# User Acceptance and Effectiveness of AutoML Systems in Predicting Training Success: A Case Study of the DTS Program

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**Abstract -** The advancement of digital technologies has transformed workforce demands, emphasizing digital literacy, adaptability, and innovation. Indonesia's Digital Talent Scholarship (DTS) program, launched in 2018, has trained over 500,000 participants in IT skills. However, completion rates vary significantly (57%–96%), highlighting challenges in participant engagement and program effectiveness. This study integrates the DeLone and McLean Information Systems Success Model and the Technology Acceptance Model (TAM) to evaluate system effectiveness and user acceptance. Variables from the DeLone model—System Quality, Information Quality, and Service Quality—were incorporated into TAM constructs, influencing Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and User Satisfaction, which shape Attitude Toward Use (ATU) and Behavioral Intention (BI). Survey data from 342 DTS administrators were analyzed using Structural Equation Modeling (SEM). Results show PEOU significantly influenced PU (path coefficient = 0.900) and ATU (0.594), while PU and ATU collectively explained 70.3% of BI. High PEOU (0.91) and PU (0.87) scores highlight the importance of system usability and utility. However, low ATU stems from organizational misalignment, as the system's focus on participant quality contrasts with the DTS priority on participant numbers. Addressing this misalignment, enhancing system features, and improving service quality can boost adoption and foster a digitally skilled workforce aligned with Indonesia's evolving demands.
**Keywords**: AutoML, digital skills, technology adoption, TAM, system quality

## INTRODUCTION

The Fourth Industrial Revolution (Industry 4.0) has significantly reshaped workforce demands, placing a strong emphasis on digital literacy, adaptability, and the ability to innovate in response to rapidly advancing technologies (Company, 2022; O'Brien & Downie, 2024). Technologies such as artificial intelligence (AI) and machine-learning (ML) are transforming traditional systems and processes, requiring organizations and governments to invest in large-scale digital upskilling programs to close the emerging competency gaps (Watson, 2022). Indonesia's Digital Talent Scholarship (DTS) program, launched in 2018, aims to address this challenge by equipping participants with critical IT skills (Ubaldi et al., 2021). Despite the program's success in training over 500,000 individuals, its training completion rates remain inconsistent, ranging from 57% to 96%. Previous studies have attributed these variations to factors such as socioeconomic disparities, accessibility issues, and varying levels of digital literacy (Miah, 2023; World Economic Forum, 2022). While these barriers have been broadly recognized, systematic approaches to identifying participants at risk of non-completion and proposing effective interventions remain underexplored.

This study introduces Automated Machine Learning (AutoML) with Random Forest as the chosen and tested algorithm to predict participant success in the DTS program. Random Forest was selected due to its superior performance, achieving the highest test scores, highest accuracy, and the lowest prediction time among the evaluated models. AutoML streamlines the machine-learning process by automating model selection, optimization, and evaluation, allowing administrators to make accurate, data-driven decisions efficiently and without requiring extensive technical expertise (Almaiah et al., 2020; Hutter et al., 2022). By analyzing participant data such as demographics, education, and professional attributes (employment status and job role), AutoML identifies individuals with a higher likelihood of completing the program. These predictions allow administrators to allocate resources more efficiently and provide timely interventions, ultimately improving program outcomes.

However, accurate predictions alone do not ensure practical implementation. For AutoML to be adopted successfully, administrators must perceive its

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value and usability, as stakeholder acceptance plays a critical role in integrating technology into organizational workflows. Resistance to adopting new tools often arises from concerns about usability, reliability, and alignment with existing processes (Rahman et al., 2024; Susan Maestro & Puja Rana, 2024). To evaluate user acceptance, this study employs the Technology Acceptance Model (TAM) (Al-Fraihat et al., 2020), which identifies Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) as primary drivers of technology adoption. These constructs influence users' Attitude Toward Use (ATU), which directly affects their Behavioral Intention (BI) to adopt a system (Jiao & Cao, 2024; Rahimi et al., 2018; Zhang et al., 2022).

To provide a more comprehensive evaluation of AutoML's adoption, this study also integrates the DeLone and McLean Information Systems (IS) Success Model (Al-Fraihat et al., 2020; DeLone & McLean, 1992, 2003). This model expands the assessment of system adoption by incorporating six interrelated dimensions: System Quality, Information Quality, Service Quality, Use, User Satisfaction, and Net Benefits. System Quality measures the performance, reliability, and ease of use of the AutoML system, aligning closely with TAM's PEOU. Information Quality refers to the accuracy and relevance of the AutoML predictions, which influence PU and trust in the system. Service Quality reflects the technical support provided, which can influence user satisfaction and acceptance. Together, these dimensions impact user satisfaction, system usage, and the overall net benefits, such as improved decision-making, resource optimization, and program success.

This study focuses on understanding the relationships between TAM and DeLone and McLean's IS Success constructs to explain how PEOU, PU, and system quality influence ATU and BI. Specifically, the research addresses three questions: (1) How does the perceived ease of use (PEOU) of the AutoML system influence perceived usefulness (PU) and attitude toward using (ATU) the system? (2) How does the perceived usefulness (PU) of the AutoML system influence administrators' attitudes toward its use (ATU) and their intention (BI) to use it? (3) How does administrators' attitude toward using (ATU) the AutoML system affect their behavioral intention (BI) to adopt it? (4) What are the key factors driving adminsitrators' behavioral intention (BI) to use the AutoML system for participant selection?

The findings of this study are expected to bridge the gap between technical performance and user acceptance, providing actionable insights into the adoption of predictive technologies in educational programs. By integrating TAM and the DeLone and McLean IS Success Model, this research evaluates both the technical and user-centered dimensions of AutoML adoption. This dual perspective ensures that the system is not only accurate and effective but also user-friendly, reliable, and aligned with stakeholder needs. The results aim to help program administrators optimize AutoML systems, improve user satisfaction, and maximize the net benefits of data-driven decision-making. Ultimately, the study contributes to the DTS program's broader goals of enhancing digital literacy and supporting Indonesia's efforts to build a competitive, technologically skilled workforce.

## RESEARCH METHOD

### Study Design

The study utilizes the **Technology Acceptance Model (TAM)** framework to analyze the factors influencing the adoption of AutoML systems for predicting participant training success, implemented on the Digital Talent Participant Selection Page. TAM constructs, including **Perceived Ease of Use (PEOU)**, **Perceived Usefulness (PU)**, **Attitude Toward Use (ATU)**, and **Behavioral Intention (BI)**, are tested for their interrelationships through a Structural Equation

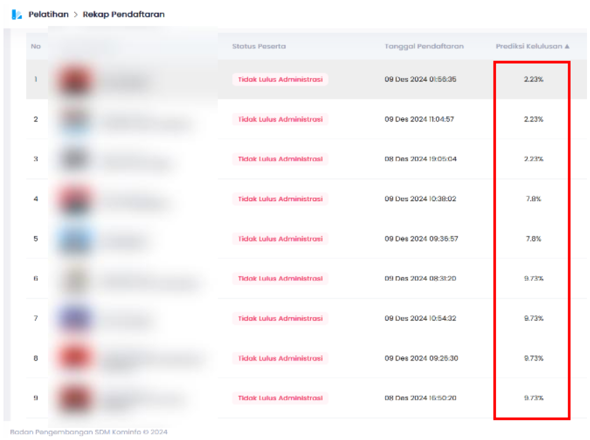


**Figure 1** AutoML Prediction Outcomes for Participant Selection on the DTS Platform

Model (SEM). The AutoML-based workflow used in this study involves data collection, preprocessing, model training, and prediction, as summarized in **Figure 2**, and basis to choose random forest as predictive algorithm is based on result of final dataset training test using Autogluon shown in F**igure 3**.

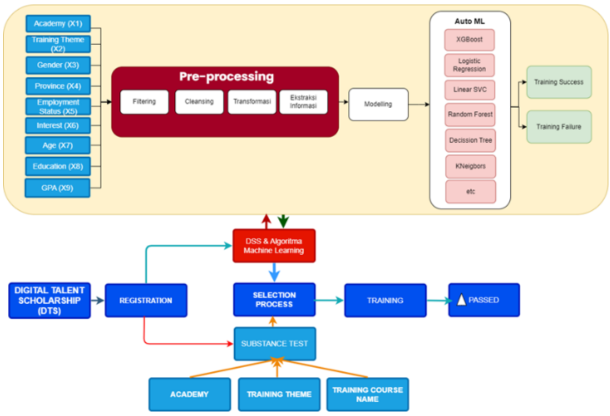


**Figure 2** AutoML Based Worklflow

| No | Model Name | Test Score | Validation Score | Evaluation Metric | Prediction Time (test) | Prediction Time (validation) | Training Time | Marginal Prediction Time (test) | Marginal Prediction Time (validation) | Marginal Training Time | Stacking Level | Inference Capability | Training Order |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | RandomForestEntr_BAG_L1_F | 0.93 | NaN | accuracy | 0.16 | 0.59 | 1.30 | 0.16 | 0.59 | 1.30 | 1 | TRUE | 14 |
| 2 | RandomForestEntr_BAG_L1 | 0.93 | 0.85 | accuracy | 0.16 | 0.59 | 1.30 | 0.16 | 0.59 | 1.30 | 1 | TRUE | 6 |
| 3 | RandomForestGini_BAG_L1 | 0.93 | 0.84 | accuracy | 0.16 | 0.63 | 1.20 | 0.16 | 0.63 | 1.20 | 1 | TRUE | 5 |
| 4 | RandomForestGini_BAG_L1_F | 0.93 | NaN | accuracy | 0.18 | 0.63 | 1.20 | 0.18 | 0.63 | 1.20 | 1 | TRUE | 13 |
| 5 | WeightedEnsemble_L3_FULL | 0.93 | NaN | accuracy | 1.20 | NaN | 20.13 | 0.00 | NaN | 0.34 | 3 | TRUE | 16 |
| 6 | WeightedEnsemble_L2_FULL | 0.93 | NaN | accuracy | 1.20 | NaN | 20.08 | 0.00 | NaN | 0.28 | 2 | TRUE | 15 |
| 7 | LightGBM_BAG_L1_FULL | 0.93 | NaN | accuracy | 0.20 | NaN | 1.69 | 0.20 | NaN | 1.69 | 1 | TRUE | 12 |
| 8 | LightGBMXT_BAG_L1_FULL | 0.87 | NaN | accuracy | 0.81 | NaN | 17.29 | 0.81 | NaN | 17.29 | 1 | TRUE | 11 |
| 9 | KNeighborsDist_BAG_L1 | 0.74 | 0.68 | accuracy | 0.06 | 0.05 | 0.00 | 0.06 | 0.05 | 0.00 | 1 | TRUE | 2 |
| 10 | KNeighborsDist_BAG_L1_FULL | 0.74 | NaN | accuracy | 0.06 | 0.05 | 0.00 | 0.06 | 0.05 | 0.00 | 1 | TRUE | 10 |
| 11 | KNeighborsUnif_BAG_L1_FUL | 0.71 | NaN | accuracy | 0.06 | 0.05 | 0.01 | 0.06 | 0.05 | 0.01 | 1 | TRUE | 9 |
| 12 | KNeighborsUnif_BAG_L1 | 0.71 | 0.66 | accuracy | 0.07 | 0.05 | 0.01 | 0.07 | 0.05 | 0.01 | 1 | TRUE | 1 |
| 13 | WeightedEnsemble_L2 | NaN | 0.85 | accuracy | NaN | 2.59 | 85.18 | NaN | 0.00 | 0.28 | 2 | FALSE | 7 |
| 14 | WeightedEnsemble_L3 | NaN | 0.85 | accuracy | NaN | 2.60 | 85.24 | NaN | 0.00 | 0.34 | 3 | FALSE | 8 |
| 15 | LightGBM_BAG_L1 | NaN | 0.83 | accuracy | NaN | 0.63 | 75.22 | NaN | 0.63 | 75.22 | 1 | FALSE | 4 |
| 16 | LightGBMXT_BAG_L1 | NaN | 0.77 | accuracy | NaN | 1.32 | 82.39 | NaN | 1.32 | 82.39 | 1 | FALSE | 3 |

**Figure 3** Autogluon Dataset Training Test Output

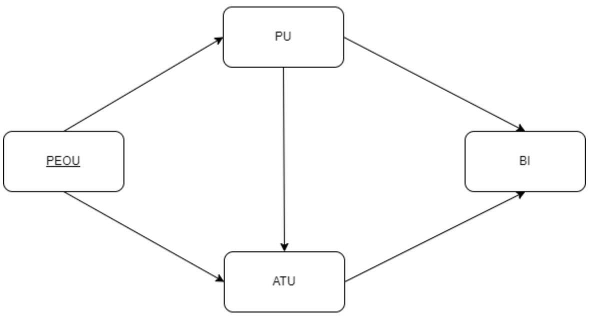


**Figure 4** Conceptual Framework

This systematic approach ensures efficient identification of participants likely to succeed in training. The conceptual framework of this analysis, as illustrated in Figure 3, simplifies the hypothesized relationships between the key constructs:

1. Perceived Ease of Use (PEOU) influences Perceived Usefulness (PU) and Attitude Toward Use (ATU).
2. Perceived Usefulness (PU) directly influences both Attitude Toward Use (ATU) and Behavioral Intention (BI).Attitude Toward Use (ATU) acts as a mediating variable, influencing Behavioral Intention (BI).

This structural model allows for evaluating the pathways through which ease of use and perceived utility impact users' attitudes and their intention to adopt the AutoML system.

The decision to focus on only four variables for this initial study was guided by their suitability to the research context, relevance to the objectives, and practical constraints of the study. As a preliminary or "mini-research," this study is designed to establish a foundation for subsequent, more extensive research. The rationale behind this approach reflects both theoretical considerations and practical limitations.

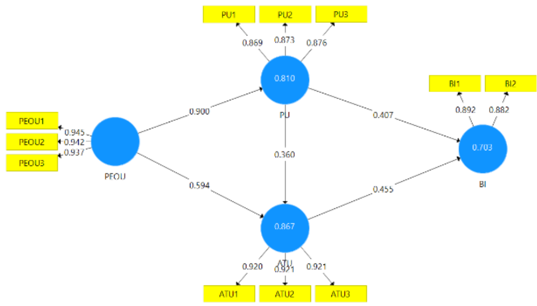


**Figure 5** SEM PLS Analysis Diagram

The TAM was selected as the conceptual framework for this research due to its well-established structure and applicability. TAM identifies two core variables, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), as the primary predictors of technology acceptance. Davis, (1989) explained that these two variables significantly influence behavioral intentions, making them critical components of the model. Over time, extensions to TAM have incorporated additional variables, such as Attitude Toward Using ATU and BI, to expand its explanatory power. These four variables—PU, PEOU, ATU, and BI—were deemed the most relevant for this research, as they provide a robust yet focused framework for analyzing technology acceptance.

Using a limited number of variables offers significant advantages in a study of this nature. A streamlined approach allows for a more focused analysis and minimizes the risk of overfitting, a common issue in statistical modeling. Venkatesh & Davis (2000) emphasized that modifications to TAM should only be made when the research context necessitates it, highlighting the importance of simplicity and relevance. Therefore, this study deliberately limits its scope to four variables to ensure clarity and alignment with its initial objectives.

Moreover, the choice of variables was tailored to the research's specific goals, as aligning the framework with the study's focus is essential for generating accurate and valid results. Taylor & Todd (1995) stressed that the selection of variables in TAM should reflect the unique aspects of the research to maintain its precision and practical applicability. This reinforces the decision to use only the most critical variables at this stage.

Practical constraints such as time, budget, and resource availability further influenced this decision. Simpler models are not only easier to manage but also yield more reliable results, particularly in applied research settings. Straub et al. (1995) highlighted that straightforward models are better suited for contexts where resources are limited, as they ensure feasibility without compromising the study's rigor.

In summary, the selection of four variables—PU, PEOU, ATU, and BI—was a deliberate and strategic decision. This approach balances theoretical relevance with practical considerations, allowing the research to achieve its objectives within the limitations of its scope. By laying a solid foundation, this study paves the way for future research that can expand on these findings by incorporating additional variables and exploring broader dimensions of technology acceptance.

### Research Sample

The data for this study were gathered through a survey distributed via Google Forms to administrators involved in the participant selection process across all work units within the Digital Talent Scholarship (DTS) program. The survey was conducted between October 21, 2024, and November 9, 2024, collecting a total of 342 responses from 611 registered administrators. Of these, 342 responses were verified as valid and subsequently included in the statistical analysis. The survey utilized a 7-point Likert scale, with responses ranging from 1 (Strongly Disagree) to 7 (Strongly Agree), to measure each construct of the Technology Acceptance Model (TAM).

### Data Analysis

The relationships among the TAM constructs were analyzed using **SmartPLS 3** software. The analysis was conducted in two stages:

1. **Measurement Model Assessment**: Evaluated indicator reliability (outer loadings), construct reliability (Cronbach's Alpha), and validity (convergent and discriminant).
2. **Structural Model Assessment**: Examined path coefficients and the $R^2$ values to test the strength of the relationships and the explanatory power of the model.
3. **Path Analysis and Hypothesis testing**: Path coefficients represent the strength and direction of the relationships between independent and dependent variables (e.g., PEOU → PU or PU → BI). These coefficients are tested for statistical significance using t-statistics and p-values derived from bootstrapping techniques. A significant path coefficient ($p < 0.05$) indicates that the hypothesized relationship is supported.

As depicted in **Figure 2**, the pathways among PEOU, PU, ATU, and BI provide a clear overview of the simplified analysis process. The model identifies how user perceptions of ease of use and usefulness influence their attitudes and, ultimately, their intention to adopt the system.

## RESULTS AND DISCUSSION

### Results

The SEM analysis, as depicted in Figure 3, grounded in the TAM framework, examined the factors influencing administrators' intention to adopt the AutoML system for predicting training success. The measurement model demonstrated robust reliability and validity, with all indicator loadings exceeding 0.8 (Table 1).

PEOU showed the highest outer loadings, all exceeding 0.9, highlighting that administrators found the AutoML system straightforward to operate and effective for analyzing participant data. Similarly, PU demonstrated strong indicator loadings, ranging from 0.869 to 0.876, reflecting the system's perceived effectiveness in improving decision-making and training outcomes. BI exhibited reliable indicator loadings of 0.882 and 0.892, signifying a strong commitment among administrators to adopt the AutoML system.

The structural model highlighted significant relationships among the TAM constructs (Table 2). PEOU had a substantial influence on PU, with a path coefficient of 0.900 (t-statistic = 76.333, $p < 0.05$). This indicates that ease of operation and system clarity significantly enhance perceptions of usefulness. PU also significantly impacted BI, with a path coefficient of 0.407 (t-statistic = 6.218, $p < 0.05$), confirming that administrators' perceptions of the system's utility directly influenced their intention to adopt it.

The explanatory power of the model is reflected in its $R^2$ values (Table 3). PEOU explained 81% of the variance in PU, while PU explained 70.3% of the variance in BI when combined with other influencing factors. These results underscore the central role of PEOU and PU in shaping administrators' adoption intentions.

**Table 1** Outer Loading Result

| Latent Variable | Indicators | Outer Loadings | Interpretation |
|---|---|---|---|
| **Perceived Ease of Use (PEOU)** | PEOU1, PEOU2, PEOU3 | 0.945, 0.942, 0.937 | Indicators for PEOU demonstrate very high loadings (> 0.9), signifying that administrators perceive the AutoML system as intuitive and easy to use. |
| **Perceived Usefulness (PU)** | PU1, PU2, PU3 | 0.869, 0.873, 0.876 | High reliability of indicators reflects administrators' perceptions of AutoML's utility in improving training outcomes, decision-making, and productivity. |
| **Attitude Toward Use (ATU)** | ATU1, ATU2, ATU3 | 0.920, 0.921, 0.921 | Strong loadings suggest administrators have a very positive attitude toward using AutoML, showing overall favorability and enthusiasm for adoption. |
| **Behavioral Intention (BI)** | BI1, BI2 | 0.892, 0.882 | Indicators reliably measure administrators' intention to continue using AutoML, with strong loadings indicating clear commitment to adopting the technology. |

To summarize the findings, all hypothesized relationships in the model were statistically significant at $p < 0.05$, as presented in Table 4. The strongest relationship, between PEOU and PU (path coefficient = 0.900), emphasizes the importance of system efficiency and clarity in driving perceptions of usefulness. PU also demonstrated a significant impact on BI (path coefficient = 0.407), highlighting the importance of demonstrating the system's value in encouraging adoption.

**Table 2** Path Coefficient Report

| Relationship | Path Coefficient | Interpretation |
|---|---|---|
| **PEOU → PU** | 0.900 | A very strong and significant relationship; ease of use directly enhances perceptions of usefulness. |
| **PEOU → ATU** | 0.594 | A moderate to strong effect; user-friendly design fosters favorable attitudes toward using AutoML. |
| **PU → ATU** | 0.360 | A moderate positive effect; usefulness contributes to positive attitudes, though less so than ease of use. |
| **PU → BI** | 0.407 | Administrator who find AutoML useful are moderately likely to use it for predicting training success. |
| **ATU → BI** | 0.455 | The strongest predictor of behavioral intention; positive attitudes lead to higher likelihood of usage. |

**Table 3** Model Explanation Value

| Dependent Variable | $R^2$ Value | Interpretation |
|---|---|---|
| **PU** | 0.810 | PEOU explains 81% of the variance in PU, highlighting ease of use as the primary driver of perceived usefulness. |
| **ATU** | 0.867 | PEOU and PU explain 86.7% of the variance in ATU; attitudes are strongly shaped by ease of use and usefulness. |
| **BI** | 0.703 | PU and ATU explain 70.3% of the variance in BI, though other factors could further improve prediction. |

**Table 4** Result of Path Analysis and Hypothesis Testing

| | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistics (\|O/STDEV\|) | P Values | Support |
|---|---|---|---|---|---|---|
| ATU -> BI | 0.455 | 0.453 | 0.065 | 7.024 | 0.000 | Accepted |
| PEOU -> ATU | 0.594 | 0.592 | 0.045 | 13.194 | 0.000 | Accepted |
| PEOU -> PU | 0.900 | 0.900 | 0.012 | 76.333 | 0.000 | Accepted |
| PU -> ATU | 0.360 | 0.362 | 0.046 | 7.829 | 0.000 | Accepted |
| PU -> BI | 0.407 | 0.408 | 0.065 | 6.218 | 0.000 | Accepted |

The results highlight that improving both the PEOU and PU of the AutoML system is critical for increasing administrators' acceptance and adoption. By focusing on the system's ability to enhance decision-making and productivity, organizations can significantly improve administrators' intention to adopt the system. These insights provide a strong foundation for understanding the key factors driving the successful integration of AutoML in training processes.

## Discussion

This study provides valuable insights into the factors influencing administrators' intention to adopt the AutoML system for predicting training success, guided by the TAM. The analysis highlights the critical roles of PEOU, PU, ATU, and BI in shaping administrators' acceptance of the system.

The findings demonstrate that PEOU plays a foundational role in the adoption process, significantly influencing PU, with a substantial path coefficient of 0.900. This aligns with prior research that suggests systems perceived as easy to navigate enhance users' perceptions of usefulness, as reported in studies on e-payment adoption (Noer et al., 2023). In the context of AutoML, administrators who found the system efficient and clear were more likely to recognize its utility in improving participant outcomes. This reinforces the broader literature on predictive analytics, which emphasizes that usability fosters trust and confidence in system outputs (Noer et al., 2023)

PU emerged as a key driver of BI, with a significant path coefficient of 0.407. This finding is consistent with studies in financial technology adoption, where perceived usefulness was identified as a strong predictor of users' intentions to embrace new tools (Chawla et al., 2023). In this study, the AutoML system's ability to enhance decision-making by predicting participants more likely to complete training resonated with administrators. This underscores that practical advantages, such as optimizing participant selection, are central to driving adoption. Moreover, research in technology acceptance highlights how systems perceived as useful are more likely to be integrated into workflows, particularly when their benefits align with organizational goals (Chawla et al., 2023).

ATU was identified as the strongest predictor of BI, with a path coefficient of 0.455. Administrators with favorable attitudes toward the system were significantly more likely to adopt it. Similar findings have been reported in studies on mobile wallet adoption, where positive user attitudes strongly influenced their intention to use the technology (Oraini et al., 2024). However, in the case of AutoML, organizational priorities that emphasize participant numbers over quality pose a barrier to fostering positive attitudes. This misalignment between the system's design and institutional goals may limit enthusiasm for its adoption, even when its utility is recognized. Previous studies on organizational alignment suggest that integrating system capabilities with institutional priorities significantly enhances acceptance (Alsyouf et al., 2023).

A notable limitation in fostering adoption is the lack of alignment between the system's objectives and the organization's focus on participant quantity. Addressing this challenge requires reframing institutional goals to balance quality and quantity, ensuring the system's potential is fully realized. Studies have shown that aligning system capabilities with organizational strategies fosters user acceptance and strengthens adoption intentions (Alsyouf et al., 2023).

Although this study does not directly address trust, it remains an important consideration in technology adoption. Research has shown that perceived trust significantly influences users' intentions to adopt new systems, including AI-powered applications (Murrar et al., 2025). In the case of AutoML, building trust through transparent processes and reliable predictions could enhance administrators' confidence and willingness to use the system. Future studies could explore how trust mediates the relationship between TAM constructs and BI in the context of predictive systems.

This study contributes to the growing body of research on technology acceptance by highlighting the interplay between PEOU, PU, ATU, and BI in the adoption of AutoML. While PEOU indirectly influences BI through PU, the central role of PU and ATU in shaping intention emphasizes the need to align system design with organizational priorities. Future research could explore additional factors, such as trust, organizational support, or cultural influences, to build on these findings and provide a more comprehensive understanding of technology adoption.

In conclusion, the results underscore the importance of usability, utility, and organizational alignment in driving the successful adoption of AutoML. By addressing both technical and institutional factors, organizations can foster positive attitudes and stronger intentions to integrate predictive tools into their decision-making processes, thereby enhancing both operational outcomes and long-term success.

## Conclusion

This study examined the factors influencing administrators' intention to adopt the AutoML system for predicting training success, using the TAM framework to explore the relationships between PEOU, PU, ATU, and BI. The findings provide critical insights into the adoption process, emphasizing the foundational role of PEOU in shaping PU, the central importance of PU in driving BI, and the influence of ATU in fostering positive intentions toward system adoption.

The results demonstrate that PEOU is a crucial determinant of PU, highlighting that when administrators find the system efficient and straightforward to operate, they are more likely to perceive it as beneficial. PU, in turn, was identified as a significant predictor of BI, reinforcing the importance of showcasing the system's practical advantages, such as its ability to improve decision-making and prioritize participants with a higher likelihood of completing training. While ATU emerged as the strongest direct predictor of BI, the findings also reveal a potential organizational challenge: the focus on maximizing participant numbers over optimizing participant quality may temper administrators' overall enthusiasm for adopting the system. Addressing this misalignment is critical for ensuring the successful integration of AutoML in training processes.

These findings are significant in the context of the research questions, as they reveal the nuanced relationships between usability, perceived utility, and adoption intentions. By confirming the roles of PEOU and PU as enablers of BI and identifying ATU as a key driver, this study contributes to a deeper understanding of technology acceptance in administrative decision-making contexts. Moreover, the results emphasize the need for alignment between a system's capabilities and organizational priorities to maximize its potential impact.

Practically, these insights have implications for organizations seeking to implement predictive tools like AutoML. Policymakers and decision-makers should prioritize designing systems that simplify operational processes (enhancing PEOU), demonstrate clear utility (strengthening PU), and foster positive attitudes toward their use (improving ATU). Additionally, organizational policies must be adapted to align with the system's objectives. Shifting from a focus on participant quantity to a balance between quantity and quality will not only maximize the system's value but also enhance its acceptance among administrators.

This study also provides a foundation for future research. While the TAM framework offered valuable insights into the factors driving adoption, further studies could explore additional variables that influence BI, such as organizational culture, external support, or the perceived risk of adopting algorithmic tools. Investigating these factors would provide a more comprehensive understanding of the barriers and facilitators to technology acceptance in similar contexts.

However, this study is not without limitations. The sample, while robust, was constrained to administrators within a specific training program, which may limit the generalizability of the findings to other contexts. Additionally, the study relied on self-reported data, which may introduce response biases. Furthermore, the cross-sectional nature of the research limits its ability to capture longitudinal changes in administrators' attitudes and intentions over time. Future research could address these limitations by employing a longitudinal design or exploring diverse organizational settings.

Finally, it is important to acknowledge potential assumptions and biases inherent in the methodology. The study assumes that administrators interact with the AutoML system consistently and that their responses accurately reflect their perceptions and intentions. Confounding factors, such as variations in administrators' technical expertise or differences in organizational priorities, may have influenced the results. These considerations should be taken into account when interpreting the findings.

In conclusion, this study highlights the importance of aligning technological design with organizational goals to drive adoption. By addressing usability, demonstrating value, and fostering positive attitudes, organizations can effectively integrate predictive tools like AutoML into their workflows. The findings contribute to the growing body of knowledge on technology acceptance and offer practical guidance for improving the implementation of advanced decision-making systems in training contexts.

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