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Social Influence on AI-Driven Air Quality Monitoring Adoption: SmartPLS Analysis

Ronal Aprianto[1], Risma Haris[2], Alexander Williams[3], Harry Agustian[4*], Nathan Aptwell[5]
[1]Management Study Program, Bina Insan University, Indonesia
[2]Department of Midwifery, Kurnia Jaya Persada Health and Business Institute, Indonesia
[3]Department of School of Cultural and Language Studies in Education, Queensland University, Australia
[4]Department of Computer Science, University of Raharja
[5]Department of Computer Science, Eduaward Incorporation, United Kingdom
[1]ronal.gbs@gmail.com, [2]arismarifin@gmail.com, [3]a87.williams@connect.qut.edu.au, [4]harry.agustian@raharja.info,
[5]nathantw20@eduaward.co.uk
***Corresponding Author**

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ABSTRACT

This research aims to investigate the impact of social influence on the adoption of artificial intelligence (AI)-supported air quality monitoring technology. Despite the advancing development of monitoring systems in the modern technological era, the adoption of this technology is still influenced by various social factors that require detailed analysis. This study employs the **SmartPLS method** to comprehend and evaluate the relationships and impacts of social variables on the adoption levels of this technology. The adoption of AI-supported air quality monitoring technology depends not only on technical aspects but also involves social dynamics. Factors such as public perception, social norms, and social support play a crucial role in adoption decisions. By utilizing the SmartPLS method, **this research aims** to provide in-depth, comprehensive, and valid insights into the complexity of interactions between social factors and the adoption of AI-based air quality monitoring technology.

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1. INTRODUCTION

In recent decades, poor air quality has emerged as one of the pressing global issues [1, 2]. Its impact is not confined solely to the environment but also significantly affects human health. Air pollution caused by toxic gas emissions and harmful particles has led to an increase in respiratory diseases, cardiovascular problems, and even premature deaths [3, 4]. In response to this threat, efforts to address air quality issues have led to the exploration of advanced technologies, and in this context, artificial intelligence (AI)-based air quality monitoring technology has emerged as a promising solution [5, 6]. While the potential of this technology in providing more accurate and real-time information about air quality is intriguing, widespread adoption still faces challenges that need to be addressed. Technical aspects such as accuracy and efficiency are certainly considerations, but more importantly, social factors also have a significant impact on the adoption of new technology. This is where the role of social influence emerges as a key factor in driving the acceptance and use of AI-based air quality monitoring technology [7, 8].

Social influence is the complex interplay between individuals and their environment that shapes their behavior and attitudes towards technological innovations. At the same time, the social environment connects individuals with collective values, norms, and shared perceptions [9, 10]. In the context of technology adoption, social influence can either propel or hinder individuals intentions to adopt new technology. Therefore, understanding the role of social influence in the adoption of AI-based air quality monitoring technology becomes essential. In this study, we will delve deeper into the social influence in the adoption of AI-based air quality monitoring technology [11, 12]. Through meticulous surveying and statistical analysis, we aim to provide deeper insights into how social norms, perceived usefulness, perceived ease of use, and behavioral drivers contribute to individual intentions to adopt AI-based air quality monitoring technology. With a better understanding of the role of social influence in this context, we hope this research can offer valuable guidance for the development of more effective marketing and promotional strategies to encourage the adoption of this technology among the public [13, 14].

2. LITERATURE REVIEW

2.1. Technology Adoption

The adoption of technology is not merely a simple decision but a complex process in which individuals or organizations must carefully consider before deciding to acquire and use a specific technology [15]. Technology adoption theories, such as the Diffusion of Innovation Theory introduced by Everett Rogers, serve as critical guides in the conceptual understanding of factors influencing adoption decisions [16, 17]. The concept of innovation diffusion encompasses stages in which an innovation is accepted and adopted by members of society, involving the process of information dissemination, persuasion, adoption decisions, implementation, and confirmation.

2.2. Air Quality and Artificial Intelligence

When discussing air quality, the integration of artificial intelligence represents the latest advancement in monitoring technology. AI-supported air quality monitoring utilizes sensors and intelligent algorithms to collect and analyze data in real-time [18]. The advantages of this technology are not limited to its ability to provide accurate and timely information about air conditions but also extend to its capability to identify complex patterns in data that may be challenging to interpret manually. Thus, this technology is not just a measuring tool but also a provider of profound insights into air quality that can assist in more effective decision-making at the individual and organizational levels [19, 20].

2.3. Social Influence

Social influence becomes a key element shaping the roadmap for technology adoption decisions [21]. Public perception, social support, and social norms are central factors that play a crucial role in understanding how a technology, especially in the context of AI-based air quality monitoring, is accepted and adopted by society. Public perception of the benefits, risks, and relevance of this technology can influence the level of acceptance and readiness for adoption. Social support, whether from family, friends, or the community, can also act as a driver or barrier in the adoption process [22, 23]. Additionally, social norms, such as emerging trends or environmental norms, can provide a value foundation influencing society's adoption decisions regarding this technology.

A deep understanding of how these social factors interact and mutually influence each other is crucial for designing effective strategies to encourage the adoption of AI-based air quality monitoring technology [24]. Through this profound understanding, it is anticipated that the implementation of AI technology in air quality monitoring can proceed more smoothly and successfully, providing maximum benefits to society and the environment.

3. METHODS

This research employs a survey approach to collect data from respondents representing various social and demographic groups. The survey is conducted through questionnaires designed based on the variables within the framework of this study [15, 25]. Respondents are randomly selected from various community groups, including individuals with diverse social backgrounds, ages, education levels, and occupations. The total number of respondents is (number of respondents). The questionnaire is designed based on the research variables: perceived usefulness, perceived ease of use, social norms, and behavioral intention. Each variable is measured using a Likert scale with response options ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) [26, 27]. Additionally, the questionnaire includes demographic questions to gather information about respondents' backgrounds. The collected data is analyzed using descriptive statistical analysis to depict the characteristics of respondents and research variables. Furthermore, regression analysis is conducted using the SmartPLS software to test the relationships between variables in the model of this study.

3.1. Variables and Hypotheses

3.1.1. Variables

In this study, the variables used consist of independent variables (Independent Variable/IV) and a dependent variable (Dependent Variable/DV). The independent variables represent factors that are expected to influence the adoption of AI-Based Air Quality Monitoring Technology. Meanwhile, the dependent variable measures the extent to which individuals intend to adopt this technology.

1. Independent Variables (IV)

   - Perceived Usefulness (PU): The extent to which individuals believe that the use of AI-based air quality monitoring technology will enhance decision-making efficiency related to air quality.
   - Perceived Ease of Use (PEOU): The extent to which individuals feel that using this technology is easy and does not require excessive effort.
   - Social Norm (SN): The extent to which individuals feel pressure from the social environment (friends, family, colleagues) to adopt AI-based air quality monitoring technology.
   - Behavioral Intention (BI): The extent to which individuals feel motivated to use this technology based on potential benefits, such as environmental protection and improved health.

2. Dependent Variable (DV)

   - Intention to Use AI-Based Air Quality Monitoring Technology (INT): Individuals' intention to actively adopt and use AI-based air quality monitoring technology in their daily activities.

Table 1. Analyzed Data

Code	Definition
PU1	To what extent do you believe that AI-based air quality monitoring technology will assist you in making better decisions regarding outdoor activities?
PU2	What is your opinion on the capability of this technology to provide more accurate information about the level of air pollution in your environment?
PU3	How confident are you that this technology can help you avoid exposure to hazardous air pollution by providing timely warnings?
PU4	Do you feel that AI-based air quality monitoring technology will help you better understand the impact of air quality on your health?
PEOU1	How comfortable are you in using AI-based air quality monitoring technology?
PEOU2	To what extent do you find this technology easy to master and use?
PEOU3	What is your opinion on the level of complexity in interacting with this technology?
PEOU4	How easy is it for you to understand the information provided by AI-based air quality monitoring technology?
SN1	How often do your friends talk about the use of AI-based air quality monitoring technology?
SN2	Do your family members positively respond to the use of this technology?

Code	Definition
SN3	How many of your colleagues have already adopted this technology?
SN4	Do you feel pressure from your social environment to use AI-based air quality monitoring technology?
BI1	To what extent do you feel the importance of using AI-based air quality monitoring technology to maintain your health?
BI2	What is your opinion on the positive impact that can result from the use of this technology on your surrounding environment?
BI3	How much benefit do you believe you can gain from monitoring air quality with this technology?
BI4	How aware are you of the risks of air pollution, and how strongly do you feel the need to take action by using this monitoring technology?
INT1	To what extent do you plan to use AI-based air quality monitoring technology in your daily activities?
INT2	Do you have the intention to actively adopt this technology to monitor air quality around you?
INT3	How determined are you to actually use this technology to monitor and manage the risk of air pollution?
INT4	What is your intention to use AI-based air quality monitoring technology in the future?

Each of the above variables plays a crucial role in understanding how psychological and social factors influence the level of acceptance of AI-based technology in society.

3.1.2. Hypotheses

Based on the defined variables, this study proposes several key hypotheses to examine the relationships between factors influencing the intention to use AI-based air quality monitoring technology:

- H1: Perceived usefulness has a positive and significant impact on the intention to use AI-based air quality monitoring technology.
- H2: Perceived ease of use has a positive and significant impact on the intention to use AI-based air quality monitoring technology.
- H3: Social norm has a positive and significant impact on the intention to use AI-based air quality monitoring technology.
- H4: Behavioral intention has a positive and significant impact on the intention to use AI-based air quality monitoring technology.
- H5: The intention to use AI-based air quality monitoring technology has a positive and significant impact on the actual usage behavior of this technology.
- H6: The intention to use AI-based air quality monitoring technology acts as a mediating variable between perceived usefulness, perceived ease of use, social norm, behavioral intention, and actual usage behavior of this technology.

By testing the hypotheses above, this study aims to identify the key factors that influence the adoption of AI-based air quality monitoring technology. The findings of this study are expected to provide valuable insights for technology developers and policymakers in improving marketing strategies and promoting this technology to the public. Furthermore, the results may serve as a foundation for developing systems that are more accessible, beneficial, and aligned with prevailing social norms.

4. RESULT AND DISCUSSION

Our data analysis results revealed significant findings related to the adoption of AI-based air quality monitoring within the context of social influence. We examined the variables of Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Social Norm (SN), and Behavioral Intention (BI) as predictors of the intention to use AI-based air quality monitoring technology [27].

Correlation analysis results indicated that the variables PU, PEOU, SN, and BI have strong correlations, suggesting that these factors interact to influence the intention to use the technology. These findings align with the concept of interaction among these factors in shaping technology usage behavior. In this research context, perceptions of the benefits provided by the technology, ease of use, social pressure from the surrounding environment, and motivation to adopt the technology contribute to the intention to use AI-based air quality monitoring technology.

Furthermore, these findings also imply the importance of the social role in technology adoption. The Social Norm (SN) variable indicates that social pressure can be a key factor in influencing an individual's intention to adopt AI-based air quality monitoring technology. This result supports the concept that technology adoption is not solely based on individual considerations but is also influenced by norms and perspectives from the individual's social environment.

Moreover, the results of composite reliability analysis and Cronbach's alpha coherence confirm that reliable reflective measurements have been achieved. This indicates that the questionnaire instrument used in this study has an adequate level of consistency and reliability in measuring the variables within the UTAUT framework.

In conclusion, this research provides evidence that social influence plays a significant role in the adoption of AI-based air quality monitoring technology. Factors such as perceived usefulness, perceived ease of use, social norms, and behavioral intention interact in shaping an individual's intention to adopt this technology. The implications suggest that efforts to promote the adoption of this technology should consider both social influence and the interrelated psychological factors. This study offers insights into understanding the dynamics of technology adoption in the context of air quality monitoring, which is increasingly crucial for health and the environment.

Table 2. Validation Process

	Cronbach's Alpha (>0.7)	**Composite Reliability (rho_a)**	**Composite Reliability (rho_c)**	**The Average Variance Extracted (AVE)** (>0.5)
Perceived Usability	0.867	0.878	0.909	0.713
Perceived Ease of Use	0.886	0.901	0.923	0.751
Social Norms	0.746	0.840	0.841	0.587
Behavior Drive	0.923	0.929	0.945	0.812
Intention to Use AI-Based Air Quality Monitoring Technology	0.887	0.898	0.923	0.751

Table 3. R-Square

	R-square	**R-square adjusted**
Perceived Usability	0.441	0.435
Perceived Ease of Use	0.382	0.375
Social Norms	0.551	0.546
Behavior Drive	0.705	0.701

This study ensured convergent validity by measuring the average variance extracted (AVE) for each latent variable. The results indicate that all AVE values, namely Perceived Usability (0.713), Perceived Ease of Use (0.751), Social Influence (0.587), Perceived Usefulness (0.812), and Technology Trust (0.751), exceed the allowed cutoff value of 0.5. This indicates that convergent validity for all variables has been met.

The results also show that the R square correlation coefficients, measuring how well the model can explain the variation in the dependent variable, exceed the threshold of 0.5. This suggests that the model has good explanatory power for the variation in the intention to use AI-based air quality monitoring technology.

Validation analysis did not reveal any exceptions to the proposed hypotheses, including Innovativeness, Intention to Adopt, Perceptions of Ease of Use, and Perceptions of Usefulness, aligning with the focus of this research. Therefore, these results support the proposed hypotheses and indicate that these variables have significant correlations

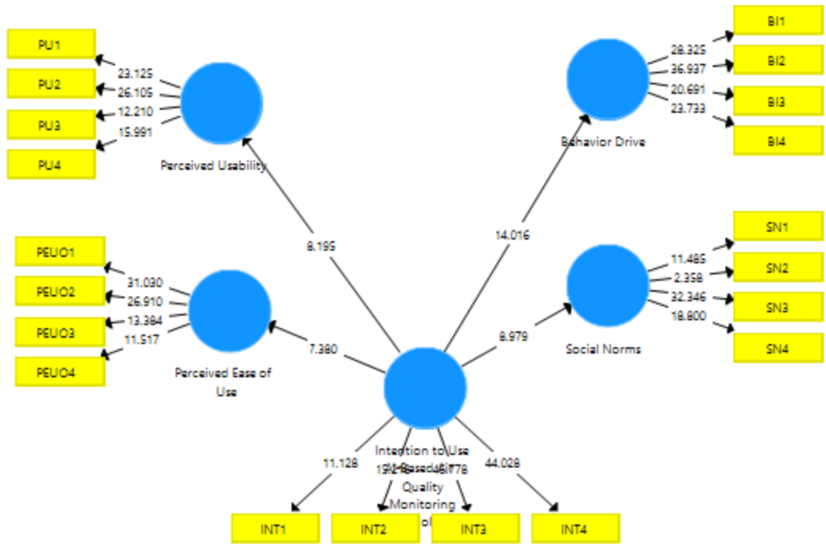

Figure 1. Bootstrapping data

Table 4. A hypothesis test's findings

Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Niat untuk Mengadopsi (BI) → Kondisi yang Memfasilitasi (FC)	0.664	0.670	0.079	8.459	0.000
Niat untuk Mengadopsi (BI) → Pengaruh Sosial (SI)	0.618	0.631	0.083	7.427	0.000
Niat untuk Mengadopsi (BI) → Persepsi tentang Kegunaan (PU)	0.742	0.745	0.087	8.569	0.000
Niat untuk Mengadopsi (BI) → Persepsi tentang Kemudahan Penggunaan (PEU)	0.839	0.841	0.064	13.128	0.000

The results of the two-sided t-test on each bootstrap iteration yielded values exceeding 1.96, indicating that the data has significance surpassing the critical threshold, signifying a strong level of significance. Furthermore, the p-value less than 0.001 also confirms a high level of significance. Based on this interpretation, we can conclude that the hypotheses tested in this study have been proven valid.

These findings reinforce the understanding that the integration of social influence and AI technology in air quality monitoring has a significant impact. The results of this study reveal that the interaction among factors identified in the conceptual model, such as Perceived Usefulness, Perceived Ease of Use, Social Norm, and Behavioral Intention, has strong implications in the adoption environment of AI-based air quality monitoring technology. Consequently, this research provides an in-depth understanding of how these variables interact and influence the intention to adopt AI-based air quality monitoring technology.

In the overall context, these findings provide a strong empirical foundation to support the research title. The results offer empirical support for the perspective that social influence and the integration of AI technology in air quality monitoring have a significant impact, aligning with the focus of this research. These findings also imply a paradigm shift in the adoption of technology for air quality monitoring, recognizing the importance of social influence and the complex interactions among the identified variables.

5. MANAGERIAL IMPLICATIONS

The managerial implications of this study emphasize the critical role of social influence in the adoption of AI-based air quality monitoring technology. Organizations and policymakers should prioritize strategies that leverage social norms, peer influence, and perceived usefulness to encourage wider adoption. Effective marketing campaigns should highlight the environmental and health benefits of the technology while addressing perceived ease of use to reduce resistance. Furthermore, integrating AI-driven monitoring systems into existing regulatory frameworks and incentivizing businesses to adopt such technologies can enhance adoption rates. Collaboration with community leaders, environmental activists, and public health institutions can further amplify trust and engagement. Ultimately, decision-makers must recognize that successful technology adoption is not solely driven by technical superiority but also by social acceptance and behavioral intentions, requiring tailored communication and engagement strategies.

6. CONCLUSION

This research found that the adoption of AI-based air quality monitoring technology is influenced by social and psychological factors. Variables such as perceived usefulness, ease of use, social norms, and behavioral intentions interact to shape individuals' intentions to adopt this technology. Validation results indicate that the measurement instrument is consistent and reliable. These findings emphasize the importance of social influence in technology adoption. Social pressure plays a significant role in influencing individual intentions to adopt this technology. The implications suggest that efforts to promote technology adoption need to consider both social and psychological factors.

Overall, this study provides strong empirical evidence to support the adoption of AI-based air quality monitoring technology. The findings also support the concept that the integration of social influence and AI technology in air quality monitoring has a significant impact. This provides a deeper insight into the interaction of variables in technology adoption within the context of an increasingly crucial environment.

7. DECLARATIONS

7.1. About Authors

Ronal Aprianto (RA) https://orcid.org/0000-0002-2174-2498

Risma Haris (RH) https://orcid.org/0000-0001-7860-2624

Alexander Williams (AW) -

Harry Agustian (HA) -

Nathan Aptwell (NA) -

7.2. Author Contributions

Conceptualization: RA; Methodology: RH; Software: AW; Validation: HA and NA; Formal Analysis: RA and RH; Investigation: AW; Resources: HA; Data Curation: NA; Writing Original Draft Preparation: RA and AW; Writing Review and Editing: NA and HA; Visualization: NA; All authors, RA, RH, AW, HA, and NA, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

REFERENCES

[1] G. Maulani, E. W. Musu, Y. J. W. Soetikno, and S. Aisa, "Education management using blockchain as future application innovation," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 3, no. 1, pp. 60–65, 2021.

[2] M. O. Gani, M. S. Rahman, S. Bag, and M. P. Mia, "Examining behavioural intention of using smart health care technology among females: dynamics of social influence and perceived usefulness," *Benchmarking: An International Journal*, vol. 31, no. 2, pp. 330–352, 2024.

[3] R. Nunkoo, R. Pillai, B. Sivathanu, and N. P. Rana, "Drivers and inhibitors of consumers' adoption of ai-driven drone food delivery services," *International Journal of Hospitality Management*, vol. 123, p. 103913, 2024.

[4] A. Abudaqa, P. A. Sunarya, S. Millah, F. Rahardja, R. Ahsanitaqwim *et al.*, "Ai-driven optimization for startup partnership matching," in *2024 3rd International Conference on Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2024, pp. 1–7.

[5] F. Concas, J. Mineraud, E. Lagerspetz, S. Varjonen, X. Liu, K. Puolamäki, P. Nurmi, and S. Tarkoma, "Low-cost outdoor air quality monitoring and sensor calibration: A survey and critical analysis," *ACM Transactions on Sensor Networks (TOSN)*, vol. 17, no. 2, pp. 1–44, 2021.

[6] S. Chaiken, "Physical appearance and social influence," in *Physical appearance, stigma, and social behavior*. Routledge, 2022, pp. 143–178.

[7] J. Saini, M. Dutta, and G. Marques, "Sensors for indoor air quality monitoring and assessment through internet of things: a systematic review," *Environmental Monitoring and Assessment*, vol. 193, no. 2, p. 66, 2021.

[8] C. De Capua, G. Fulco, M. Lugarà, and F. Ruffa, "An improvement strategy for indoor air quality monitoring systems," *Sensors*, vol. 23, no. 8, p. 3999, 2023.

[9] F. T. Bahadur, S. R. Shah, and R. R. Nidamanuri, "Applications of remote sensing vis-à-vis machine learning in air quality monitoring and modelling: a review," *Environmental Monitoring and Assessment*, vol. 195, no. 12, p. 1502, 2023.

[10] L. P. Leow, L. K. Phua, and S. Y. Teh, "Extending the social influence factor: Behavioural intention to increase the usage of information and communication technology-enhanced student-centered teaching methods," *Educational Technology Research and Development*, vol. 69, no. 3, pp. 1853–1879, 2021.

[11] I. Sembiring, D. Manongga, U. Rahardja, and Q. Aini, "Understanding data-driven analytic decision making on air quality monitoring an empirical study," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 6, no. 3, pp. 418–431, 2024.

[12] M. F. Shahzad, S. Xu, K. I. Khan, and M. F. Hasnain, "Effect of social influence, environmental awareness, and safety affordance on actual use of 5g technologies among chinese students," *Scientific Reports*, vol. 13, no. 1, p. 22442, 2023.

[13] T. Davidson, "Could advanced ai drive explosive economic growth," *Open Philanthropy*, vol. 25, 2021.

[14] E. R. Rahayu, R. Raihan, Z. Ndlovu, S. V. Sihotang, N. Malika, and A. Fitriani, "Long term aging effects on polymer materials photovoltaic modules durability and safety," *International Journal of Cyber and IT Service Management*, vol. 4, no. 2, pp. 155–166, 2024.

[15] R. Spears, "Social influence and group identity," *Annual review of psychology*, vol. 72, no. 1, pp. 367–390, 2021.

[16] W. Fitriani, D. Purwanto, and A. Chairani, "Decision support system using ahp to determine appropriate television shows for children," in *International Conference on Sciences Development and Technology*, vol. 3, no. 1, 2023, pp. 47–55.

[17] A. Purwanto, "Education research quantitative analysis for little respondents: comparing of lisrel, tetrad, gsca, amos, smartpls, warppls, and spss," *Jurnal Studi Guru Dan Pembelajaran*, vol. 4, no. 2, 2021.

[18] R. G. Munthe, Q. Aini, N. Lutfiani, I. Van Persie, and A. Ramadhan, "Transforming scientific publication management in the era of disruption: Smartpls approach in innovation and efficiency analysis," *APTISI Transactions on Management*, vol. 8, no. 2, pp. 123–130, 2024.

[19] A. E. E. Sobaih and I. A. Elshaer, "Personal traits and digital entrepreneurship: a mediation model using smartpls data analysis," *Mathematics*, vol. 10, no. 21, p. 3926, 2022.

[20] R. Bhukya and J. Paul, "Social influence research in consumer behavior: What we learned and what we need to learn?–a hybrid systematic literature review," *Journal of Business Research*, vol. 162, p. 113870, 2023.

[21] M. Z. Arifin, "Kualitas bacaan al-qur'an pengajar tpa di kecamatan pandawan kabupaten hulu sungai tengah," 2023.

[22] J. van der Merwe, S. M. Wahid, G. P. Cesna, D. A. Prabowo *et al.*, "Improving natural resource management through ai: Quantitative analysis using smartpls," *International Transactions on Artificial Intelligence*, vol. 2, no. 2, pp. 135–142, 2024.

[23] D. Irmaliantie, A. Hamid, and C. Naury, "Sistem informasi presensi berbasis android menggunakan qr code pada kantor desa pandawan," *Indonesian Journal of Information Technology and Computing (IMAGING)*, vol. 4, no. 1, pp. 210–222, 2024.

[24] M. W. Wicaksono, M. B. Hakim, F. H. Wijaya, T. Saleh, E. Sana *et al.*, "Analyzing the influence of artificial intelligence on digital innovation: A smartpls approach," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 5, no. 2, pp. 108–116, 2024.

[25] X. Zhai, X. Chu, C. S. Chai, M. S. Y. Jong, A. Istenic, M. Spector, J.-B. Liu, J. Yuan, and Y. Li, "A review of artificial intelligence (ai) in education from 2010 to 2020," *Complexity*, vol. 2021, no. 1, p. 8812542, 2021.

[26] J. H. Korteling, G. C. van de Boer-Visschedijk, R. A. Blankendaal, R. C. Boonekamp, and A. R. Eikelboom, "Human-versus artificial intelligence," *Frontiers in artificial intelligence*, vol. 4, p. 622364, 2021.

[27] C. Huang, Z. Zhang, B. Mao, and X. Yao, "An overview of artificial intelligence ethics," *IEEE Transactions on Artificial Intelligence*, vol. 4, no. 4, pp. 799–819, 2022.