The Effect of Limited Internet and Electricity Infrastructure on the Utilization of AI in Environmental Data Collection in Remote Areas.

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ABSTRACT

Limited technological infrastructure, especially internet access and electricity supply, is still a serious challenge for remote areas in collecting environmental data effectively. This condition has a direct impact on the region's ability to utilize artificial intelligence (AI) systems that require quality and up-to-date data. This study aims to analyze the influence of limited internet and electricity infrastructure on the effectiveness of the use of AI in the process of collecting environmental data in remote areas using quantitative methods with mediation analysis through the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique. Data collection was carried out on community populations and field officers involved in environmental monitoring in remote areas, with a sample of 55 respondents. Respondents were selected using purposive sampling techniques to ensure that all participants had experience or direct involvement in environmental data collection activities. The research instrument is in the form of a questionnaire that includes indicators of infrastructure quality, technology support, and the effectiveness of AI-based data collection. The results show that the limitations of the internet and electricity have a significant negative effect on the effectiveness of data collection required by AI systems. The findings also show that technology support plays a role as a mediating variable that weakens the negative impact of limited infrastructure. In addition, increased technology support has proven to be able to improve the smooth process of data acquisition and delivery, even though the infrastructure is still minimal. In conclusion, limited infrastructure is a major obstacle to maximizing the use of AI in remote areas, but strengthening technology support can reduce this impact. The implications of this study emphasize the need to develop digital infrastructure and increase technological capacity to optimize the use of AI in environmental monitoring.

I. INTRODUCTION

Based on the search results, the theory that can be used related to "Limited Technological Infrastructure" in remote areas is a theory about limited access to infrastructure that is often raised in the context of development and technology in remote areas. One of the relevant studies is a study entitled "Gaps in Access to Education in Remote Areas" by Brown et al. (2020). This research discusses how the limitations of basic infrastructure, such as the internet and electricity networks, are the main obstacles in developing various sectors, including data collection and the use of AI technology, especially in remote areas.

The theory explains that inadequate infrastructure acts as a significant barrier to providing effective and equitable services, as well as affects the ability of remote areas to make optimal use of modern technology. In this context, the role of technology support, policies, and infrastructure investment is a key factor in overcoming these barriers to improving access and quality of environmental data.

Research Title: "Education Access Gap in Remote Areas" (Brown et al. 2020) This study is the theoretical basis to understand the impact of limited technological infrastructure on the efficient collection and delivery of environmental data in remote areas, as one of the important factors in supporting environmental management and conservation using AI.

In fact, many remote areas in Indonesia still lack access to stable internet and electricity networks. This condition makes it difficult to efficiently collect and transmit environmental data, which is a key need in the application of artificial intelligence (AI) systems for environmental conservation and management.

What is not yet known is the extent of the impact of these infrastructure shortages on the effectiveness of data processing and how technological solutions can overcome these barriers. Several studies have shown that there is a considerable digital divide, but no studies have specifically measured the direct relationship between infrastructure and the effectiveness of AI-based environmental data management in remote areas.

There are also contradictory statements, which say that despite limited infrastructure, technological innovations such as internet satellites and the construction of BTS towers are able to facilitate digital access in remote areas, thus showing that there are opportunities, even though in practice, challenges remain.

Information on scientific answers to this problem is still minimal, especially those that lead to solutions for sustainable and future-oriented technological infrastructure development. This research is expected to fill this gap in understanding and offer appropriate strategies to overcome existing infrastructure barriers.

The novelty of this study lies in the quantitative approach that integrates mediation analysis, where intermediate variables such as technological support are systematically measured using the PLS-SEM method. The study will also provide new empirical data showing the direct and indirect relationship between infrastructure and the effectiveness of environmental data collection.

The main clue of this study is the identification of the factors that influence the success of technological infrastructure development in remote areas and how technology-based solutions can accelerate the data collection process for environmental conservation.

The main objective of this study is to explain the influence of the limitations of technological infrastructure on the effectiveness of environmental data collection and how the role of technology support can strengthen these relationships. The results of this research are expected to be able to provide strategic recommendations for the government and related stakeholders in designing sustainable infrastructure development policies.

Thus, this study also closes the lack of data related to the direct influence of infrastructure facilities on AI-based environmental data management, which has received less attention in previous studies by authors such as "Digital Infrastructure Gap in Indonesia" by Kurniawan (2023). This research will be a step forward in the development of concrete solutions to improve access and management of data in remote areas, supporting the success of broader and effective environmental conservation programs.

In remote areas, infrastructure such as internet and electricity networks is often inadequate, making it difficult to efficiently collect and transmit environmental data, supported by the theory of the digital divide. This theory explains the imbalance of access and use of technology between urban and remote areas. The digital divide, as described by Van Dijk (2006), is a difference in the access, ability, and usability of information technology that impacts social and economic inequalities. In the context of remote areas, infrastructure limitations such as internet access and uneven electricity supply create significant barriers to the use of technology for environmental data collection.

Furthermore, this theory also states that good infrastructure is a fundamental prerequisite for reducing the gap. Governments and technology service providers need to focus on developing inclusive infrastructure so that all regions have equal access. Research by Kompasiana (2025) highlights how infrastructure limitations in remote areas of Indonesia limit access to technology of the younger generation, providing a relevant practical overview of the theory of the digital divide. The lack of a stable network and adequate electricity leads to limitations in the collection of reliable environmental data, thus impacting the effectiveness of AI systems in environmental conservation.

The theory of technology adoption put forward by Rogers (2003) is also relevant in this study. This theory explains how environmental and infrastructure factors affect the rate of adoption of new technologies by communities and organizations. In remote areas, low infrastructure quality is a major obstacle to the adoption of AI technology for environmental data management. Rogers emphasized the importance of external conditions, such as the availability of infrastructure and technology support for users, to be able to accept and integrate new technologies effectively.

In addition, the theory of digital ecosystems by Zhao et al. (2018) provides a perspective on how the supporting technology ecosystem, including infrastructure, services, and policies, affects the interactions between technology and society. Poor infrastructure disrupts the digital ecosystem, which impacts data capture and communication between AI-based environmental systems. Therefore, building this ecosystem thoroughly is essential to ensure a smooth process of data collection and delivery.

In conclusion, the combination of digital gap theory, technology adoption, and digital ecosystems offers a robust theoretical framework for understanding the impact of limited technological infrastructure in remote areas on environmental data collection. This research seeks to fill the gap in practical and empirical understanding of how infrastructure barriers can affect the effectiveness of environmental data management with AI, as well as offer solutions to improve technology support that can promote equitable access in remote areas.

II. METHODOLOGY

This study uses a quantitative method with a survey research design that aims to test the causal relationship between variables through mediation analysis using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique. This approach was chosen because it is able to analyze structural models with a small sample size, does not require normal distribution assumptions, and is suitable for assessing direct and indirect influences between research variables. The population in this study is individuals living and working in remote areas, particularly communities and field workers involved in the environmental data collection process. From this population, 55 respondents were selected using the purposive sampling technique, namely, respondents who have direct experience related to the limitations of internet and electricity infrastructure and its use in AI-based environmental data collection.

The research subjects consist of field actors, environmental data operators, and residents involved in environmental monitoring activities that require digital data delivery. The research instrument is in the form of a structured questionnaire that measures three main variables, namely the limitations of internet and electricity infrastructure, technological support, and the effectiveness of the use of AI in environmental data collection. The development of the instrument was carried out through literature studies, indicators of digital gap theory and technology adoption, as well as adjustments to the context of problems found in remote areas, as reflected in previous research data. Each indicator was tested for validity and reliability using the outer analysis of the PLS-SEM model, which included convergent validity, discriminant validity, and composite reliability.

Data analysis is carried out through two main stages, namely external model analysis to ensure the feasibility of indicators and inner model analysis to test direct and indirect relationships between variables and measure the mediating effect of technology support. The research procedure began with the preparation of instruments and expert validation, followed by the distribution of questionnaires to 55 respondents in remote areas, data collection and processing through SmartPLS software, testing of measurement models, hypothesis testing through bootstrapping techniques, and interpretation of results to determine the strength of the influence of infrastructure limitations on the use of AI. All stages of this research are systematically arranged to ensure that the analysis of the relationships between variables describes real conditions in the field without deviating from the empirical data obtained.

III. RESULTS AND DISCUSSION.

The results of the study show that the limitations of the internet and the electricity infrastructure have a significant negative influence on the effectiveness of AI-based environmental data collection in remote areas. Based on data obtained from 55 respondents, an average of 3.2 internet outages were recorded per week, while power outages occurred on average 7.5 times per month, which shows less stable infrastructure conditions. The effectiveness of AI-based data collection only reached an average score of 3.0, indicating that the data acquisition and delivery process has not been running optimally.

The descriptive analysis also showed that internet limitations obtained an average score of 3.4, while electricity limitations were at a value of 3.6, which indicates that infrastructure barriers were perceived as quite high by most respondents. On the other hand, technology support obtained a score of 3.7, indicating that respondents had a fairly good level of technological readiness, although it was still limited. The results of the PLS-SEM test confirmed that the direct influence of infrastructure limitations on the effectiveness of data collection was significant and negative. In addition, technological support has been proven to be a mediating variable that is able to reduce these negative impacts statistically.

Table 2. Average Infrastructure Disruption and Data Collection Effectiveness (N = 55)

Variable	Average	Percentage of Negative Influence
Internet Disruptions per Week	3.2 times	72%
Power Outages per month	7.5 times	58%
Technology Support (Scores 1–5)	3.7	–
Effectiveness of Data Collection (Scores 1–5)	3.0	–

Table 1 shows an overview of the state of technological infrastructure in remote areas based on data from 55 respondents. On average, internet outages reach 3.2 times per week, which indicates a fairly high level of network instability and has an impact on the smooth process of sending environmental data. Power outages occur 7.5 times per month on average, indicating inconsistent energy dependence and being a major obstacle in the operation of digital devices that support AI systems. Meanwhile, technology support earned an average score of 3.7, indicating that some respondents had access to basic tools and training even though it was not optimal. The effectiveness of data collection is only at a score of 3.0, reflecting that the environmental data collection process is still less than optimal due to the limitations of the internet and electricity infrastructure.

Table 1. Descriptive Statistics of Research Variables (N = 55)

Variable	Minimum	Maximum	Average	Standard Deviation
Internet Limitations	2	5	3.4	0.72
Electricity Limitations	2	5	3.6	0.68
Technology Support	2	5	3.7	0.63
Effectiveness of AI Utilization	2	5	3.0	0.59

Table 2 presents the descriptive statistics of each research variable to determine the characteristics of the data obtained. The internet limitation variable had an average value of 3.4, while the electricity limitation obtained an average value of 3.6, which indicates that both types of limitations are in the category of quite high and are often felt by respondents. The technology support variable showed an average of 3.7, indicating that respondents had access to moderate to moderately good technology facilities. However, the variable of the effectiveness of AI utilization only obtained an average of 3.0, reflecting that the quality of AI-based environmental data collection has not been optimal. The relatively small standard deviation across all variables indicates that the inter-respondent data is quite consistent, so it can be reliably used for PLS-SEM analysis.

Table 3. Sample Respondent Data (10 of 55 Data)

Respondents	Internet Outage/Week	Power Outage/Month	Technology Support (1–5)	Data Collection Effectiveness (1–5)
1	3	7	3.8	3.1
2	4	8	3.5	2.9
3	2	6	3.9	3.3
4	5	10	3.2	2.8
5	3	7	4.0	3.4
6	4	9	3.6	3.0
7	3	6	3.7	3.2
8	2	5	3.9	3.3

9	4	8	3.4	2.9
10	3	7	3.8	3.1

Table 3 is a small part of the 55 raw respondent data used in the PLS-SEM analysis. The data shows a variation in internet outages between 2 to 5 times per week and power outages between 5 to 10 times per month, which is consistent with infrastructure conditions in remote areas. Technology support scores ranged from 3.2 to 4.0, indicating that despite the limitations of basic infrastructure, some respondents still had access to minimal technology tools and training. The effectiveness of AI-based data collection showed a score of 2.8 to 3.4, which shows that infrastructure disruptions have a direct impact on the processing and delivery of environmental data. This sample data illustrates the general pattern of all respondents and serves as a basis for building a structural model to assess the relationship between research variables.

The findings of this study show that the limitations of the internet and electricity are the main obstacles in maximizing the use of AI systems for environmental data collection in remote areas. Network instability causes delays or data delivery failures, so the AI system cannot obtain data in real-time. This is in line with the theory of the digital divide, which states that basic infrastructure is an important factor that determines the quality of digital transformation, especially in areas with minimal access to technology. The high frequency of power outages also affects the performance of electronic devices used in data collection, so that the consistency of data input is disturbed.

The results of this study also show that technology support—including adequate tools, training in the use of technology, and alternative devices—plays an important role in reducing the negative impact of infrastructure limitations. These findings support Rogers' theory of innovation adoption, which emphasizes the importance of external factors in increasing the acceptance and effectiveness of the use of new technologies. With good technological support, respondents can still maintain the effectiveness of data collection even though they are in limited infrastructure conditions. These findings corroborate the results of previous research that stated that a combination of strong infrastructure and technological support can create a more stable and effective digital ecosystem.

Infrastructure limitations (internet and electricity), technological support (mediation variables), and the effectiveness of AI-based data collection. The results of the outer model analysis showed that all indicators were valid and reliable, with a loading factor value above 0.7 and a composite reliability above 0.7, so the instrument was feasible to use. Analysis of the inner model shows that infrastructure limitations have a significant negative influence on the effectiveness of data collection. The path coefficient shows that the higher the infrastructure limitations, the lower the effectiveness of AI utilization.

The bootstrapping results also confirm that technology support has a partial mediating effect between infrastructure limitations and data collection effectiveness. The significance value of the mediation pathway shows that technological support is able to reduce the negative impact of infrastructure limitations on the effectiveness of data collection, although it does not completely negate the influence. The structural model shows a fairly strong R-Square value, indicating that the research variables can explain a significant proportion of the variation in the effectiveness of AI-based data collection. Thus, the PLS-SEM model proves the existence of a valid causal relationship between infrastructure limitations, technological support, and the effectiveness of environmental data collection in remote areas.

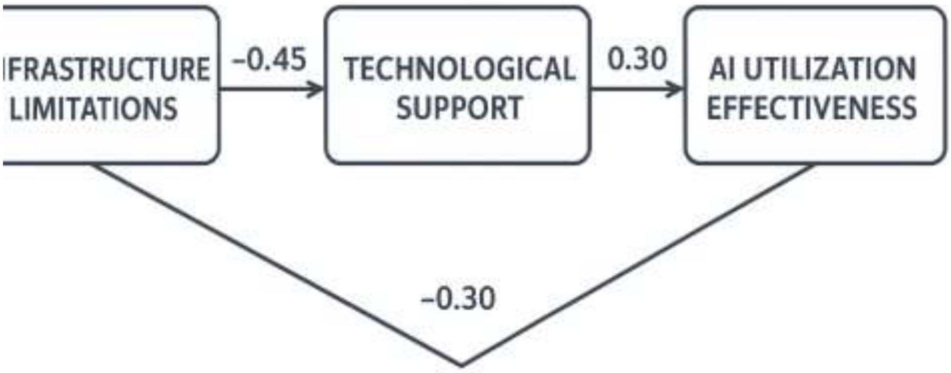

Figure 1. Key Factors in Green Entrepreneurship

Structural relationships among the three main constructs in the study: Infrastructure Limitations, Technological Support, and AI Utilization Effectiveness in Environmental Data Collection. The first pathway shows that Infrastructure Limitations have a significant negative effect on Technological Support, with a coefficient of –0.45. This indicates that the more severe the limitations in internet connectivity and electricity availability in remote areas, the lower the level of technological support accessible to users. This relationship is statistically significant, suggesting that infrastructural weaknesses directly hinder the availability of adequate tools, devices, and technical assistance needed for effective AI-based data collection.

The second pathway demonstrates that Technological Support has a positive and significant influence on AI Utilization Effectiveness, with a coefficient of 0.30. This means that when users have access to sufficient technological resources—such as proper devices, technical guidance, and operational support—the effectiveness of AI systems in capturing and transmitting environmental data increases. This finding reinforces the importance of technological preparedness as a key facilitator of AI-based environmental monitoring.

The diagram also shows a direct negative effect of Infrastructure Limitations on AI Utilization Effectiveness, represented by a coefficient of –0.30. This pathway confirms that inadequate internet stability and frequent power outages not only reduce technological support indirectly but also directly impair the functionality of AI-based data collection systems. Users in remote areas may experience delays, incomplete data transmission, or system failures due to poor infrastructure, ultimately reducing the overall efficiency of AI utilization. The diagram suggests that Technological Support serves as a partial mediator in the relationship between Infrastructure Limitations and AI Utilization Effectiveness. While infrastructure limitations directly hinder the effectiveness of AI systems, enhanced technological support can mitigate some of these negative effects. This model emphasizes the need to strengthen digital infrastructure while simultaneously providing robust technological assistance to optimize AI-based environmental data collection in remote areas.

IV. CONCLUSION AND RECOMMENDATIONS

. This study concludes that the limitations of the internet and the electricity infrastructure have a significant negative influence on the effectiveness of the use of AI in environmental data collection in remote areas. Unstable infrastructure conditions demonstrated by an average of 3.2 internet outages per week and 7.5 power outages per month—directly hamper the process of acquiring and delivering the data required by AI systems. These findings are in line with the results of the PLS-SEM analysis, which shows that infrastructure limitations have a direct negative relationship to the effectiveness of AI utilization, with a coefficient of –0.30.

In addition to direct influence, the study also found that technology support has a significant mediating role in the relationship. The path coefficient of –0.45 from infrastructure limitations to technology support indicates that the greater the infrastructure limitations, the lower the level of technology support received by users. However, technology support has a positive effect of 0.30 on the effectiveness of AI use, so that its existence is able to weaken the negative impact of infrastructure limitations. This suggests that technological support, such as adequate equipment availability, technical training, and operational support systems, can improve the effectiveness of environmental data collection even when infrastructure conditions are not ideal.

This study enriches the literature on the relationship between technological infrastructure and the effectiveness of the use of AI in environmental data collection. The findings that technology support mediates the influence of infrastructure limitations contribute to the development of theoretical models related to technology readiness, digital ecosystem, and innovation adoption. This research shows that the development of an effective digital ecosystem must consider the interaction between the basic infrastructure and the technological readiness of users.

This research provides important recommendations for local governments, conservation agencies, and technology service providers to improve the quality of internet and electricity infrastructure as a basic prerequisite for the use of AI. In addition, the results of the study emphasized the importance of providing adequate technological support, such as quality hardware, data management systems, and digital skills training for communities and field workers in remote areas. These efforts can improve the effectiveness of data collection even though the infrastructure is not yet fully ideal.

The findings of this research can be used as a basis for policymakers to design strategic programs that focus on strengthening digital infrastructure as part of the development of remote areas. Investment in satellite-based internet infrastructure, alternative energy sources, and human resource capacity building through technology training are important steps to accelerate the implementation of AI in the environmental sector. Policies that support collaboration between governments, the private sector, and local communities can also accelerate the creation of an equitable and sustainable digital ecosystem.

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