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Adopting Artificial Intelligence Technology for Network Operations in Digital Transformation

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Abstract: This study aims to define factors that affect Artificial Intelligence (AI) technology introduction to network operations and analyze the relative importance of such factors. Based on this analysis of critical factors, a rational decision-making framework is suggested to promote network operations with AI technology. As affecting factors were derived based on related previous studies, the study model was designed to consist of 22 attribute factors under 6 key factors: relative advantage, compatibility, top management support, organizational readiness, competitive pressure, and cooperative relation. The questionnaire was designed and analyzed using the Delphi method and Analytics Hierarchy Process (AHP) method based on the Technology–Organization–Environment (TOE) framework. To collect data, a survey was conducted among 30 experts in network operations and AI. The importance of attribute factors was in the order of 'goals and strategies', 'commitment of resources', 'leadership competency', 'financial readiness', and 'technology readiness'. As the importance of factors was analyzed comparatively between the demander group and provider group, organizational factors were important in the demander group. In contrast, technological factors were important in the provider group. In conclusion, there was a difference in perspectives between demanders and providers regarding adopting AI technology to network operations.

Keywords: network operation; AI; digital transformation; AHP; TOE framework

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1. Introduction

Artificial Intelligence for IT Operations (AIOps) provides IT operations with consistent insight through big data and AI technology (Andenmatten 2019; Mordor Intelligence 2023). AIOps is a type of AI software that predicts and solves various problems in IT operations by collecting and analyzing data from multiple sources. It can enhance the efficiency of IT operations. AI technology is mainly applied to network management, network assistance, network deployment, anatomy detection, intelligent automation, threat analysis, etc., in network operations. Most problems in network operations stem from IT complexity, as applications, data, tools, and systems grow across many domains, increasing operational complexity, increasing system dependencies, and increasing monitoring tools. For network operations in this environment, AI is an orchestrator that automates, systematically, and procedurally changes many of the network operations that were performed manually with existing silos based on maximum connectivity within the organization (Aghili et al. 2023; Kitsios and Kamariotou 2021; Verhoef et al. 2021).

Specifically, in the statistical analysis of scalability insights that predict growing network traffic and in the process of identifying traffic patterns and detecting risks by type, artificial intelligence technology is adapted to improve customer service problems. In addition, advanced machine learning technology is used to optimize the location of network devices and predict and prevent conflicts between network devices. Recently, 'Generative AI' has been introduced to conduct network comparison evaluation or benchmarking related to network performance, efficiency, and security (Hinings et al. 2018; Nambisan et al. 2019). However, adopting AI to network operations involves many challenges, such as difficulty in value measurement, data management cost, implementation and operation complexity, and integration with existing tasks. Brock and Von Wangenheim (2019) pointed out the risk of unconditionally adopting AI technology without analysis or strategy. Ransbotham et al. (2017) emphasized that the challenge of AI value measurement and the lack of understanding and expertise on the effects of its adoption would cause significant difficulties.

Nevertheless, recently, many enterprises have adopted and implemented AIOps to upgrade their IT operations because network operations inevitably require the innovative technology elements adopted, such as AI, big data, cloud, etc., to support business activities in the digital age. In reflection of such needs, the number of suppliers, including BigPanda, BMC, Broadcom, IBM, Juniper, Moogsoft, and PagerDuty, continues to increase (Schwertner 2017; Huang and Rust 2018). Gartner (2023) pointed out that the annual growth rate of the AIOps market was about 19%, suggesting that by 2025, the market scale would increase to about USD 2.1 billion. This phenomenon shows that although there are technical limitations so far, companies are trying to find ways to continuously secure a competitive advantage by adapting AI into network operations. Accordingly, companies need to make decisions about adapting AI technology and consider efficient operation methods.

However, looking at related studies, most of the studies point out the technology limitations for the adaptation of AI technology or seek to build a technical system. There are still few studies suggesting AI technology adaptation methods or concrete plans. In the case of network operation based on AI adaptation, it can be dealt with in terms of external partner selection and technology collaboration rather than internal technology development, and strategic discussions on effective introduction methods are needed accordingly. In these backgrounds, the study was conducted based on the research questions: "What factors should be considered the most in introducing AI technology for corporate network operation?"; "What decisions do companies need to make to operate AI technology-based networks?"; and "What management activities are required to build and sustain an effective AI technology-based network?".

Accordingly, this study presents critical factors that affect the adoption of AI technology in corporate network operations. It also offers a model for proper decision-making and the importance of substantial factors, suggesting the importance of adopting AI technology efficiently. Specifically, significant factors are considered from technological, organizational, and environmental perspectives to seek ways for enterprises to make decisions strategically and efficiently for their network operations. The comparative analysis between demanders and providers is also included in this study to compare their respective perspectives and significant factors in their decision-making processes. As shown in Figure 1, this article is designed with the research background and necessity in the introduction of Section 1, and prior research on the factors influencing the introduction of AI technology through the theoretical background in Section 2. In Section 3, research models and methods are presented, and in Section 4, analysis results are presented. In Sections 5 and 6, the interpretation and implications of the research results are presented.

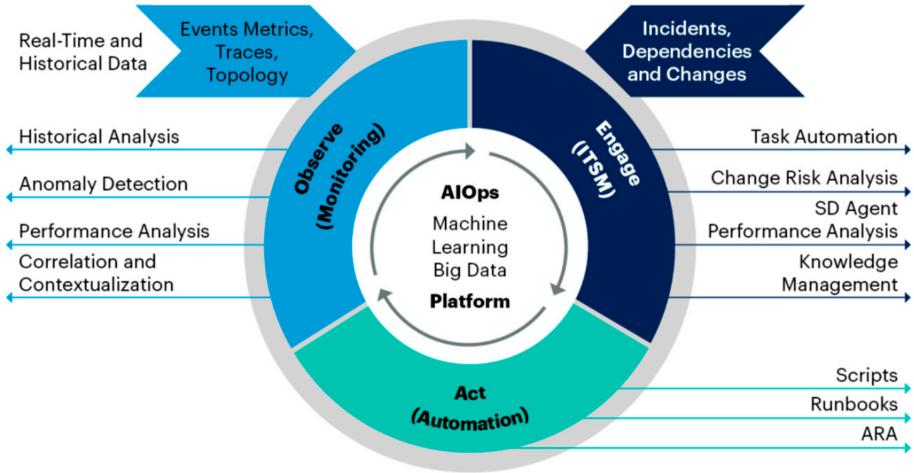

Figure 1. AIOps platform and tasks to automate with AIOps (Source: Prasad and Rich 2018).

2. Literature Review

2.1. Network Operations and AI

Network technology has continued to grow in line with technological developments in various areas such as transmission and exchange, control and management, wired and wireless means, multimedia, etc. Recently, AI utilization has been sought for various operation issues in networks closely connected with IoT, Cloud, 5G Mobile, and AI. AI operates systems to analyze data, perform simulations, and produce results (Shrestha et al. 2019). Thus, there are many attempts to solve unsettled, complicated network issues through AI technology (Mata et al. 2018). Specific areas that involve rapid changes to the adoption of AI technology include preventive network security, proactive troubleshooting, automated and autonomous network operation management, optimization of optical transmission signal processing, and so forth (Astakhova and Medvedev 2020; Cheng et al. 2023).

Organizations face many challenges related to IT operations as their information technology management expands. This is because the interconnectivity among tasks within each organization becomes closer and requires a more complicated ecosystem (Palacin et al. 2020). Accordingly, network operators continue to put forth efforts to enhance their complex operation environments through automation (Huang et al. 2020). The lack of standardized data formats and the rapid evolution of networks make it challenging to embody AI in a large-scale network and share it within an organization. However, adopting AI technology is considered continually to minimize operators' tasks in solving network issues, such as the dynamic management of network resources, network traffic classification and management, etc. (Bostan et al. 2011; Shen et al. 2020).

AIOps is a crucial concept of basic network operations. This means combining big data and AI to automate the IT operation process, specifically including event correlation, anomaly detection, and decisions on the causal relation. As shown in Figure 1, the primary purpose of AIOps is to enhance IT operation availability, expandability, and efficiency. In the context of network operations management, this reflects the concept of DevOps software development to adopt AI to an organization's network operation and management (Prasad and Rich 2018).

Operation tasks that could be automated and IT operation platforms applying the concept of AIOps in the context of IT operation management, including network environments. Big data and AI are vital elements of this platform, and the primary process was defined with the circulative process of task observation, participation, and automation. Tasks in each step were also determined, including event correlation, anomaly detection, automation, performance analysis, etc. A network often involves failures due to its inevitable vulnerabilities, such as hardware complexity, configuration provisioning, risk of change, etc. Network failures affect business services, ruin reliability, and cause a serious financial burden. For this reason, AI's adoption into network operations tasks is increasing, especially regarding troubleshooting issues, such as anomaly detection, root cause analysis (RCA), and recovery (Yuan et al. 2014).

Traditional network operations require intuitive and relatively simple implementation technology. Therefore, it has the characteristics of low initial investment and maintenance costs, and it can have stable and high reliability. However, it has the disadvantages of lack of flexibility, difficulty in processing large amounts of data, and late problem solving. The adoption of AI technology can maximize the efficiency and effectiveness of the work process according to the automation of the operating system that can maximize these shortcomings, and flexible and real-time problem solving is possible because data analysis and prediction are possible in real-time. Of course, adopting AI technology for network operation is considered important for companies in a business environment that requires real-time information prediction based on big data, although it has disadvantages such as high initial investment cost, understanding complex algorithms, requiring experts, and managing data security and quality.

Especially, AI technology is introduced for more advanced network operation management, such as enhancing the efficiency of network operation management, solving problems, and reducing risks, in line with the purpose of the company's needs. As shown in Figure 2, it is used for statistical analysis, design builder, policy variation analysis, graph theory, and similar activities for risk mitigation simulation. In addition, text or natural language is used for configuration analysis, insights, and active analysis for risk mitigation clustering and automated fault management.

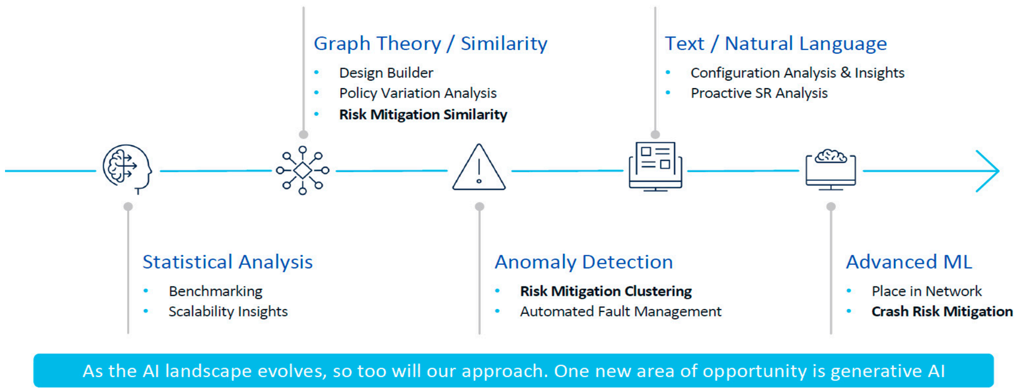

Figure 2. AI landscape to network operations (Source: Cisco 2023).

Moreover, advanced machine learning can be applied in place in network or crash risk mitigation. As a corporate instance, Cisco Systems, Inc. in San Joes, California, USA defines network infrastructures as a combination of hardware and software that make it possible to form a network and to communicate among users, devices, Apps, and the Internet. Specifically, in the statistical analysis of scalability insights that predict growing network traffic and in the process of identifying traffic patterns and detecting risks by type, artificial intelligence technology is introduced to improve customer service problems. In addition, advanced machine learning technology is used to optimize the location of network devices and predict and prevent conflicts between network devices. Recently, 'Generative AI' has been introduced to conduct network comparison evaluation or benchmarking related to network performance, efficiency, and security (Cisco 2023).

When implementing AI technology in network operations, data availability and quality are important. Data collection for AI analysis in network operations is performed from network devices or controllers via protocols such as Simple Network Management Protocol (SNMP), Telemetry (Telemetry), Application Programming Interface (API), and Command Line Interface (CLI). Most collect state information of network devices. A sufficient amount of data and accurate and reliable data quality greatly affect the insights of AI that support network operators' decision-making. In reality, the lack of available data can also act as a major obstacle to AI technology adoption. Linkages and compatibility between network components and technologies that have already been introduced are important.

The adoption of AI technology into network operations presupposes many connections. Consequently, connectivity with many of the technology elements introduced is inevitable. When technologies are introduced without considering connectivity and compatibility, excessive customization makes it difficult to use AI technology at the originally intended level. In this case, it is difficult to quickly scale and support the network according to the needs of the business. In order to overcome the challenges that may arise from the introduction of AI technologies, such as data quality, interoperability, scalability, and others, answers can be found in building strong governance for network operations and standardizing in terms of processes, architectures, technologies, and management tools. Most networks have multivendor and multidomain structures. In other words, since they operate in complex structures in non-standardized forms, the establishment and standardization of operational governance must precede the successful introduction of AI.

In this status, adopting AI to network operations involves many challenges, such as difficulty in value measurement, data management cost, implementation and operation complexity, and integration with existing tasks. Brock and Von Wangenheim (2019) pointed out the risk of unconditionally adopting AI technology without analysis or strategy. Ransbotham et al. (2017) emphasized that the challenge of AI value measurement and the lack of understanding and expertise on the effects of its adoption would cause significant difficulties. Notaro et al. (2020) extracted and analyzed more than 1000 items where AIOps contributed to IT operations, including network management, with most of them (62.1%) being related to troubleshooting: failure prediction (26.4%), failure detection (33.7%), and root cause analysis (RCA) (26.7%).

In this respect, Rijal et al. (2022) examined the benefits and challenges an organization can expect when adopting AIOps for IT operations, including network management. Findings indicate that AIOps contributed to task monitoring, task time saving, collaborative work, failure prevention, and mean time to repair (MTTR) reduction. At the same time, challenges to overcome include doubt about AI efficiency, low-quality data, few use cases, and changes in engineering methods. Dang et al. (2019) emphasized the importance of close cooperation with academic circles, pointing out the difference in ideas and collaborative methods among individuals in different areas, changes in engineering methods, and difficulties in AI modeling.

However, AIOps contributed to service quality, customer satisfaction, operation productivity and cost-saving (Ambrosch et al. 1989). A practical method to maximize the availability of an IT operation process by combining large-scale data and AI technology in cloud infrastructures (Hinings et al. 2018). Notably, they classified AI tasks within an organization into anomaly detection, failure prediction, RCA, and automation, stating the issues of each task and their solutions. As such, an intelligent network provides a framework for a network operator to adopt, control, and manage services by using an architecture to control network services more effectively and economically than the current network architecture (Rana et al. 2014).

The combination of a network and AI embodies an intelligent network, and the network intelligence technology makes this possible. Automatic data collection from a network and its analysis and autonomous decision-making using AI technology automate specific tasks, such as network configuration, control, management, and orchestration (Von Krogh 2018). Based on this network intelligence technology, a network can predict and prevent failures, enhance network reliability, and secure the autonomy of the network, involving minimal human intervention (Lyu and Yin 2020).

2.2. Critical Factors Affecting AI Technology Adaption

AI was developed based on the emergence of new data sources, performance upgrade computation, and cloud-based service innovation (Davenport and Ronanki 2018). As its importance among organizations is emphasized, AI is utilized in various areas such as production, service, process, etc. (Duan et al. 2019). The study trends show that in addition to the general effects of AI on business management, the impact of AI technology on decision-making (Raisch and Krakowski 2021), potentials of automation (Helo and Hao 2022), operation management (Keller et al. 2019), and production prediction and maintenance (Zhao et al. 2022) are also topics that are actively examined. Regarding organizational aspects, certain factors of AI adoption, such as strategic direction and resource and network support, are emphasized (Fragapane et al. 2022).

Coronado et al. (2022) stated that, regarding AI adoption in chatbots, voicebots, personalized recommendations, process automation, and anomaly detection and prediction, the organization is more important than technologies or environments. They also pointed out that critical factors in this respect include data, leadership competency, and strategy and that attribute factors include data availability and quality, strategies and business needs, customer readiness and support, AI implementation and utilization capabilities, and cooperation and communication between organizations. In addition, Gramaglia et al. (2022) analyzed the success factors of AI adoption, emphasizing the importance of support from the top management, technology capabilities, data, budgets, and employees' roles and abilities to implement AL algorithms and interpret the results. Pillai and Sivathanu (2020) stated that the top management's support is a deciding factor, while other factors, such as technological capability, external support and competition pressure, are slightly influential. Matt et al. (2015) stated that ethical issues are the most important, followed by data governance, security and confidentiality, data availability and quality, and IT infrastructures, in that order.

Wang et al. (2022) examined the adoption of AI technology specifically regarding the following aspects: field service operation optimization, predictive detection of 'unhealthy' line connections, peripatetic warehouse deployment, and automated inventory replenishment supported by IoT. They defined the lifecycle of adopting AI in an organization with pre-development, deployment, and post-deployment concepts. Table 1 shows the suggested critical success factors (CSF). Study findings point out that AI affects service operations significantly in terms of cost-saving, time-saving and productivity improvement. In addition, they emphasized the importance of the standard Technology Readiness Level (TRL) protocol, a framework to evaluate the maturity of AI, human-centered approaches, and AI initiative portfolios.

Table 1. Critical success factors for AI in technology operations.

Pre-Development	Deployment	Post-Deployment
▪ Strategy formulation ▪ Top management support ▪ Stakeholder buy-in ▪ Sufficient in-house expertise ▪ Collaborative work among business, IT, and analytics ▪ Problem formulation Data quality, integrity, and availability	▪ Stakeholder engagement ▪ Training everyone who engages with the algorithms ▪ Effective communications ▪ Explainable AI (transparency and fairness) ▪ AI governance ▪ Codifying the proper AI logic into operations	▪ Set of KPIs in place to monitor AI's impact on operations performance ▪ Regular review of the fitness of AI algorithms ▪ Revisiting and modifying AI algorithms when business changes AI ownership

Reference: Wang et al. (2022).

Raisch and Krakowski (2021) and Laut et al. (2021) emphasized the importance of constructive thinking and AI technology characteristics of each organization as factors that affect AI adoption for network support. Angerschmid et al. (2022) stated that when an organization attempts to realize data-centered network operations, essential factors of AI introduction include such technological aspects as IT infrastructures, relative advantage, data quality, instrument availability, transparency, explainability, and such organizational aspects as top management support, capability, resource, fairness, ability to absorb and cultural and environmental elements such as industrial pressure, governmental regulation, customer readiness, reliability and sense of responsibility. They also emphasized the importance of interactions among social and technological components regarding AI implementation.

Pumplun et al. (2019) stated that governmental regulations could cause either positive or negative effects on an organization's adoption of innovative technology. They also explained that whether or not the organization trusts the new technology is essential and that its financial burden and momentum may function as a resistance-inducing factor to its adoption. Jäntti and Cater-Steel (2017) presented technological considerations, the complexity of implementation and quality assurance, organizational considerations, understanding AI technology and the lack of top management support, environmental considerations, market regulations, and moral concerns. Suggesting the organization's structural change and business process digitalization as the driving force of adoption, they emphasized innovative integration with existing operational functions.

2.3. AI Technology Adaptation in Network Operations

Network operations management includes business management activities to plan, organize, direct, and control an enterprise's production and operation procedures. Specifically, planning, scheduling, process designing, product designing, etc., are involved (Subramanian and Ramanathan 2012). In previous studies, various factors have been suggested for the success of network operation management. Chatterjee et al. (2017) suggested technical, operational, social, and human factors to 5G network operation. Duman and Eliiyi (2021) identified the factors of sustainable network operation management as efficiency, service quality, capacity utilization, flexibility, availability, reliability, security, etc. Zhang and Gregory (2011) mentioned network structure, operations processes, governance system, support infrastructure, external relationships, etc., as critical success factors of global network operations. Further, Yang and Rossi (2021) indicated planning and design, delivery, deployment, provisioning, monitoring, and optimization of network automation solutions.

Especially, AI technology is adapted for more advanced network operation management, such as enhancing the efficiency of network operation management, solving problems, and reducing risks, in line with the purpose of the company's needs. It is used for statistical analysis, design builder, policy variation analysis, graph theory, and similarity activities for risk mitigation simulation. In addition, text or natural language is used for configuration analysis, insights, and active analysis for risk mitigation clustering, and automated fault management. Moreover, advanced machine learning can be applied in place in network or crash risk mitigation (Loureiro et al. 2021).

Accordingly, Grover et al. (2022) suggested six areas that affect AI utilization in network operations management tasks, such as the manufacturing, product development, service, and supply network of an organization: job fit, complexity, perceived consequences, effect towards use, social factors, and facilitating conditions. The following were also presented as related factors: organizational efficiency, return on investment (ROI), quality, innovation, customer satisfaction, and employee empowerment. Chang et al. (2008) argued that the factors influencing the introduction of AI technology are different according to the network operation management process. Radhakrishnan and Chattopadhyay (2020) examined the facilitating and hindrance factors of AI adoption to network operation management. As a result, they suggested that organizational factors include technology capability, strategy and roadmap, top management support, digital maturity, reliability, competitive environment, compatibility, relative advantage, cost, external pressure, and organization innovation. Stenberg and Nilsson (2020) and Smith (2022) suggested the following as essential factors: relative advantage, compatibility, and complexity from a technological perspective; top management support, employee capability, and ethics from an organizational perspective; and regulatory environment and competitive pressure from an environmental perspective. Chen et al. (2021) viewed AI adoption as significant, considering compatibility, relative advantage, complexity, managerial support, government involvement, and vendor partnership.

3. Research Method

3.1. Research Framework and Variables

Factors affecting AI technology's adoption for network operations are designed as in Figure 3 based on the TOE framework. Integrated models dealing with technology or system adoption include Organization–Environment Framework (TOE), Diffusion of Innovation (DOI and Unified Acceptance and Use of Technology (UTAUT). Among these models, a hierarchical structure of factors derived from the TOE model, which deals with technology acceptance in terms of companies and organizations rather than individual or user-level adoption approaches, was designed. This framework is intended to have 3 layers—evaluation areas, decision-making factors, and decision attributes—to facilitate the decision-maker's intuitive and prompt decision-making.

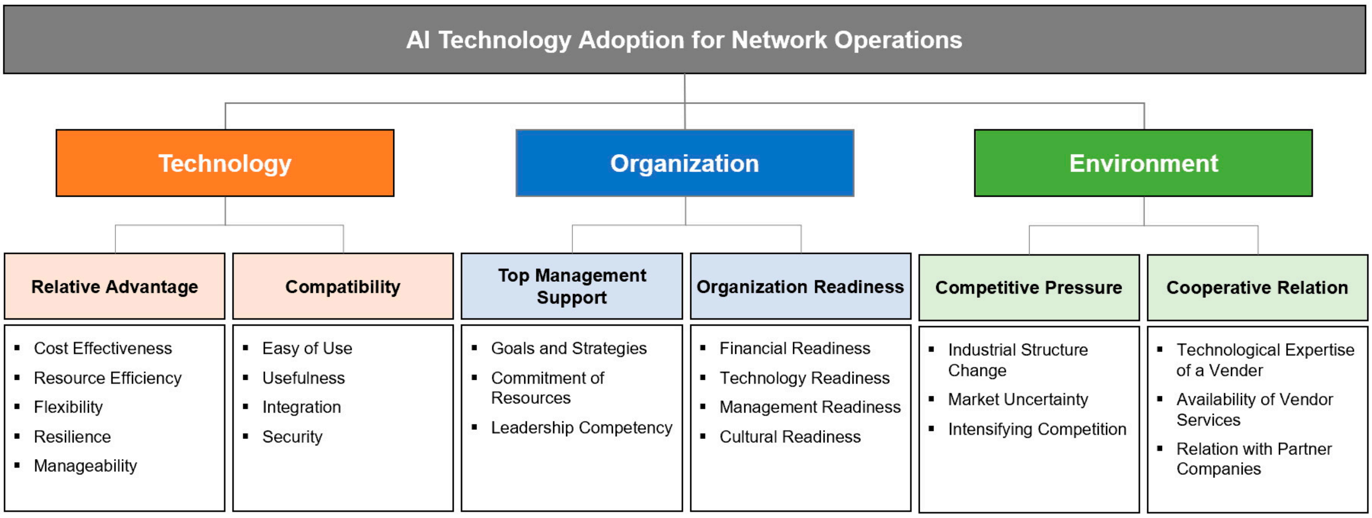

Figure 3. Research concept framework.

As described in Sections 2.2 and 2.3, the factors affecting AI technology options and AI technology adaptation in network operations were first analyzed through previous studies, and the factors of influence mentioned in related previous studies were derived. All factors verified in previous studies and the Delphi technique regarding AI technology adoption for network operations were considered in this study as options for study model factors and attributes and included as factors and attributes of the framework. Finally, in total, 22 attributes, 6 factors, and 3 areas were verified (see Figure 3, Table 2). 'Relative advantage' factors of technology were cost-effectiveness, resource efficiency, flexibility, resilience, and manageability. 'Compatibility' factors were ease of use, usefulness, integration, and security. 'Top management support' factors were goals and strategies, commitment of resources, and leadership competency. 'Organizational readiness' factors were financial readiness, technology readiness, management readiness, and culture readiness. 'Competitive pressure' factors were industrial structure change, market uncertainty, and intensifying competition. 'Cooperative relation' factors were the technological expertise of a vendor, availability of vendor services, and relation with partner companies.

Table 2. Evaluation factors and definition.

Evaluation Area	Evaluation Factors	Evaluation Attributes	Operational Definition	Reference
Technology	Relative advantage	Cost-effectiveness	Cost advantage of AI technology adoption for network operations	(Matt et al. 2015; Raisch and Krakowski 2021; Helo and Hao 2022)
		Resource efficiency	Efficient utilization of network resources and performance optimization	(Raisch and Krakowski 2021; Helo and Hao 2022)
		Flexibility	Adopting AI technology within network operations to respond quickly to business changes and new needs	(Matt et al. 2015; Chen et al. 2021)
		Resilience	Using AI technology for quick recovery and normal operation in case of failure and service disruption	(Mata et al. 2018; Raisch and Krakowski 2021; Helo and Hao 2022; Al Hleewa and Al Mubarak 2023)
		Manageability	Convenience in operation and maintenance	(Matt et al. 2015; Helo and Hao 2022; Coronado et al. 2022; Al Hleewa and Al Mubarak 2023)
	Compatibility	Ease of use	Use and operation convenience of AI technology	(Matt et al. 2015; Mithas et al. 2022; Coronado et al. 2022; Spring et al. 2022)
		Usefulness	Practical value of AI technology adoption for network operations	(Radhakrishnan and Chattopadhyay 2020; Stenberg and Nilsson 2020; Chen et al. 2021; Spring et al. 2022; Al Hleewa and Al Mubarak 2023)
		Integration	Connectivity and compatibility with existing network components and already adopted technologies	(Raisch and Krakowski 2021; Duman and Eliiyi 2021; Solaimani and Swaak 2023; Dhamija and Bag 2020)
		Security	Security concerns about AI technology in large-scale connection and data processing	(Stenberg and Nilsson 2020; Spring et al. 2022)

Table 2. *Cont.*

Evaluation Area	Evaluation Factors	Evaluation Attributes	Operational Definition	Reference
Organization	Top management support	Goals and strategies	Clear goals and strategies to be achieved with the adoption of AI technology	(Radhakrishnan and Chattopadhyay 2020; Coronado et al. 2022; Spring et al. 2022; Wollenberg and Sakaguchi 1987)
		Commitment of resources	The top management's active internal support for resources required to adopt AI technology	(Stenberg and Nilsson 2020; Chen et al. 2021; Duman and Eliiyi 2021)
		Leadership competency	Top management's understanding and will regarding the adoption of AI technology	(Stenberg and Nilsson 2020; Radhakrishnan and Chattopadhyay 2020; Duman and Eliiyi 2021; Laut et al. 2021; Chen et al. 2021)
		Goals and strategies	Clear goals and strategies to be achieved with the adoption of AI technology	(Wollenberg and Sakaguchi 1987; Radhakrishnan and Chattopadhyay 2020; Spring et al. 2022)
	Organizational readiness	Financial readiness	Securing investment budgets and readiness for economic changes	(Wollenberg and Sakaguchi 1987; Radhakrishnan and Chattopadhyay 2020; Duman and Eliiyi 2021; Al Hleewa and Al Mubarak 2023)
		Technology readiness	The technological foundation of the enterprise and related human resources' understanding of AI technology	(Chatterjee et al. 2017; Laut et al. 2021; Chen et al. 2021)
		Management readiness	The organization's readiness for AI technology and related workforce and processes	(Matt et al. 2015; Chatterjee et al. 2017; Raisch and Krakowski 2021; Spring et al. 2022)
		Culture readiness	Corporate openness to changes and preparation for acceptance of new values	(Stenberg and Nilsson 2020; Radhakrishnan and Chattopadhyay 2020; Laut et al. 2021; Al Hleewa and Al Mubarak 2023)

Table 2. *Cont.*

Evaluation Area	Evaluation Factors	Evaluation Attributes	Operational Definition	Reference
Environment	Competitive pressure	Industrial structure change	Necessity of structural change and adaptation to the industry that the enterprise belongs to	(Chang et al. 2008; Laut et al. 2021; Duman and Eliiyi 2021)
		Market uncertainty	Necessity of proper response to the instability and unpredictability of the competitive market	(Stenberg and Nilsson 2020; Chen et al. 2021; Laut et al. 2021)
		Intensifying competition	The necessity to secure a competitive edge in the relatively intensifying competition circumstances	(Chatterjee et al. 2017; Chen et al. 2021; Al Hleewa and Al Mubarak 2023)
	Cooperative relation	Technological expertise of a vendor	Technological professionalism of the AI technology supplier	(Duan et al. 2019; Raisch and Krakowski 2021; Chen et al. 2021)
		Availability of vendor services	Service availability of the AI technology supplier	(Duan et al. 2019; Raisch and Krakowski 2021; Chen et al. 2021)
		Relation with partner companies	Relation with the technology supplier or its entrusted operator	(Stenberg and Nilsson 2020; Chen et al. 2021)

3.2. Delphi Method

A Delphi analysis was conducted to confirm the validity of the derived factors and the constructed framework based on the main influencing factors derived from previous studies and to receive additional suggestions for factors that affect decision-making. The in-depth interview progressed for two weeks in July 2023 with the five experts, including directors of global network companies, managers of financial groups, and team leaders of cloud service providers (see Table 3).

Table 3. In-depth interviewers of the Delphi technique.

Section	Industry	Title	Ages	Experience	Expertise
A	High-tech	Senior Managing Director	50s	26	Network operations strategy
B	High-tech	Team Manager	50s	28	AI training and cloud
C	Telecommunication	Team Manager	50s	26	Network automation and optimization
D	Manufacturing	Team Manager	50s	24	Network analytics and prediction
E	Finance	Head Manager	50s	28	Network security and cloud

The interviewees were selected as experts with more than 20 years of experience in network-related industries or companies and who have thought about or considered making decisions about AI adopting for the network operation. In consideration of the aspects of providers and demanders, we considered experts in network solution provision and experts in companies receiving AI-based network solutions and selected major experts in cloud and platform services related to network business. Accordingly, various industries and business groups were considered, and interviewees were selected so that the influencing factors of AI introduction for the network operation of the company could be proposed by considering the factors of the company from an enterprise perspective, targeting the person in charge of strategy, marketing, and personnel organization departments other than technical experts.

The in-depth interview was conducted as a process of receiving three points. Based on the first previous study, it was confirmed from an expert's point of view whether the major influencing factors considered in the introduction of AI technology in network operation were valid. Second, it was checked whether there were any factors that could cause conceptual confusion or overlapping factors. Third, factors considered for the actual introduction of AI technology other than the factors presented were presented. As a result, many sub-attributes of the technology's relative advantage factors were integrated into the manageability attribute, and government regulatory factors with little impact on network operation were excluded from the final stage. In addition, 'management readiness', 'cultural readiness', and 'leadership competency' factors were added through the opinions of experts.

3.3. Analytic Hierarchy Process (AHP)

This study attempted to derive major influencing factors to consider in adopting AI technology for network operation management and to suggest major decision-making strategy directions to consider in order to derive successful implications. Decision-Tree Methodology is used to analyze decision-making in uncertain situations through the commercial relationship between goals and situations in decision-making. The Analytical Network Process (ANP) aims to form a network structure in a form that considers feedback, and the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) induces rational choices by considering the best and worst simultaneously. However, in this study, the AHP was selected to compare and analyze factors with independence between classes and factors through a scale within a limited range because it aims to form a strategic basis for AI adopting management activities through decision-making based on estimation of the most importance among various consideration factors.

The AHP analysis method used in this study is the hierarchical decision-making analysis method developed by Saaty (1972). While decision-making based on ordinary strategic analysis methods may be more scientific and objective, its use has limitations if the comparison scale is different or nonexistent. The above-stated method was designed to overcome this problem. The AHP analysis method supports a systematic hierarchical decision-making process by simultaneously analyzing quantitative and qualitative data of importance and priority with the ratio scales and digitizing the relative information of major affecting factors for comparison.

The AHP analysis method evaluates the relative importance through a pairwise comparison to determine the decision-making hierarchy among key factors derived from survey participants' expertise, experience, and intuition. The AHP analysis method is helpful in various areas that require decision-making in consideration of multiple attributes, particularly regarding factors and priorities of decision-making related to planning, resource allocation, and prediction (Saaty 1990). The AHP method is also an effective method of study in social sciences. It is utilized for decision-making processes for general business management and studies on diversified information systems (Saaty 2008; Ngai 2003).

In pairwise comparison, the AHP method applies weights on the contribution of upper-level elements on a 9-point scale. Thus, n alternatives for each paired standard are analyzed with the $n(n-1)/$two formula. The pairwise comparison matrix A takes a reverse form with the following square as the basis:

$$A = \begin{bmatrix} 1\ w_1/\ w_2\ \cdots\ w_1/\ w_2 \\ \\ w_1/\ w_2\ 1\ \cdots\ w_1/\ w_2 \\ \\ \vdots\ \vdots\ 1\ \vdots \\ w_1/\ w_2\ w_1/\ w_2\ \ \cdots\ 1 \end{bmatrix}$$

Weights were then calculated, followed by the normalization process to evaluate the relative importance. To calculate the relative importance, the geometric average was calculated along with each line of the matrix and then normalized. H_j indicates the geometric average of the j line of Matrix A.

$$H_j = \left(\prod_{i=1}^{n} a_{ji}\right)^{1/n} = \sqrt[n]{a_{j1}a_{j2}\ldots a_{jn}}$$

Among n factors, the weight for normalization of k factors is W_k, calculated as below:

$$the\ W_k = H_k \Big/ \textstyle\sum_{i=1}^{n} H_{i,}$$

The layer model was configured based on the derived factors. The relative importance was determined based on the geometrical mean of each factor. The consistency index (CI) and consistency ratio (CR), calculated to secure the consistency of survey answers, were presented as a basis for reliability and validity.

$$\mathrm{CI} = \frac{\lambda\mathrm{max}-n}{n-1}\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \times 100(\%)$$

3.4. Data Collection and Research Validity and Reliability

This study was conducted according to the Delphi–AHP research method and process suggested by Udo (2000). In addition, in order to secure the validity and reliability of the study, the study was conducted in consideration of structural validity, internal validity, external validity, and reliability, which are the qualitative research design measurement factors suggested by Creswell and Miller (2000). In order to secure reliability, factors were derived through publicly trusted journal thesis data, and the interview results were complemented and applied. In order to obtain compositional validity, interviews were conducted with a group of experienced experts, and objectivity was confirmed through experts on the composition of frames and factors for research. In addition, the TOE model, which presents an organizational perspective, was used among the technology acceptance models to secure internal validity.

This study used a pairwise comparison method and a consistency analysis to ensure the reliability and validity of the analysis results since all variable comparisons may not be completely consistent. In particular, in order to provide the validity of the analysis results, the consistency of the analysis results was verified through the consistency index and the consistency ratio. Based on the principles proposed by Udo (2000), the criterion was applied that the results were sufficiently consistent when the consistency ratio was less than or equal to 0.1, and the validity of systematic analysis and analysis results can be obtained based on these principles.

The AHP questionnaire was prepared to analyze factor weights based on the designed model. The survey was conducted for 5 weeks, from July to August 2023. Participants in the survey for analysis data collection included Microsoft, VMware, ServiceNow, NVIDIA, Cisco Systems, Inc., Red Hat, Amazon Web Service, etc., which are global enterprises leading the market in each area based on the source technology of AI. These were classified as the provider group. The demander group included enterprises in Korea that adopted or considered adopting AI technology to their network operations to secure a competitive edge in businesses, including Korean companies like SK Telecom, KT, LG+, POSCO, Hana Tour, Kyobo Life Group, and Toss Bank. The survey was conducted among sales, planning, strategy, and operation experts, including executives, team heads, and committee members at these enterprises who were directly or indirectly related to network operations and AI technology.

The survey was conducted in a one-on-one interview through a video conference app. A detailed guideline was provided so that respondents could accurately understand the background and key factors of this survey in advance. For the comparative analysis of the provider group and demander group, it was expected that 15 copies from each group would be collected, and 31 copies in total were collected. Except for 1 copy with inconsistent answers, the other 30 copies were used to derive data and then analyzed using Microsoft Excel 2019 software. Only responses whose consistency ratio was at least 0.1 or less were analyzed to secure the reliability of survey results.

As shown in Table 4, 96.7% of the respondents were men, and 3.3% were women. A total of 63.3% were in their 50s, the largest portion, 33.3% were in their 40s, and 3.3% were in their 30s. As for work experience, 73.3%, the largest portion, had 20 to 30 years of experience, 20.0% had 10 to 20 years of experience, and 6.7% had at least 30 years of experience. Finally, the provider and demand groups accounted for 50% of the analyzed respondents.

Table 4. Demographic information.

Characters		Frequency	Ratio (%)
Gender	Male	29	96.7
	Female	1	3.3
	Total	30	100
Age	30s	1	3.3
	40s	10	33.3
	50s	19	63.3
	Total	30	100
Work Experience	10–20 years	6	20
	20–30 years	22	73.3
	Over 30 years	2	6.7
	Total	30	100
Professional Area	Demander Group	15	50
	Provider Group	15	50
	Total	30	100

4. Results

4.1. Weights and Priority of Evaluation Variables

The reliability (CR) of factors affecting the adoption of AI technology for network operations was 0.0034–0.0436, which is valid. Table 5 resents the weights and priorities of evaluation areas, factors, and attributes of the comprehensive perspectives of both demanders and providers. Regional weights are used to measure the priorities of each evaluation area, factor, and attribute. Global weights are used to comprehensively measure the priorities of all evaluation areas, factors, and characteristics in the framework.

Table 5. Weights and priority of evaluation areas.

Evaluation Areas	The Weights of Areas	
	Importance	**Priority**
Technology	0.404	2
Organization	0.493	1
Environment	0.103	3

From the perspective of network operations and AI technology experts from domestic and overseas enterprises running a business in Korea, the weight of the organization area was 0.493, the highest; the technology area (0.404) was the second highest; the environment area (0.103) was the lowest priority.

Among the evaluation factors, the weight of top management support was 0.336, the highest; organizational readiness (0.239) was the second highest priority; compatibility (0.154) was the third highest priority; relative advantage (0.107) was the fourth highest priority; competitive pressure (0.084) was the fifth highest priority; cooperative relation (0.081) was of the lowest priority.

Among 22 evaluation attributes, the highest weight of goals and strategies was 0.149; commitment of resources (0.101) was the second highest priority; leadership competency (0.087) was the third highest priority; financial readiness (0.071) was the fourth highest priority; and technology readiness (0.071) was the fifth highest priority; cooperative relation (0.009) was of the lowest priority. Specifically, top management support (0.336) and goals and strategies (0.439) in the organization area (0.493), compatibility (0.154), and security (0.315) in the technology area (0.404) and competitive pressure (0.084) and industrial structure change (0.499) in the environment area (0.103) turned out to be the most important (See Table 6, Figure 4).

Table 6. Weights and priority of evaluation factors and attributes.

Evaluation Factors	The Weights of Areas (Priority)	Evaluation Attributes	The Weights of Evaluation Factors			
	Local	**Local**	**Local ***	**Priority**	**Global ****	**Priority**
Relative advantage	0.107 (4)	Cost-effectiveness	0.203	3	0.022	18
		Resource efficiency	0.238	1	0.025	14
		Flexibility	0.156	5	0.017	21
		Resilience	0.224	2	0.024	16
		Manageability	0.178	4	0.019	20
Compatibility	0.154 (3)	Ease of use	0.174	4	0.027	13
		Usefulness	0.289	2	0.044	10
		Integration	0.223	3	0.034	12
		Security	0.315	1	0.048	7
Top management support	0.336 (1)	Goals and strategies	0.439	1	0.148	1
		Commitment of resources	0.301	2	0.101	2
		Leadership competency	0.260	3	0.087	3
		Financial readiness	0.298	1	0.071	4

Table 6. *Cont.*

Evaluation Factors	The Weights of Areas (Priority)	Evaluation Attributes	The Weights of Evaluation Factors			
	Local	Local	Local *	Priority	Global **	Priority
Organizational readiness	0.239 (2)	Technology readiness	0.296	2	0.071	5
		Management readiness	0.210	3	0.050	6
		Culture readiness	0.196	4	0.047	8
Competitive pressure	0.084 (5)	Industrial structure change	0.499	1	0.042	11
		Market uncertainty	0.273	2	0.023	17
		Intensifying competition	0.229	3	0.019	19
Cooperative relation	0.081 (6)	Technological expertise of a vendor	0.572	1	0.046	9
		Availability of vendor services	0.313	2	0.025	15
		Relation with partner companies	0.116	3	0.009	22

* Local: mean value of evaluation factors in each group of criteria. ** Global: mean value of evaluation factors in total criteria.

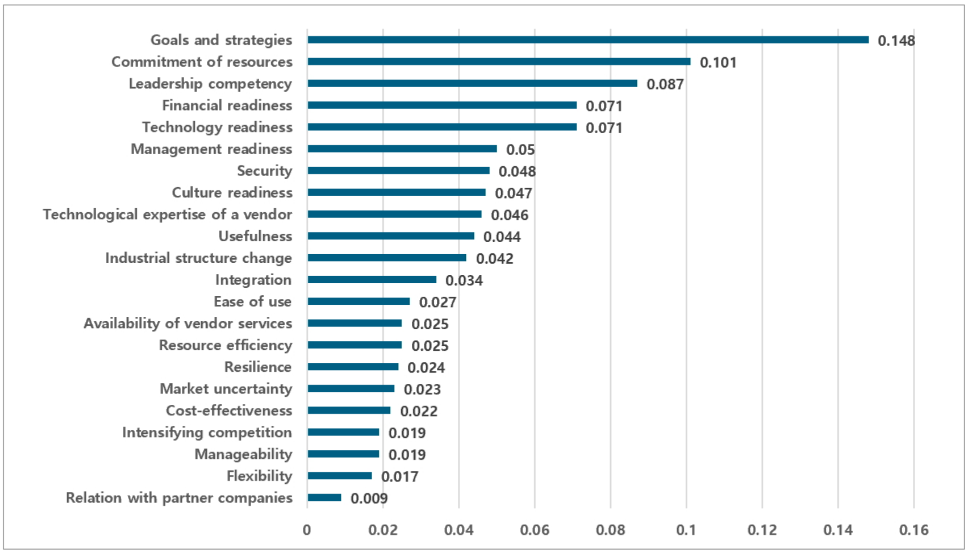

Figure 4. Weight of evaluation attributes.

4.2. Comparison of Evaluation Variables between Demander and Provider Group

Table 7 shows the results of comparing the provider group and demander group regarding the evaluation areas. In the provider group, the priority was in the order of technology (0.513), organization (0.383), and environment (0.104), while in the demander group, the priority was in the order of organization (0.607), technology (0.297), and environment (0.096). The environment area was the same rank in both groups and not the most important. In the provider group, the technology area was more important than the organization area. In contrast, the organization area was more important than the technology area in the demander group.

Table 8 compares the provider and demander groups regarding the evaluation factors. In the provider group, the priority was in the order of top management support (0.368), organizational readiness (0.187), compatibility (0.180), relative advantage (0.100), and cooperative relation (0.095). In contrast, the priority in the demander group was in the order of organizational readiness (0.299), top management support (0.296), compatibility (0.129, 3rd), relative advantage (0.111), competitive pressure (0.098), and cooperative relation (0.067).

Table 7. Comparison analysis result on evaluation areas.

Evaluation Areas	The Weights of Areas			
	Demander Group		Provider Group	
	Importance	Priority	Importance	Priority
Technology	0.297	2	0.513	1
Organization	0.607	1	0.383	2
Environment	0.096	3	0.104	3

Table 8. Comparison analysis result on evaluation areas.

Evaluation Factors	The Weights of Areas			
	Demander Group		Provider Group	
	Importance	Priority	Importance	Priority
Relative advantage	0.111	4	0.100	4
Compatibility	0.129	3	0.180	3
Top management support	0.296	2	0.368	1
Organizational readiness	0.299	1	0.187	2
Competitive pressure	0.098	5	0.070	6
Cooperative relation	0.067	6	0.095	5

In the provider group, top management support was the most critical, and organizational readiness was the second most important. In the demander group, organizational readiness was more important than top management support. Compatibility and relative advantage were the same priorities in the third and the fourth groups. Competitive pressure was the lowest priority in the provider group, while cooperative relation was the lowest in the demander group.

4.3. Comparison of Evaluation Attributes between Demander and Provider Group

As shown in Table 9 and Figure 5, 22 evaluation attributes of the two groups were comparatively analyzed, specifically regarding adopting AI technology for network operations. As a result, it was verified that goals and strategies were the highest priority in both groups, while the relationship with partner companies was the lowest priority. As the top five evaluation attributes of the two groups were compared, those of the provider group were in the order of goals and strategies (0.146), commitment of resources (0.116), leadership competency (0.106), security (0.067), and technology readiness (0.065). Those of the demander group were in the order of goals and strategies (0.142), financial readiness (0.111), commitment of resources (0.085), technology readiness (0.071), and leadership competency (0.069).

Table 9. Comparison analysis result on evaluation attributes.

Evaluation Factors	The Weights of Evaluation Factors				Priority of Factors (by Global)	
	Local		Global			
	Provider Group	Stakeholder Group	Provider Group	Stakeholder Group	Provider Group	Stakeholder Group
Cost-effectiveness	0.252	0.160	0.028	0.016	13	19
Resource efficiency	0.214	0.256	0.024	0.026	17	15
Flexibility	0.161	0.146	0.018	0.015	20	21

Table 9. *Cont.*

Evaluation Factors	The Weights of Evaluation Factors				Priority of Factors (by Global)	
	Local		Global			
	Provider Group	Stakeholder Group	Provider Group	Stakeholder Group	Provider Group	Stakeholder Group
Resilience	0.229	0.216	0.025	0.022	16	17
Manageability	0.143	0.222	0.016	0.022	21	16
Ease of use	0.203	0.146	0.026	0.026	14	14
Usefulness	0.347	0.234	0.045	0.042	8	10
Integration	0.198	0.247	0.025	0.045	15	7
Security	0.253	0.372	0.033	0.067	11	4
Goals and strategies	0.480	0.396	0.142	0.146	1	1
Commitment of resources	0.286	0.316	0.085	0.116	3	2
Leadership competency	0.234	0.288	0.069	0.106	5	3
Financial readiness	0.372	0.236	0.111	0.044	2	8
Technology readiness	0.239	0.350	0.071	0.065	4	5
Management readiness	0.187	0.228	0.056	0.043	7	9
Culture readiness	0.202	0.186	0.060	0.035	6	12
Industrial structure change	0.451	0.543	0.044	0.038	9	11
Market uncertainty	0.311	0.239	0.031	0.017	12	18
Intensifying competition	0.238	0.218	0.023	0.015	18	20
Partner companies' technological expertise	0.585	0.555	0.040	0.053	10	6
Availability of vendor services	0.280	0.346	0.019	0.033	19	13

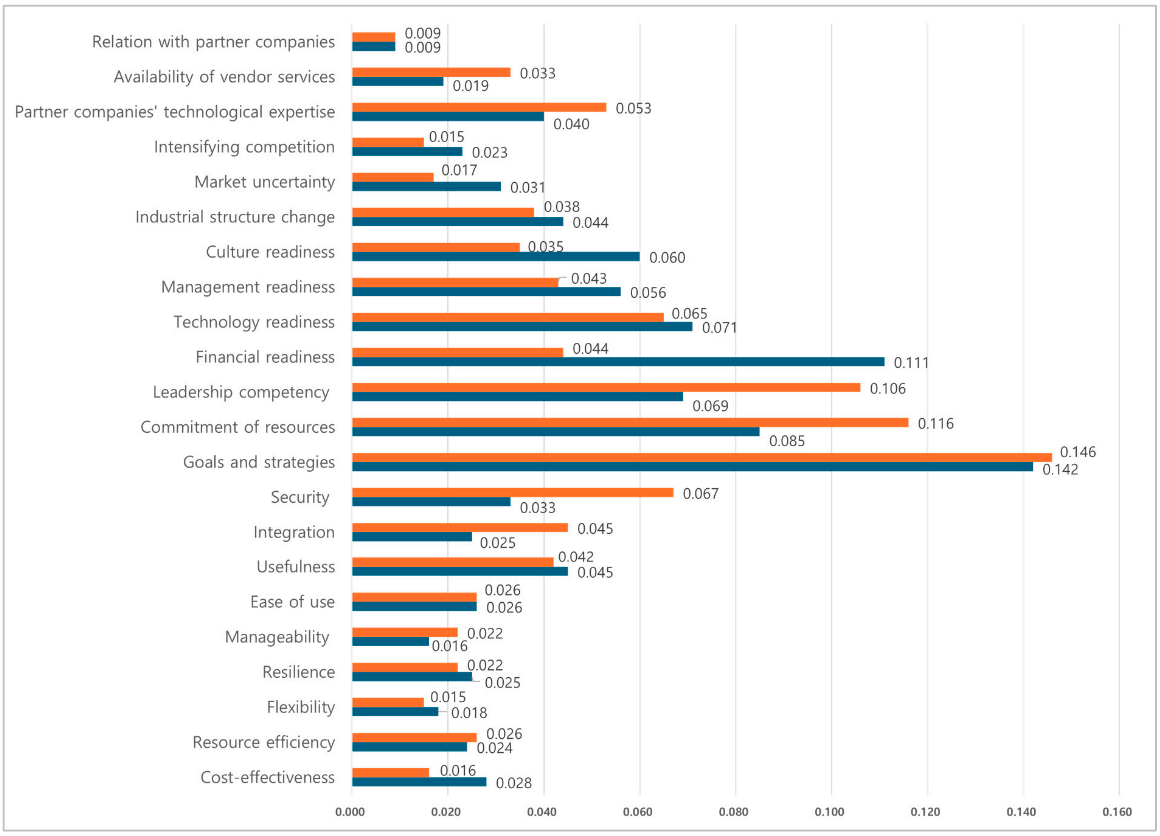

Figure 5. Weight comparison of evaluation attributes.

As the lowest 5 evaluation attributes of the two groups were compared, those of the provider group were in the reverse order of the relation with partner companies (0.009), flexibility (0.015), intensifying competition (0.015), cost-effectiveness (0.016), and market uncertainty (0.017). Those of the demander group were in the reverse order of the relation with partner companies (0.009), manageability (0.016), flexibility (0.018), availability of vendor services (0.019), and intensifying competition (0.023).

5. Discussion

This study identifies the 22 attributes from previous AI-related studies based on the TOE framework of technology, organization, and environment. In summary of the study findings, it was verified that top management support is the most critical factor in an organization. The importance of attributes was in the order of goals and strategies, commitment of resources, and leadership competency. Among technological factors, compatibility turned out to be the most important. The importance of attributes was in the order of security, usefulness, integration, and ease of use. Among environmental factors regarded as least important, competitive pressure was the most important. The importance of attributes was in the order of industrial structure change, market uncertainty, and intensifying competition.

Based on the research results, first, it was found that the introduction of AI into network operations has a greater impact on organizational factors than technical and environmental factors. As Andenmatten (2019) mentioned, the relative competitiveness of technology and environmental aspects is also important, but in the end, organizational strategies and readiness of organizations that introduce AI are also important factors in introducing AI technologies into network operations. In particular, environmental factors were identified as the lowest influencing factors in this study. As Cheng et al. (2023) pointed out, the introduction of AI technology into digital transformation activities of general companies is highly influenced by legal regulations or market environments.

However, the results of this study show different results from the introduction of these general digital technologies. This difference is linked to the characteristics of the network operation market. Currently, unlike cloud, communication, and software, there are no clear regulations on the introduction of artificial intelligence technology for network operation. Therefore, artificial intelligence technology for network operation tends to be centered on internal decision-making within the company. In the end, since the impact on government or external regulations is low, it was confirmed that this phenomenon still appears in the research results. In addition, the introduction of artificial intelligence technology for network operation is still in its infancy and is partially taking place in the area of observability related to network monitoring.

The adoption of AI technology is in the form of purchasing vendor products or self-development using verified artificial intelligence algorithms. Therefore, in this environment, discussions such as market competition and introduction differentiation strategies have not yet been strengthened. It also was confirmed that the adoption of AI technology in network operation in this situation is more closely related to changes in the internal system of a company than external environmental factors or technical characteristics. Hence, these results suggest that when adopting AI in network operations, strategic approaches need to be considered with more consideration of the organization's internal factors than external ones.

Second, the demander group of companies that adopted AI emphasized the technical factors, while the supplier group of AI technology providers emphasized the technical factors. This result confirmed that the providers of AI technology push for AI adoption by focusing on network operation performance and AI technology performance compared to the consumer group. As Jäntti and Cater-Steel (2017) mentioned, these results are the same as the argument that in the case of the expert group that promotes the introduction of AI technology, the technology introduction strategy focuses on the differentiation and performance of the technology and the usability of the technology for safe introduction. In contrast, the suppliers group emphasized the organizational efficiency of AI adoption for existing processes and systems when considering the organization's business and general management operations.

As Pumplun et al. (2019) and Angerschmid et al. (2022) argued, it was confirmed that the introduction of AI to organizational managers who are not technology experts is also a subject of sensitive technological acceptance, but when it comes to the introduction strategy, decisions are made from business and organizational perspectives. After all, differences between technology developers and organizational managers are inevitable when it comes to the perspective of technology adoption. Technology developers consider technology performance and top-tier system operations. At the same time, organizational managers focus on the general aspects of organizational operations related to budget and anticipate organizational changes after technology adoption. Therefore, this research result shows that cooperation and communication between these two groups are essential for the successful adoption and smooth adoption of AI technology for network operations.

Third, it verified that 'support of top management' and 'organizational readiness' are the most important factors among the core factors. Above all, it has been confirmed that the adoption of AI technology for network operation also requires the will and active support of management for the introduction of new digital technologies. As Davenport and Ronanki (2018) pointed out, no matter how good the technology is, it will fail to introduce the organization unless management's interest and active support are provided. The introduction of network operation artificial intelligence technology requires financial investment following the introduction of new technologies, and the will of the top decision-making body, the management, is important because it leads to important decisions such as the transformation of work processes according to corporate organizational changes.

Moreover, implementing and operating an intelligent network means an organizational change beyond a change in the work system. In the end, these changes in the enterprise-wide system are greatly influenced by the capabilities and willingness of members to accept new technologies. Introducing an intelligent network requires sufficient training and prior knowledge for members as existing work methods or processes are systematically matched and reorganized, and new operational methods are introduced through automation. Even if there is a new technology, if a new AI-based network operation method and system are not established within the organization, the inefficiency of work promotion increases, so internalization of the organization, not technology, and user consideration may be paramount.

There are previous studies on the adoption of AI technology for actual network operations that take into account which technology and how to introduce it, focusing on technical issues. However, this study clearly shows that adopting AI technology for network operation in companies should not simply be a matter of technology, but management issues within the organization linked to organizational innovation and change should be emphasized, which can emphasize the differentiation of the study. Moreover, network operation is not an issue at the level of an expert or team that manages the network but rather an issue of culture and communication about the leadership of the top decision maker and technological resistance within the organization, which is a matter of concern.

6. Conclusions

6.1. Implications

With the recent development of digital IT technology, real-time data sharing and hyper-connected socialization are rapidly developing. In particular, with the change in AI technology, companies are building systems and network operation methods based on digital transformation, and based on this, they are creating new businesses and industries. Accordingly, the introduction of AI technology in network operation is recognized as an inevitable management activity of a company, and for this purpose, strategic and clear decision-making and specific methods are required. In this background, the study emphasizes the necessity of transitioning into an intelligent network and the importance of networks based on analyzing factors related to AI adoption for network operations.

The above research results support the following significance. First, network operation is established as an essential strategy for a company's organizational system and management operation. However, the digitization of network operations in a digital technology environment needs to be carried out correctly based on AI and digital technologies. As network-based corporate businesses increase, network failures and operators' mistakes related to security threats from outside cause financial losses to the company and ruin its corporate image. For this reason, companies that operate large-scale networks for various businesses, such as security networks, office networks, plant networks, and overseas networks, recognize the importance of network operations and actively consider introducing AI. Therefore, companies preparing to introduce AI for intelligent network operations must have a clear understanding of digital technologies and artificial intelligence technologies to be introduced and be able to design clear technology strategies and technology operations through professional partners or experts. Moreover, since network operation affects the entire company's work, not just one part of the business, it is necessary to establish a thorough operation plan for risk management, such as security and disability, in consideration of this. Accordingly, not only artificial intelligence technology but also all-round technology management for related infrastructure and technologies such as security, cloud, and computer networks should be combined.

Second, it was confirmed that the most important factor when AI is adopted into the network operation is the support of the top management. Goals and strategies, willingness to resource, and leadership competencies represent the leadership capabilities and commitments of top management. It acts as a lubricant for the efficiency and productivity of AI-based network operations. The network supports various business activities of the enterprise. For this reason, the goals and strategies established by the management team are essential for the change and management of the organization after the introduction of AI, that is, the paradigm of operation. These changes require the maximum support and dedication of resources. In this process, the management team should give sufficient authority to the organizations and employees in charge of adopting AI and build a reward system that transcends interests between organizations so that the efficiency and productivity of network operations can lead to business performance. In addition, the management should exercise its leadership capabilities based on the correct understanding and continuous interest in AI to preserve the driving force of introducing AI. In the end, we can consider that the digital leadership of the management team can also affect the adoption of AI technology in the network operation.

Third, the adoption of AI for network operations relies more heavily on inherent technical and organizational factors than on environmental factors. In general, AI adoption begins mainly because of changes in industrial structure, market uncertainty, or intensifying market competition. However, when it comes to network operations, IT-related tasks such as troubleshooting and prevention support companies behind the scenes. Therefore, technology adoption is implemented to induce changes in the organization within the enterprise. Therefore, it is necessary to raise awareness about the necessity of adopting AI for network operations and promote internal coordination and cooperation for the compatibility and usefulness of the organization and compatibility with existing systems. Because changes in network operations require approaches to changes and growth in internal organizations rather than market and product competitiveness, experts who support the adoption of AI technology for network operations should understand these characteristics when leading related projects. After all, it is necessary to approach the new changes by taking into account the resistance to change that members of a company have or the connectivity to systems and work processes linked to organizational culture.

Fourth, protecting from threats caused by damage, leakage, and misuse of data or networks is called security. All stakeholders involved in data require that their data be secured. Data collected in network operations can contain sensitive information. Personal information protection may be threatened if such data are accessed and leaked without permission. In addition, there can be damage, such as stealing important information or paralyzing the system due to malicious cyber attacks. This directly affects the stability and reliability of network operations. The rapid development of information and communication technology has brought security vulnerabilities as well as significant benefits to corporate businesses. Due to frequent cyber threats from unauthorized access to data infringement, the importance of improving security vulnerabilities and systematic response within companies is growing. The role of artificial intelligence in cybersecurity, such as anomaly detection, threat prediction, and automatic response, should be noted, and the introduction of security vulnerability management strategies applied with artificial intelligence technology and the automation of security vulnerability management tasks such as checking vulnerabilities should be considered. As a strategy to alleviate these security concerns, it is necessary to recommend the establishment and implementation of strong policies and procedures for data security and network protection. In addition, sensitive data must be encrypted and protected. In addition, in order to strengthen cybersecurity by establishing surveillance and intrusion detection systems and, above all, to comply with regulations and laws such as GDPR and HIPAA, compliance processes should be established and compliance should be strengthened within the organization.

6.2. Research Limitations and Future Plans

This study is significant in that it handles issues regarding network operations and AI adoption not only from a technological perspective but also from environmental and organizational perspectives. It also suggests ways for a successful adoption. However, this study has the following research limitations: first, the survey was conducted among experts only in Korea about network operations and AI within an organization. Also, the expert's age was not considered, and young executive groups can be classified differently by the characteristics of the IT industry. Thus, this study has limitations in generalizing its findings. Future studies must present more generalized findings by surveying experts from different continents and countries. In addition, the prospective research needs to deliver results of various comparative analyses on AI adoption for network operations among global enterprises of other industries, businesses, and scales so that the findings can be a basis for adoption strategies in reflection of specific business needs.

Moreover, this study uses the AHP analysis method to define domains, key factors, and attributes and analyze their weights and priorities. However, AHP is a research methodology that is heavily influenced by individual subjects and finds the objectivity of the results by subjective comparison and weighting. Therefore, it cannot be said that the importance of the derived factors has been verified with empirical effects. In future research, it is necessary to empirically perform factor analysis through objective data collection and causal relationship of whether factors affect actual success factors. In addition, research on the behavior of AI technology in network operations can be conducted by applying various management scientific techniques that can be approached in more dynamic and systemic thinking, such as game modeling methods and system dynamics.

Finally, a complementary relationship in terms of network technology connecting distributed artificial intelligence and artificial intelligence technology for stable network operation has recently been developed. In particular, the development and convergence of innovative technologies such as quantum computing, edge computing, and blockchain, along with the softwareization of networks, are expected to accelerate the development of two technologies, network and artificial intelligence, in a hyperconnected society. Due to the development of these innovative technologies, companies will face many challenges, such as preparing new strategies, acquiring technologies, and investing, but with strong artificial intelligence and related technologies, we can expect a shift in the paradigm of next-generation network operation that enables zero-touch service and self-healing based on network visibility and insight, and in this respect, research can be considered.

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