From AI Awareness to Socio-Economic Value Creation: Conceptualising Community Readiness, Acceptance and Governance in Malaysia

Sharifah Nazatul Faiza Syed Mustapha Nazri[1], Sharina Tajul Urus[1*], Zarinah Abdul Rasit[1], and Sharmila Mohammed Salleh[2]

[1]Faculty of Accountancy, Universiti Teknologi MARA, Cawangan Selangor, Kampus Puncak Alam, Selangor, Malaysia

[2]Department of Social Innovation, Yayasan Inovasi Malaysia (YIM), Ministry of Science, Technology and Innovation (MOSTI), Kuala Lumpur, Malaysia

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ABSTRACT

Artificial intelligence (AI) now reaches ordinary citizens through freely available generative AI tools, so Malaysia's national AI strategy depends on whether communities such as small traders, youth, students, farmers and civil-society actors are ready, willing and able to use AI productively and responsibly. However, AI-acceptance research has largely modelled the individual consumer or employee, and research on community AI adoption in developing countries remains nascent. Based on a review of the AI-acceptance, technology-readiness, AI-literacy, trust and digital-divide literature, and supported by pilot evidence from 136 participants in AI workshops at six Ruang Daya Cipta (RDC) community innovation hubs of Yayasan Inovasi Malaysia (YIM), this concept paper develops the Community AI Readiness–Acceptance–Value (CARAV) framework, which links four readiness dimensions, through trust and acceptance, to socio-economic value in eight propositions. The pilot evidence reveals a readiness–capability paradox: very high stated readiness (97.8% interested in learning AI) coexists with only moderate foundational skills, use concentrated on free generative tools, and strong demand for human oversight and regulation. Four governing issues are identified: privacy, security and ethics; regulation; infrastructure and infostructure gaps; and lack of skill and knowledge. The study contributes to understanding how community AI adoption is conceptualised, how it has evolved and what hinders it. Practically, it offers recommendations on how AI capacity-building programmes can be designed and evaluated to deliver inclusive socio-economic value and contribute to the national AI agenda.

Keywords: Community AI readiness, AI acceptance, AI governing issues, Socio-economic value creation, Ruang Daya Cipta (RDC), Yayasan Inovasi Malaysia.

INTRODUCTION

The fourth industrial revolution has placed artificial intelligence (AI) at the centre of economic and social transformation. AI refers to the capability of machines to perform tasks that normally require human intelligence, including learning from data, recognising patterns, reasoning and making decisions (Russell & Norvig, 2021). These capabilities now reach ordinary users through machine learning, natural language processing, computer vision and, most visibly, generative AI (Dwivedi et al., 2023). Adoption is no longer confined to large organisations: public agencies use AI for service delivery and data-driven policy, while small enterprises use it for marketing, content creation and financial risk management (McKinsey & Company, 2023).

The diffusion of AI has been remarkably rapid. ChatGPT, released in November 2022, was estimated to have reached 100 million monthly active users within two months, making it the fastest-growing consumer application recorded at that time (Hu, 2023). Experimental studies show that generative AI can reduce the time

needed for professional writing tasks by about 40% while improving output quality (Noy & Zhang, 2023), and can raise the productivity of customer-support agents by 14% on average and by 34% among novice workers (Brynjolfsson et al., 2025). Such gains suggest that AI could narrow, rather than widen, skill gaps provided that people can access and use it well.

Malaysia has positioned AI as a pillar of its digital transformation. The Malaysia National AI Roadmap 2021–2025, the Malaysia Digital Economy Blueprint (MyDIGITAL) and the Twelfth Malaysia Plan identify AI as a catalyst for productivity and national competitiveness (MOSTI, 2021; Economic Planning Unit, 2021a, 2021b). The government has since launched the *AI untuk Rakyat* public AI-literacy programme, published the National Guidelines on AI Governance and Ethics (AIGE) and established the National AI Office (NAIO) (MOSTI, 2024; MyDIGITAL Corporation, 2024a, 2024b). The returns on these investments, however, depend on a condition that national strategies rarely measure: whether *communities* outside the formal technology sector are ready, willing, and able to use AI productively and responsibly.

Despite this momentum, research on community AI adoption in developing countries remains nascent. Technology-acceptance research has overwhelmingly modelled the individual employee or consumer in organisational or commercial settings (Kelly et al., 2023), leaving the community, particularly the semi-urban and rural community served by public innovation hubs, under-theorised as a unit of AI adoption. The literature also tends to conflate *readiness* (a predisposition and capacity), *acceptance* (intention and use), and *value realisation* (productivity, income and employment), so it cannot explain why high enthusiasm often fails to yield economic benefit. Furthermore, the governing issues of community AI use are still worth further investigation, since users frequently cannot understand the rationale behind AI outputs, producing a trust gap, misconceptions about what AI does, and exposure to privacy and misinformation risks (Glikson & Woolley, 2020; Ji et al., 2023; Shin, 2021). Hence, this paper aims to explore the conceptualisation of community AI readiness and acceptance, and the governing issues surrounding it, based on a review of the literature and supported by pilot evidence from Malaysia's Ruang Daya Cipta (RDC) community innovation hubs under Yayasan Inovasi Malaysia (YIM.

The study contributes to understanding community AI readiness and acceptance, how they manifest, and how AI adoption has evolved. This concept paper also sheds light on AI-adoption research by identifying the governing issues surrounding community AI use and by proposing the Community AI Readiness–Acceptance–Value (CARAV) framework for empirical testing. From a practical perspective, the recommendations on how AI capacity-building programmes can be designed and evaluated would positively affect Malaysian communities and contribute to the national AI agenda.

COMMUNITY AI READINESS AND ACCEPTANCE: CONCEPTUALISATION

Definition of Community AI Readiness and Acceptance

Technology acceptance has been explained mainly through the Technology Acceptance Model (TAM), which holds that perceived usefulness and perceived ease of use drive the intention to use a technology (Davis, 1989), and through the Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies performance expectancy, effort expectancy, social influence and facilitating conditions as determinants (Venkatesh et al., 2003). UTAUT2 extended the model to consumer contexts by adding hedonic motivation, price value, and habit (Venkatesh et al., 2012). A systematic review confirms that these constructs transfer to AI, but also shows that AI-specific factors such as trust and perceived risk carry substantial explanatory weight (Kelly et al., 2023).

Yet, Acceptance models do not explain *who is able* to form beliefs about usefulness and ease of use in the first place. Technology readiness captures an individual's propensity to embrace new technology through two enablers (optimism and innovativeness) and two inhibitors (discomfort and insecurity) (Parasuraman, 2000; Parasuraman & Colby, 2015), while AI literacy refers to the competencies that enable people to evaluate AI critically, communicate and collaborate with it, and use it as a tool (Long & Magerko, 2020; Ng et al., 2021). Drawing on these streams, this paper defines *community AI readiness* as the collective knowledge,

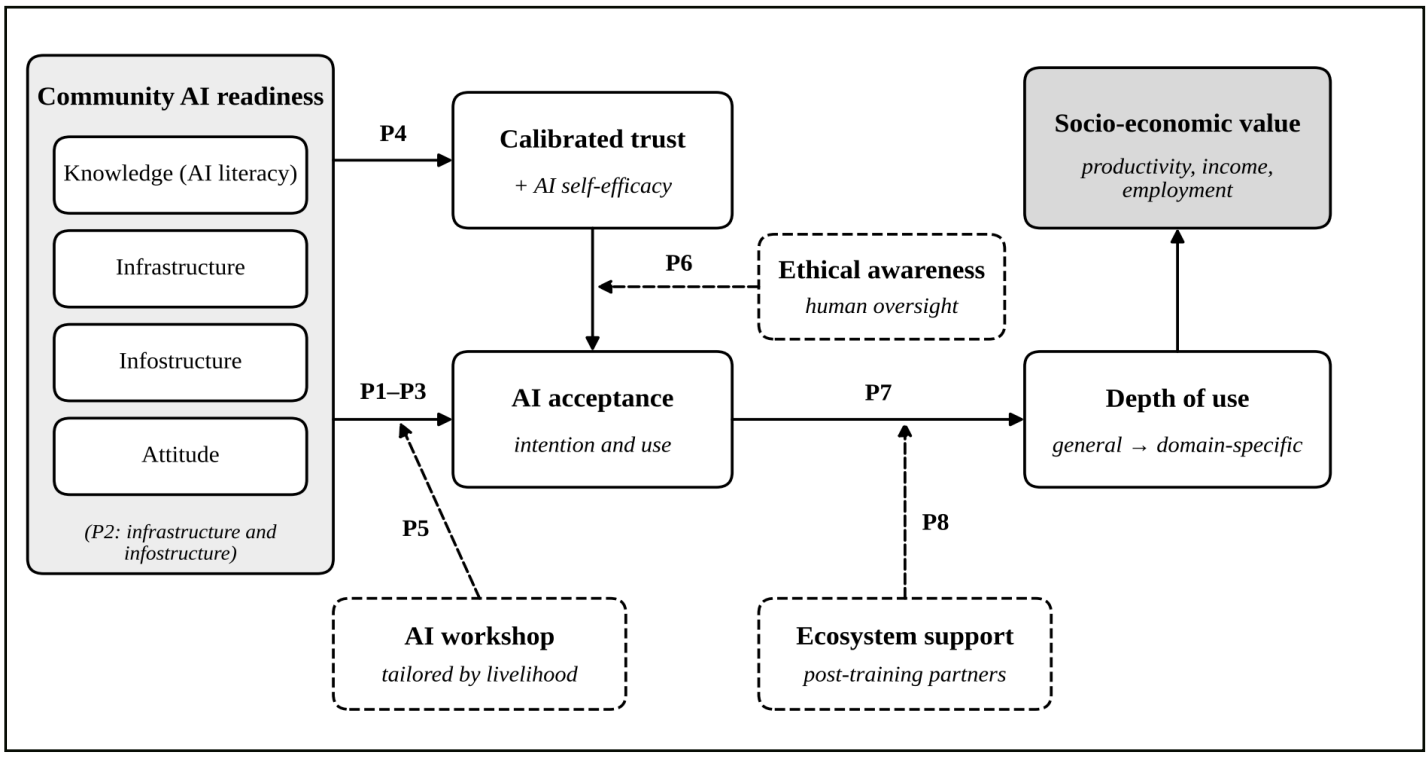
infrastructure, infostructure and attitudes that enable members of a community to engage with AI; *community AI acceptance* as the intention to use and actual use of AI by community members; and *community AI value* as the productivity, income and employment outcomes that result when acceptance matures into sustained and purposeful use.

Community AI Readiness Dimension

Community readiness is both *dispositional* and *structural*. Organisational adoption research shows that infrastructure and environmental support condition uptake (Tornatzky & Fleischer, 1990), and digital-divide research has progressed from access, to skills and usage, to outcomes (van Deursen & van Dijk, 2014; van Dijk, 2020). Accordingly, this paper proposes four dimensions of community AI readiness: (1) knowledge, (2) infrastructure, (3) infostructure, and (4) attitude. Figure 1 illustrates the Community AI Readiness–Acceptance–Value (CARAV) framework built on these dimensions.

Figure 1

The Community AI Readiness–Acceptance–Value (CARAV) Framework



Note. P1–P8 denote propositions; dashed arrows denote moderating conditions.

(Source; Authors' Own Construct)

Knowledge readiness refers to the community's AI literacy: understanding what AI is, what it can and cannot do, and how to apply it. *Infrastructure readiness* refers to access to devices, connectivity and physical facilities. *Infostructure readiness* refers to access to the information resources, platforms, support services and institutional arrangements such as RDC hubs that make use meaningful. *Attitudinal readiness* refers to optimism, openness and perceived benefit, net of discomfort and insecurity (Parasuraman & Colby, 2015). Readiness influences acceptance directly and through *calibrated trust* and self-efficacy, because users must rely on systems whose reasoning they cannot fully inspect (Bandura, 1977; Compeau & Higgins, 1995; Glikson & Woolley, 2020). Three conditions shape the chain: capability-building workshops strengthen the link from readiness to acceptance (Kirkpatrick & Kirkpatrick, 2006); ethical awareness conditions the link from trust to acceptance (Floridi et al., 2018; Jobin et al., 2019); and ecosystem support conditions whether acceptance deepens into domain-specific use that produces value (Heeks, 2022).

The framework yields eight propositions for empirical testing as follows:

(1) Knowledge readiness is positively associated with community AI acceptance, and this effect is partially mediated by AI self-efficacy (P1).

(2) Infrastructure and infostructure readiness act as facilitating conditions that positively shape AI acceptance, with stronger effects in rural and peripheral communities than in urban ones (P2).

(3) Attitudinal readiness is positively associated with AI acceptance, but its effect on sustained use is weaker than that of knowledge readiness when foundational digital skills are low, that is, the readiness–capability paradox (P3).

(4) Trust in AI mediates the relationship between readiness and AI acceptance, and perceived explainability and transparency strengthen this trust (P4).

(5) Participation in a capability-building AI workshop strengthens the readiness–acceptance relationship, particularly when content is tailored to the participant's livelihood group (P5).

(6) Ethical awareness moderates the trust–acceptance relationship: high awareness combined with confidence in human oversight and regulation yields calibrated and sustained acceptance, whereas high awareness without such assurances weakens acceptance (P6).

(7) AI acceptance is positively associated with productivity, income and new employment, and this relationship is mediated by depth of use, from general-purpose to domain-specific applications (P7).

(8) The acceptance–value relationship is stronger where multi-stakeholder ecosystems provide continued support after initial training (P8).

Community AI Application

AI applications available to communities are no longer limited to specialised enterprise systems. Many are free or low-cost consumer tools that embed AI into everyday tasks such as writing, designing, video editing, learning and farming (McKinsey & Company, 2023). For communities, the distinction that matters are between *general-purpose* use, such as asking a chatbot for information, and *domain-specific* use, such as diagnosing crop disease or automating customer engagement, because the latter is more directly linked to livelihood outcomes (van Deursen & van Dijk, 2014). Table 1 depicts some examples of AI applications used by community users.

Table 1

Community AI Applications

Application of AI	**Example**	**Usage**
Generative AI assistants	ChatGPT	Answer questions, draft text, summarise information and support learning and work tasks through a conversational interface.
	Google Gemini	
	Microsoft Copilot	
AI-assisted design	Canva (Magic Studio)	Generate and edit images, posters and social-media content, enabling small traders to produce marketing material without specialist skills.

AI-assisted video editing	CapCut	Automate captioning, editing and effects for short promotional and educational videos.
AI for agriculture	Plantix	Identify crop diseases and pests from smartphone photographs and suggest treatments for farmers.
AI for learning	Duolingo Max	Provide personalised explanations, practice and feedback to learners.
	Khanmigo	

Community AI Benefits and Challenges

AI offers communities several potential benefits. Generative AI lowers the cost of producing text, images, and video, enabling micro-entrepreneurs to market products without hiring specialists, and it can deliver personalised explanations to learners at any time (Dwivedi et al., 2023). Experimental evidence shows substantial time savings and quality gains in writing tasks (Noy & Zhang, 2023), and field evidence shows that the largest productivity gains accrue to less experienced workers (Brynjolfsson et al., 2025). Estimates suggest that around 80% of the United States workforce could have at least 10% of their work tasks affected by large language models (Eloundou et al., 2024), indicating that the benefits and disruptions of AI will extend well beyond the technology sector.

AI also presents significant challenges. Large language models can generate fluent but false content, commonly termed hallucination, which users without domain knowledge may struggle to detect (Ji et al., 2023). Machine-learning systems can reproduce and amplify biases present in their training data (Mehrabi et al., 2021), and the use of AI tools raises concerns about the privacy and security of personal data. Moreover, when communities adopt technology without the skills or support to capture its value, digital incorporation can be adverse rather than empowering (Heeks, 2022). These challenges imply that acceptance is a necessary but insufficient condition for socio-economic benefit, and they foreshadow the governing issues discussed later in this paper.

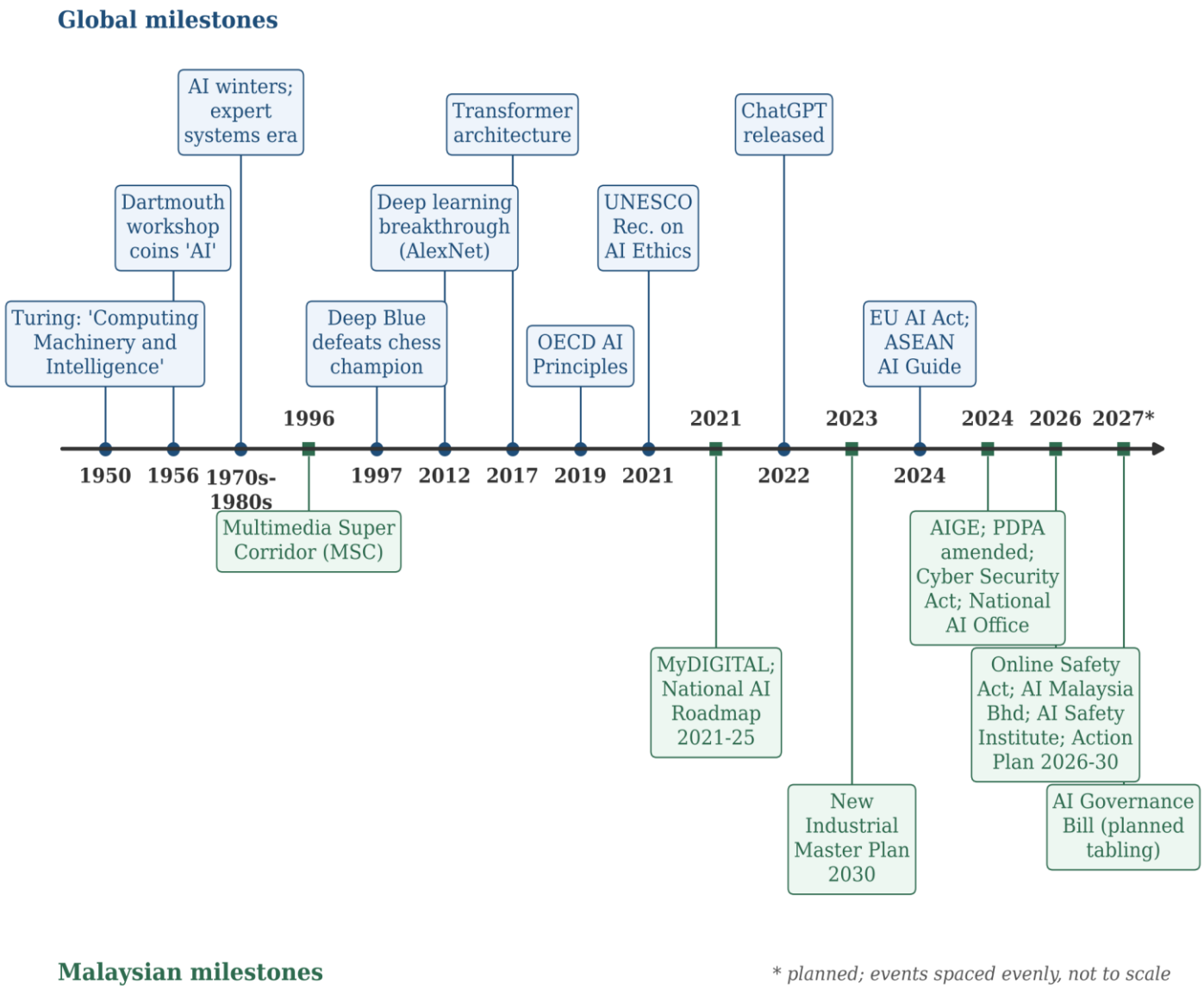
EVOLUTION AND DEVELOPMENT OF AI

Global and Malaysia AI Evolution

The history of AI is commonly described as a sequence of waves separated by “AI winters,” periods in which inflated expectations collapsed and funding declined. The first wave, following Turing (1950) and the 1956 Dartmouth workshop (McCarthy et al., 2006), was dominated by symbolic reasoning and search. The second wave in the 1980s centred on expert systems that encoded human rules, which proved brittle and costly to maintain. The third wave was driven by statistical machine learning and, from 2012, by deep learning, when convolutional neural networks trained on graphics processors dramatically improved image recognition (Krizhevsky et al., 2012). The transformer architecture introduced by Vaswani et al. (2017) enabled the large language models that underpin today’s generative AI, which reached mass public use with the release of ChatGPT in November 2022 (Dwivedi et al., 2023).

Governance evolved alongside the technology, though with a lag. Between 2016 and 2019, governments, firms and civil society organisations issued more than eighty sets of AI ethics principles, which converged around transparency, justice and fairness, non-maleficence, responsibility and privacy (Jobin et al., 2019). The OECD Recommendation on AI (2019, revised 2024) and the UNESCO Recommendation on the Ethics of AI (UNESCO, 2021) provided intergovernmental reference points. From 2021, the focus shifted from voluntary principles to binding regulation, described as a move from a “race to AI” to a “race to AI regulation” (Smuha, 2021). The European Union’s AI Act, which entered into force in 2024, established the first comprehensive risk-based legal regime (European Union, 2024; Veale & Zuiderveen Borgesius, 2021), while ASEAN adopted a voluntary Guide on AI Governance and Ethics in 2024 (ASEAN, 2024). Figure 2 summarises the key milestones globally and in Malaysia.

Figure 2 *Milestones in the development of AI and AI governance, Global and Malaysian*



(Compiled by the authors)

AI in the Generative AI Era

The public release of ChatGPT in November 2022 marked a turning point in the diffusion of AI. For the first time, a highly capable AI system was available free of charge through a conversational interface that required no technical expertise, and it reached an estimated 100 million monthly users within two months (Hu, 2023). Global surveys describe 2023 as generative AI's breakout year, with organisations rapidly experimenting with the technology across functions (McKinsey & Company, 2023).

Unlike earlier waves of AI, which were deployed mainly within organisations, generative AI is adopted directly by individuals. This shift creates opportunities for communities that were previously excluded from advanced technology, but it also transfers responsibility for judging the accuracy, fairness and appropriateness of AI outputs to ordinary users (Dwivedi et al., 2023; Ji et al., 2023). Consequently, AI literacy, calibrated trust and ethical awareness have become prerequisites for safe and productive use at the community level.

AI in Malaysia

From the Malaysian perspective, the development of AI is encouraging. The National AI Roadmap 2021–2025 set out strategies for AI governance, research and development, digital infrastructure, talent and ecosystem

development (MOSTI, 2021), aligned with the MyDIGITAL blueprint and the Twelfth Malaysia Plan (Economic Planning Unit, 2021a, 2021b). Large-scale private investment in digital infrastructure has followed: in May 2024, Microsoft announced a US$2.2 billion investment in cloud and AI over four years, and Google announced a US$2 billion investment in its first Malaysian data centre and cloud region (Khaw, 2024).

The government has also taken initiatives to promote AI literacy and responsible use. The *AI untuk Rakyat* self-learning programme, launched on 16 January 2024, was completed by more than one million Malaysians in less than six months (MyDIGITAL Corporation, 2024a). On 20 September 2024, the Ministry of Science, Technology and Innovation (MOSTI) launched the AIGE, which sets out seven principles: fairness; reliability, safety and control; privacy and security; inclusiveness; transparency; accountability; and the pursuit of human benefit and happiness (MOSTI, 2024). On 12 December 2024, the NAIO was launched under the Ministry of Digital to lead AI adoption, strengthen policy frameworks and prioritise security and ethics in AI deployment (MyDIGITAL Corporation, 2024b). These developments indicate that AI is expected to grow continually in the Malaysian environment. The following are some of the key trends observed at the community level, drawing on pilot evidence from the RDC hubs.

Grassroots Innovation Hubs as Channels for AI Literacy

Yayasan Inovasi Malaysia (YIM), with funding from MOSTI, delivers the *AI 4 Youth and Community* workshops at RDC community innovation hubs. To ground this paper, a structured questionnaire was administered to workshop participants at six hubs between August and November 2025 (n = 136; Table 2). The instrument covered background; awareness and acceptance of AI; readiness (knowledge, infrastructure, infostructure and attitude); workshop effectiveness; and understanding of AI and its ethics, measured on five-point Likert scales.

Table 2

Pilot Survey Data Collection by RDC Hub

RDC hub	State	Mode	Data collection	Respondents (*n*)
Tumpat	Kelantan	Face-to-face	6-Aug-25	18
Tanjung Malim	Perak	Face-to-face	21-Sep-25	27
Bera	Pahang	Face-to-face	28-Sep-25	27
Manong	Perak	Face-to-face	13-Oct-25	18
Lahad Datu	Sabah	Online	3–4 Nov 2025	28
Miri	Sarawak	Face-to-face	12–13 Nov 2025	18
Total				**136**

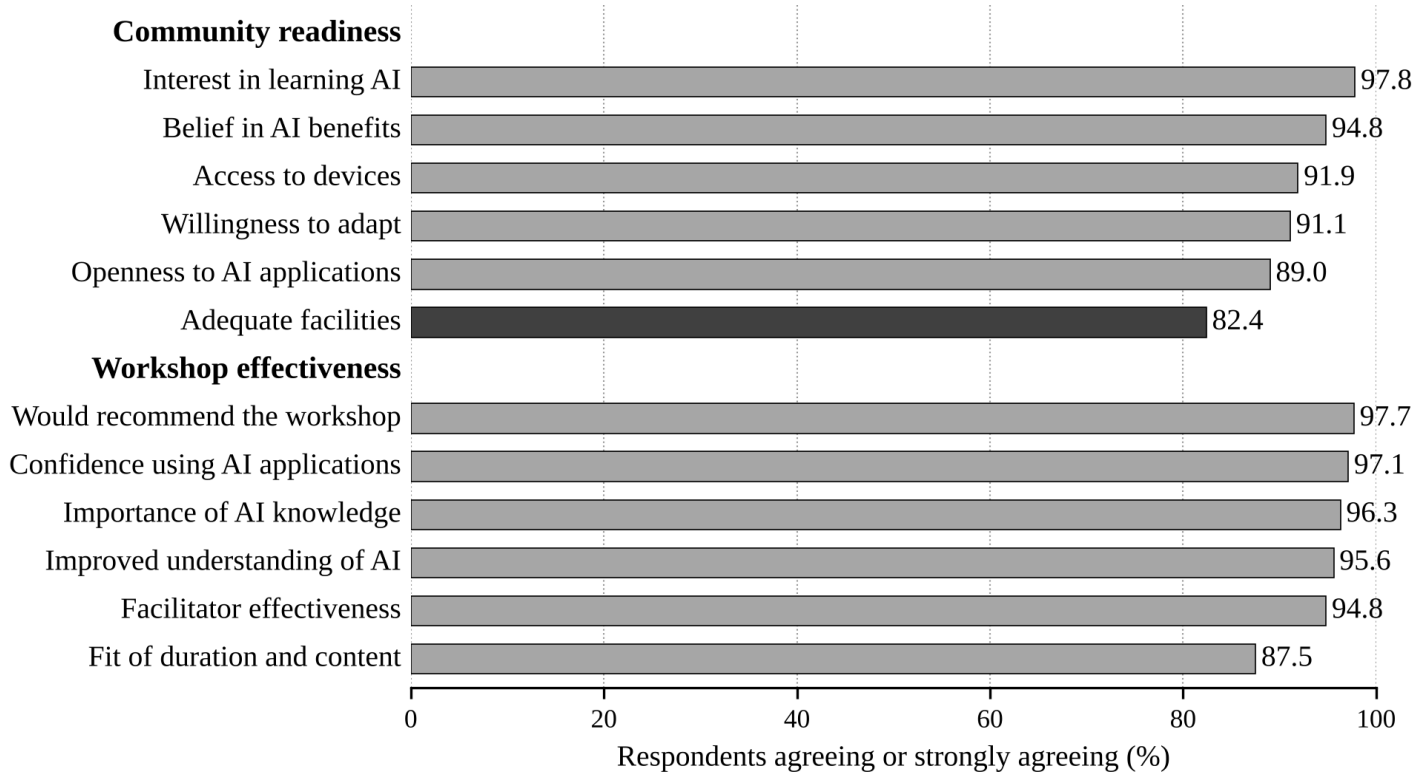
Respondents were 55.8% male and predominantly Malay (79.3%), with Iban, Chinese, and other Sabah and Sarawak ethnic groups (Dusun and Bajau) also represented. Ages were evenly distributed from under 20 to over 50 years, secondary-school leavers formed the largest education group (46.1%), and 54.5% were employed. Small traders were the largest participant group, followed by youth, secondary-school students and members of non-governmental organisations or village committees (JKKK); farmers, community teachers and single mothers participated in smaller numbers.

High Enthusiasm Alongside Moderate Foundational Skills

Stated readiness and workshop outcomes were very high, with every indicator exceeding 80% agreement (Figure 3). However, the modal self-rating of basic technology, science and innovation skills was only *moderate* (36.8%), revealing a gap between enthusiasm and capability, which this paper terms the readiness–capability paradox. Adequacy of facilities recorded the lowest agreement (82.4%).

Figure 3

Community Readiness and Workshop Effectiveness Indicators



Note. Percentage of respondents agreeing or strongly agreeing (n = 136).

Generative AI as the Entry Point

Community use is concentrated on free, general-purpose tools: ChatGPT Free (53.5%), Canva with AI (24.0%) and CapCut with AI (15.3%). These tools are applied to personal matters (22.2%), work (21.6%), business (21.0%) and school tasks (20.1%), but rarely to farming (5.6%), indicating that use has not yet deepened into domain-specific, livelihood-oriented applications.

Ethically Alert Communities

Respondents most often strongly agreed that humans must remain the final decision-makers (57.4%) and that AI-specific legislation is needed (55.9%). The modal response regarding fear of job loss was disagreement (32.4%), and that regarding privacy concerns was neutral (29.4%). Communities thus appear optimistic about AI but expect safeguards.

Despite the rising trend and popularity of AI, the governing issues surrounding its use at the community level are crucial. The following section discusses these issues, specifically in the Malaysian context.

GOVERNING ISSUES OF COMMUNITY AI ADOPTION IN MALAYSIA

The rise of AI in Malaysia also gives rise to several issues and challenges. Users who cannot inspect the reasoning behind AI outputs may either over-rely on or reject the technology (Glikson & Woolley, 2020), while the risks associated with AI use, including privacy breaches, misinformation, bias and exclusion, may affect communities unevenly (Heeks, 2022). Many of these issues emerge at different stages of adoption. The following subsections highlight four governing issues based on prior literature, national developments and the pilot evidence.

Privacy, Security and Ethical Issues

Community members routinely enter personal, business and family information into AI tools, often without understanding how such data are stored or reused. Malaysia's Personal Data Protection (Amendment) Act 2024 strengthens obligations by introducing mandatory notification of personal data breaches, requirements to appoint data protection officers, a right to data portability, the classification of biometric data as sensitive personal data and higher maximum penalties (Rajah & Tann Asia, 2024). Nevertheless, awareness of these protections among ordinary users is uncertain; in the pilot, the modal response on privacy concerns was neutral (29.4%), suggesting limited reflection on data risks.

Ethical risks extend beyond privacy. Generative AI may produce hallucinated content (Ji et al., 2023) and biased outputs (Mehrabi et al., 2021), and users with limited literacy may accept such outputs uncritically. Global ethics frameworks converge on transparency, justice, non-maleficence, responsibility and privacy (Floridi et al., 2018; Jobin et al., 2019), and the AIGE translates these into seven national principles (MOSTI, 2024). The challenge is to convert these principles into practices that community users understand and apply.

Regulatory Issue

As AI grows, so does the need for an appropriate regulatory framework. The AIGE provides guidance to developers, deployers and users, and is intended to serve as a foundation for future sector-specific guidelines and legislation (MOSTI, 2024). Malaysia has not yet enacted AI-specific legislation, whereas the European Union has adopted a comprehensive risk-based AI Act (European Union, 2024). Communities appear to favour stronger safeguards: in the pilot, respondents most often strongly agreed that AI-specific legislation is needed (55.9%) and that humans must remain the final decision-makers (57.4%).

Regulating AI is complicated by the speed of technological change, the global nature of AI platforms and the diversity of use cases, from entertainment to financial and health advice. Regulators must therefore balance innovation with protection, ensuring that safeguards do not become barriers for small users while still addressing misuse, misinformation and consumer harm (UNESCO, 2021). Clear communication of national guidelines to the public is as important as their formulation, since trust depends on users' confidence that oversight exists (Shin, 2021).

Infrastructure and Infostructure Gap

Large investments in data centres and cloud regions strengthen national AI capacity, but they do not automatically translate into access for semi-urban and rural communities. Digital-divide research shows that differences in access, skills and outcomes persist even as connectivity expands (van Deursen & van Dijk, 2014; van Dijk, 2020). In the pilot, adequacy of facilities recorded the lowest agreement among readiness indicators (82.4%), and the Lahad Datu workshop in Sabah was delivered online, illustrating the logistical constraints faced by peripheral communities.

Beyond physical infrastructure, communities need *infostructure*: relevant content, platforms, technical support and institutional arrangements that make use meaningful. RDC hubs perform this role, but their capacity to provide continuing support after a single workshop is limited. Without such support, initial enthusiasm may fade before use deepens into domain-specific applications that produce value (Heeks, 2022).

Lack of Skill and Knowledge

Although public enthusiasm for AI is high, foundational skills remain uneven. The pilot's readiness–capability paradox, characterised by a very high willingness to learn alongside only moderate self-rated technology, science and innovation skills, suggests that positive attitudes alone are insufficient to sustain productive use. AI literacy encompasses understanding, application, evaluation and ethics (Ng et al., 2021), yet most community use remains limited to general-purpose tools for personal tasks.

Skill gaps also affect the calibration of trust. Users who lack the knowledge to evaluate AI outputs are vulnerable both to over-reliance on hallucinated content and to unwarranted rejection of useful tools (Glikson & Woolley, 2020; Ji et al., 2023). Because the largest productivity gains from generative AI accrue to less experienced workers (Brynjolfsson et al., 2025), closing these skill gaps is central to ensuring that AI narrows rather than widens socio-economic inequalities.

RECOMMENDATION

Tiered, Livelihood-Specific AI Literacy

To move communities from awareness to productive use, AI capacity-building programmes should progress beyond introductory sessions. Short, hands-on training is the principal lever through which public programmes build literacy and self-efficacy, and its effects should be evaluated at the levels of reaction, learning, behaviour and results (Kirkpatrick & Kirkpatrick, 2006). Programmes should therefore offer tiered modules tailored to livelihood groups, including:

(1) AI for digital marketing, customer analysis and promotional content for small traders and micro-entrepreneurs.

(2) AI as a learning and research aid, with guidance on verification and academic integrity, for students and youth.

(3) Digital agriculture, crop diagnosis and yield-data management for farmers and rural communities.

(4) Practical AI use for community administration and service delivery for NGO and village committee (JKKK) members.

Strengthening Hub Infrastructure and Infostructure

Connectivity and equipment at RDC hubs should be improved, particularly in rural Sabah and Sarawak, and accompanied by continuing technical support. Hubs should also strengthen their infostructure by curating Bahasa Malaysia learning resources, providing follow-up clinics after workshops and connecting participants with peer networks. Such support converts one-off training into sustained use and enables the deepening of use from general-purpose to domain-specific applications that the CARAV framework links to socio-economic value.

Embedding Ethics and a Clear Regulatory Framework

Ethics should be embedded in every module rather than treated as a separate topic, so that trust is calibrated rather than blind. Consistent with the AIGE principles (MOSTI, 2024) and international guidance (UNESCO, 2021), the following measures are recommended:

(1) Teach practical verification of AI outputs, including recognising hallucination and bias.

(2) Explain users' rights and organisations' obligations under the Personal Data Protection (Amendment) Act 2024.

(3) Reinforce the principle that humans remain the final decision-makers in consequential matters.

(4) Communicate national AI guidelines in accessible language and channels for community audiences.

(5) Consider proportionate, risk-based AI legislation that protects users without burdening small-scale innovation.

Multi-Stakeholder Ecosystem and Rigorous Evaluation

Government agencies, educational institutions, industry and community organisations should collaborate to sustain AI use after training ends, through innovation incubators, community AI project competitions and knowledge-sharing platforms. For MOSTI, the Ministry of Digital and NAIO, the CARAV framework offers a measurable logic model for evaluating public investment in AI literacy. Because the pilot evidence is descriptive, a three-phase, explanatory sequential mixed-methods evaluation is recommended to test the propositions:

(1) *Instrument development*: adapt validated scales (Table 3), translate and back-translate them into Bahasa Malaysia, establish content validity with an expert panel and pre-test the instrument.

(2) *Quasi-experimental survey*: measure participants before, immediately after and three months after the workshop, with a waiting-list comparison group from non-participating RDC hubs, stratified by livelihood group and region, with sample size set by a priori power analysis.

(3) *Longitudinal outcomes and qualitative explanation*: track productivity, income and employment at 6 and 12 months, and interview selected participants and hub managers to explain how use deepens or stalls.

Table 3

Operationalisation of the CARAV Constructs

Construct	Operational definition	Proposed measure/source
Knowledge readiness	Understanding of what AI is, what it can and cannot do, and how to apply it	AI-literacy items (Long & Magerko, 2020; Ng et al., 2021)
AI self-efficacy	Belief in one's capability to use AI applications for a given task	Adapted computer self-efficacy scale (Compeau & Higgins, 1995)
Infrastructure readiness	Access to devices, connectivity and physical facilities	UTAUT2 facilitating conditions (Venkatesh et al., 2012)
Infostructure readiness	Access to information resources, platforms, support services and hub arrangements	UTAUT2 facilitating conditions, adapted (Venkatesh et al., 2012)
Attitudinal readiness	Optimism and innovativeness, net of discomfort and insecurity	TRI 2.0 (Parasuraman & Colby, 2015)
Trust in AI	Willingness to rely on AI outputs, informed by explainability and transparency	Gefen et al. (2003); Shin (2021)
Ethical awareness	Awareness of privacy, data security, integrity, risk, regulation and human oversight	Scale built from global AI-ethics principles (Jobin et al., 2019)
AI acceptance	Behavioural intention to use and actual use of AI	UTAUT2 intention and use items (Venkatesh et al., 2012)
Depth of use	Progression from general-purpose to domain-specific AI applications	Usage-differentiation items (van Deursen & van Dijk, 2014)
Socio-economic value	Changes in productivity, income and employment	Self-reported and record-based outcomes at 6 and 12 months

The measurement and structural models should be estimated using partial least squares structural equation modelling (PLS-SEM), assessing reliability, convergent validity and discriminant validity with the heterotrait–monotrait (HTMT) criterion (Hair et al., 2022; Henseler et al., 2015). Moderation (P2, P5, P6 and P8) can be

tested using interaction terms and multi-group analysis, and mediation (P1, P4 and P7) using bootstrapped indirect effects, while common-method bias should be addressed procedurally and statistically (Podsakoff et al., 2003). Replication in other Southeast Asian economies would further establish the framework's cross-cultural validity.

CONCLUSION

With the rapid diffusion of generative AI, community AI adoption will continue to grow in the coming years. Acknowledging this, the paper set out to address the conceptualisation of community AI readiness and acceptance and its governing issues, based on a review of the literature and supported by pilot evidence from Malaysia's RDC community innovation hubs. The study conceptualises community AI adoption as a chain from readiness, comprising knowledge, infrastructure, infostructure and attitude, through trust and acceptance, to socio-economic value, conditioned by capability-building workshops, ethical awareness and ecosystem support. Eight propositions summarise these relationships in the CARAV framework.

The paper also traced the evolvement of AI from the Dartmouth proposal to the generative AI era and highlighted Malaysia's encouraging progress, including the National AI Roadmap, the *AI untuk Rakyat* programme, the AIGE and the NAIO. Pilot evidence shows that communities are enthusiastic, open and ethically alert, but that foundational capability and depth of use lag behind their enthusiasm. The governing issues that hinder effective community AI adoption include privacy, security and ethics; regulation; infrastructure and infostructure gaps; and lack of skill and knowledge. However, we do acknowledge that the pilot findings are descriptive and self-reported, and that Propositions P1–P8 remain conceptual hypotheses awaiting empirical testing rather than validated relationships.

To address these issues, the paper recommends tiered, livelihood-specific AI literacy; stronger hub infrastructure and infostructure; ethics embedded in every module within a clear regulatory framework; and a multi-stakeholder ecosystem supported by rigorous evaluation. The pilot evidence is preliminary, being based on a post-workshop, self-reported survey of 136 participants from six hubs, so the propositions require longitudinal, multi-group validation before firm conclusions can be drawn.

This paper contributes to AI-adoption and information systems research by establishing the community as a distinct unit of analysis and by separating readiness, acceptance and value realisation from a theoretical perspective. From a practical standpoint, the recommendations on how AI capacity-building programmes can be designed and evaluated would positively affect Malaysian communities and contribute to the national AI agenda.

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