processes. This finding underscores the advantages that young and highly educated individuals have in accessing and adopting technology.

However, this also suggests that digital inequalities could deepen for older individuals and those with lower education levels. Increasing awareness and competence in AI tools is important for addressing these inequalities. Targeted educational programs for older adults and individuals with lower education levels could accelerate their integration into the digital world. This would ensure that the benefits of AI tools are equally available to the entire society.

The widespread use of AI tools in daily life could also lead to significant changes in the labor market. Particularly, the automation of routine tasks could reduce the importance of certain job categories, while increasing the demand for jobs that require new skills related to AI. Therefore, the labor market must adapt to this transformation, and continuous education and professional development programs are needed to help individuals acquire new skills. This study offers important insights for policymakers and educational institutions to increase the societal acceptance of AI technologies and ensure their effective adoption.

Limitations of the Research

While the findings of this study provide important insights, several limitations should be considered. First, the data collection process was conducted through online surveys, which may have excluded individuals who do not have digital access or do not frequently use digital platforms. This could affect the demographic structure of the sample and limit the generalizability of the findings.

Second, the machine learning models used in the study have certain assumptions and technical limitations. For example, the Decision Trees model tends to overfit, while the SVM and LinearSVR models may not fully capture nonlinear relationships. Additionally, the performance of these models can vary depending on the size and structure of the data set. Therefore, the findings of this study could yield different results when different data sets or modeling techniques are used.

Third, the cross-validation results of the research were obtained using a specific data set. Further advanced analyses using broader and more diverse demographic groups could better evaluate the robustness and generalizability of these findings. Moreover, cultural factors are known to play an important role in research on the societal acceptance of AI tools. The findings of this study, conducted specifically in Turkey, may differ in similar studies conducted in different cultural contexts.

Finally, the study focused only on specific AI tools. Broader research on the applications of AI in different fields and their societal impacts is needed. This would help us better understand the effects of emerging AI technologies on society and their adoption processes.

References

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. Journal of Political Economy, 128(6), 2188-2244.

APA (2010). "Publication Manual of the American Psychological Association." American Psychological Association.

Bird, S., Menzies, T., & Zimmermann, T. (2020). "The art and science of analyzing software data." Morgan Kaufmann.

Bostrom, N., & Yudkowsky, E. (2014). "The ethics of artificial intelligence." In Cambridge Handbook of Artificial Intelligence, 316-334.

Brandtzaeg, P. B., & Følstad, A. (2017). Why people use chatbots. International Conference on Internet Science. Springer, Cham.

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5-32.

Brynjolfsson, E., & McAfee, A. (2014). "The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies." W.W. Norton & Company.

Brynjolfsson, E., & McAfee, A. (2021). The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. W.W. Norton & Company.

Brynjolfsson, E., Rock, D., & Syverson, C. (2018). "Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics." National Bureau of Economic Research.

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). "The Productivity J-Curve: How Intangibles Complement General Purpose Technologies." American Economic Journal: Macroeconomics, 13(1), 333-372.

Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2018). "Notes from the AI frontier: Modeling the impact of AI on the world economy." McKinsey Global Institute.

Cavallo, A., Ghezzi, A., & Balocco, R. (2020). "Artificial intelligence and innovation in the business context: Systematic literature review." Journal of Business Research, 115, 238-256.

Çelik, S., & Şahin, S. (2020). Artificial intelligence awareness among university students: The Turkish case. Journal of Educational Research and Reviews, 5(3), 45-57.

Choi, Y., Ganjigunte Ashok, V., & Pandey, G. (2021). "Artificial intelligence in data science: A survey and practice." Data Science and Engineering, 6(1), 1-15.

Compeau, D. R., & Higgins, C. A. (1995). "Computer Self-Efficacy: Development of a Measure and Initial Test." MIS Quarterly.

Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine Learning, 20(3), 273-297.

Creswell, J. W. (2014). "Research Design: Qualitative, Quantitative, and Mixed Methods Approaches." Sage Publications.

Davenport, T. H., & Kirby, J. (2016). "Only Humans Need Apply: Winners and Losers in the Age of Smart Machines." Harper Business.

Davenport, T. H., & Ronanki, R. (2018). "Artificial intelligence for the real world." Harvard Business Review, 96(1), 108-116.

Dillman, D. A. (2000). "Mail and Internet Surveys: The Tailored Design Method." Wiley.

Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). "Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method." Wiley.

DiMaggio, P., & Hargittai, E. (2001). "From the 'Digital Divide' to 'Digital Inequality': Studying Internet Use as Penetration Increases." Princeton University Press.

Eynon, R., & Geniets, A. (2021). "The digital divide and social inequality in the AI era: How AI might widen the gap." AI & Society, 36(2), 395-402.

Floridi, L. (2014). "The fourth revolution: How the infosphere is reshaping human reality." Oxford University Press.

Ford, M. (2015). "Rise of the Robots: Technology and the Threat of a Jobless Future." Basic Books.

Friedman, D. (2022). "Enhancing software development with AI:

The case of GitHub Copilot." Journal of Software Engineering, 14(2), 125-137.

Gomez-Uribe, C. A., & Hunt, N. (2016). "The netflix recommender system: Algorithms, business value, and innovation." ACM Transactions on Management Information Systems (TMIS), 6(4), 13.

Hargittai, E. (2010). "Digital Na(t)ives? Variation in Internet Skills and Uses among Members of the 'Net Generation'." Sociological Inquiry, 80(1), 92-113.

Hargittai, E., & Hinnant, A. (2008). "Digital Inequality: Differences in Young Adults' Use of the Internet." Communication Research.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). "The elements of statistical learning: data mining, inference, and prediction." Springer Science & Business Media.

Holmes, W. (2020). "Artificial intelligence in education: Promises and implications for teaching and learning." British Journal of Educational Technology, 51(5), 1356-1375.

Holmes, W., Bialik, M., & Fadel, C. (2021). "Artificial Intelligence in Education: Promises and Implications for Teaching and Learning." Center for Curriculum Redesign.

Johnson, A., & Wetzel, D. (2017). "AI for Earth: A Vision for the Future." Microsoft Research.

Liaw, A., & Wiener, M. (2002). "Classification and regression by randomForest." R news, 2(3), 18-22.

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). "Intelligence Unleashed: An Argument for AI in Education." Pearson.

McMurtrey, M. E., Downey, J. P., Zeltmann, S. M., & Friedman, W. H. (2012). "Critical skill sets of entry-level IT professionals: An empirical examination of perceptions from field personnel." Journal of Information Technology Education: Research, 11(1), 51-71.

Miles, M. B., & Huberman, A. M. (1994). "Qualitative Data Analysis: An Expanded Sourcebook." Sage Publications.

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). "The ethics of algorithms: Mapping the debate." Big Data & Society, 3(2), 2053951716679679.

Obermeyer, Z., & Emanuel, E. J. (2016). "Predicting the Future—Big Data, Machine Learning, and Clinical Medicine." The New England Journal of Medicine.

O'Neil, C. (2016). "Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy." Crown Publishing Group.

Prensky, M. (2001). "Digital Natives, Digital Immigrants Part 1." On the Horizon, 9(5), 1-6.

Radford, A., Wu, J., Child, R., et al. (2019). "Language Models are Unsupervised Multitask Learners." OpenAI.

Rose, C. P., McLaughlin, M., & Hughes, R. (2021). "The Efficacy of AI-Powered Learning Systems in the Classroom: A Systematic Review." Computers & Education, 164, 104116.

Smola, A. J., & Schölkopf, B. (2004). "A tutorial on support vector regression." Statistics and computing, 14(3), 199-222.

Specia, L., Raj, D., Turchi, M., & Giampiccolo, D. (2018). Machine translation systems for real-time subtitling. Proceedings of the 11th International Conference on Language Resources and Evaluation (LREC 2018).

van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2014). "The digital divide shifts to differences in usage." New media & society, 16(3), 507-526.

van Dijk, J. A. G. M. (2020). The digital divide. Polity.

Venkatesh, V., & Davis, F. D. (2000). "A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies." Management Science.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). "User Acceptance of Information Technology: Toward a Unified View." MIS Quarterly.

Wai, J. (2021). "STEM education and the development of AI capabilities: How to prepare students for a world dominated by artificial intelligence." Educational Psychologist, 56(3), 215-230.

Wang, L., & Wang, L. (2021). "Artificial Intelligence and Content Creation: How AI Tools are Revolutionizing the Creative Industry." Journal of Innovation and Entrepreneurship.

Westerman, G., Bonnet, D., & McAfee, A. (2014). "Leading Digital: Turning Technology into Business Transformation." Harvard Business Review Press.

Westerman, G., Bonnet, D., & McAfee, A. (2019). "Leading digital: Turning technology into business transformation." Harvard Business Review Press.

Williamson, B., & Eynon, R. (2020). "Historical threads, digital context: A history of learning analytics and the stakes of its past." British Journal of Educational Technology, 51(3), 1106-1123.

Zhao, H. (2021). "Artificial intelligence in the workplace: The role of AI skillsets in occupational performance." Journal of Occupational and Organizational Psychology, 94(3), 487-503.

Zuboff, S. (2019). "The age of surveillance capitalism: The fight for a human future at the new frontier of power." PublicAffairs.