

Adoption of AIOps Technology in IT Service Operations in Corporate Enterprises Using the Technology-Organization-Environment (TOE) Model

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Abstract: Along with the rapid technological developments in the current digital era, more companies are integrating artificial intelligence (AI) technology into IT operations services. This technological development also leads to increasingly sophisticated technology being used and an increasing amount of data received, the complexity and risk that can impact IT services in companies. Artificial intelligence technology for IT operations services (AIOps) addresses this challenge by integrating AI features comprehensively into all solutions available in IT operations services. AIOps changes the approach to handling incidents from a reactive to a proactive one by identifying potential problems before they occur. The purpose of this study is to define the factors influencing the adoption of AIOps technology in IT services in companies and analyze its impact on productivity and service stability. The Technology-Organization-Environment (TOE) method is used in this study because it has been widely applied in various adoption studies of various IT innovations ranging from e-commerce, ERP, Cloud Computing to the most recent adoption of AIOps technology. The TOE research method can accommodate various indicators of technology adoption that are tested by considering internal (organizational), technological and external (external environment) aspects to provide a comprehensive picture of the readiness and level of technology adoption within the company.

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INTRODUCTION

Currently, there have been many developments and applications of artificial intelligence-based applications (*Artificial Intelligence/AI*) which encourages companies to adopt the technology in supporting business operational activities. The era of digital transformation has driven the complexity of Information Technology systems (*Information Technology/IT*) to an unprecedented level. *Artificial Intelligence for IT Operations (AIOps)* emerged as a solution to help IT operations teams manage the flood of data and infrastructure complexity more effectively. A study conducted by Seagate projected Global data volume reach 175 zettabytes by 2025 (Reinsel et al., 2018). Without intelligent analytics tools, these data spikes can lead to Possible missed alerts and costly downtime for companies. *AIOps* Combine *Machine Learning* and big data analytics in IT service operations, with the ability to monitor performance, detect anomalies, correlate events, and automate responses incidents in real-time. *AIOps* in other words, it is an AI approach that helps IT systems proactively detect and resolve issues before impacting users, thereby improving operational efficiency and service reliability (Gartner, 2017; InsideHPC, 2022).

Adoption *AIOps* in the industry today is still in its infancy although the prospect of benefits is very promising for the productivity and stability of IT services as it provides actual information on incident data and allows for faster decision-making at critical times (Cheng et al., 2023). Gartner first

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introduced the concept of "AIOps" in 2016; two years later, less than 5% of large companies using AIOps for monitoring their infrastructure. A Loom Systems survey in 2019 confirmed that only about 5% of organizations have implemented AIOps in full. However, trends are changing fast: Gartner estimates 30% of large enterprises will adopt AIOps in 2023. The AIOps market value is also growing rapidly – it is projected to reach \$2.1 billion by 2025 at a CAGR of ~19% (Gartner, 2017). The drivers include the post-pandemic multi-cloud complexity and the demands of digital transformation that drive continuous automation. The biggest challenge in the adoption of this technology is the doubt about added value AIOps where there are concerns about data limitations or difficulty integrating it with legacy processes (Alsheibani et al., 2018).

A multinational study conducted by Riverbed in 2025 also called AIOps the "inevitable future" for reliable IT operations. Concrete examples include HCL Technologies collaborating with Moogsoft to implement AIOps solutions on incident management. The results are quite impressive where the Mean Time to Restore (MTTR) incident decreased by around 33%, and the number of helpdesk tickets decreased by 62%. As a result, IT operations teams are more productive and services are more stable. Even Infosys' "Live Enterprise Automation Platform (LEAP)" platform adopted by multinational companies has succeeded in creating predictive, *always-on*, and *auto-healing IT operations services*. The implementation of LEAP with an "AI First" approach shows that the integration of AIOps with *Site Reliability Engineering* (SRE) practices is able to deliver IT operations without manual touches and is highly resilient to disruptions.

Although the concept is revolutionary, the widespread adoption of AIOps is still in its developing stage. Based on a Gartner and Loom Systems survey, in 2018–2019 only about 5% of organizations have actually implemented AIOps solutions. Many companies at that time were still in the experimental or pilot stages. However, over the past few years, awareness of the benefits of AIOps has increased. Gartner predicts a surge in adoption of up to 30% of large enterprises using AIOps by 2023, as the need to manage increasingly complex modern IT environments such as hybrid cloud, microservices and other IT technologies. The Global Market Insights report estimates that the AIOps market could surpass \$10 billion by 2027. The driver of this increase was partly due to the COVID-19 pandemic forcing the acceleration of migration to the cloud, which then put a new focus on AIOps to address blind spots in cloud operations.

Many studies that highlight the technical limitations of AIOps implementation or focus more on how to implement AIOps systems effectively with more emphasis on theoretical foundations and conceptual applications. The limited studies that present a decision-making framework for the adoption of AIOps at the organizational level lead to a lack of hypothesis testing and empirical verification that are able to consider important aspects from the technological, organizational and environmental sides. Alsheibani et al. (2018) said that many organizations are not ready to implement AI because they are influenced by culture, skills, and data infrastructure. Doubts about the reliability of AI (e.g. fear of false alarms or over-alerting) as well as poor data quality are also challenges (Rijal et al., 2022).

Previous studies predominantly focus on the technical implementation of AIOps, system architecture, operational benefits, and performance optimization. However, empirical studies examining organizational adoption decisions using a comprehensive framework that simultaneously considers technological, organizational, and environmental factors remain limited. As a result, the determinants influencing AIOps adoption at the organizational level are still not fully understood, particularly in the context of corporate IT service operations.

Based on the gaps that arise, further research is needed to answer the question of what important factors need to be considered for the successful adoption of AIOps technology and what are the most influential factors in making the decision to adopt it. The purpose of this study is to show how companies can benefit from the use of AIOps by considering a holistic view regarding the benefits and limitations of technology to improve the productivity and stability of IT services. In this study, the relationship between factors influencing the adoption of AI in network operations is empirically explored to assist the organization's strategic approach in an effective AIOps technology adoption plan. Thus, the research is expected to provide scientific contributions and practical recommendations for IT management in corporations in the implementation of AIOps technology.

The novelty of this study lies in the integration of the Technology–Organization–Environment (TOE) framework with empirical PLS-SEM analysis to identify the key determinants of AIOps adoption in corporate IT service operations. Unlike previous studies that primarily discuss AIOps from a technical or conceptual perspective, this study provides empirical evidence regarding the relative influence of technological, organizational, and environmental factors on organizational adoption decisions.

To answer the research question, a case study on several corporate companies was conducted using the *Technology-Organization-Environment (TOE) theoretical framework* to identify the factors influencing the adoption of AIOps in companies. The TOE framework was selected because AIOps adoption represents an organizational-level innovation involving technological readiness, organizational capabilities, and external environmental influences. In contrast, TAM and UTAUT primarily focus on individual user acceptance and behavioral intentions, while DOI emphasizes the diffusion characteristics of innovation. Since AIOps implementation requires organizational resources, managerial support, technical capabilities, and ecosystem readiness, the TOE framework provides a more comprehensive perspective for explaining organizational adoption decisions.

RESEARCH METHOD

Types and approaches of Research

This study uses a quantitative approach with the type of explanatory research and Structural Equation Modeling-Partial Least Squares (SEM-PLS) analysis. This approach was chosen because the indicators in the dependent variables (TOE factor) have indirect relationships, so a method is needed that can analyze data with multiple constructs (abstract variables) and simultaneous relationships between variables, measurement of validity and realism as well as testing of causal relationships with independent variables (Adoption of AI Ops technology). With this approach, the researcher seeks to provide an empirical understanding of how strongly technological, organizational (internal) and environmental (external) factors influence the adoption of AIOps technology on IT services in corporate companies.

Population and Sample

The population in this study includes all IT practitioners who use AI technology who work in corporate companies in the Jakarta, Surabaya and other cities on the island of Java. Because the respondent population cannot be known definitively, the determination of the sample size refers to the Structural Equation Modeling (SEM) analysis guideline, which is 5–10 times the number of research indicators (Hair et al., 2022). With a total of about 30 indicators used, the ideal sampling ranges from 150 to 300 respondents to meet the bootstrapping criteria. To ensure the strength of

the statistical value of the research results, the results of data collection that have been carried out are 168 respondents.

Sampling Techniques

The sampling technique in this study uses a purposive sampling method that targets respondents based on certain criteria that are in accordance with the purpose of the study. The targeted respondent criteria are as follows:

1. Working in the IT field or as an IT practitioner in a corporate company, whether permanent employee, contractor or other status.
2. Know or be involved in support activities or projects related to monitoring, observability, automation or AI systems.
3. Have a minimum position as an IT analyst/expert, engineer or manager.

The above criteria were chosen because AIOps is a special technology where not everyone can answer validly, so respondents who have knowledge according to the context and can contribute effectively to the research are needed.

Data Types and Sources

This study uses primary data obtained through the distribution of online questionnaires (e.g. *Google Form*, *Microsoft Form*, *Qualtrics*) to IT practitioners working in corporate companies to achieve the required target number of respondents.

Research Instruments

The research instrument used in this study was a closed questionnaire with measurements using a five-point Likert scale, which ranged from 1 = strongly disagree to 5 = strongly agree. The Likert scale was chosen because it is considered effective in measuring respondents' attitudes, perceptions, and evaluations of research objects quantitatively (Likert, 1932; Sekaran & Bougie, 2016).

The questionnaire is organized into two main parts. The first section contains questions related to the demographic characteristics of respondents, including gender, age, length of employment, employee status, job title, frequency of use of AI and current city of residence. This information is important to provide an overview of the respondent profile and support descriptive analysis in the research (Sekaran & Bougie, 2016).

The second section contains statements designed to measure research variables. Measuring the magnitude of the influence of technology, internal and external factors of the company referring to the TOE/Technology-Organization, Environment model on the variable adoption of AIOps technology in IT services in corporate companies (Tornatzky & Fleischer, 1990).

Validity and Reliability Tests

Before data analysis is carried out, the research instrument is first tested to ensure the quality of the measurement. The validity test was carried out using the Corrected Item-Total Correlation with a minimum limit of ≥ 0.30 , while the reliability test used the Alpha Cronbach coefficient with the reliability criterion if the value $\alpha \geq 0.70$ (Hair et al., 2022; Nunnally, 1978). This stage is important to ensure that each indicator is able to measure constructs consistently and accurately.

Data Analysis Techniques

Data analysis was carried out using SmartPLS software version 4.1.1.8 with the Partial Least Squares – Structural Equation Modeling (PLS-SEM) approach. This method was chosen because it

is able to analyze the relationships between latent variables with many indicators and is suitable for a moderate number of samples. The analysis stages include Descriptive Analysis – to describe the respondent profile and the distribution of answers, External Model Test (Measurement Model) – to evaluate convergent validity, discriminant validity, and reconstruction.

RESULTS AND DISCUSSION

The questionnaire sent online received 168 respondent responses, of which 72.02% were men and the remaining 27.98% were women. In terms of age, the smallest population was 1.19% for respondents aged above 55 years while the largest population was respondents aged less than 25 years old at 33.93%. The largest population of working years in this company is respondents who have worked for more than 10 years at 37.5% while the smallest is those who have worked for 2-5 years, which is 16.07%. In terms of employee status, the largest population is respondents who are permanent employees at 45.24% while the smallest population is respondents with other statuses at 12.5%. Based on Position, the largest population is IT Engineer at 31.55% while the smallest is IT Analyst/Expert at 19.05%. Respondents who answered this questionnaire as many as 51.79% often use AI in their daily work (10-30 times every week) while the smallest population is those who rarely use it (<5x every week) which is 7.74%. For additional information, 82.14% of respondents are domiciled in Surabaya, 8.33% are domiciled in Jakarta and 9.52% are domiciled in other cities on the island of Java.

The analysis was carried out to produce a percentage calculation of the indicator variables *Relative Advantage* (RA), *Compatibility* (CT), *Complexity* (CX), *Management Support* (MS), *Organizational Readiness* (OR), *Team Capability* (TC), *Competitive Pressure* (CP), *Customer Expectation* (CE) and *Vendor Support* (USA). To analyze the data from each construct variable, the data description results are displayed in the form of interval values with the following categories: Maximum Index value = 5, Minimum Index value = 1, Interval = $(5-1)/5 = 0.80$ so that the interval value used for the Strongly Disagree category is 1.00-1.80, the Disagree category is 1.81-2.60, the Neutral category is between 2.61 – 3.40, the Agree category is 3.41 – 4.20 and the interval value is 4.21 – 5.00 for the Strongly Agree category.

Based on the analysis of the data collected calculations, it can be seen that from the technology variable where the average value of the value for the indicator *Relative Advantage* is 4.34 which can be concluded that most respondents answered Strongly Agree. For indicators *Compatibility* with an average score of 3.79 which means that most respondents answered Yes while the indicator *Complexity* has an average score of 3.78 which also means that most respondents answered Yes. For organizational variables, the *Management Support* has an average score of 4.32 which means that most respondents answered Strongly Agree, the *Organizational Readiness* with an average score of 4.30 which can be concluded that most respondents also answered Strongly Agree and indicators *Team Capability* which has an average score of 3.72 which means that most respondents answered Yes. From the side of the Environment variable, it can be seen that the *Competitive Pressure* has an average score of 3.97 which means that most respondents answered Yes, the *Customer Expectation* with an average score of 4.26 so it can be confirmed that most of the respondents answered very Agree and indicators *Vendor Support* with an average score of 3.71 which means that most of the respondents answered Yes. On the other hand, the AIOps technology adoption variable has an average value of 4.30 which can be concluded that most respondents answered Strongly Agree.

Sampling Technique

Evaluation of the Outer Model

Convergent Validity Test

Convergent validity test is used to evaluate the validity of the relationship between indicators and latent constructs or variables. The measurement criteria in this validation test used a loading factor ≥ 0.7 . The test results show that the lowest loading factor is 0.723 while the highest is 0.921. Since all loading factors are above 0.5, it can be concluded that all indicators used are valid and can explain the relationship with each variable used.

Average Variance Extracted (AVE)

The *Average Variance Extracted (AVE)* method is used to evaluate the convergent validity results for each construct or latent variable. The test results are declared valid if the AVE for each indicator is more than 0.5 where based on the test results it can be seen that the AVE value for each indicator used is more than 0.5. It can therefore be stated that all indicators can be used to measure each variable.

Discriminant Validity Test

The discriminant validity test is used to ensure that the construct or abstract variable in the measurement model actually measures different things using cross loading where the indicator/statement is declared valid if the loading value of each criterion is higher than the loading value of the other indicator. Based on the test results in the table below, it is stated that each indicator on each variable has a higher cross loading than the cross-loading value of the indicator on the same or another variable.

Reliability Test

The reliability test used *Cronbach's alpha* and *composite reliability* parameters. The test criteria state that if *the composite reliability* is above 0.7 and *Cronbach alpha* is above 0.6, the construct is declared reliable. Based on the test results, it can be stated that each variable indicator has *Cronbach's alpha* above 0.6 and Composite Reliability above 0.7 which means that all indicators are declared reliable for the measurement of each variable.

Inner Model Evaluation

Internal model evaluation or structural model is a stage to evaluate the suitability between variables including coefficient validation and checking hypotheses.

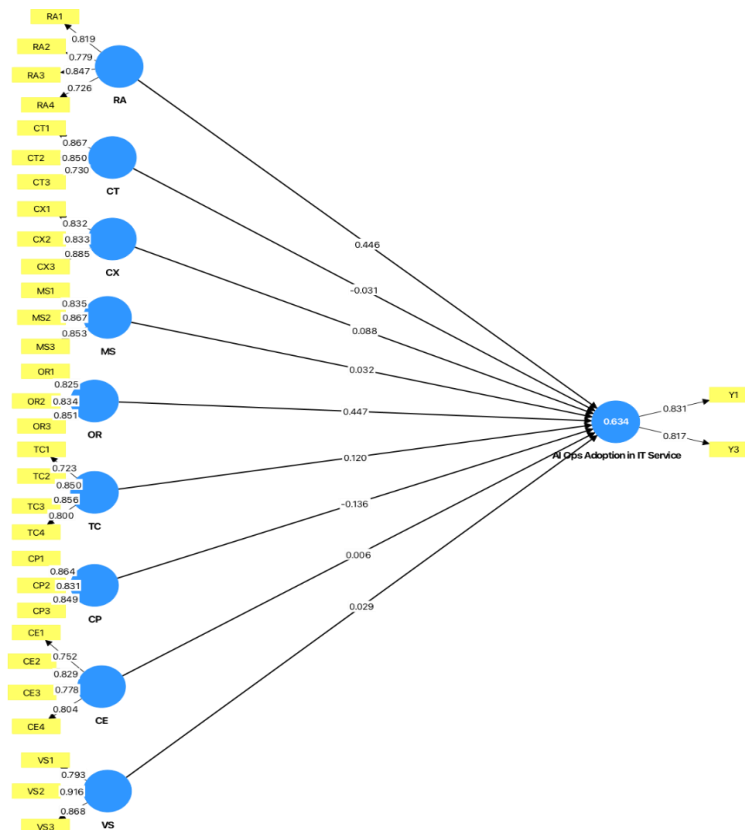


Figure 1. Standardized Model

Stage 1 Testing: Regression Equations

Based on Figure 1 above, the regression equation produced is as follows:

$$0.446RA - 0.031CT + 0.088CX + 0.032MS + 0.447OR + 0.120TC - 0.136CP + 0.006CE + 0.029VS, R \text{ Square} = 0.634$$

From the results of this equation, it can be concluded that:

1. The Adoption Value of AI Ops was 0.634 which means that its adoption rate was influenced by RA, CT, CX, MS, OR, TC, CP, CE and VS by 63.4% while the rest (36.6%) was influenced by other factors not studied in this study.
2. The coefficients for RA, CX, MS, OR, TC, CE and VS have positive values which means the relationship is one-way.
3. The coefficients for CT and CP have a negative value which means that the relationship between variables is two-way.

Stage 2 Testing: Equation Fit Models

In this test, the fit model was tested using SRMR and NFI where the SRMR value was 0.075 indicating the fit of the model because it was smaller than criterion (0.1) while the NFI value was between 0 and 1 which showed high suitability if the value was close to 1.

Level 3 Testing: Coefficient of Determination (R^2)

The Coefficient of Determination (R^2) is used to determine the magnitude of the endogenous variable's ability to explain the diversity of exogenous variables, or in other words to determine the magnitude of the contribution of exogenous variables to endogenous variables. The output results range from 0 to 1, with 1 representing the perfect accuracy of the prediction. With prediction

accuracy levels of 0.67 (strong), 0.33 (medium) and 0.19 (weak). From the tests it can be seen that the R^2 value of AI Ops adoption is 0.634 (close to the strong category) meaning that the adoption of AIOps is directly influenced by the constructs RA, CT, CX, MS, OR, TC, CP, CE and VS.

Bootstrapping Hypothesis Testing (Path Analysis)

Testing hypothesis testing in PLS-SEM is used to evaluate the relationships between latent variables in the model so that they can be considered statistically significant. This testing process uses the *Bootstrapping* Technique which calculates the *path coefficient* value and standard error from the sampling data so that the t-statistic and p-value can be determined. The relationship between variables is considered significant if the p-value is smaller than the significant alpha level of 5% (0.05) or the t-statistical value $\geq$ T-Table (1.96). The path coefficient with a significant degree indicates that the relationship between independent variables and latent dependents has strong statistical support so that the proposed hypothesis is acceptable. The following results of the research model bootstrapping with the *path coefficient* results can be seen in Figure 2 below.

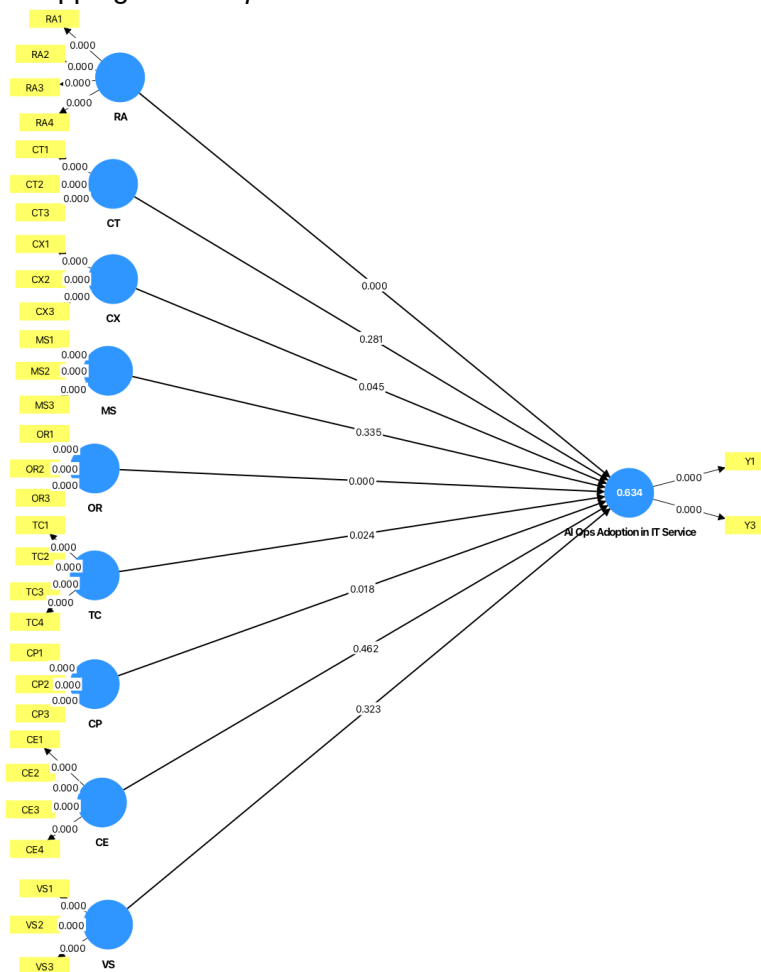


Figure 2. T-Statistical Model

The explanation of the results of the Path Coefficient Bootstrapping direct effect in Figure 2 above is as follows:

1. **H1: Relative Advantage has a positive influence on the adoption of AIOps technology in IT operational services**

The results of PLS-SEM show that the relative advantage has a path coefficient of $\beta = 0.446$ with T-statistic = 6.020 and p-value = 0.000. Since these values meet the criteria of the path coefficient, then **This hypothesis is accepted**. A large and significant positive β value indicates that the greater the relative advantages perceived from the implementation of AIOps (compared to current conventional IT practices), the higher the adoption rate of AIOps in the organization. This hypothesis is in line with many recent studies where the relative advantages possessed by an organization are the main drivers of the adoption of technological innovations (Badghish & Soomro, 2024; Horani et al., 2025). The perception that AIOps offers superior performance benefits, such as increased efficiency, reduced costs, or improved quality of service will significantly encourage organizations to implement AIOps

2. H2: Compatibility has a positive influence on the adoption of AIOps technology in IT operational services

The H2 hypothesis tests the effect of Compatibility (the suitability of innovation with existing values and systems) on AIOps Adoption. Based on the PLS-SEM output, the β path coefficient = -0.031 with T-statistic = 0.578 and p-value = 0.281, so this relationship is not significant at the level of 5%. A small β coefficient and a p-value above 0.05 indicate that compatibility does not have a conclusive effect on the adoption rate of AIOps. Negative value β value (even if it is not Significant) indicates that the increased compatibility is not related to the increased adoption of AIOps in this study. Since the p-value exceeds 0.05, this hypothesis is stated **not supported (rejected)**. AIOps is one of the innovations that is quite disruptive so that organizations are willing to adapt to the systems they are currently using in the hope of getting great benefits (Horani et al., 2025). In the context of this study, the variable Compatibility indicator is not considered as a determining factor for the adoption of AIOps technology where corporate companies are willing to adapt to overcome potential IT system incompatibilities as long as they can get the benefits offered.

3. H3: Complexity has a positive influence on the adoption of AIOps technology in IT operational services

The H3 hypothesis assesses the influence *Complexity* (complexity of use/understanding of AIOps) towards AIOps Adoption. The results of PLS-SEM show a coefficient of the β path = 0.088 with T-statistic = 1.691 and p-value = 0.045, showing a significant positive relationship at $\alpha \leq 5\%$. Thus, this hypothesis is stated **supported (accepted)**. Positive β coefficient values mean that higher complexity correlates with increased adoption of AIOps, although the effect is relatively small. This result is somewhat contradictory because usually increasingly complex innovations can reduce interest in adoption. These findings are actually in line with the results of other studies that state that the perception of complexity does not hinder an organization from adopting technology as long as its implementation can provide great benefits (Sharma et al., 2024). Therefore, it can be concluded that organizations that plan to adopt AIOps seem to have readiness in dealing with technical complexity so that complexity is not a barrier, it can even be a reflection of the sophistication of the solution that can be utilized.

4. H4: Management Support has a positive influence on the adoption of AIOps technology in IT operational services

The results of PLS-SEM show that the H4 path coefficient is very small ($\beta = 0.032$), with T-statistic = 0.427 and p-value = 0.335 (greater than 0.05). This means the relationship between the support Management The peak and adoption rate of AIOps are insignificant at a value of 5%. In other words, management support has not been shown to have a direct effect on the adoption

of AIOps based on research data. This hypothesis is stated **not supported (rejected)**. These results indicate that the presence or absence of top management support did not differentiate the adoption rate of AIOps in the context of this study. Theoretically, Support top management is often considered crucial in the successful implementation of IT innovation. For example, research from Low et al. (2021) showing top management support has a significant positive effect on the adoption of Cloud computing. Similarly, Nguyen et al. (2022) reports top management support as a critical factor driving AI adoption in the enterprise environment. However, the insignificance of the variables of management support indicators in this study can be due to the fact that management support in corporate companies in most of the respondents is relatively high and uniform, so that it is not a distinguishing factor in the decision to adopt AIOps technology.

5. H5: Organizational readiness has a positive influence on the adoption of AIOps technology in IT operational services

This hypothesis evaluates the influence of Organizational Readiness (*Organizational Readiness*) against the Adoption of AIOps. The PLS-SEM results showed a path coefficient $\beta = 0.447$ with a T-statistic = 6.477 and a p-value = 0.000, which is well below 0.05. This indicates that organizational readiness has a significant positive effect on the adoption rate of AIOps. The β coefficient of 0.447 is one of the highest in the model, showing its strong influence. Thus, this hypothesis **Supported (accepted)** and in line with other research that states that the internal readiness of an organization is the main prerequisite for the adoption of IT technology innovation (Badghish & Soomro, 2024; Johnk et al., 2021). The higher the readiness of an organization, for example in terms of infrastructure, finance, internal processes or other resources, it will have an impact on the higher the tendency of the organization to adopt new IT technology.

6. H6: Team Capability has a positive influence on the adoption of AIOps technology in IT operational services

This hypothesis tests *Team Capabilities* (Team Capability) is the IT team's competence and technical expertise towards the adoption of AIOps technology. The results of PLS-SEM showed a path coefficient $\beta = 0.120$ with T-statistic = 1.979 and p-value = 0.024. This value indicates that *higher team capabilities are associated with increased adoption of AIOps*, although the effect is not as big as the organizational readiness factor. Thus this hypothesis **Supported (accepted)** where the competencies and capabilities of the IT team have a very important role in increasing the adoption of AIOps in the organization. Choudrie et al. (2023) In its research, it is emphasized that the high level of digital skills and employee knowledge is positively correlated with the attitude and readiness of companies in adopting AI technology. IT teams that have data analytics expertise, knowledge and experience using AI tools are better able to integrate AIOps technology into the operational process of IT services than teams that do not.

7. H7: Competitive Pressure has a positive influence on the adoption of AIOps technology in IT operational services

This hypothesis examines the effect of *Competitive Pressure* on the Adoption of AIOps. The results of PLS-SEM showed a coefficient of the β path = -0.136 with T-statistic = 2.098 and p-value = 0.018. A T value that exceeds the critical limit (± 1.96) and $p < 0.05$ indicate that competitive pressures have a significant effect on the adoption rate of AIOps. Thus, this hypothesis **is statistically supported**, but it is drawn towards a negative coefficient, which means that increased competitive pressures are associated with declining adoption rates of

AIOps. These findings indicate that companies that experience higher competitive pressures tend to be slower or lower in adopting AIOps, compared to those with lower competitive pressures.

Theoretically, competitive pressures in the context of environmental factors (*environmental context*) plays a role in encouraging companies to adopt technological innovations in order to maintain a competitive advantage. Another study related to AI adoption in large companies states that competition forces companies to move faster in adopting intelligent technologies so as not to lag behind their competitors (Ramus & Jin, 2022). Therefore, the negative direction of the relationship of competitive pressure to the adoption of AI technology is a contradictory but explainable result where the adoption of AIOps requires a large investment of resources and time in process adaptation. Companies that face stiff competition are practically more focused on short-term strategies (cost efficiency or traditional marketing) than on making long-term investments in complex new technologies.

8. H8: Customer *Expectation* has a positive influence on the adoption of AIOps technology in IT operational services

This hypothesis considers the influence of Customer Expectations (*Customer Expectation*) against the Adoption of AIOps. Based on PLS-SEM analysis, the coefficient of the β path = 0.006 was obtained with T-statistic = 0.096 and p-value = 0.462. These values indicate that the effect of customer expectations no significant to the adoption rate of AIOps (because $p > 0.05$ and T-statistic are well below the critical value). In other words, the adoption of AIOps is not much influenced by the magnitude of customer expectations or demands. Therefore, this hypothesis can be stated **not supported (rejected)**. In theory, the customer expectation factor is part of the environmental context in the adoption model. Customer expectations reflect the demands of the client or end user for service providers to improve their capabilities, for example with advanced technologies such as AI to improve service quality. Several studies in the field of innovation show that customer expectations can motivate companies to innovate (Tran et al., 2025). However, in the context of the adoption of AIOps for IT services, the results of this study did not find a significant association Significant because the adoption of AIOps is more internal and not directly visible to customers, so external pressure from customers is less felt. Customers certainly expect improved performance of IT services (e.g. faster response times, proactive detection of outages), but they do not specifically demand the use of AIOps technology.

9. H9: Third-party/vendor support has a positive influence on the adoption of AIOps technology in IT operational services

This hypothesis analyzes the effects of Third-party/Vendor Support (*Vendor Support*, i.e. technical assistance/knowledge from technology service providers) towards AIOps Adoption. The results of PLS-SEM showed a coefficient of the β path = 0.029 with T-statistic = 0.460 and p-value = 0.323. With $p > 0.05$, the influence of vendor support was not statistically significant. This means that the availability of support from AIOps technology suppliers has not been proven to directly influence AIOps adoption decisions within organizations. Thus, this hypothesis is stated **Not supported (rejected)** by the results of this study. Third-party support (*Vendor support*) is often considered an important element in the adoption of technology, especially for complex new technologies. Another study states vendor support positively drives AI adoption intentions in Corporate companies (Horani et al., 2025). However, the results of other studies also indicate that vendor support is not the main determinant of AIOps adoption when internal

organizational factors are already dominant. In the context of this study, it can be concluded that the average respondent already has adequate internal capabilities (human resources and infrastructure) to develop AIOps independently, so that the role of vendors becomes less dominant. This is consistent with previous hypothetical findings that internal team capabilities significantly drive adoption, so competent organizations can self-sustain AIOps implementations without a high reliance on vendor support. In addition, not all IT vendors have a strong ability to adopt new technologies such as AIOps, so the variation in vendor support among respondents is low and has no real effect.

CONCLUSION

The results of this study as a whole show that technology and organizational factors have the most prominent influence on the adoption of AIOps in IT services, while environmental factors tend to be less dominant. Of the nine hypotheses (H1–H9), five of them proved significant (H1, H3, H5, H6, H7) and the other four were not (H2, H4, H8, H9). The relative advantage of AIOps (H1) emerges as a strong driver of adoption – organizations are more motivated to implement AIOps when the technology clearly offers higher performance benefits than traditional approaches (Rogers, 2003). In contrast, the existing compatibility factor (H2) did not have a significant effect on adoption, indicating that the suitability of innovation with the current IT environment is not a determining factor in this context. The complexity of AIOps (H3) is positively and significantly related to the adoption of a finding because the theory of innovation diffusion predicts complexity inhibits adoption (Rogers, 2003). These results suggest organizations will adopt AIOps when they see its superior benefits and feel internally prepared, even if the technology is complex or requires adjustment. External factors such as competitive pressures and outside expectations play less of a direct role in AIOps adoption decisions.

Overall, the integration of the findings in this study contributes to the AI adoption literature by reaffirming the importance of technology fit and organizational benefits while showing that the TOE framework needs to be adaptive: technology factors (benefits & complexity) and organizational factors (resources & expertise) are more dominant in driving AIOps adoption, while environmental factors may play a more contextual or nonlinear role.

The results of this study are expected to provide input to IT management to ensure that AIOps can provide real business benefits such as increased response speed, disruption reduction, or operational efficiency (Rogers, 2003). In this case before deciding on implementation, the company must clearly identify what the main values are to be achieved by adopting AIOps technology such as reducing downtime by up to 30%, increasing user satisfaction, reducing the number of incidents and other objectives so that they can be used as the main business justification in making a business case project. The study also recommends that companies measure the readiness of their IT infrastructure, data quality, and existing operational processes to support AIOps algorithms and automation (Sun et al., 2018). If there are gaps, plan for HR development through training or hiring before making full adoption. In addition, a phased approach will help manage risk and change (Nguyen et al., 2022) so that the company must glorify with pilot projects in limited IT service areas that have the potential to provide *Quick Wins* such as applying AIOps for anomaly detection on one critical system first.

The scope of this study is limited to several indicator variables that are generally used to carry out the adoption of AIOps technology. For further research, it is expected to use other broader

indicator variables such as human resource factor variables, data quality, organizational culture, company regulations and other relevant indicators in explaining the phenomenon of AIOps technology adoption or similar IT invocation in the future. In addition, the use of mediation variables that show the productivity and stability of IT services can be considered to see its effect on the adoption of AIOps technology. From a methodological point of view, the next study is expected to collect a wider and more diverse data sample from the side of the company where the respondents work so that the data collected can be analyzed to produce a deeper understanding of the factors of adopting AIOps technology. Qualitative research approaches can also be considered to be applied simultaneously so that other contextual aspects can complement the findings obtained through a quantitative approach so that a more holistic understanding of AIOps technology adoption decisions can be produced in the future.

REFERENCES

- Alsheibani, S., Cheung, Y., & Messom, C. (2018). *Artificial intelligence adoption: AI-readiness at firm level BT - Proceedings of the Pacific Asia Conference on Information Systems (PACIS 2018)*. 1–15.
- Badghish, S., & Soomro, Y. A. (2024). Artificial intelligence adoption by SMEs to achieve sustainable business performance: Application of the technology-organization-environment framework. *Sustainability*, 16(5), 1864. <https://doi.org/10.3390/su16051864>
- Cheng, M., Chiu, T. K. F., Xia, Q., & Zhou, X. (2023). Systematic literature review on opportunities, challenges and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, 4, 100118. <https://doi.org/10.1016/j.caeai.2022.100118>
- Choudrie, J., Castro, C., Chike-Obuekwe, C., & Manandhar, N. (2023). *Hey Siri, Google! Can you help me? A qualitative case study of smartphones AI functions in SMEs BT - Proceedings of the International Systems Conference (IS Conference 2023)*.
- Gartner. (2017). *AIOps: Artificial intelligence for IT operations combines big data and machine learning to automate IT operations processes*. Gartner Research.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (3 ed.). Sage Publications.
- Horani, O. M., Al-Adwan, A. S., Yaseen, H., Hmoud, H., Al-Rahmi, W. M., & Alkhalifah, A. (2025). The critical determinants impacting artificial intelligence adoption at the organizational level. *Information Development*, 41(3), 1055–1079. <https://doi.org/10.1177/02666669231166889>
- InsideHPC. (2022). *What is AIOps? Artificial intelligence for IT operations explained*. <https://insidehpc.com/2022/06/what-is-aiops/>
- Johnk, J., Weißert, M., & Wyrski, K. (2021). Ready or not, AI comes: An interview study of organizational AI readiness factors. *Business & Information Systems Engineering*, 63(1), 5–20. <https://doi.org/10.1007/s12599-020-00676-7>
- Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology*, 140, 1–55.
- Low, S. T. H., Sakhardande, P. G., Lai, Y. F., Long, A. D. S., & Kaur-Gill, S. (2021). Attitudes and perceptions toward healthcare technology adoption among older adults in Singapore: A qualitative study. *Frontiers in Public Health*, 9, 588590. <https://doi.org/10.3389/fpubh.2021.588590>
- Nguyen, T. L., Nguyen, V. P., & Dan, T. V. D. (2022). Critical factors affecting the adoption of artificial intelligence: An empirical study in Vietnam. *Journal of Asian Finance, Economics and Business*, 9(5), 225–239. <https://doi.org/10.13106/jafeb.2022.vol9.no5.0225>
- Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). McGraw-Hill.
- Ramus, T., & Jin, Y. (2022). Competitive pressure and organizational adoption of AI: A TOE framework analysis. *Technology in Society*, 70, 101992.

- <https://doi.org/10.1016/j.techsoc.2022.101992>
- Reinsel, D., Gantz, J., & Rydning, J. (2018). *The digitization of the world from edge to core*. International Data Corporation (IDC).
- Rijal, A. S., Mooi, W. K., & Ahmad, M. N. (2022). Small and medium enterprises' business sustainability based on the Industry 4.0 Internet of Things adoption: A Malaysian Bumiputera case study. *Serbian Journal of Management*, 17(1), 99–110. <https://doi.org/10.5937/sjm17-35505>
- Rogers, E. M. (2003). *Diffusion of Innovations* (5 (ed.)). Free Press.
- Sekaran, U., & Bougie, R. (2016). *Research Methods for Business: A Skill-Building Approach* (7th ed.). Wiley.
- Sharma, S., Singh, G., Islam, N., & Dhir, A. (2024). Why do SMEs adopt artificial intelligence-based chatbots? *IEEE Transactions on Engineering Management*, 71(5), 2293–2306. <https://doi.org/10.1109/TEM.2022.3203469>
- Sun, S., Cegielski, C. G., Jia, L., & Hall, D. J. (2018). Understanding the factors affecting the organizational adoption of big data. *Journal of Computer Information Systems*, 58(3), 193–203. <https://doi.org/10.1080/08874417.2016.1222891>
- Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.
- Tran, G. T. C., Le Dinh, T., & Vu, M. C. (2025). Artificial intelligence in SMEs: Enhancing business functions through technologies and applications. *Information*, 16(5), 415. <https://doi.org/10.3390/info16050415>