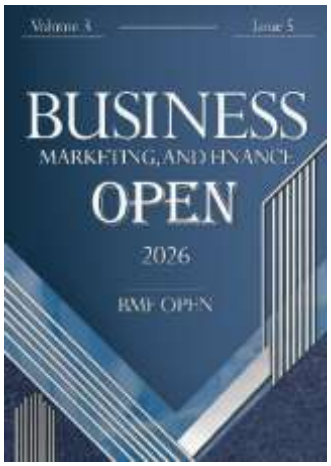
Investigating the Impact of Machine Learning and Artificial Intelligence on Activity-Based Project Costing

Reza Asadi[1], Artin Beytari [2,*] and Mohammadreza Ghorbaniyan [3]

[1] Department of Accounting, Ki.C., Islamic Azad University, Kish, Iran;
[2] Department of Accounting, ShQ.C., Islamic Azad University, Tehran, Iran;
[3] Department of Business Management, ShQ.C., Islamic Azad University, Tehran, Iran;

* Correspondence: Beytari@iau.ac.ir



Citation: Asadi, R., Beytari, A., & Ghorbaniyan, M. (2026). Investigating the Impact of Machine Learning and Artificial Intelligence on Activity-Based Project Costing. *Business, Marketing, and Finance Open*, 3(5), 1-19.

Received: 10 March 2026
Revised: 10 August 2026
Accepted: 17 August 2026
Published: 01 September 2026

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Abstract: This study aimed to investigate the impact of artificial intelligence and machine learning capabilities on the effectiveness of activity-based project costing among professionals working in project-oriented organizations in Tehran. This applied, quantitative, cross-sectional study was conducted in 2026 among professionals involved in project management, project control, cost engineering, accounting, financial management, information systems, and data analysis in project-oriented organizations in Tehran. Using purposive and stratified sampling, 286 valid responses were obtained from 320 distributed questionnaires. Data were collected using a researcher-developed questionnaire assessing artificial intelligence utilization, machine learning capability, automated activity classification, intelligent cost-driver identification, predictive cost forecasting, and activity-based project costing effectiveness. Content validity was evaluated by experts, while construct validity and reliability were assessed using confirmatory factor analysis, Cronbach's alpha, composite reliability, and average variance extracted. Data were analyzed using Pearson correlation coefficients and structural equation modeling. Structural equation modeling showed that artificial intelligence utilization had a significant positive effect on activity-based project costing effectiveness ($\beta = .24$, $p < .001$). Machine learning capability also significantly predicted costing effectiveness ($\beta = .29$, $p < .001$). Automated activity classification ($\beta = .13$, $p = .009$), intelligent cost-driver identification ($\beta = .21$, $p < .001$), and predictive cost forecasting ($\beta = .31$, $p < .001$) each demonstrated significant positive effects. Predictive cost forecasting produced the strongest direct effect. Collectively, the predictor variables explained 68% of the variance in activity-based project costing effectiveness ($R^2 = .68$). The structural model demonstrated satisfactory fit indices ($\chi^2/df = 2.24$, CFI = .946, TLI = .937, RMSEA = .066, SRMR = .054). Artificial intelligence and machine learning can substantially enhance activity-based project costing by improving predictive forecasting, cost-driver identification, activity classification, cost allocation accuracy, and managerial decision support, thereby strengthening cost management in complex project environments.

Keywords: Artificial Intelligence; Machine Learning; Activity-Based Costing; Project Cost Management; Predictive Cost Forecasting; Cost-Driver Identification

1. Introduction

Project cost management is one of the most critical dimensions of successful project governance because the ability to estimate, allocate, monitor, and control expenditures directly affects the achievement of project objectives, organizational profitability, and the efficient utilization of limited resources. In contemporary project environments, increasing technological complexity, supply-chain volatility, uncertain market conditions, changing client requirements, resource constraints, and interdependencies among project activities have made cost

management considerably more difficult than in traditional project settings. Cost overruns remain a persistent concern across construction, information technology, infrastructure, engineering, and other project-based industries, demonstrating that conventional estimating and monitoring procedures are often unable to adequately capture the dynamic and nonlinear nature of project cost behavior. Evidence from large-scale project environments indicates that cost escalation can arise from deficiencies in forecasting, scope uncertainty, inadequate risk identification, design changes, resource shortages, delays, weak coordination, and ineffective cost-control mechanisms [1]. Similar concerns have been reported in complex and unstable project contexts, where project cost performance is influenced by managerial, institutional, environmental, contractual, and operational factors that may interact in unpredictable ways [2]. The persistence of these problems has increased the demand for more adaptive and analytically advanced approaches to project costing capable of integrating large quantities of historical and real-time information into managerial decision-making.

Traditional project costing systems commonly rely on predetermined rates, historical averages, expert judgments, linear assumptions, and periodic budget comparisons. Although these approaches can provide useful baseline information, their effectiveness may decline when projects include numerous interdependent activities, multiple categories of indirect costs, dynamic cost drivers, uncertain resource consumption, and rapidly changing operating conditions. Cost structures in contemporary projects are increasingly complex because expenses do not arise solely from direct labor and materials but also from project coordination, engineering support, information technology, procurement, quality control, logistics, risk management, administrative services, equipment usage, rework, and other indirect activities. Consequently, accurate allocation of overhead and indirect expenditures becomes a significant managerial challenge. Research on the integration of cost breakdown structures and work breakdown structures has demonstrated the importance of systematically connecting project activities with corresponding cost components in order to enhance planning, monitoring, and control [3]. Likewise, conventional cost-control approaches such as earned value management provide important information about deviations between planned and actual performance, but their usefulness is strongly dependent on the accuracy and timeliness of the underlying cost and schedule information [4]. These limitations indicate that project cost management increasingly requires analytical systems capable of representing the actual consumption of organizational resources at the activity level rather than relying primarily on broad cost pools or aggregated allocation mechanisms.

Activity-based costing provides an important conceptual framework for addressing this challenge because it assigns costs to organizational activities before allocating those costs to projects, products, services, or other cost objects on the basis of identifiable cost drivers. When applied to project management, activity-based project costing can provide managers with a more detailed representation of how particular project activities consume financial and operational resources. Such an approach may improve transparency, strengthen cost-driver analysis, reveal non-value-adding activities, and support more accurate allocation of indirect expenditures. It can also help decision-makers understand why costs arise rather than simply determining how much has been spent. This distinction becomes increasingly important in project environments in which cost performance is affected by numerous interconnected technical and managerial processes. Cost-reduction research in construction and project management has emphasized that sustainable project performance depends not merely on reducing expenditures but on identifying the underlying sources of unnecessary or inefficient resource consumption [5]. Similarly, optimization research has shown that project decision-making frequently involves simultaneous trade-offs among cost, time, quality, and resource availability, making simplistic cost allocation mechanisms insufficient for complex planning environments [6]. Activity-based project costing therefore offers a potentially powerful framework for

integrating operational processes with financial information; however, its effectiveness depends on the ability of organizations to identify activities accurately, determine appropriate cost drivers, estimate resource consumption, and process large amounts of project data.

The difficulty of performing these tasks through conventional analytical procedures has created considerable interest in artificial intelligence and machine learning as potential technologies for improving project costing. Artificial intelligence broadly refers to computational systems capable of performing tasks that typically require elements of human intelligence, including pattern recognition, classification, prediction, optimization, learning, and decision support. Machine learning represents a major branch of artificial intelligence in which algorithms identify relationships within data and improve predictive or classificatory performance without requiring every decision rule to be explicitly programmed. These technologies have become increasingly relevant to project management because projects generate extensive volumes of structured and unstructured data relating to schedules, expenditures, contracts, procurement, productivity, resources, risks, changes, quality, and stakeholder interactions. Artificial intelligence can potentially transform these data into predictive and actionable knowledge. Professionals in project-based sectors have increasingly recognized the potential of AI systems to enhance forecasting, risk analysis, planning, automation, and managerial decision-making [7]. More broadly, the integration of AI into construction management has been associated with improvements in project efficiency, cost effectiveness, resource utilization, risk identification, and operational decision support [8]. These developments suggest that AI can play a significant role not only in project scheduling or risk management but also in the architecture of project costing systems.

Machine learning is particularly relevant to project cost estimation because it can model complex relationships among multiple predictors that may not be adequately represented through conventional parametric techniques. Historical project data can be used to train predictive algorithms to identify patterns linking project characteristics, resource consumption, activity durations, contract conditions, technical complexity, market fluctuations, and organizational factors with final project costs. Systematic evidence has shown growing interest in the use of machine learning for project cost estimation, with models increasingly employed to improve prediction accuracy and reduce dependence on purely subjective estimation procedures [9]. Research on artificial intelligence in construction cost estimation has similarly indicated that AI-based techniques can improve the ability to process multidimensional project information and identify complex nonlinear patterns affecting expenditure levels [10]. More advanced hybrid approaches combine machine learning algorithms with metaheuristic optimization techniques to strengthen the prediction of final project cost and completion time, demonstrating the potential value of computational intelligence when conventional estimating relationships are insufficient [11]. These capabilities are directly relevant to activity-based project costing because accurate activity-level cost allocation depends on understanding how combinations of project characteristics and operational conditions influence resource consumption.

One of the most important contributions of machine learning to project costing may therefore be its capacity to improve predictive cost forecasting. Traditional forecasting frequently extrapolates from historical averages or relies on managerial judgment, whereas machine-learning models can continuously identify changing relationships within project data. This capacity becomes particularly valuable where cost overruns are not normally distributed or where relatively rare projects generate extremely large losses. Empirical analysis of information technology projects, for example, has demonstrated that project cost overruns may exhibit a power-law distribution, indicating that extreme overruns can occur more frequently than would be expected under conventional assumptions [12].

Such findings emphasize the limitations of forecasting techniques that assume stable, linear, or normally distributed project outcomes. Machine learning can potentially respond to this problem by incorporating multiple interacting predictors, recognizing nonlinear relationships, and updating forecasts as additional project information becomes available. Predictive systems can also support early identification of high-risk projects. Bayesian-network-based approaches have demonstrated the usefulness of probabilistic machine-learning techniques for assessing and predicting cost-overrun risk in construction projects [13]. In this sense, machine learning may move project costing from a predominantly retrospective function toward a predictive and anticipatory management mechanism.

Artificial intelligence may also improve activity-based project costing through automated activity classification and intelligent identification of cost drivers. In large projects, thousands of transactions, work packages, tasks, resource records, invoices, and operational events may need to be categorized before costs can be accurately assigned. Manual classification can be costly, inconsistent, and vulnerable to subjective judgments. AI-based classification algorithms can assist in recognizing patterns among expenditures and linking transactions to corresponding activities. Likewise, machine-learning methods can help identify which operational variables best explain the consumption of resources within particular categories of activities. Such intelligent cost-driver identification is especially important because the validity of an activity-based costing system depends heavily on selecting drivers that accurately represent causal relationships between activities and resource consumption. Recent work directly addressing the integration of artificial intelligence into activity-based project costing has argued that AI technologies can enhance both the accuracy and efficiency of project cost management by improving activity recognition, automated data processing, cost attribution, and forecasting [14]. A qualitative model developed specifically for machine learning and artificial intelligence in activity-based project costing has likewise highlighted the importance of integrating intelligent analytical capabilities with cost allocation processes and project decision-making [15]. These studies establish an emerging conceptual basis for viewing AI as an enabling architecture for more sophisticated activity-based costing systems.

The value of AI-supported costing becomes even more apparent when project managers are required to make decisions under conditions of uncertainty. Project costs are affected not only by internal organizational activities but also by supply-chain disruptions, economic conditions, resource availability, stakeholder decisions, contractual arrangements, and external shocks. The COVID-19 pandemic demonstrated how rapidly project assumptions can become invalid when supply networks, labor availability, procurement lead times, and resource prices are disrupted. Scenario-based robust time-cost optimization models have therefore been proposed to assist managers in addressing uncertainty and maintaining project performance under supply-chain disturbances [16]. Such work demonstrates that project cost decisions increasingly require flexible analytical capabilities rather than static budgeting mechanisms. AI and machine learning can enhance this flexibility by incorporating updated data into cost predictions and by detecting emerging deviations before they are fully reflected in conventional financial reports. At the same time, project management capability itself remains essential because technological systems generate value only when organizations possess the managerial structures required to interpret and operationalize their outputs. Research has shown that project management contributes to organizational capability transformation and can support the development of more adaptive and performance-oriented organizational systems [17]. Therefore, the integration of AI with activity-based project costing should be understood as a sociotechnical process involving technology, data, costing architecture, and managerial capability rather than as a purely computational intervention.

Another important issue concerns the relationship between cost management and the broader configuration of project delivery systems. Project costs can be affected by outsourcing structures, transaction arrangements, contractor capabilities, and governance mechanisms. Recent research has demonstrated that high outsourcing performance in construction projects depends on combinations of transaction-cost considerations and organizational capabilities rather than on any single isolated factor [18]. Such findings are relevant to activity-based project costing because cost drivers can originate both within the organization and across external project relationships. Artificial intelligence may assist managers in integrating data from contractors, suppliers, activities, resource systems, and project-control databases, enabling a more comprehensive representation of project cost behavior. Similarly, system-dynamics research on underground metro projects has shown that cost claims and financial consequences frequently emerge from interacting causal pathways rather than from individual isolated events [19]. This complexity reinforces the need for analytical methods capable of identifying hidden patterns and interdependencies among variables. AI-enabled activity-based costing may provide a mechanism through which operational and financial information can be integrated at a sufficiently detailed level to reveal these pathways.

The applicability of these technologies is not limited to construction. Financial institutions, technology firms, engineering companies, and other project-intensive organizations also depend on accurate project costing. Research on cost-estimation models used by banks and fintech companies has demonstrated that different organizational environments require alternative estimating approaches depending on available data, project characteristics, and decision-making requirements [20]. This diversity suggests that there is no universally optimal project costing model. Instead, organizations require flexible systems capable of adapting to different activities, cost structures, and levels of technological maturity. Machine learning offers such flexibility because predictive models can be trained on organization-specific data and recalibrated as conditions change. In activity-based project costing, this adaptability can be especially valuable because the relevance of cost drivers and resource-consumption relationships may differ substantially across organizations and project types. AI can therefore support more context-sensitive costing systems that learn from historical project performance rather than imposing a fixed allocation structure across heterogeneous projects.

Despite these opportunities, the successful application of artificial intelligence to activity-based project costing cannot be assumed. AI systems depend on the quality, completeness, consistency, and accessibility of project data. Inaccurate coding, fragmented databases, missing historical records, inconsistent activity definitions, and weak integration between accounting and project-management information systems can limit algorithmic performance. Moreover, machine-learning models may generate apparently accurate predictions without offering transparent explanations for why particular costs are expected, creating difficulties for managers who require interpretability and accountability. The effective use of intelligent systems therefore requires careful integration between algorithmic predictions and professional judgment. It also requires organizational investment in digital infrastructure, data governance, staff competencies, and cross-functional collaboration among project managers, accountants, cost engineers, information systems specialists, and data analysts. These requirements are especially significant because the objective of project costing is not merely prediction; costing information must also support planning, resource allocation, accountability, performance evaluation, and managerial control. Therefore, the effectiveness of AI in this domain should be evaluated in terms of its contribution to actual costing performance rather than solely by technical prediction metrics.

A further research problem is that much of the existing literature examines artificial intelligence in project estimation, construction management, risk prediction, scheduling, or general project performance without directly

assessing its impact on activity-based project costing as an integrated managerial accounting system. Existing studies demonstrate the usefulness of AI in cost estimation [10], machine learning in predictive project analytics [9], probabilistic methods in cost-overrun assessment [13], and hybrid intelligent models in final cost and time forecasting [11]. Other studies emphasize the broader role of AI in project efficiency and cost effectiveness [8], the organizational expectations surrounding AI-enabled construction management [7], and the emerging conceptual integration of intelligent technologies with activity-based project costing [14, 15]. However, empirical evidence simultaneously examining artificial intelligence utilization, machine learning capability, automated activity classification, intelligent cost-driver identification, predictive cost forecasting, and the effectiveness of activity-based project costing remains comparatively limited. This gap is important because these capabilities represent distinct but complementary mechanisms through which intelligent technologies may improve costing accuracy and managerial usefulness.

The need for such empirical investigation is particularly relevant in rapidly developing project-oriented economies and large metropolitan business environments such as Tehran, where construction, engineering, infrastructure, manufacturing, consulting, and technology organizations operate under conditions of cost volatility, competitive pressure, digital transformation, and resource constraints. In such contexts, traditional project costing systems may be increasingly inadequate for processing the volume and complexity of available information. Organizations may adopt artificial intelligence technologies without fully understanding whether these investments translate into measurable improvements in cost allocation, cost-driver identification, forecasting, cost control, and decision support. A systematic investigation of these relationships can therefore contribute both theoretically and practically by connecting the fields of artificial intelligence, machine learning, project management, and managerial accounting. It can also clarify whether predictive and classificatory capabilities provide value beyond conventional cost-management practices and whether the integration of AI with activity-based costing can strengthen the financial management of complex projects.

Accordingly, the aim of this study was to investigate the impact of artificial intelligence and machine learning on the effectiveness of activity-based project costing, with particular emphasis on artificial intelligence utilization, machine learning capability, automated activity classification, intelligent cost-driver identification, and predictive cost forecasting among professionals working in project-oriented organizations in Tehran.

2. Methodology

This study employed an applied, quantitative, cross-sectional research design to investigate the impact of machine learning and artificial intelligence on activity-based project costing in project-oriented organizations. The study was conducted in Tehran, Iran, during 2026. The target population consisted of professionals whose occupational responsibilities were directly related to project planning, project cost management, management accounting, financial control, budgeting, data analysis, project management information systems, and the implementation or use of artificial intelligence-based technologies in organizational decision-making. Participants were recruited from project-oriented organizations operating in construction, engineering, information technology, manufacturing, consulting, and infrastructure-related sectors in Tehran. These organizations were selected because project costing constitutes an important component of their budgeting, resource allocation, cost monitoring, and managerial decision-making processes. To ensure that respondents possessed sufficient familiarity with the research concepts, participation was restricted to professionals with at least two years of relevant work experience and direct or indirect involvement in project costing, activity-based costing, project control, financial analysis, or

technology-assisted decision-making. A total of 320 questionnaires were distributed among eligible professionals using a purposive and stratified sampling approach intended to provide representation across different professional positions and organizational sectors. After eliminating incomplete questionnaires and responses with substantial missing or inconsistent data, 286 valid questionnaires were retained for the final analysis, corresponding to a usable response rate of approximately 89.4%. The final sample therefore consisted of 286 project managers, project control specialists, cost engineers, accountants, financial managers, information systems specialists, data analysts, and other professionals working in project-based organizations located in Tehran. Participation was voluntary, respondents were informed of the academic purpose of the research, and confidentiality and anonymity of individual responses were maintained throughout the research process.

Data were collected using a structured researcher-developed questionnaire constructed on the basis of the conceptual dimensions of artificial intelligence, machine learning, activity-based costing, project cost estimation, cost allocation, forecasting accuracy, cost-control efficiency, and managerial decision support. The questionnaire consisted of three principal sections. The first section collected demographic and occupational information, including age, gender, educational attainment, field of specialization, professional position, years of work experience, organizational sector, experience with project costing systems, and level of familiarity with artificial intelligence and machine learning applications. The second section assessed the extent to which artificial intelligence and machine learning technologies were implemented or utilized in project-related financial and costing activities. The items addressed areas such as automated analysis of historical project data, identification of cost patterns, prediction of resource requirements, automated classification of project activities, detection of cost anomalies, estimation of activity consumption, prediction of cost overruns, processing of large financial datasets, real-time analysis of project information, and AI-assisted managerial decision-making. The third section measured the effectiveness of activity-based project costing, focusing on the accuracy of assigning costs to project activities, identification of cost drivers, estimation of activity-level resource consumption, reduction of arbitrary overhead allocation, accuracy of project cost forecasts, timely identification of cost deviations, transparency of project expenditures, cost-control effectiveness, budgeting quality, and usefulness of costing information for managerial decisions. Items were evaluated on a five-point Likert scale ranging from 1, indicating strongly disagree, to 5, indicating strongly agree, with higher scores representing greater use of intelligent technologies or greater effectiveness of activity-based project costing.

To establish content validity, the preliminary version of the questionnaire was evaluated by a panel of university faculty members and practitioners specializing in project management, management accounting, cost engineering, information systems, artificial intelligence, and quantitative research methodology. The reviewers assessed the relevance, clarity, comprehensiveness, and conceptual consistency of the items, and modifications were made in accordance with their recommendations. A pilot administration was subsequently conducted with 30 professionals who met the study eligibility criteria but were not included in the final sample. Feedback from the pilot phase was used to improve the wording and comprehensibility of the questionnaire and to eliminate potentially ambiguous items. Internal consistency reliability was examined using Cronbach's alpha and composite reliability coefficients. Values greater than 0.70 were considered indicative of satisfactory reliability. Construct validity was evaluated through confirmatory factor analysis, while convergent validity was assessed using standardized factor loadings and average variance extracted. An average variance extracted value of at least 0.50 was regarded as acceptable evidence of convergent validity. Discriminant validity was also examined to establish that machine learning, artificial intelligence utilization, and activity-based project costing performance represented empirically

distinguishable constructs. The final questionnaire was administered electronically and, where necessary, in printed form to qualified respondents working in selected project-oriented organizations in Tehran.

Data analysis was performed using SPSS and structural equation modeling software. Before hypothesis testing, the dataset was screened for incomplete observations, data-entry errors, outliers, and response patterns that could threaten the reliability of the analysis. Descriptive statistics, including frequency, percentage, mean, standard deviation, minimum, maximum, skewness, and kurtosis, were calculated to describe the demographic characteristics of the respondents and the distribution of the principal research variables. The distributional properties of the variables were examined before inferential analysis, and skewness and kurtosis coefficients were used to assess deviations from normality. Multicollinearity among predictor variables was investigated using tolerance statistics and variance inflation factors, with variance inflation factor values below the conventional threshold indicating the absence of problematic multicollinearity. The reliability of the measurement model was evaluated through Cronbach's alpha and composite reliability, whereas construct validity was investigated using confirmatory factor analysis, factor loadings, average variance extracted, and discriminant validity criteria.

Pearson correlation coefficients were initially calculated to determine the direction and magnitude of the relationships among artificial intelligence utilization, machine learning capabilities, and activity-based project costing performance. Subsequently, structural equation modeling was employed to test the proposed relationships simultaneously and to estimate the direct effects of artificial intelligence and machine learning on the effectiveness of activity-based project costing. The structural model examined whether greater organizational use of AI-supported data processing, predictive analytics, automated activity classification, intelligent cost-driver identification, and machine learning-based forecasting was associated with increased accuracy, efficiency, transparency, and decision usefulness of project costing. Standardized path coefficients, corresponding test statistics, probability values, and coefficients of determination were used to evaluate the strength and statistical significance of the hypothesized relationships. The explanatory power of the model was assessed by examining the proportion of variance in activity-based project costing explained by artificial intelligence and machine learning capabilities. Where appropriate, effect-size and predictive-relevance indices were also examined to determine the substantive importance and predictive adequacy of the structural relationships. Model fit was evaluated using appropriate goodness-of-fit indicators for the selected structural equation modeling approach. All statistical tests were conducted at a significance level of 0.05, while findings with probability values below 0.01 were interpreted as providing particularly strong statistical evidence. This analytical procedure enabled an integrated assessment of whether and to what extent the adoption of machine learning and artificial intelligence contributes to more precise cost allocation, more accurate project cost forecasting, improved identification of activity-based cost drivers, enhanced cost-control processes, and higher-quality managerial decision-making in project-oriented organizations.

3. Findings and Results

The final analysis was conducted on data obtained from 286 professionals working in project-oriented organizations in Tehran. Of the participants, 187 (65.4%) were male and 99 (34.6%) were female. The mean age of the respondents was 39.47 years (SD = 7.82), with participants ranging from 25 to 58 years of age. In terms of educational attainment, 42 respondents (14.7%) held a bachelor's degree, 177 (61.9%) held a master's degree, and 67 (23.4%) held a doctoral or equivalent professional degree. The participants represented a relatively experienced professional sample; their mean occupational experience was 11.63 years (SD = 6.18), and 189 respondents (66.1%) reported more than eight years of professional experience. Regarding occupational position, 61 participants (21.3%)

were project managers or deputy project managers, 56 (19.6%) were project control specialists, 48 (16.8%) were cost engineers or cost-control specialists, 45 (15.7%) worked in accounting or financial management, 39 (13.6%) were information systems or data-analysis specialists, and 37 (12.9%) held other project-related technical or managerial positions. Participants were recruited from construction and civil engineering organizations (31.8%), information technology and technology-intensive firms (21.0%), manufacturing organizations (18.2%), consulting and engineering-service companies (16.8%), and infrastructure and other project-oriented organizations (12.2%). Furthermore, 237 participants (82.9%) reported direct professional involvement in budgeting, costing, cost control, or project financial analysis, while 212 (74.1%) reported at least moderate familiarity with organizational applications of artificial intelligence or machine learning. These characteristics indicated that the sample consisted predominantly of experienced and appropriately qualified professionals with sufficient exposure to project costing and technology-supported decision-making to provide informed responses regarding the principal constructs investigated in the study.

Table 1. Descriptive Statistics of the Main Study Variables

Variable	Possible Range	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
Artificial Intelligence Utilization	1–5	3.74	0.63	1.83	5.00	-0.41	-0.18
Machine Learning Capability	1–5	3.61	0.67	1.67	5.00	-0.32	-0.27
Automated Activity Classification	1–5	3.68	0.66	1.50	5.00	-0.36	-0.11
Intelligent Cost-Driver Identification	1–5	3.72	0.65	1.75	5.00	-0.39	-0.08
Predictive Cost Forecasting	1–5	3.79	0.62	1.80	5.00	-0.45	0.06
Activity-Based Project Costing Effectiveness	1–5	3.87	0.58	2.00	5.00	-0.47	0.13
Cost Allocation Accuracy	1–5	3.91	0.61	1.80	5.00	-0.50	0.09
Cost-Control Efficiency	1–5	3.83	0.64	1.60	5.00	-0.42	-0.16
Decision-Usefulness of Cost Information	1–5	3.89	0.60	1.80	5.00	-0.46	0.17

As shown in Table 1, the mean scores of all principal variables were above the theoretical midpoint of 3.00, indicating that the participating organizations generally demonstrated moderate-to-high utilization of artificial intelligence and machine learning and relatively favorable levels of activity-based project costing effectiveness. Artificial intelligence utilization had a mean of 3.74 (SD = 0.63), whereas machine learning capability produced a slightly lower mean of 3.61 (SD = 0.67), suggesting that broader AI-enabled applications were somewhat more established than specialized machine-learning capabilities. Among the technology-related dimensions, predictive cost forecasting obtained the highest mean score (M = 3.79, SD = 0.62), followed by intelligent cost-driver identification (M = 3.72, SD = 0.65) and automated activity classification (M = 3.68, SD = 0.66). The overall mean for activity-based project costing effectiveness was 3.87 (SD = 0.58), indicating a comparatively favorable evaluation of the organizations' ability to generate accurate and managerially useful activity-based costing information. Cost allocation accuracy obtained the highest mean among the activity-based costing dimensions (M = 3.91, SD = 0.61), followed closely by decision-usefulness of cost information (M = 3.89, SD = 0.60), while cost-control efficiency had a mean of 3.83 (SD = 0.64). Examination of skewness and kurtosis values showed that all coefficients were well within conventional acceptable limits, with skewness ranging from -0.50 to -0.32 and kurtosis ranging from -0.27 to 0.17. Thus, there was no evidence of severe univariate non-normality, and the distributions were considered sufficiently appropriate for subsequent parametric analyses and structural equation modeling.

Table 2. Correlations Among Artificial Intelligence, Machine Learning, and Activity-Based Project Costing Variables

Variable	1	2	3	4	5	6
1. Artificial Intelligence Utilization	1.00					
2. Machine Learning Capability	0.64**	1.00				
3. Automated Activity Classification	0.59**	0.62**	1.00			
4. Intelligent Cost-Driver Identification	0.61**	0.66**	0.60**	1.00		
5. Predictive Cost Forecasting	0.63**	0.69**	0.58**	0.65**	1.00	
6. Activity-Based Project Costing Effectiveness	0.68**	0.72**	0.61**	0.69**	0.74**	1.00

The correlation analysis presented in Table 2 demonstrated statistically significant positive relationships among all principal study variables. Artificial intelligence utilization was positively associated with machine learning capability ($r = .64$, $p < .01$), automated activity classification ($r = .59$, $p < .01$), intelligent cost-driver identification ($r = .61$, $p < .01$), predictive cost forecasting ($r = .63$, $p < .01$), and overall activity-based project costing effectiveness ($r = .68$, $p < .01$). Machine learning capability exhibited an even stronger relationship with activity-based project costing effectiveness ($r = .72$, $p < .01$), suggesting that organizations with more developed machine-learning capabilities tended to report substantially higher levels of costing accuracy, efficiency, and decision usefulness. The strongest bivariate association with activity-based project costing effectiveness was observed for predictive cost forecasting ($r = .74$, $p < .01$), followed by machine learning capability ($r = .72$, $p < .01$) and intelligent cost-driver identification ($r = .69$, $p < .01$). Automated activity classification was also significantly associated with activity-based project costing effectiveness ($r = .61$, $p < .01$). Although several of the predictor variables were moderately to strongly intercorrelated, none of the coefficients exceeded .80, indicating that the constructs were related but not statistically redundant. Supplementary multicollinearity diagnostics were consistent with this interpretation: variance inflation factor values ranged from 1.71 to 2.64 and tolerance values ranged from .38 to .59, remaining within acceptable limits. Accordingly, the relationships among the explanatory variables were not sufficiently large to compromise the stability or interpretability of the subsequent structural model.

Table 3. Measurement Model Reliability and Convergent Validity

Construct	Standardized Factor Loading Range	Cronbach's Alpha	Composite Reliability	AVE
Artificial Intelligence Utilization	0.72–0.86	0.88	0.91	0.59
Machine Learning Capability	0.74–0.89	0.90	0.92	0.62
Automated Activity Classification	0.71–0.85	0.86	0.89	0.57
Intelligent Cost-Driver Identification	0.76–0.90	0.91	0.93	0.65
Predictive Cost Forecasting	0.77–0.91	0.92	0.94	0.67
Activity-Based Project Costing Effectiveness	0.75–0.89	0.93	0.94	0.64
Cost Allocation Accuracy	0.74–0.88	0.89	0.92	0.61
Cost-Control Efficiency	0.72–0.87	0.88	0.91	0.59
Decision-Usefulness of Cost Information	0.76–0.90	0.91	0.93	0.65

The measurement-model results reported in Table 3 confirmed satisfactory reliability and convergent validity for all constructs included in the study. Standardized factor loadings were consistently above the recommended minimum level of .70, ranging from .71 to .91 across the measurement model, indicating that the observed questionnaire items were strong indicators of their respective latent constructs. Cronbach's alpha coefficients ranged from .86 for automated activity classification to .93 for overall activity-based project costing effectiveness, demonstrating high internal consistency. Composite reliability coefficients ranged from .89 to .94, exceeding the

conventional criterion of .70 for every construct. Average variance extracted values were also above the required .50 threshold, ranging from .57 for automated activity classification to .67 for predictive cost forecasting. These findings indicated that each construct explained more than half of the variance in its associated indicators and therefore demonstrated acceptable convergent validity. In addition, examination of the interconstruct relationships and the square roots of the AVE values indicated satisfactory discriminant validity, as the latent constructs shared stronger relationships with their own measurement indicators than with conceptually distinct constructs. The confirmatory factor analysis further demonstrated an acceptable overall measurement-model fit, $\chi^2/df = 2.18$, comparative fit index (CFI) = .948, Tucker–Lewis index (TLI) = .939, root mean square error of approximation (RMSEA) = .064, and standardized root mean square residual (SRMR) = .052. Taken together, these results established that the measurement instrument possessed adequate psychometric quality and supported the use of the latent variables in the structural model.

Table 4. Structural Model Results for the Effects of AI and Machine Learning on Activity-Based Project Costing

Structural Path	Standardized β	SE	t/CR	p	Result
Artificial Intelligence Utilization → Activity-Based Project Costing Effectiveness	0.24	0.058	4.36	<.001	Supported
Machine Learning Capability → Activity-Based Project Costing Effectiveness	0.29	0.061	4.91	<.001	Supported
Automated Activity Classification → Activity-Based Project Costing Effectiveness	0.13	0.052	2.63	.009	Supported
Intelligent Cost-Driver Identification → Activity-Based Project Costing Effectiveness	0.21	0.056	3.92	<.001	Supported
Predictive Cost Forecasting → Activity-Based Project Costing Effectiveness	0.31	0.060	5.27	<.001	Supported

Model statistics: $R^2 = .68$; Adjusted $R^2 = .67$; $\chi^2/df = 2.24$; CFI = .946; TLI = .937; RMSEA = .066; SRMR = .054.

Table 4 presents the principal structural-equation-modeling results and provides direct evidence regarding the impact of artificial intelligence and machine learning on activity-based project costing. All hypothesized structural paths were positive and statistically significant. Artificial intelligence utilization exerted a significant positive direct effect on activity-based project costing effectiveness ($\beta = .24$, SE = .058, CR = 4.36, $p < .001$), indicating that greater utilization of AI-enabled data processing, automated decision support, and intelligent analytical systems was associated with improved activity-level cost allocation, greater transparency, and enhanced usefulness of costing information. Machine learning capability also had a significant positive effect on activity-based project costing effectiveness ($\beta = .29$, SE = .061, CR = 4.91, $p < .001$), demonstrating that the capacity to learn from historical project data and identify complex cost patterns contributed independently to improved project costing performance. Automated activity classification had a smaller but nevertheless statistically significant effect ($\beta = .13$, SE = .052, CR = 2.63, $p = .009$), suggesting that automated identification and categorization of project activities contributed to more systematic cost assignment, although its effect was weaker than those of the more analytically sophisticated AI and machine-learning functions. Intelligent cost-driver identification demonstrated a significant positive effect on activity-based project costing effectiveness ($\beta = .21$, SE = .056, CR = 3.92, $p < .001$), indicating that AI-supported identification of the factors responsible for resource consumption enhanced the correspondence between actual project activities and allocated costs. Predictive cost forecasting produced the strongest standardized direct effect in the model ($\beta = .31$, SE = .060, CR = 5.27, $p < .001$), indicating that the ability to predict future activity costs, resource consumption, and potential cost overruns represented the most influential specific technological capability examined in relation to activity-based project costing. Collectively, the predictor variables explained 68% of the variance in activity-based project costing effectiveness ($R^2 = .68$; adjusted $R^2 = .67$), representing substantial

explanatory power. The structural model also demonstrated satisfactory overall goodness of fit, with $\chi^2/df = 2.24$, CFI = .946, TLI = .937, RMSEA = .066, and SRMR = .054. These indicators collectively supported the adequacy of the proposed structural relationships and indicated that the empirical data were consistent with the conceptual proposition that AI and machine-learning capabilities contribute substantially to the effectiveness of activity-based project costing.

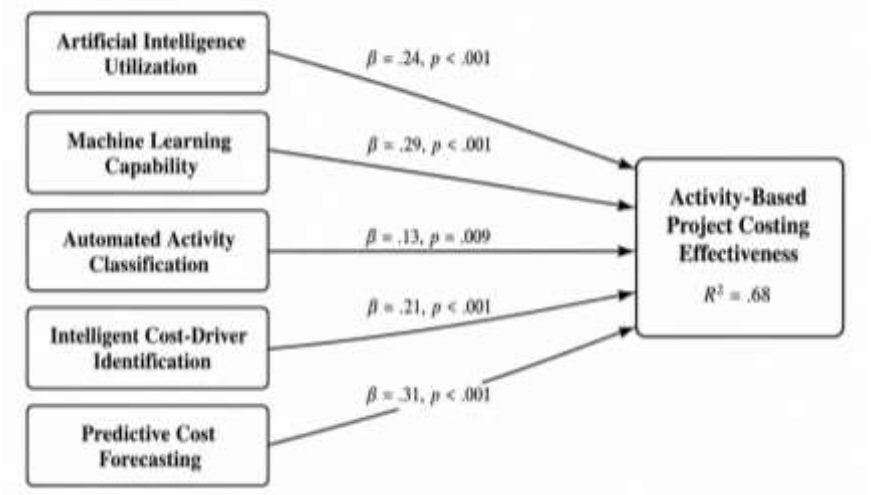


Figure 1. Structural Model of the Effects of Artificial Intelligence and Machine Learning Capabilities on Activity-Based Project Costing Effectiveness

The structural pattern summarized in Figure 1 further illustrates the relative magnitude of the significant pathways identified in the analysis. Predictive cost forecasting demonstrated the largest direct contribution to activity-based project costing effectiveness (β = .31), followed by machine learning capability (β = .29), artificial intelligence utilization (β = .24), intelligent cost-driver identification (β = .21), and automated activity classification (β = .13). The ordering of these effects indicates that the impact of artificial intelligence on project costing was not confined to the automation of routine costing procedures. Rather, the strongest contributions were associated with analytical functions capable of extracting patterns from historical project information, estimating future cost behavior, identifying meaningful drivers of resource consumption, and supporting anticipatory cost-control decisions. The model therefore suggests that the principal value of AI and machine learning in an activity-based project costing environment lies in their capacity to transform large volumes of project and financial data into more precise, timely, and predictive cost information. Overall, the findings supported the study's central proposition that higher levels of artificial intelligence utilization and machine learning capability are associated with more effective activity-based project costing and that these technologies improve costing performance through complementary mechanisms involving automated activity classification, intelligent cost-driver identification, and predictive cost forecasting.

4. Discussion and Conclusion

The present study investigated the impact of artificial intelligence and machine learning on the effectiveness of activity-based project costing among professionals working in project-oriented organizations in Tehran. The findings provided consistent empirical support for the proposed relationships and demonstrated that artificial intelligence utilization, machine learning capability, automated activity classification, intelligent cost-driver identification, and predictive cost forecasting were all positively associated with activity-based project costing

effectiveness. The structural model explained 68% of the variance in activity-based project costing effectiveness, indicating substantial explanatory power. Among the predictors, predictive cost forecasting exerted the strongest direct effect on activity-based project costing effectiveness ($\beta = .31$, $p < .001$), followed by machine learning capability ($\beta = .29$, $p < .001$), artificial intelligence utilization ($\beta = .24$, $p < .001$), intelligent cost-driver identification ($\beta = .21$, $p < .001$), and automated activity classification ($\beta = .13$, $p = .009$). The correlation analysis similarly showed strong positive relationships between activity-based project costing effectiveness and predictive cost forecasting, machine learning capability, intelligent cost-driver identification, and artificial intelligence utilization. Collectively, these results indicate that artificial intelligence and machine learning can substantially strengthen project costing by improving the capacity of organizations to process project information, recognize cost patterns, identify relevant cost drivers, classify activities, predict future expenditures, and transform operational data into more accurate and useful cost information.

The significant positive effect of artificial intelligence utilization on activity-based project costing effectiveness supports the proposition that AI provides project-oriented organizations with capabilities that extend beyond the automation of routine accounting processes. The finding suggests that organizations using AI-supported data processing, intelligent decision support, automated monitoring, and advanced analytical systems are better positioned to assign costs accurately to project activities and to generate timely information for managerial control. This result is consistent with Judijanto, who emphasized that integrating artificial intelligence into activity-based project costing can increase both the accuracy and efficiency of project cost management through enhanced information processing, improved attribution of expenditures, and more systematic interpretation of costing data [14]. It is also closely aligned with the qualitative model proposed by Asadi and colleagues, in which machine learning and artificial intelligence were identified as important enabling mechanisms for strengthening activity-based project costing and transforming traditional costing procedures into more intelligent and adaptive systems [15]. The current findings extend this conceptual argument by demonstrating quantitatively that higher AI utilization is significantly associated with greater effectiveness of activity-based project costing in an organizational sample.

The positive contribution of artificial intelligence can also be understood in relation to the growing complexity of project-management environments. Modern projects generate substantial volumes of information concerning activities, resource consumption, procurement, schedules, subcontractors, financial transactions, quality, changes, and risks. Processing these data manually is increasingly difficult, particularly when relationships among variables are nonlinear or change during project implementation. Holzmann and Lechiara showed that professionals expect artificial intelligence to contribute meaningfully to planning, forecasting, risk analysis, and managerial decision-making in construction projects, although successful implementation depends on organizational readiness and appropriate technological integration [7]. Similarly, Obiuto and colleagues argued that AI integration in construction management can improve project efficiency and cost effectiveness by enhancing planning, resource utilization, monitoring, and decision support [8]. The present findings are compatible with these observations because activity-based costing depends on the continuous transformation of operational information into financial information. AI can facilitate this transformation by processing large datasets, detecting irregularities, and providing managers with more immediate insight into the financial implications of project activities.

Machine learning capability produced the second strongest direct effect on activity-based project costing effectiveness, with a standardized coefficient of $\beta = .29$. This finding indicates that organizations capable of learning from historical project information and identifying complex patterns in cost behavior are more likely to achieve

accurate and useful activity-based costing outcomes. Machine learning is especially relevant where project costs are determined by combinations of technical, organizational, contractual, environmental, and temporal variables that cannot be adequately modeled through simple linear relationships. The result is consistent with the systematic review by Kwak and colleagues, which demonstrated the growing importance of machine-learning techniques in project cost estimation and highlighted their capacity to improve predictive accuracy by learning from historical project datasets [9]. Zhang and Li similarly reported that artificial intelligence-based cost-estimation approaches can process multidimensional construction information and improve cost predictions relative to purely conventional estimating methods [10]. The present study therefore suggests that machine learning has value not only for estimating total project cost but also for improving the broader activity-based costing system through more sophisticated interpretation of relationships between project activities and resource consumption.

The observed effect of machine learning is also supported by studies demonstrating the usefulness of advanced computational models in predicting final project cost and project duration. Bakhshi and colleagues showed that hybrid schemes combining machine-learning methods with metaheuristic optimization can improve the prediction of final project cost and time, illustrating the advantages of integrating learning algorithms with computational optimization [11]. Such capabilities are important for activity-based costing because more accurate predictions regarding resource requirements and activity durations improve the quality of cost allocation and future cost forecasts. Machine-learning models can also be continuously recalibrated as additional project data become available, allowing the costing system to adapt to changing patterns during project execution rather than relying exclusively on assumptions established at the planning stage. This dynamic property is particularly important in projects characterized by uncertainty, frequent scope adjustments, price fluctuations, or changing resource conditions.

Predictive cost forecasting had the strongest effect among all investigated predictors, indicating that the capacity to anticipate future cost behavior is particularly influential in determining the effectiveness of activity-based project costing. This result is theoretically meaningful because project costing is not limited to documenting historical expenditures. Effective project cost management requires managers to anticipate future resource consumption, detect emerging budget deviations, estimate cost-at-completion, and intervene before unfavorable cost patterns become irreversible. The significance of predictive forecasting is consistent with research demonstrating that project cost overruns can be severe and difficult to anticipate using conventional statistical assumptions. Flyvbjerg and colleagues found that information technology project cost overruns display power-law characteristics, indicating that extremely large overruns may occur more frequently than traditional forecasting frameworks would suggest [12]. Such findings strengthen the rationale for predictive systems capable of identifying unusual combinations of risk factors and updating forecasts as new data emerge. The current study shows that predictive forecasting is not simply an ancillary function of project management but may represent one of the most important pathways through which AI and machine learning enhance activity-based project costing.

The significant effect of predictive cost forecasting is further supported by research on probabilistic and intelligent cost-overrun prediction. Ashtari and colleagues demonstrated that Bayesian network classifiers can be used effectively to assess and predict cost-overrun risks in construction projects by modeling probabilistic relationships among relevant risk factors [13]. The ability to predict deviations at an early stage can enhance activity-based project costing because expected resource consumption can be recalculated at the level of individual activities before major financial consequences emerge. Furthermore, the importance of forecasting must be considered in relation to broader project uncertainty. Hajiagha and colleagues showed that project time-cost

decisions can be substantially disrupted by external shocks such as supply-chain disturbances and developed a scenario-based robust optimization model to manage such uncertainty [16]. In such environments, static cost estimates can quickly become outdated. AI-enabled predictive models can provide a more responsive basis for updating activity costs when prices, availability, lead times, or operational assumptions change.

Intelligent cost-driver identification also had a statistically significant positive effect on activity-based project costing effectiveness. This finding is particularly important because identifying valid cost drivers constitutes one of the central methodological challenges of activity-based costing. If inappropriate drivers are selected, costs may be assigned to activities in ways that do not reflect actual resource consumption, thereby reducing the accuracy and managerial usefulness of the entire costing system. The positive coefficient found in the present study suggests that artificial intelligence can help organizations identify stronger empirical relationships between project activities and the resources they consume. This interpretation is consistent with the emphasis placed by Cerezo-Narváez and colleagues on integrating cost structures with work breakdown structures in construction projects, thereby creating a closer relationship between project activities and financial information [3]. By analyzing historical transactions and operational indicators, machine-learning systems can assist managers in determining which variables most consistently explain changes in activity costs, thereby strengthening the causal foundation of cost allocation.

The contribution of intelligent cost-driver identification is also relevant to the broader problem of cost reduction and resource optimization. Farnam and colleagues emphasized that effective cost reduction in construction projects should be linked to sustainable project management and to the identification of mechanisms through which unnecessary expenditures arise [5]. Likewise, Cherouideh and Shahraki demonstrated that project selection and planning involve simultaneous consideration of time, cost, quality, and resource constraints, highlighting the multidimensional nature of cost-related decisions [6]. AI-supported identification of cost drivers can help organizations distinguish between activities that genuinely create value and those that consume resources disproportionately. As a result, intelligent activity-based costing can provide a stronger analytical basis for cost reduction than across-the-board budget cuts because it allows managers to target specific activities, processes, or resource patterns responsible for inefficient expenditure.

Automated activity classification also significantly predicted activity-based project costing effectiveness, although its standardized effect was smaller than the effects of the other predictors. This pattern suggests that automated classification is useful, but its contribution may primarily be foundational rather than strategic. Accurate activity classification is necessary before costs can be assigned to appropriate activity pools; however, classification alone does not provide the same managerial value as forecasting or intelligent interpretation of cost drivers. Nevertheless, automation can reduce the administrative burden associated with coding large numbers of project transactions and can improve consistency across projects. This is especially relevant in organizations where complex work breakdown structures and cost breakdown structures generate large quantities of financial records. The importance of connecting work activities to cost structures has been emphasized in previous project-management research [3]. Automated classification can strengthen this connection by assigning transactions to predefined or learned activity categories more rapidly and consistently than purely manual procedures.

The findings also have implications for conventional project cost-control systems. Earned value approaches, for example, remain widely used for comparing planned and actual cost and schedule performance. Alves and colleagues demonstrated the usefulness of earned value management for analyzing project cost performance and detecting differences between planned and realized project outcomes [4]. However, the quality of such control systems depends fundamentally on the accuracy of the underlying cost data. Activity-based costing supported by

AI may therefore complement established project-control methods rather than replace them. More accurate activity classification and cost-driver identification can improve the reliability of actual cost information, while machine-learning forecasting can provide an additional forward-looking dimension that conventional earned value indicators may not fully capture. In this way, AI-supported activity-based project costing can integrate retrospective performance measurement with predictive financial intelligence.

The strong explanatory power of the model can also be interpreted in light of the broader determinants of project cost performance. Gurumayum's analysis of project delays and cost overruns emphasizes that cost performance is affected by interacting factors such as planning deficiencies, resource problems, design changes, coordination failures, and managerial weaknesses [1]. Kakar and colleagues similarly demonstrated that project cost performance in conflict-sensitive construction environments depends on multiple contextual and managerial factors rather than a single variable [2]. Because such influences are multidimensional and interdependent, intelligent analytical techniques may be particularly useful for identifying combinations of conditions associated with unfavorable cost outcomes. The finding that the investigated AI-related predictors jointly explained 68% of activity-based costing effectiveness indicates that intelligent technologies may provide an important analytical infrastructure for managing this complexity, although technological factors should still be understood as part of a wider organizational and managerial system.

The study's results also reinforce the importance of organizational capabilities in realizing the benefits of intelligent project-costing technologies. Costa and colleagues showed that project management can contribute to capability transformation, suggesting that the value of new technologies depends partly on organizations' capacity to integrate them into managerial processes [17]. Similarly, Zhang and colleagues demonstrated that project performance in outsourcing environments depends on configurations of transaction-cost conditions and organizational capabilities rather than isolated determinants [18]. This perspective helps explain why merely acquiring AI software is unlikely to improve activity-based costing automatically. Organizations must also possess adequate data quality, accounting structures, project-management procedures, technical skills, and cross-functional coordination. AI and machine learning should therefore be treated as organizational capabilities that interact with managerial accounting systems rather than as stand-alone technological tools.

The findings are additionally compatible with evidence showing that project costs often emerge from interconnected causal pathways. Wang and colleagues demonstrated, through a system-dynamics approach, that cost claims in underground metro projects can arise through complex interactions among project conditions and managerial processes [19]. Activity-based project costing supported by machine learning may help reveal such interactions because the system can analyze cost behavior at a more granular level and identify combinations of activities associated with later financial consequences. The relevance of adaptive costing systems is also evident outside construction. Pedroza and Fortes found that banks and fintech organizations employ multiple project cost-estimation models according to project characteristics and organizational requirements [20]. This diversity indicates that cost estimation and allocation should be responsive to organizational context. AI and machine learning can potentially increase this adaptability by learning organization-specific relationships rather than imposing a single universal cost model.

Overall, the results provide strong empirical support for the emerging literature that conceptualizes artificial intelligence and machine learning as important components of modern project-cost management. The results are particularly aligned with Judijanto's argument that AI integration can increase the accuracy and efficiency of activity-based project costing [14] and with the qualitative framework developed by Asadi and colleagues

emphasizing intelligent technologies as mechanisms for transforming activity-level costing [15]. The present study extends previous work by quantitatively differentiating several mechanisms through which this transformation may occur. Predictive cost forecasting emerged as the strongest mechanism, followed by machine-learning capability, general AI utilization, intelligent cost-driver identification, and automated activity classification. These findings suggest that the greatest organizational value may be realized when AI is used not merely to automate existing accounting procedures but to create predictive and analytically adaptive costing systems capable of continuously learning from project data.

Several limitations should be considered when interpreting the findings. First, the study employed a cross-sectional design, and therefore the identified relationships cannot establish definitive causal effects over time despite the structural model being theoretically directional. Second, participants were drawn from project-oriented organizations located in Tehran, which may limit the generalizability of the results to organizations operating in other geographical, economic, or institutional contexts. Third, the study relied predominantly on self-reported perceptions of AI utilization, machine-learning capabilities, and activity-based project costing effectiveness, creating the possibility of common-method bias and socially desirable responses. Fourth, project-oriented organizations represented several industries, and differences in technological maturity, project complexity, data infrastructure, and accounting practices may have influenced the responses. Fifth, the study evaluated organizational capabilities rather than directly comparing the predictive accuracy of specific machine-learning algorithms. Finally, rapidly evolving artificial intelligence technologies may alter the relative importance of particular capabilities, meaning that the relationships observed in the present study may change as intelligent project-management systems become more sophisticated and widely implemented.

Future studies should employ longitudinal and experimental research designs to determine whether the implementation of artificial intelligence and machine-learning systems produces measurable improvements in project costing over time. Researchers could compare actual cost-allocation errors, forecasting accuracy, cost variance, cost overruns, and decision quality before and after the adoption of intelligent costing systems. Comparative studies across industries, regions, and countries would help determine whether organizational context moderates the effectiveness of AI-supported activity-based costing. Future research could also compare specific machine-learning algorithms, including regression-based models, decision trees, random forests, gradient boosting, neural networks, and probabilistic methods, using actual historical project datasets. Additional studies should investigate potential mediators and moderators such as data quality, organizational digital maturity, employee AI competencies, top-management support, information-system integration, project complexity, and environmental uncertainty. Qualitative studies may also examine how project managers, accountants, cost engineers, and data specialists interpret and use algorithmic recommendations in practice. Finally, future models could investigate whether AI-supported activity-based costing improves broader organizational outcomes such as profitability, resource productivity, project portfolio performance, risk management, and strategic decision-making.

Project-oriented organizations should consider integrating artificial intelligence and machine-learning capabilities directly into their project-cost management architecture rather than treating them as isolated technology initiatives. Particular priority should be given to predictive cost forecasting because it demonstrated the strongest relationship with activity-based project costing effectiveness. Organizations should develop integrated databases connecting project schedules, work breakdown structures, accounting records, procurement information, resource utilization, and historical project performance so that intelligent systems can operate on consistent and

sufficiently detailed data. Managers should also use machine-learning techniques to periodically reassess cost drivers rather than assuming that traditional allocation bases remain valid across all projects. Automated activity classification can be implemented to reduce manual coding burdens and improve the consistency of expenditure allocation. At the same time, organizations should maintain human oversight of algorithmic recommendations, particularly when major financial or contractual decisions are involved. Training should be provided to project managers, accountants, financial specialists, cost engineers, and information-system personnel so that they can interpret predictive outputs and understand the limitations of machine-learning models. Effective implementation should therefore combine technological investment, high-quality data governance, appropriate accounting structures, professional expertise, and continuous evaluation of whether intelligent costing systems are actually improving the accuracy, timeliness, transparency, and managerial usefulness of project cost information.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

Acknowledgments

Authors thank all participants who participate in this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

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