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AWARENESS AND ACCEPTANCE OF MACHINE LEARNING TECHNOLOGY IN CONSTRUCTION PROJECTS AMONG CONSTRUCTION PROFESSIONALS WORKING IN TURKISH CONTRACTORS

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ABSTRACT

The construction industry, which contributes to 13% of global gross production and 8.6% of global employment, has been falling behind other industries in terms of innovation, profitability, and efficiency, and this gap has continued to widen rapidly in recent years. In Turkey, where the construction industry plays a vital role in the economy, Turkish Contractors have witnessed an increase in their average turnover over the last two decades due to projects carried out in Turkey and abroad. However, in the face of high competition and low-profit margins in the international arena, it is crucial for Turkish Contractors to enhance their efficiency and productivity to expand their market share and profitability. This presents an opportunity for Turkish Contractors to leverage machine learning technology, which has gained popularity in the last five years. This study aims to address a notable gap in the literature by examining the perspectives of construction professionals working in Turkish Contractors regarding machine learning and its latest applications. The research seeks to explore the professionals' awareness and knowledge levels, identify the barriers to implementation, and provide insights into how machine learning technology can serve as a support and control mechanism for construction professionals. A comprehensive literature review was conducted to identify machine learning applications in construction project management. Subsequently, a detailed questionnaire was administered to 63 construction professionals, including engineers, surveyors, and architects. The findings indicate that machine learning technology can be utilised in the pre-construction, construction, and post-construction phases. However, only 11% of the participants exhibited a high level of familiarity and knowledge about machine learning and its application areas, while 49% demonstrated low familiarity and knowledge. Despite this, 83% of the participants recognised that machine learning technology would have a positive impact on construction delivery. Notably, the p-values of responses regarding familiarity level and acceptance level indicated that there were no statistically significant differences between socio-demographic groups. Furthermore, the factor analysis identified that the barriers to implementation were company-related and employee-related from the perspective of construction professionals who work in Turkish Contractors, even though the literature classifies them as economic, social, and technical barriers. In conclusion, this study highlights the potential benefits of machine learning technology in the construction industry and provides insights into the perspectives of construction professionals working in Turkish Contractors. The findings underscore the importance of increasing awareness and knowledge about machine learning technology among construction professionals to overcome the identified barriers to implementation.

Keywords: Machine Learning, Construction Project Management, Turkish Contractors

1. INTRODUCTION

The construction industry plays a crucial role in driving economic growth across countries and has a significant impact on various sectors. This symbiotic relationship is marked by the industry's capacity to increase demand across more than two hundred secondary sectors, thereby positively impacting employment across many areas (Öcal et al., 2007; Aladag et al., 2016). In a quantifiable sense, the construction industry's contribution to the global GDP stood at 13% in 2021, with projections anticipating an escalation to 19.2% by 2035 (Ribeirinho et al., 2020). Given its labour-intensive nature, the industry serves as a significant source of employment, encompassing 8.6% of global employment (Mella & Savage, 2018). Turkey's construction industry, particularly since the 1980s, holds substantial national importance. Facilitated by economic and political policies, Turkish Contractors have embraced a new role, extending their domestic and international activities, especially across the Middle East, Africa, and Asia (Erol & Unal, 2015). This strategic shift has resulted in an impressive 81% growth in construction activities from 1998 to 2014, contributing 8.1% to the GDP and covering 7.4% of overall employment (KPMG, 2020).

Despite these contributions, the construction industry struggles with challenges, particularly concerning performance and productivity. Efforts to enhance efficiency, productivity, and profitability have generated modest outcomes, as the industry's productivity saw a mere 10% increase from 1997 to 2017, significantly lagging behind the overall economy's 43%, and the manufacturing sector's 65% growth (Barbosa et al., 2017). The industry's profit margins stand far below the 5% threshold recognised as sustainable (Galaev, 2018). This dilemma has led to its characterisation as conservative, marked by limited efficiency, low productivity growth, modest profit margins, and a lack of innovation. McKinsey's 2020 report underlines the necessity for transformative measures, particularly within contractor firms, urging the attraction and training of skilled professionals to shape the industry's future.

In a landscape marked by domestic and international competition, particularly for contractors, profit margins have experienced a decline. International contractors' total revenue dropped from USD 543 billion in 2013 to USD 473 billion in 2019, while the market share of Turkish Contractors surged from 3.8% to 4.6% between 2013 and 2019 (ENR, 2014, 2020). In this competitive environment, companies that plan to protect or increase their market share should either grow their value-added services or reduce their project costs compared to other companies (Korkmaz & Messner, 2008). These cost dynamics rotate primarily around material, labour, and machinery activities. Given that material prices show minimal variance across project locations, cost reduction centres on increasing labour and machinery productivity, minimising material wastage, and mitigating risk factors that could lead to delays and cost overruns (ibid.).

Artificial Intelligence (AI) emerges as a transformative opportunity for Turkish Contractors, holding the potential to lower project costs and concurrently improve profitability and market share, both nationally and internationally. While AI was introduced in the 1950s, its significance and associated academic output have surged in the last decade. An increase from 40,000 AI-related articles in 2015 to over 120,000 in 2019 emphasises its exponential growth (Zhang et al., 2021). Economically, the Made in China 2025 Plan forecasts China's AI industry to be valued at USD 150 Billion by 2030, projecting a 14% rise in global GDP and a 37% improvement in productivity by 2035 through AI-related technologies (Kreutzer & Sirrenberg, 2021; Bughin et al., 2018). One of the subgroups of AI, Machine Learning (ML), stands out as a particularly promising field for construction projects (Xu et al., 2021). The academic literature has shown a growing interest in evaluating the accuracy of ML algorithms to strengthen construction project performance. These algorithms could reform the delivery of construction projects. (Pan & Zhang, 2021). Furthermore, ML algorithms in construction project management should be perceived as tools supporting construction professionals in decision-making, event prediction, calculation accuracy comparison, and the execution of daily tasks based on ML-driven suggestions (Ahiaga-Dagbui & Smith, 2014). This underlines the fundamental role of construction professionals in utilising ML technology, requiring an understanding of ML, its applications within construction project management disciplines, its influence on projects, and potential implementation difficulties.

This study addresses this critical aspect, as no prior research has explored the awareness of ML among construction professionals working with Turkish Contractors. The findings of this study could be helpful for policymakers, Turkish construction companies, and educational institutions. Policymakers can leverage the results to incentivise greater ML technology adoption among Turkish Contractors, while companies could design training and conferences based on gender, age, education, and experience levels; and educational institutions align construction-related degree programs by providing or increasing the number of ML courses.

2. LITERATURE REVIEW

In order to carry out this study, a thorough review of the literature was conducted and subsequently categorised into separate sections before implementing the chosen research methodology. (1) The understanding of artificial intelligence and machine learning; (2) the applications of machine learning in construction; and (3) the challenges of implementation of machine learning in the construction industry.

A. The Understanding of Artificial Intelligence and Machine Learning

The artificial intelligence (AI) journey stretches back to Alan Turing's Enigma machine and his article "Computer Machinery and Intelligence" in 1950. The formal manifestation of AI occurred in a seminal seminar held in 1956 in New Hampshire, organised by Marvin Minsky and John McCarthy (Manning, 2020). Despite a period of relative calm in the 1970s due to budgetary limitations, AI resurged highly, with a significant milestone marked by Google's AlphaGo triumph in 2015 (Haenlein & Kaplan, 2019). Defining AI has created various interpretations. Stanford's AI Committee (2016) conceives AI as a technology mirroring human learning processes. Haenlein and Kaplan (2019) emphasise the extraction of meaningful insights from data and learning to achieve specific goals. Expanding on this thought, Kreutzer and Sirrenberg (2021) integrate cognitive tasks into the AI framework. Recent years have witnessed a surge in AI-related publications and applications, particularly within construction (Zhang et al., 2021; Pan & Zhang, 2021). This recovery is driven by the ever-increasing availability of data and the advancement of hardware systems, which are integral for training AI models (Schmidt et al., 2019). The domain of AI encompasses various fields, including machine learning, natural language processing, and more, as explained in the illustrative framework by Kayid (2020). However, this study focuses on machine learning (ML), characterised by its algorithmic utilisation of data for predictive purposes (Salehi & Burgueño, 2018).

ML technology, in principle, enables algorithms to learn from historical data and anticipate future events or patterns. (Singh, Thakur, and Sharma, 2016), and is categorised into three main branches: supervised, unsupervised, and reinforcement learning (Moubayed et al., 2018). It is noteworthy, however, that reinforcement learning's application within construction project management remains limited within the current literature. Therefore, a comparative overview between supervised and unsupervised learning is tabulated in Table 1, which presents key differences across several parameters.

Parameter	Supervised Learning	Unsupervised Learning
Input Data	Labelled	Unlabeled
Accuracy	High	Less
Complexity	Less	High
Time Consuming	High	Less
Dataset	Smaller than unsupervised	Larger than supervised

Table 1. Differences between supervised and unsupervised learning

Notably, the landscape of machine learning is populated by diverse algorithms, with artificial neural networks, decision trees, and random forests being notable standouts in the literature, so this research mainly concerns their applications within construction management.

B. Applications of Machine Learning in Construction Projects

Machine learning applications in construction projects are categorised into three phases: pre-construction, construction, and post-construction. In the pre-construction phase, optimal design decisions significantly influence a project's time, cost, quality, and safety. Structures like bridges and overpasses have traditionally been optimised for cost and weight, but increasing emphasis on sustainability necessitates consideration of environmental impact, durability, and constructability (Butlewski et al., 2015). Garcia-Segura, Yepes, and Frangopol (2017) employed Artificial Neural Networks (ANNs) to optimise bridge design. The algorithm, trained on data from 4500 bridges and 34 constraints, generated alternatives considering cost, safety, and corrosion time. Greco (2018) extended this concept, employing ML to optimise steel structures for cost-effective designs. These studies demonstrate how ML aids engineers in making cost-effective and sustainable design choices. Moreover, buildings consume 40% of global energy, triggering energy-saving regulations (Wang et al., 2021). Balancing cost, quality, and energy performance in designs presents challenges. Yigit (2021) used ML to predict heating and cooling loads, aiding optimal design decisions. Using 30,000 samples and various parameters, the model found optimal insulation thickness, building orientation, aspect ratio, and colour for different cities in Turkey. This study showcases ML's effectiveness in overcoming simulation-based method challenges, guiding designers toward energy-efficient solutions.

During the construction phase, ML applications play a crucial role in managing costs, budgets, delays, safety, and risk management fields. The budgeting process for projects is linked with strategic objectives and investment expectations. However, initial budget projections from the conceptual design phase often require adjustments during project execution (Petroutsatou et al., 2012). While conventional feasibility studies ensure accuracy, engaging experts continuously is burdensome and costly (Arabzadeh et al., 2018). ML technology has also influenced the field of cost estimation, resulting in a collection of articles addressing this subject (Klychova et al., 2014), aiming to maintain budgetary control and maximise accuracy. Arabzadeh (2018) employed artificial neural networks (ANNs) and hybrid regression to forecast spherical storage tank construction costs, achieving over 90% correlation. Petroutsatou et al. (2012) applied regression neural networks to early road tunnel cost estimation, surpassing traditional regression models with 95.35% accuracy. Hola and Schabowicz (2010) used neural networks to optimise excavation activity’s time and cost in machinery-intensive tasks like earthworks. Ahiaga-Dagbui and Smith (2014) evaluated ML accuracy for project cost prediction, achieving a 5% error margin for 77% of projects, 5-10% for 15%, and >10% for 8%. These studies collectively emphasise ML's potential to enhance construction cost estimation and decision-making.

Effective planning and timely project completion are vital in construction. Project delays can result in cost overruns, disputes, and reputational damage. ML applications offer promising solutions to identify and manage factors leading to delays. Gondia et al. (2020) developed an ML-based data analytics tool to identify and predict project delay reasons. They collected data from 51 construction projects across 28 companies, analysing meeting records and delay occurrences. The tool aimed to assist construction project managers in proactive risk management by predicting future delay risks and durations. The tool used classification algorithms, such as Naïve Bayes and decision trees, to identify delay factors. While achieving accuracies of 51.2% and 47.2%, respectively, the study highlighted the complexity of predicting delay factors due to the diverse range of contributing variables. Wang, Yu, and Chan (2012) focused on predicting project schedule success. They utilised an adaptive boosting artificial neural network algorithm on data from the early planning phase of 92 building projects. The algorithm aimed to forecast the projects' end dates with an accuracy rate of 80%. This study underscored ML's potential in predicting project timeline outcomes, helping decision-makers maintain efficient project schedules. Yaseen et al. (2020) employed genetic random forest (RF) algorithms to predict delay problems with enhanced accuracy. Their dataset gathered from 40 different projects and expert questionnaires encompassed similar risk factors as Gondia's study. The genetic RF algorithm achieved an accuracy of 91.76%, demonstrating its potential for precise prediction of delay events. This research demonstrated that ML models, particularly those employing advanced algorithms, can improve predicting and managing project delays substantially. Collectively, these studies highlight the growing importance of ML in planning and delay management. While predicting delay factors with a high accuracy remains a challenge due to the complex relationship of events, ML's predictive capabilities have the potential to enhance decision-making and risk management strategies in construction projects.

The construction industry is considered one of the most dangerous sectors due to the high work-related injury and fatality rate. In Turkey, the construction industry accounted for 20% of total accident days and 40% of fatal accidents in 2019 (SGK, 2020). Factors contributing to the industry's dangerous nature include reliance on craftsmanship, heavy machinery utilisation, hazardous tools and materials, and a dynamic work environment (Gunduz et al., 2018). Consequently, health and safety have emerged as top concerns. Ayhan and Tokdemir (2019) constructed a model predicting construction site injury events, achieving 82.18% to 99.77% accuracy using artificial neural networks (ANNs). The model's average prediction accuracy for event outcomes stood at 84%, though refining accuracy for at-risk behaviour and lost work-day cases is a priority. Baker, Hallowell, and Tixier (2020) conducted a broader study utilising a dataset encompassing 91,638 safety reports, and the algorithm achieved 85% accuracy in predicting injury severity, 84% for injury type, and 43% for incident type. Impacted body parts were predicted with varying accuracies: eye injuries (83%), finger injuries (48%), head injuries (27%), and hand injuries (20%).

In the risk management field, construction projects face complicated risks impacting outcomes positively or negatively. Traditional risk identification and management in construction projects are manual, yet recent trends demonstrate the potential of ML algorithms as supportive tools.

Rios-Morales et al. (2009) employed ML techniques to predict countries' political risk factors with up to 80% accuracy. Economic instability was addressed through Baasher and Fakhr's (2011) and Chandrinos's (2018) studies on predicting currency volatilities and developing risk management tools. Hassan (2019) designed an ML model for a 95% accurate identification of supply chain risks. Chattapadhyay and Putta (2021) created an ML model to identify, assess, and predict risks in mega-construction projects. Hybrid ML methods were employed by Fan (2020) to evaluate defects and interconnected operational risks. These studies collectively showcase the potential of ML algorithms in helping construction professionals' risk management endeavours.

During the post-construction phase, structures naturally undergo wear and tear over their lifespan, impacting both durability and functionality, resulting in economic losses and potential human risks (Ghiasi et al., 2015). Literature has focused on predicting damage before it occurs, forming the basis of structural health monitoring. Structural health monitoring employs real-time sensor data to monitor and report engineering structures' behaviour and integrity against natural forces such as earthquakes. While these systems detect structural vibrations from factors like environmental conditions or applied loads, identifying the underlying reasons for damage, environmental or structural lifespan-related, remains challenging (Lam & Ng, 2008). Notably, techniques like linear regression, artificial neural networks (ANNs), and the random forest (RF) method have been applied to various bridge structures (Laory et al., 2014). Laory et al. (2014) used RF to investigate the Tamar Suspension Bridge's health over three years, and the measured frequency and predicted frequency were almost the same. Consequently, ML algorithms, including ANN and RF, have the potential for construction professionals to detect damage and discern its root cause. Conversely, facility management requires controlling assets, maintenance, and replacements. Atkin and Bildsten (2017) foresee AI-driven facility management with sustainability at its core. Marzouk and Zaher (2020) propose a machine learning system for cost-effective maintenance, helping facility managers proactively. For efficient campus facility management, Cao, Song, and Wang (2015) developed a system predicting requests based on energy, safety, and satisfaction. This integration of AI and machine learning has the potential to optimise operations, sustainability, and user experiences in built environments.

C. Challenges in Implementing ML in the Construction Industry

While ML applications have the potential to transform construction projects, the implementation of ML in the industry has been met with a series of challenges. These can be broadly categorised into economic, technical, and social barriers within the literature.

Economic barriers appear prominent, with investment cost being a primary concern (Paranjape et al., 2021). Employing supervised learning, which necessitates labelled data, demands not only the allocation of employee efforts but also additional budget allocations. Even in the case of unsupervised learning, which does not demand labelled data, human involvement is essential to train and enhance the model. Moreover, transitioning to an ML-driven framework requires comprehensive training of the workforce, which can be financially heavy (Ganah & Rennie, 2009). The technical challenge lies in access to the vast amounts of data necessary to train ML models effectively. A substantial training dataset is critical to ensure the accuracy of predictions (Schmidt et al., 2019). However, construction project data often contains sensitive and confidential information. Consequently, companies are hesitant to share their data with third parties for the purpose of training datasets (Hunt et al., 2018). In addition, a lack of understanding regarding ML capabilities among construction practitioners presents a knowledge gap. This limited understanding can prevent employees from supporting this emerging technology. Cubric (2020) emphasises that construction professionals not only should be aware of the estimation and outcome of the ML model but also need to understand which type of algorithm should be used for training the model. Addressing this knowledge gap becomes pivotal in the successful integration of ML technologies. Moreover, another barrier from a social perspective is concerns about job security. Kelley et al. (2021) note that while some employees fear that ML technology might make their roles redundant, others see it as a tool to enhance human capabilities and improve quality of life.

3. RESEARCH METHODOLOGY

This research utilises the quantitative approach. The questionnaire survey was conducted, and consequently, a wide range of samples about the familiarity and awareness levels of construction professionals as well as their views on the barriers to implementation, was obtained. As this study aims to assess the familiarity, awareness, and potential barriers of implementing ML technology among construction professionals working in Turkish contractors, the target population includes engineers, architects, and surveyors employed by Turkish Contractors, irrespective of their gender, age, education, or experience level. The research employed the snowball sampling technique, a non-probabilistic method, due to the challenge of accessing the specific population. This method involves participants aiding in expanding the survey's reach. While efficient in terms of cost and time, its limitation lies in its inability to be generalised (Dragan & Isaic-Maniu, 2013). The survey was distributed through mobile phones, emails, and social media, with participants encouraged to share the survey link with colleagues. In line with the quantitative approach, a questionnaire was developed based on the literature to collect primary data via a survey. The questionnaire comprises four sections, and each section concentrates on distinct aspects, utilising a 5-scale format to capture respondents' views, as follows: (1): Social-demographic questions (gender, age, education, experience); (2) Assessing familiarity with ML technology in construction project management fields; (3) Assessing acceptance of the benefits of ML applications; (4) Evaluating perceptions of barriers to ML implementation in construction projects.

4. FINDINGS

Data collected from construction professionals was analysed using MS Excel and IBM SPSS. The Likert scale format was converted to numerical values in Excel, and the survey data was analysed using independent t-tests or Anova tests in IBM SPSS to assess the familiarity and acceptance level of ML technology and participants' views on implementation barriers.

Regarding socio-demographic results, out of the over 100 participants, 65 completed the survey. Two participants not employed by Turkish Contractors were excluded. The socio-demographic composition of participants is presented in Table 2, including gender, age range, education level, and experience. Most respondents were male (79.4%), aged 25-40 (73%), and held bachelor's degrees (55.6%). The majority had 4-10 years of experience (50.8%).

Variable	Percentage
Gender	**100%**
Male	79.4%
Female	20.6%
Age Range	**100%**
18 - 24	3.2%
25 - 40	73.0%
41 - 55	20.6%
56 - 75	3.2%
Education Level	**100%**
High School	0.0%
Bachelor's Degree	55.6%
Master's or PhD Degree	44.4%
Years of Experience	**100%**
0 - 3	6.3%
4 - 10	50.8%
11 - 20	31.7%
21 - 30	9.5%
31 - 50	1.6%
Overall	**100%**

Table 2. Socio-demographic structure of participants

Participants' familiarity with machine learning (ML) applications in construction project management was evaluated through 9 questions. The reliability of the responses was verified using Cronbach's alpha (0.919), exceeding the minimum requirement of 0.70. The familiarity levels were quantified using a Likert-scale format: never heard (1), heard but no knowledge (2), know a little (3), know something (4), and know a lot (5). The mean familiarity level for Artificial Intelligence was highest at 2.9683, indicating "know a little." Machine learning followed with a mean of 2.5238, also indicating "know a little." Familiarity levels with ML applications in construction project management fields were consistent. Gender, age range, education level, and experience level had minimal impact on familiarity levels. The analysis indicated similar familiarity levels across these socio-demographic groups. The highest familiarity was in planning and delay management (mean: 2.0952), while the lowest was in facility management (mean: 2.0161), illustrated in Table 3 below.

	N	Minimum	Maximum	Mean	Std. Deviation
Artificial Intelligence	63	1.00	5.00	2.9683	.76133
Machine Learning	63	1.00	4.00	2.5238	.85868
Design Management	63	1.00	4.00	2.0635	.87755
Cost and Budget Mgmt.	63	1.00	5.00	2.0635	1.01398
Planning and Delay Mgmt.	63	1.00	5.00	2.0952	1.04286
Health and Safety Mgmt.	62	1.00	4.00	2.0323	1.00764
Risk Mgmt.	63	1.00	5.00	2.0317	1.01550
Structural Damage Detection	63	1.00	5.00	2.0635	1.11981
Facility Management	62	1.00	4.00	2.0161	.99987

Table 3. Descriptive statistics of familiarity level questions

Participants were then categorised by familiarity levels for further analysis: Low-knowledge-level: $X \leq 18$; Medium-knowledge-level: $18 < X < 27$; High-knowledge-level: $X \geq 27$. These findings provide insights into participants' familiarity with various aspects of ML technology and its applications in construction project management, as shown in Table 4.

Variable	Low	Med	High
Gender			
Male	50%	38%	12%
Female	46%	46%	8%
Age Range			
18 - 24	100%	0%	0%
25 - 40	39%	50%	11%
41 - 55	69%	15%	15%
56 - 75	100%	0%	0%
Education Level			
High School			
Bachelor's Degree	51%	37%	11%
Master's or PhD Degree	46%	43%	11%
Years of Experience			
0 - 3	75%	25%	0%
4 - 10	47%	44%	9%
11 - 20	35%	45%	20%
21 - 30	83%	17%	0%
31 - 50	100%	0%	0%
Overall	**49%**	**40%**	**11%**

Table 4. Familiarity level and socio-demographic structure

A Likert-scale survey consisting of 13 statements was used to assess the acceptance level, with response options ranging from strongly disagree (1) to strongly agree (5). The reliability of responses was verified using Cronbach's alpha, which yielded a coefficient value of 0.915, surpassing the 0.70 threshold. Findings revealed that the statement "ML can increase projects' efficiency and productivity" had the highest mean acceptance level (3.95), while "ML can be used to determine reasons for project delay" had the lowest (3.58). The results are presented as follows:

	N	Minimum	Maximum	Mean	Std. Deviation
ML can be used for design optimisation	62	2.00	5.00	3.7097	.77644
ML can be used to design the energy efficient buildings	63	2.00	5.00	3.9206	.78907
ML can be used to decrease the projects' cost	62	2.00	5.00	3.8226	.87823
ML can be used to forecast the project's cost accurately	63	1.00	5.00	3.7143	.95763
ML can be used to determine the project's budget more accurately at the initial stage	63	2.00	5.00	3.7143	.58000
ML can be used to determine the reasons of project delay	63	2.00	5.00	3.5873	.68709
ML can be used to forecast the project end date	63	1.00	5.00	3.7302	.70038
ML can increase the construction projects' efficiency and productivity	63	2.00	5.00	3.9524	.63318
ML can be used to decrease injury events on the construction site	63	2.00	5.00	3.7778	.72833
ML can be used to predict the accidents earlier on the construction site	63	2.00	5.00	3.7143	.68223
ML can be used to determine the projects' risk factors	63	2.00	5.00	3.7302	.62750
ML can be used to detect structural damages	63	1.00	5.00	3.6508	.82616
ML can be used in the facility management process	63	2.00	5.00	3.6825	.64321

Table 5. Descriptive statistics of acceptance level questions

Participants were further classified based on their acceptance levels: Low-acceptance-level: $X \leq 26$; Medium-acceptance-level: $26 < X < 39$; High-acceptance-level: $X \geq 39$. Demographic analyses were performed to assess the relationship between acceptance levels and factors like gender, age range, education level, and experience, as illustrated in Table 6 below.

Variable	Low	Med	High
Gender			
Male	2%	16%	82%
Female	0%	15%	85%
Age Range			
18 - 24	0%	0%	100%
25 - 40	2%	15%	83%
41 - 55	0%	23%	77%
56 - 75	0%	0%	100%
Education Level			
High School			
Bachelor's Degree	0%	11%	89%
Master's or PhD Degree	4%	21%	75%
Years of Experience			
0 - 3	0%	0%	100%
4 - 10	0%	16%	84%
11 - 20	5%	20%	75%
21 - 30	0%	17%	83%
31 - 50	0%	0%	100%
Overall	**2%**	**16%**	**83%**

Table 6. Acceptance level and socio-demographic structure

Overall, the survey revealed that construction professionals positively accepted ML benefits in various project management disciplines, and demographic factors did not significantly impact these attitudes.

To examine the views on barriers covering economic, social and technical, a Likert-scale survey consisting of 6 statements was used, with responses ranging from strongly disagree (1) to strongly agree (5). The reliability of responses, confirmed through Cronbach's alpha, produced a coefficient value of 0.745, surpassing the 0.70 threshold. The lowest mean values were associated with two economic barriers: "Construction companies spend enough budget for employee training" (2.24) and "Construction companies invest enough in new technologies" (2.25). The highest mean value (3.71) was for the statement, "Construction professionals should learn machine learning technology.", as tabulated below.

	N	Minimum	Maximum	Mean	Std. Deviation
Construction companies spare enough budget for employee training	63	1.00	5.00	2.2381	1.05821
Construction companies invest enough to new technologies	63	1.00	5.00	2.2540	.98322
Machine Learning technology can increase the unemployment in construction industry	63	2.00	5.00	3.1111	.84455
Construction professionals tend to learn new technologies	63	1.00	5.00	3.1111	1.00179
Construction companies tend to share the projects' information and data	63	1.00	4.00	2.2698	.91944
Construction professionals should learn machine learning technology	63	1.00	5.00	3.7143	.83141

Table 7. Descriptive statistics of the view of participants about the barriers

The participants' views on the barriers were also analysed based on socio-demographic factors, such as gender, age range, education level, and experience, and shown in Table 8. Following the results, Gender-based responses showed differences in mean values for statements 1, 2, 4, and 5. Males had mean values of 2.42, 2.42, 3.24, and 2.42 for these statements, while females had values of 1.53, 1.61, 2.62, and 1.69.

Variable	4.1	4.2	4.3	4.4	4.5	4.6
Gender						
Male	2.42	2.42	3.12	3.24	2.42	3.76
Female	1.54	1.62	3.08	2.62	1.69	3.54
Age Range						
18 - 24	2.00	2.00	5.00	3.00	2.00	4.00
25 - 40	2.11	2.20	3.00	2.96	2.28	3.74
41 - 55	2.46	2.38	3.23	3.62	2.31	3.54
56 - 75	4.00	3.00	3.00	3.50	2.00	4.00
Education Level						
High School						
Bachelor's Degree	2.11	2.26	3.06	3.11	2.29	3.74
Master's or PhD Degree	2.39	2.25	3.18	3.11	2.25	3.68
Years of Experience						
0 - 3	2.50	2.75	4.00	3.25	2.50	4.25
4 - 10	1.94	2.03	3.03	2.91	2.28	3.75
11 - 20	2.45	2.40	3.15	3.20	2.10	3.50
21 - 30	2.67	2.67	2.83	3.83	2.67	3.83
31 - 50	4.00	2.00	3.00	3.00	2.00	4.00
Overall Mean	**2.24**	**2.25**	**3.11**	**3.11**	**2.27**	**3.71**

Table 8. Socio-demographic structure and view on the barriers

The statistical analysis indicated that as per the two-sided p values, there are statistically significant differences between groups for statements 1 and 5, which are "Statement 1:

Construction companies spare enough budget for employee training, and Statement 5: Construction companies tend to share the projects' information and data. Age Range responses unveil that there is a significant difference for statement 3. The Gabriel post-hoc test revealed significant differences between the 18-24 age group and both the 24-40 and 41-55 age groups. Regarding the Education Level, although the mean values for statement 1 differed slightly between BSc holders (2.11) and MSc/PhD holders (2.40), the independent t-test showed no statistically significant difference between the groups. Finally, the statistical analysis of Experience Level responses did not reveal any statistically significant differences between groups.

Furthermore, a factor analysis was conducted to reduce variables and identify underlying factors related to the barriers. The Kaiser-Meyer-Olkin (KMO) and Bartlett's Sphericity tests were conducted to ensure the appropriateness of the factor analysis. The KMO result (0.676) indicated suitability and the Bartlett's test result (<0.001) supported this. The factor analysis revealed two components: Component 1 (Company-Related Barriers): This component grouped statements related to construction companies, such as budget allocation for employee training, investment in new technologies, and data sharing in projects. Component 2 (Employee-Related Barriers): This component encompassed statements linked to construction professionals themselves, including employability and willingness to learn ML technology. The analysis provides insights into how construction professionals perceive barriers to implementing ML applications in construction projects, and how these perceptions differ based on socio-demographic factors.

5. DISCUSSION AND CONCLUSION

Findings of participants' familiarity level with ML and its applications indicated a relatively low familiarity level, with most participants having limited awareness of ML applications. The overall knowledge level was deemed inadequate. While socio-demographic differences did not produce statistically significant differences, deeper analysis revealed lower familiarity among Generation Z (18-24 years) and baby boomers (56-75 years). Millennials (25-40 years) exhibited the highest familiarity level. Notably, female participants aged 25-40, holding MSc or PhD degrees with 11-20 years of experience, showed the highest familiarity.

Moreover, most participants expressed high acceptance levels, indicating a positive impact on the industry. Despite the lower familiarity, Generation Z and Baby Boomers exhibited higher acceptance. This situation aligns with Belache's study (2019): people with low familiarity accept machine learning more than those with high familiarity. It advises that companies must customise their strategies according to familiarity groups, as the way innovation is perceived differs depending on the level of knowledge of the subject. (Belanche et al., 2019). Specific demographics, such as female participants aged 25-40 with advanced degrees and 11-20 years of experience, showed greater acceptance.

In terms of potential barriers, this study identified six statements addressing economic, social, and technical barriers. Economic barriers primarily pertain to construction companies' perspectives on innovation and staff training. Professionals perceive that Turkish Contractors lack investment in both new technologies and employee development. This stands as a critical obstacle to the adoption of machine learning technology, which requires human involvement to train algorithms and build dataset models. Furthermore, analysis shows significant gender-based differences in perspectives regarding staff training budgets. This highlights the greater tendency of female employees toward continuous learning compared to their male counterparts. Moving to social barriers, which concern the impact on employment and employees' willingness to learn innovative technologies, no significant statistical differences were observed among socio-demographic groups, except for age groups. Specifically, the p-value for the statement pertaining to unemployment concerns, was less than 0.05 for age groups between 18-24 and 24-40, and 18-24 and 41-55, aligning with Kelley's (2021) argument. Generation Z believes that this technology may raise unemployment rates in the sector, despite their recognition of its positive impact on construction projects. This apprehension could be attributed to Turkey's high youth unemployment rate, leading them to anticipate limited opportunities within the industry, despite their relatively low familiarity with machine learning. This emphasises the need to prioritise Generation Z for machine learning training. A technical barrier, namely the sharing of project data to train algorithms, has triggered a conflict of opinions among gender groups. While both groups agree that Turkish Contractors are reluctant to share project information, female participants present a more assertive opinion on this matter. Lastly, participants' responses reveal a consensus among professionals that construction practitioners should acquire proficiency in machine learning technology. Thus, despite the modest familiarity and knowledge levels among professionals, their belief in the significance of machine learning and their intent to embrace this emerging technology is evident. In addition, factor analysis classified the six statements into two components. Statements 1, 2, 4, and 5 are aligned with construction companies, while statements 3 and 6 correspond to employees' attitudes. This factor analysis outcome and the distribution of barriers highlight that construction professionals perceive the barriers as company-related and employee-related rather than economic, social, or technical.

In conclusion, while expanding globally, the construction industry faces challenges in efficiency and productivity. The integration of technology, particularly ML technology, has gained importance in addressing these issues. This study aimed to explore the potential of ML technology in Turkish construction project management, focusing on familiarity levels, acceptance levels, and perceived barriers. Machine learning technology offers opportunities to enhance project delivery and profitability by optimising performance and mitigating time loss. The rising digitisation of project data has led to the generation of datasets vital for training ML algorithms, highlighting the significance of construction professionals' familiarity and acceptance of ML technology. This research contributes to the literature by providing insights into the knowledge, acceptance, and barriers related to ML technology in Turkish construction project management. The findings offer valuable guidance for construction companies, policymakers, and educational institutions to enhance strategies, policies, and curricula in light of the growing influence of ML technology.

Acknowledging the study's limitations, including its focus on a specific demographic, limited participant numbers, and potential bias due to snowball sampling, is important. Future research could broaden the scope by examining perspectives from construction companies and other stakeholders, allowing for a more comprehensive understanding of the challenges and opportunities presented by ML technology in the construction industry.

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