AI4Ekonomi for Economic Empowerment in Malaysia

Nor Hafiza Haron[1] , Nor Hafiza Abd Samad[2] Jihadah Ahmad[3] Nadiah Yusof[4]
Khairatul Alyani Badari[5]

[1,2,3,4,5] University Poly-Tech Malaysia, 56100 Cheras, Kuala Lumpur, Malaysia.
*Nor Hafiza Haron email: afieza@uptm.edu.my

Abstract. Poverty remains a critical challenge for low-income households (B40) in Malaysia, with traditional economic aid often being too general to address the specific needs of these families. This paper proposes an Artificial Intelligence (AI)-based recommender system designed to empower low-income households by providing tailored economic solutions. The AI4EKonomi framework leverages machine learning techniques to analyse socioeconomic data, such as household income, skills, location, and family dynamics, to generate personalized recommendations for income-generation opportunities, training programs, micro-loans, and entrepreneurship initiatives. The paper presents a conceptual model for this system, illustrating how AI can match households with relevant opportunities to improve their economic resilience. By contextualizing AI in the Malaysian socio-economic landscape, this framework aims to bridge the gap between traditional aid and data-driven, personalized support. The proposed system promises to enhance decision-making processes for policymakers and social organizations, fostering sustainable economic empowerment for disadvantaged communities. The paper also discusses the potential implications of AI adoption in the social welfare sector and highlights the challenges and opportunities of implementing such systems at the large scale.

Keywords: Recommender system, Artificial Intelligence, machine learning, challenges, socio-economic.

1 Introduction

In Malaysia, poverty and income inequality, commonly categorized under the Bottom 40% (B40) income group and remain persistent and multidimensional challenges, particularly among vulnerable demographic groups and underserved regions. Poverty is no longer understood solely as income deprivation but as a complex condition shaped by historical, structural, and socioeconomic factors that constrain individuals' ability to achieve acceptable living standards and social functioning (Küfeoğlu, 2022). These constraints manifest in economic insecurity, limited access to opportunities and systemic barriers that hinder upward social and economic mobility.

Consistent with the United Nations' multidimensional poverty framework, poverty encompasses insufficient access to education, healthcare, food security, shelter, employment opportunities, political participation and human dignity (Akma Musaddad et al., 2025). This broader conceptualization emphasizes that effective poverty alleviation requires interventions beyond short-term financial assistance. Addressing

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these deprivations is central to the United Nations Sustainable Development Goals (SDGs), particularly SDG 1 (No Poverty) and SDG 5 (Gender Equality), which collectively emphasize inclusive socioeconomic development by 2030 (Akma Musaddad et al., 2025). Despite global and national commitments, progress toward these goals remains uneven due to heterogeneous household needs and structural inequalities.

In Malaysia, government-led interventions such as the Prihatin Rakyat Economic Stimulus Package (ESP) were introduced to mitigate the socioeconomic impact of the COVID-19 pandemic on low-income populations (Kannan et al., 2021). These initiatives include cash assistance, utility subsidies, loan moratoriums, wage subsidies, and EPF/PRS withdrawals (Flanders et al., n.d.). While such programs are critical for short-term relief, they predominantly adopt a one-size-fits-all delivery model that inadequately accounts for differences in household skills, geographic context and economic potential. As a result, many beneficiaries struggle to convert temporary assistance into sustainable economic empowerment.

Parallel to these developments, advances in artificial intelligence (AI) and data analytics have transformed decision-making processes across domains such as healthcare, education, finance, and business. Recommender systems, in particular, leverage user and item attributes to generate personalized suggestions using content-based, collaborative, or hybrid approaches (Wilson et al., 2009; Fayyaz et al., 2020). However, the majority of existing recommender system applications are concentrated in commercial and consumer-oriented domains, with limited emphasis on social welfare and poverty alleviation contexts. This highlights a critical research gap in leveraging AI for inclusive and development-oriented decision support systems.

Recent studies suggest that AI-driven recommender systems and conversational agents can improve decision quality, mitigate information overload, and enhance user engagement, particularly in high-stake domains such as healthcare and public services (Ashaduzzaman & Tsai, 2025; Putra et al., 2025). Furthermore, AI-enhanced recommender systems have demonstrated improved prediction accuracy and robustness when addressing challenges such as data sparsity and cold-start conditions (Valencia-Arias et al., 2024). Nevertheless, empirical applications of such systems for household-level socioeconomic empowerment remain scarce, particularly within developing country contexts.

In response to these limitations, this paper proposes AI4EKonomi, a smart AI-based recommender system framework designed to support economic empowerment among low-income households. The framework integrates household-level attributes, including income, skills, geographic location and demographic characteristics and to generate personalized and context-aware economic recommendations. These recommendations include targeted training programs, employment pathways, micro-entrepreneurship opportunities, financial assistance schemes, and support services. Unlike conventional aid mechanisms, the system emphasizes data-driven personalization and contextualized decision-making aligned with individual household profiles and local economic ecosystems.

The objectives of this study are threefold:
(i) to conceptualize an AI-based recommender system framework tailored to the socioeconomic context of Malaysia's B40 households;
(ii) to demonstrate how AI-driven personalization can enhance the effectiveness of poverty alleviation interventions; and
(iii) to identify measurable outcomes and implementation implications for policymakers, NGOs, and social development agencies.

By bridging artificial intelligence and community development, the system contributes both theoretically and practically to the growing discourse on technology-enabled social innovation. The proposed framework establishes a foundation for future empirical validation and pilot deployment, supporting more targeted, scalable, and sustainable poverty alleviation strategies that are responsive to the diverse realities of low-income households.

2 LITERATURE REVIEW

Recent studies increasingly acknowledge the potential of AI-based recommender systems as enablers of sustainable development and social empowerment. Felfernig et al. (2023) argue that recommender systems integrating machine learning, case-based reasoning, and inclusive AI principles can contribute meaningfully to the achievement of the Sustainable Development Goals (SDGs), particularly SDG 1 (No Poverty). While this work establishes strong theoretical justification for AI-driven recommendations in development contexts, it remains largely conceptual and does not sufficiently address real-world constraints such as data quality, adoption barriers, and trust among marginalized populations.

Extending this perspective, Figueroa-Torres (2025) adopts a socio-ecological approach, emphasizing that recommender systems designed with awareness of environmental conditions, social influences, and individual needs can enhance equity-oriented outcomes. This perspective strengthens the argument for contextualized system design; however, it also reveals persistent challenges related to data reliability, ethical governance, and user acceptance particularly in low-income communities with limited digital literacy. These findings suggest that technical accuracy alone is insufficient for effective poverty alleviation interventions.

Parallel research on AI chatbots further reinforces this conclusion, Labadze et al. (2023), through a systematic review, demonstrate that chatbots can effectively support personalized learning and information delivery. Nevertheless, the study highlights critical limitations including response reliability, ethical risks, and the absence of regulatory safeguards. In community development settings, Sezgin et al. (2024) provide empirical evidence that AI chatbots such as DAPHNE can improve access to community support resources among low-income families. However, both studies converge on a key limitation: the success of chatbot-based interventions depends heavily on inclusive conversational design and sustained collaboration between technology developers and social service providers.

Studies focusing on economic empowerment provide further insights into AI's transformative potential. Khan and Bokhari (2024) demonstrate that advanced chatbots can enhance productivity and income generation among gig economy workers. While these findings indicate tangible economic benefits, they primarily reflect digitally active populations and may not generalize to households with limited technological access. Similarly, Hassan et al. (2024) show that machine learning models can predict household poverty status with high accuracy, enabling more precise targeting of financial assistance. However, these predictive models largely function as institutional decision-support tools rather than as empowerment mechanisms directly accessible to households.

Complementary evidence from rural development contexts further illustrates this distinction. Zhu et al. (2023) identify successful models of technological empowerment among rural women in China's digital economy, emphasizing skills development, platform access, and institutional support. Meanwhile, Parthiban et al. (2024) introduce the concept of "technoficing," which integrates traditional knowledge with affordable digital technologies to empower rural micro-entrepreneurs. Both studies emphasize that technological interventions are most effective when embedded within local socio-cultural ecosystems rather than implemented as standalone technical solutions.

Large-scale empirical evidence also supports the role of AI in improving aid targeting. Aiken et al. (2022) demonstrate that AI models leveraging mobile phone data can identify impoverished populations more accurately than conventional methods. Despite these gains, such approaches raise ethical concerns related to data privacy, transparency, and informed consent, particularly when applied to vulnerable communities.

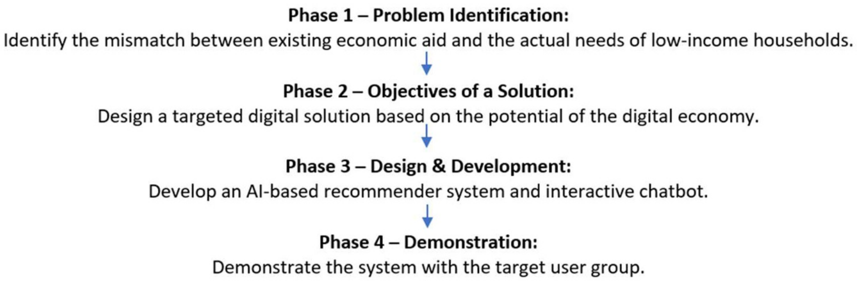
Collectively, the literature confirms the growing potential of AI-based recommender systems and chatbots as tools for socioeconomic empowerment. However, most existing approaches remain either institution-centric or limited to digitally literate populations with insufficient integration of household-level personalization. These inclusive design principles and community trust-building mechanisms. Notably, few studies propose an integrated framework that simultaneously combines recommender systems, conversational interfaces and capacity-building components tailored specifically to low-income households.

In response to these gaps, AI4EKonomi is positioned as an integrative framework that synthesizes recommender systems, inclusive chatbot design and community empowerment principles. The framework adopts a phased development approach, beginning with context-sensitive data collection and stakeholder engagement, followed by personalized recommendation generation and user-friendly conversational interfaces. Unlike prior studies that prioritize technical performance alone, AI4EKonomi explicitly incorporates social inputs from NGOs, local communities and policymakers, alongside interactive training modules and continuous feedback mechanisms to enhance adoption, ethical deployment and long-term sustainability.

3 METHODOLOGY

The research approach is a mix method which is quantitative and qualitative. For the initial step, this study adopts a Design Science Research (DSR) methodology to develop a conceptual framework for the AI4EKonomi system. DSR is widely used in information systems research for the development and validation of innovative artifacts that solve real-world problems (Hevner & Park, 2004). The approach involves iterative processes of problem identification, artifact design, demonstration and evaluation. The design process for AI4EKonomi consists of four core phases as illustrated in Figure 1. The phases include problem identification, objective definition of a solution, design and development and evaluation or demonstration.

Fig. 1. Research Design



The first phase requires us to review data such as national economic development reports, poverty alleviation programs and social welfare data. The activity was conducted to identify gaps in current intervention mechanisms. At this stage, it will be confirmed that most assistance programs lack personalization and fail to match recipients with context-relevant opportunities. The second phase is to design an AI-based recommender system that can analyse household data and produce tailored economic support suggestions. This will ensure that the system can suggest things such as training courses, job opportunities, micro-financing or entrepreneurship pathways.

Furthermore, the next phase is development, which is a high-level conceptual framework. This phase comprises the key system components such as the data collection module. The module will collect socioeconomic data from audience. The items collected include income, skills, education, location and household size. Then, the AI engine, which applies machine learning algorithms such as decision trees, clustering and collaborative filtering, will be used to analyze profiles and predict suitable interventions. Next, will be the recommendation generator. It will match user profiles with opportunities from a curated database such as training programs, government aid, NGOs, job openings and other relevant information.

Finally, the feedback loop is vital, where it will incorporate user outcomes and engagement data to improve accuracy over time. The last phase would be demonstration and evaluation of future work. While the current study focuses on framework development, future work will involve prototyping and piloting the system within selected B40 communities. The stakeholder interviews and user testing will be used to validate system relevance, usability and potential impact.

In terms of data sources, the system is designed to integrate both structured and semi-structured data from multiple sources. These would include government open data such as eKasih from the Department of Statistics Malaysia. The user-input data through mobile or web interfaces also conducted such as from partner agency databases like NGOs, training providers and micro-finance platforms. The design also considers issues of data privacy and consent for vulnerable communities in terms of bias mitigation in AI decision-making and accessibility for digitally underserved populations. It is hope that these considerations will guide the development part in term of fair, transparent and inclusive system architecture for such a system.

4 RESULT

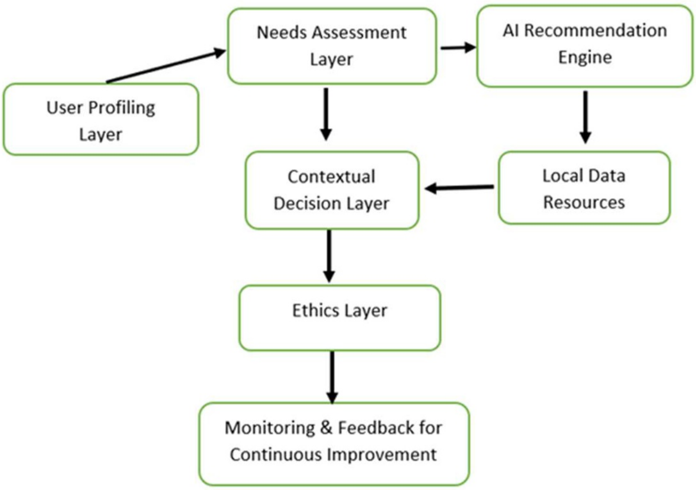
The framework has been developed as an intelligent, AI-driven recommender system that provides personalized economic empowerment suggestions to low-income households. The framework integrates machine learning algorithms with socio-economic data analytics to generate context-aware recommendations based on individual household profiles. These include income level, employment status, educational background and local economic activities. By processing multidimensional datasets, the system identifies relevant opportunities including micro-financing programs, vocational training, entrepreneurship schemes and digital marketplace participation.

The results demonstrate that the model successfully aligns data-driven insights with human-centric decision-making processes. By using predictive modelling and pattern recognition techniques, AI4EKonomi can achieves a high level of accuracy in matching households with the most suitable economic opportunities. The recommender engine employs adaptive learning to continuously refine its outputs based on user feedback and new socio-economic data. This is to ensure the system remains responsive to evolving community needs.

Additionally, the framework's modular design allows for seamless integration with existing governmental and non-governmental digital platforms in term of enabling policymakers, NGOs and development agencies to utilize the system as a decision-support tool for targeted interventions. The pilot simulations indicate that AI4EKonomi has the potential to optimize resource distribution, enhance inclusivity and improve the efficiency of support delivery mechanisms.

Overall, the framework contributes not only to the technological advancement of recommender systems in the social sector but also to the strategic goal of empowering low-income communities through data-informed and AI-enhanced economic initiatives. The system is integrated and can be adapted by local governments, NGOs or development agencies. Figure 2 illustrates the framework for such recommender system. The framework is built on four interconnected layers: the Data Input Layer, the AI Analytical Engine, the Recommendation Generation Module, and the Feedback and Adaptation Layer.

Fig. 2. AI Framework Diagram



4.1 Data Input Layer

This layer functions as the foundation of the system, which collects both structured and semi-structured data from a variety of trusted sources. These include government open datasets such as eKasih, NGO databases, micro-financing platforms, and household self-registration forms. The data covers key socioeconomic aspects related to income range, education level, skill sets, employment status, family size and geographic location.

By compiling this information, the framework builds a holistic profile for each household in term of enabling the system to detect opportunities that are most relevant and practical to their local and economic context.

At the heart of AI4EKonomi lies the analytical engine, which applies machine-learning techniques such as clustering, classification and collaborative filtering. These algorithms identify hidden trends and relationships within the socioeconomic data and learning how certain household attributes correlate with successful empowerment programs.

Through iterative refinement, the engine becomes progressively more accurate and it allows to recommend interventions such as training, financing or employment programs with increasing precision and reliability. Once the analysis is complete, the recommender module translates into concrete and personalized actions. The system can propose the following item depending on the user's profile such as:

1. Training and upskilling programs, courses that build on existing skills or prepare participants for new industries.
2. Micro-financing and entrepreneurial aid, financial schemes or grants matched to the user's income level and business readiness.
3. Employment and business opportunities, local job or small-business openings suited to the user's capabilities and location.
4. Government and NGO support programs and relevant assistance initiatives tailored to household circumstances.

A hybrid recommendation strategy combining content-based filtering by using user attributes and collaborative filtering which is learning from similar users to ensure a balance between individual relevance and community-wide learning. This layer ensures that the system evolves over time. It continuously gathers user feedback and tracks outcomes from implemented recommendations. When a program produces positive results such as income growth or successful business registration, the model updates its parameters to favor similar matches in future predictions.

This feedback loop not only enhances accuracy but also strengthens user trust by demonstrating responsiveness and fairness. In the long run, it supports a sustainable and community-driven learning process. The AI4EKonomi framework is designed to be modular, interoperable and scalable. It can be implemented through a web-based portal, mobile application or integrated dashboard for agencies. The system architecture allows seamless adoption by local authorities, NGOs and social-development partners for use in policy planning, resource allocation and community engagement.

Moreover, its flexibility enables localization to ensure that recommendations reflect the cultural and socioeconomic realities of each Malaysian state. This adaptability also positions the system as a model that could be extended to other developing regions across Southeast Asia.

5 CONCLUSION

The AI4EKonomi framework signifies a paradigm shift in the delivery of economic support to vulnerable populations. Rather than adopting traditional, one-size-fits-all approaches, the framework emphasizes data-driven personalization that is more responsive to the diverse needs and capacities of low-income households. Conventional aid mechanisms often lack sufficient granularity, leading to mismatches between program offerings and actual household needs.

For example, providing technical skills training to individuals without access to basic education or the internet results in limited engagement and low impact. By profiling users through a comprehensive set of socioeconomic indicators, AI4EKonomi ensures that recommendations are contextually relevant, practical and more likely to produce sustainable outcomes.

Furthermore, Artificial Intelligence has the potential to bridge existing information and opportunity gaps. However, this potential can only be realized when systems are designed ethically, inclusively and transparently. AI4EKonomi would leverage machine learning algorithms to uncover hidden patterns in household data and align individuals with targeted interventions. However, the system must actively address algorithmic bias, data privacy and digital literacy limitations to ensure fair access. Meanwhile, the integrated feedback loop plays a crucial role in continuously monitoring system performance and mitigating bias, thereby ensuring long-term reliability and adaptability of the system.

The proposed framework offers actionable insights for a range of stakeholders, including government agencies, NGOs and community partners. Beyond its function as a recommender tool, AI4EKonomi serves as a policy decision support system by providing real-time analytics on community needs, program effectiveness and service delivery gaps. Policymakers also can utilize the aggregated insights generated by the system to identify high-priority intervention areas or evaluate the cost-effectiveness of specific initiatives.

Furthermore, AI4EKonomi is designed to be modular and scalable, making it adaptable to different geographic regions and socioeconomic contexts. By incorporating local data sources and stakeholder inputs, the system can be localized to reflect the specific cultural, economic and infrastructural realities of various Malaysian states and potentially extended to other Southeast Asia countries. Through the integration of artificial intelligence and community development, AI4EKonomi contributes not only to scholarly discourse but also to practical policymaking aimed at fostering inclusive and sustainable economic empowerment.

This paper presents the conceptual framework foundation necessary for developing AI4EKonomi into a fully implemented system. The key challenges for future implementation include ensuring the availability and quality of input data, enhancing user trust and engagement among underserved communities and facilitating cross-agency data integration while maintaining strict compliance with privacy regulations. So, the future work will involve the development of a prototype system, pilot testing within selected B40 communities and the refinement of the recommendation engine through user-centered design and iterative feedback cycles.

In essence, the framework demonstrates how AI can be responsibly harnessed to design more effective, inclusive and sustainable strategies for poverty alleviation. By aligning technological innovation with human-centered values, the framework has the potential to empower low-income communities, inform data-driven policy decisions and serve as a model for future innovations in the broader context of social and economic development. It is hoped that this research will progress from conceptual to practical implementation, ultimately contributing to the realization of equitable and data-driven economic empowerment initiatives in Malaysia and beyond

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