An International Journal Tourism and Community Review

E-ISSN: 3048-0698
P-ISSN: 3048-121X

Research Article

Improving Digital Literacy and Indonesian Language for the Indonesian Community in Malaysia

Enik Rahayu[1]*, Hendrajaya [2], C. Susmono Widagdo [3], Henry Yuliamir [4], Nicolas Kevin Sulityawardhana [5], Anisa Eka Khatarina [6]

[1] Sekolah Tinggi Ilmu Ekonomi Pariwisata Indonesia, Jl. Lamongan Tengah No.2, Bendan Ngisor, Kec. Gajahmungkur, Kota Semarang, Jawa Tengah 50233, Indonesia; email: enikrahayu@stiepari.ac.id
[2] Sekolah Tinggi Ilmu Ekonomi Pariwisata Indonesia, Jl. Lamongan Tengah No.2, Bendan Ngisor, Kec. Gajahmungkur, Kota Semarang, Jawa Tengah 50233, Indonesia; email: hendrajaya@stiepari.ac.id
[3] Sekolah Tinggi Ilmu Ekonomi Pariwisata Indonesia, Jl. Lamongan Tengah No.2, Bendan Ngisor, Kec. Gajahmungkur, Kota Semarang, Jawa Tengah 50233, Indonesia; email: susmonowidagdo@stiepari.ac.id
[4] Sekolah Tinggi Ilmu Ekonomi Pariwisata Indonesia, Jl. Lamongan Tengah No.2, Bendan Ngisor, Kec. Gajahmungkur, Kota Semarang, Jawa Tengah 50233, Indonesia; email:; henry.yuliamir@stiepari.ac.id
[5,6] Sekolah Tinggi Ilmu Ekonomi Pariwisata Indonesia, Jl. Lamongan Tengah No.2, Bendan Ngisor, Kec. Gajahmungkur, Kota Semarang, Jawa Tengah 50233, Indonesia
* Corresponding Author: enikrahayu@stiepari.ac.id

Abstract: This study focuses on improving digital literacy and formal Indonesian language proficiency among the Indonesian diaspora community in Kampung Baru, Kuala Lumpur, Malaysia. The community faces challenges in adapting to digital technology and maintaining linguistic and cultural identity, which limits their socio-economic participation and engagement in community activities. The objective of this research is to develop and implement a community-based program that enhances digital skills while promoting national language usage and cultural preservation. The program employed a participatory and interactive approach, including workshops, hands-on practice, mentoring, role-play, and storytelling, targeting 30 participants comprising youth, MSME actors, teachers, village officials, and housewives. Pre-test and post-test evaluations, direct observation, and interviews were used to assess the impact of the program. The results show significant improvements in digital literacy, with participants demonstrating enhanced skills in e-mail usage, document sharing, e-wallet applications, and digital security awareness, with post-test gains ranging from 40% to 45%. Likewise, proficiency in formal Indonesian language, public speaking, and cultural knowledge increased by 25% to 28%, reflecting both technical and cultural skill development. The findings indicate that community-based, participatory learning integrated with cultural reinforcement effectively bridges the digital divide and strengthens linguistic identity among diaspora communities. The study concludes that such a hybrid model not only empowers participants in digital and linguistic capacities but also promotes cultural sustainability and social cohesion, offering a scalable and replicable framework for similar communities.

Keywords: Capacity Building; Community-Based Learning; Cultural Preservation; Diaspora Community; Digital Literacy.

Received: August 19, 2025;
Revised: September 03, 2025;
Accepted: September 17, 2025;
Published: September 19, 2025
Current Version: September 19, 2025

1. Introduction

Artificial Intelligence (AI) has emerged as one of the most transformative technologies of the twenty-first century, with applications spanning healthcare, education, finance, transportation, and manufacturing (Smith, J., & Zhang, 2020); (Zhang, Y., & Li, 2022). Within this broad domain, the object of this research focuses on the integration of AI-driven decision-making models with human-centered systems to enhance efficiency, adaptability, and transparency in complex environments. The rapid advancements in machine learning (ML), deep learning (DL), and natural language processing (NLP) have accelerated the deployment of intelligent systems, yet several fundamental challenges remain in ensuring fairness, interpretability, and scalability (Goodfellow, I., Bengio, Y., & Courville, 2016); (Doshi-Velez, F., & Kim, 2017).

A number of methods have been employed in prior research to address these challenges. Traditional statistical learning methods, such as regression and clustering, offered early insights into pattern recognition and prediction but lacked the capacity to generalize to high-dimensional unstructured data (Bishop, 2006). With the rise of deep learning architectures, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) achieved significant breakthroughs in vision and language tasks (LeCun, Y., Bengio, Y., & Hinton, 2015). More recently, transformer-based architectures have revolutionized NLP and multimodal learning by enabling context-aware representation learning at scale (Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, 2017). While these methods demonstrate remarkable strengths, including accuracy and flexibility, they are often limited by high computational costs, data dependency, and a lack of interpretability (Ribeiro, M. T., Singh, S., & Guestrin, 2016).

Despite these advancements, research gaps persist. The primary problem lies in the tension between performance optimization and ethical responsibility. Current AI systems are often treated as "black boxes," making it difficult to ensure trustworthiness in critical domains such as healthcare or autonomous vehicles (Caruana, R., Lou, Y., Gehrke, J., Koch, P., Sturm, M., & Elhadad, 2015). Moreover, biases embedded in training data propagate into predictive outcomes, exacerbating issues of inequality and fairness (Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., 2021). These challenges underscore the need for frameworks that integrate both algorithmic efficiency and human-centered values.

To address these problems, this research proposes a hybrid framework that combines explainable AI (XAI) techniques with adaptive learning models. By integrating interpretability layers into deep architectures and employing reinforcement learning for adaptive decision-making, the framework aims to balance predictive accuracy with transparency. Additionally, the approach emphasizes data governance protocols to mitigate bias and ensure ethical compliance.

The contributions of this research are as follows: (1) a systematic review of existing AI methodologies with respect to fairness, interpretability, and scalability; (2) the development of a novel hybrid framework that integrates XAI and adaptive reinforcement learning; (3) empirical validation of the proposed model across multiple domains, including healthcare diagnostics and intelligent transportation; and (4) recommendations for policy and governance frameworks to guide ethical AI deployment.

The remainder of this paper is organized as follows. Section 2 reviews related work on interpretability and adaptive AI systems. Section 3 outlines the proposed framework, including its conceptual design and implementation. Section 4 presents the experimental setup and evaluation results. Section 5 discusses the implications of the findings for research and practice. Finally, Section 6 concludes the paper and highlights future directions.

2. Preliminaries or Related Work or Literature Review

The rapid development of Artificial Intelligence (AI) and its applications across various domains has encouraged scholars to examine theoretical foundations and empirical practices in order to enhance technological innovation and decision-making processes. A literature review provides a systematic understanding of the research object, existing methods, as well as their respective advantages and limitations. This section discusses the most relevant prior works, identifies research gaps, and highlights the theoretical background that supports the present study.

2.1 Subsection 1: Theoretical Foundations and Related Studies

Artificial Intelligence, particularly in the domains of machine learning, deep learning, and natural language processing (NLP), has been widely explored in both academic and industrial contexts. Previous studies such as (Smith, J., & Zhang, 2020) emphasized the role of deep neural networks in predictive analytics, while (Kumar, A., Singh, M., & Sharma, 2021) highlighted reinforcement learning as a powerful tool for adaptive decision-making. Moreover, hybrid approaches integrating machine learning with optimization models have shown promising results in improving computational efficiency (Li, J., & Chen, 2019).

Despite these advancements, several limitations remain. For instance, while deep learning achieves high accuracy, it often lacks explainability, raising issues regarding trust and interpretability (Doshi-Velez, F., & Kim, 2017). Similarly, reinforcement learning models require large datasets and high computational resources, making them less suitable for real-time or resource-constrained environments (Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., ... & Hassabis, 2018). These weaknesses illustrate the need for alternative approaches that balance performance with interpretability.

2.2 Subsection 2: Research Gaps and State-of-the-Art Approaches

Recent research has attempted to address these limitations through various methods. One direction is the incorporation of explainable AI (XAI) techniques, enabling models to provide more transparent decision-making processes (Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F., & Pedreschi, 2018). Another approach involves transfer learning and federated learning, which reduce dependency on large labeled datasets and enhance model generalizability.

However, despite these contributions, current literature shows limited exploration in integrating AI models with contextual domain knowledge. While most studies focus on algorithmic improvements, fewer have investigated holistic frameworks that combine machine learning with human-centered or knowledge-based approaches (Miller, 2019). This gap highlights the novelty and contribution of the present research, which seeks to provide a more comprehensive solution by aligning algorithmic performance with interpretability and applicability in real-world settings.

In summary, existing works have laid a strong foundation in AI research but remain constrained by issues of scalability, interpretability, and practical integration. The proposed study contributes by introducing an approach that not only leverages the computational strength of machine learning but also emphasizes contextual adaptability, thus bridging the identified gaps.

2.3 Subsection 3: Benchmark Datasets and Evaluation Metrics

In the advancement of Artificial Intelligence, the availability of benchmark datasets and standardized evaluation metrics plays a critical role in validating the effectiveness of various models. For instance, large-scale datasets such as ImageNet (Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., & Fei-Fei, 2009), GLUE for natural language understanding (Wang, A., Singh, A., Michael, J., Hill, F., Levy, O., & Bowman, 2018), and OpenAI's GPT training corpora (Brown et al., 2020) have become essential references in empirical AI research. These benchmarks allow researchers to compare models under standardized conditions, ensuring fair evaluation across different methods.

Evaluation metrics also vary depending on application domains. Accuracy, precision, recall, and F1-score remain dominant in classification tasks, while BLEU (Papineni, K., Roukos, S., Ward, T., & Zhu, 2002) and ROUGE (Lin, 2004) are commonly applied in NLP tasks. More recently, fairness, robustness, and interpretability have emerged as new dimensions of evaluation (Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., 2021), reflecting the growing societal demand for trustworthy AI.

Nevertheless, benchmark reliance has been criticized for overfitting research toward optimizing performance on limited datasets, potentially reducing the generalizability of AI models in diverse real-world environments (Recht, B., Roelofs, R., Schmidt, L., & Shankar, 2019). This emphasizes the importance of moving beyond benchmark-centric evaluation toward more holistic, context-aware assessments.

2.4 Subsection 4: Comparative Studies and Methodological Limitations

Several comparative studies have attempted to synthesize the strengths and weaknesses of different AI methods. For instance, (Zhang, X., Liu, H., & Wang, 2020) conducted a meta-analysis of deep learning models for medical imaging, concluding that although accuracy improved significantly, interpretability and robustness remained problematic. Similarly, (Johnson, M., & Patel, 2021) compared reinforcement learning with heuristic-based approaches, showing that while reinforcement learning outperformed in dynamic environments, heuristic approaches maintained higher stability in resource-limited conditions.

A recurring methodological limitation lies in the lack of integration between data-driven and knowledge-driven paradigms. Data-driven approaches excel in pattern recognition but are often criticized for being "black boxes." On the other hand, symbolic or knowledge-driven methods provide transparency but may lack adaptability to large-scale, unstructured data (Marcus, 2020). Current research efforts have not yet fully reconciled these two paradigms, creating an important research opportunity.

2.5 Emerging Trends and Open Challenges

The continuous evolution of Artificial Intelligence has given rise to several emerging trends that are reshaping both theoretical research and practical applications. One of the most prominent trends is generative AI, particularly through large language models (LLMs) such as GPT and BERT-based architectures, which have demonstrated remarkable performance in natural language understanding, content generation, and conversational systems (Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., ... & Amodei, 2020). These advancements highlight the potential of AI to move beyond predictive tasks toward creative and generative capabilities.

Another growing trend is the integration of multimodal learning, where models simultaneously process diverse data types such as text, images, audio, and sensor inputs. This approach allows for richer representations and more context-aware decision-making, making AI systems more aligned with real-world complexities (Baltrušaitis, T., Ahuja, C., & Morency, 2019). Similarly, the rise of federated and decentralized learning reflects the increasing demand for privacy-preserving AI, where computation occurs locally without sharing sensitive data, addressing concerns related to data security and regulatory compliance (Kairouz, P., McMahan, H. B., Avent, B., Bellet, A., Bennis, M., Bhagoji, A. N., ... & Zhao, 2021).

Despite these advancements, several open challenges remain unresolved. First, the ethical and societal implications of AI, including bias, fairness, and accountability, continue to be pressing issues (Floridi, L., & Cowls, 2019). Second, the trade-off between accuracy and explainability is still a major barrier for adopting AI in high-stakes domains such as healthcare, law, and finance. Third, the computational and environmental cost of training large-scale models poses sustainability concerns that demand more efficient architectures and algorithms (Strubell et al., 2019). Finally, the integration of domain-specific knowledge into general-purpose AI systems remains underexplored, leaving gaps in applicability across specialized industries.

These trends and challenges underscore the necessity for research that not only advances technical performance but also ensures interpretability, ethical alignment, and sustainable implementation.

2.6 Summary

This literature review highlights the dynamic progress of Artificial Intelligence research across machine learning, deep learning, reinforcement learning, and explainable AI. While previous studies have contributed significantly to algorithmic innovations and practical applications, persistent challenges such as scalability, interpretability, and integration with contextual knowledge remain unresolved. Emerging trends including generative AI, multimodal learning, and federated learning illustrate promising directions, but they also raise new questions regarding ethics, sustainability, and fairness.

In light of these developments, the present study positions itself within the ongoing discourse by bridging algorithmic strength with contextual adaptability and human-centered approaches. By addressing both technical and practical gaps, this research aims to contribute not only to the performance of AI systems but also to their trustworthiness, interpretability, and real-world applicability.

3. Proposed Method

3.1. Location and Participants

This community service program was conducted in Kampung Baru, Kuala Lumpur, Malaysia. The participants consisted of number of participants 30 local community members, including youth, MSME actors, teachers, village officials, and housewives. Participants were selected using purposive sampling based on their involvement in social activities and their need for capacity building in digital literacy and local entrepreneurship.

3.2. Program Stages

The implementation of the community service program was carried out in several stages: (a) Preparation, Coordination with local partners such as the Village Development and Security Committee (JKKK) and local government representatives, Identification of community needs through preliminary interviews, short surveys, and focus group discussions, Development of training modules based on the identified needs, such as digital literacy, online marketing strategies, and community-based entrepreneurship. (b) Implementation, Training activities were conducted in the form of workshops, hands-on practice, and interactive discussions, The learning method applied included interactive lectures, demonstrations, independent practice, and individual mentoring, Participants engaged in real case simulations, such as strategies for marketing MSME products through social media and e-commerce platforms. (c) Assistance and Monitoring, After the training, intensive mentoring was provided for 1–2 months through field visits and online communication, Periodic monitoring was conducted to assess the application of new skills in the participants' daily activities, d. Evaluation.

Evaluation was carried out using pre-tests and post-tests to measure the improvement of participants' knowledge. Direct observations and in-depth interviews were conducted to assess changes in attitudes, skills, and the sustainability of practices introduced during the program.

3.3. Evaluation Techniques

The success of the program was measured using the following indicators: (a) Quantitative: improvement in the average score between pre-test and post-test results. (b) Qualitative: participants' level of engagement, ability to apply newly acquired skills, participant satisfaction, and the perceived social impact on the community.

3.4. Program Sustainability of Program Success

To ensure the sustainability of the program outcomes, a community learning group was established as a forum for sharing knowledge and experiences. Skilled participants were appointed as local coordinators, supported by the JKKK and university partners, so that the activities could be continued independently and sustainably.

4. Results and Discussion

This section presents the results of the community service program conducted with the Indonesian diaspora community in Johor Bahru, Malaysia. The analysis covers program implementation in two main areas: digital literacy and language and cultural preservation. Data were collected through pre-test and post-test, observation, and participant interviews. Results are presented in tables and figures, followed by analysis and discussion.

4.1. Results of Digital Literacy Training

The digital literacy training involved 30 participants with diverse educational and occupational backgrounds. Pre-test results showed that the majority of participants had limited knowledge of basic digital tools such as e-mail, Google Docs, and e-wallet applications. After attending the workshops and mentoring sessions, participants demonstrated a significant improvement in skills and confidence in applying digital technology in daily life.

Table 1. Pre-Test and Post-Test Results of Digital Literacy Training.

Indicator	Pre-Test (%)	Post-Test (%)	Improvement (%)
Ability to use e-mail	45	85	+40
Google Docs (document sharing)	35	78	+43
E-wallet usage	40	82	+42
Digital security awareness	30	75	+45

Table 1 shows that digital literacy significantly improved across all indicators after the training. The improvement aligns with the hypothesis that practical, hands-on training supported by mentoring can accelerate digital skills acquisition among non-productive economic groups. This finding is consistent with (Warschauer, 2006), who emphasized that contextual learning reduces the digital divide.

4.2. Results of Indonesian Language and Cultural Preservation

Language training activities focused on formal Indonesian usage, including letter/email writing, public speaking, and storytelling of Indonesian folklore.

Table 2. Assessment of Language Proficiency.

Skill Area	Initial Score (Average/100)	Final Score (Average/100)	Improvement
Formal writing (letters, email)	55	80	+25
Public speaking	50	78	+28
Cultural knowledge (folklore)	60	85	+25

Table 2 shows that participants gained competence in both linguistic and cultural domains after the training. The interactive learning methods such as role-play, discussion, and storytelling contributed to higher engagement levels. The increase in average scores indicates that community-based learning can effectively preserve national identity among diaspora communities (Zaim, 2018).

Figure 1. Community service activities.

4.3. Discussion

The findings demonstrate that community-based, participatory methods significantly enhanced digital literacy and formal Indonesian language proficiency among the diaspora. (1) Digital Literacy Impact: The structured modules and "digital buddy" mentoring system enabled participants to overcome technical barriers, showing that peer-assisted learning is effective for adult learners in non-formal education settings. (2) Language and Culture Impact: The incorporation of cultural elements (folklore, songs, and role-play) increased motivation and reduced participants' anxiety in formal communication. This finding is in line with (Raharjo, 2021), who found that peer learning strategies strengthen diaspora communities' engagement. (3) Sustainability Aspects: The creation of community learning groups and continued WhatsApp mentoring ensures knowledge sustainability, echoing (Chan et al., 2016) recommendation for integrating digital literacy with lifelong learning frameworks.

Overall, the results confirm the initial assumption that strengthening digital literacy and linguistic identity can empower diaspora communities to be more adaptive in both social and cultural contexts.

5. Comparison

Comparison with state-of-the-art approaches highlights the contribution and distinctiveness of this community service program. Previous studies on digital literacy initiatives (Warschauer, 2006); (Naiborhu & Susanti, 2021) have largely focused on formal education systems or government-led national programs. These models are often structured, standardized, and resource-intensive, which can limit accessibility for marginalized or diaspora communities. In contrast, the present program adopts a community-based and participatory model, emphasizing contextualized learning, peer mentoring, and cultural preservation.

Compared to conventional digital literacy interventions that primarily address technical skill acquisition (e.g., computer usage, online communication, or e-commerce), this program integrates language and cultural elements as part of the learning process. This dual approach not only strengthens participants' digital competencies but also fosters national identity and cultural belonging, aligning with the findings of (Zaim, 2018) on the importance of integrating cultural heritage in diaspora education.

Furthermore, while earlier works often relied solely on classroom-based training or online modules, this program incorporates mentoring, role-play, and storytelling, which proved effective in sustaining participant engagement and confidence. The significant post-test improvements in both digital literacy and formal Indonesian language proficiency demonstrate that a hybrid model combining practical training and cultural reinforcement can achieve outcomes that are comparable to, and in some aspects surpass, existing approaches.

Overall, the program contributes to the state-of-the-art by offering a scalable and sustainable model that not only reduces the digital divide but also preserves linguistic and cultural identity among Indonesian diaspora communities. This holistic approach represents a meaningful advancement compared to more narrowly focused digital literacy or language training programs.

6. Conclusions

This community service program successfully enhanced digital literacy and formal Indonesian language proficiency among the Indonesian diaspora community in Kampung Baru, Kuala Lumpur. The findings indicate significant improvements in participants' ability to use digital tools such as e-mail, Google Docs, and e-wallet applications, with average post-test increases ranging from 40% to 45%. Similarly, formal Indonesian language skills, including writing, public speaking, and cultural knowledge, showed notable improvements, demonstrating the effectiveness of participatory and culturally integrated learning methods.

The synthesis of these results confirms that a hybrid approach combining hands-on digital literacy training, mentoring, and cultural reinforcement aligns well with the research objectives. Participants not only acquired practical digital competencies but also strengthened their national identity and cultural engagement, highlighting the dual impact of technical and linguistic capacity-building. The participatory and community-based framework, supported by peer mentoring and role-play methods, proved to be effective in sustaining engagement and confidence, ensuring long-term applicability of the skills learned.

The program contributes to knowledge by presenting a scalable, context-aware model that bridges the digital divide while preserving linguistic and cultural identity, offering a meaningful advancement over conventional literacy or language programs. Limitations include the relatively small sample size and short-term evaluation period. Future research may explore larger participant groups, longer-term follow-ups, and the integration of advanced digital tools or AI-based learning platforms to further enhance digital literacy and language preservation in diaspora communities.

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