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Article

Harnessing Artificial Intelligence for Sustainable Island Living: An Analysis of Residents' Perceptions

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ABSTRACT

This study examined residents' perceptions of the prospective contribution of artificial intelligence (AI) to sustainable island living in Marinduque, Philippines, and tested associations between demographic factors and five sustainability dimensions. A cross-sectional descriptive-correlational survey was completed by 365 respondents drawn from the province's six municipalities through a combination of purposive, stratified, and snowball procedures. The researcher-developed questionnaire measured perceived environmental, socio-economic, technological-infrastructure, institutional-policy, and community-participation impacts. Respondents rated all five dimensions as large, with overall means ranging from 3.58 to 3.72 on a five-point scale. Five multiple regression models were statistically significant, but their explanatory power was modest (R^2 = .066–.178). Age had negative coefficients in four models, while education, income, technology access, occupation, sex, and community role showed outcome-specific associations. Because several categorical predictors were represented by single numerical codes in the available output, their coefficients were treated as coding-dependent rather than causal effects. The findings indicate broad public receptiveness to AI-enabled sustainability applications, especially early warning, sustainable tourism, institutional collaboration, infrastructure investment, and community awareness. However, the limited variance explained by demographic characteristics underscores the importance of inclusive digital infrastructure, transparent local governance, community co-design, and rigorous evaluation before large-scale implementation.

KEYWORDS

artificial intelligence; sustainable island living; community resilience; digital inclusion; disaster risk reduction; local governance; Marinduque; climate adaptation

1. Introduction

Artificial intelligence is increasingly used to support environmental monitoring, resource allocation, public-service delivery, and disaster risk reduction. Evidence from sustainable-city initiatives shows

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that AI can contribute to waste management, air-quality monitoring, transport management, and emergency response, but many applications are still designed for citizens rather than with them (Gupta & Degbelo, 2023). This distinction is especially important in small and remote communities, where technical performance alone cannot compensate for limited connectivity, uneven digital capability, or weak institutional trust.

Island communities face interconnected environmental, economic, infrastructural, and governance constraints. Recent Pacific research identifies AI-supported predictive modelling, marine monitoring, and decision support as promising climate-adaptation pathways, while also emphasizing data scarcity, skills gaps, affordability, and institutional capacity as barriers (Raj et al., 2025). A fuzzy sustainability assessment developed for small island states similarly demonstrates the need to evaluate environmental, social, and economic conditions as an integrated system rather than as isolated sectors (St Flour & Bokhoree, 2022).

Marinduque provides a salient Philippine setting for this inquiry. Village-level analysis has documented uneven drought risk across the province, shaped by topography, rainfall, agricultural dependence, and social vulnerability (Salvacion, 2023). Studies conducted across its six municipalities have also identified environmental and public-health concerns related to metals in soils, vegetables, and domestic water, reinforcing the need for reliable monitoring and risk-informed local action (Nolos et al., 2022; Senoro et al., 2022). AI and related data tools could support such work, but perceived usefulness must be distinguished from demonstrated operational effectiveness.

The wider literature supports several potential use cases. AI can assist marine ecosystem management and climate response (Gesami & Nunoo, 2024), improve coordination across disaster-management phases (Cvetković, 2026; Ocal & Torun, 2025), and strengthen real-time information sharing when paired with community engagement (Kangana et al., 2024). Smart community standards and interoperable infrastructure can further connect risk information with local services (Nguyen et al., 2024), while mobile, geospatial, robotic, and platform technologies may accelerate response when governance and usability are addressed (Calle Müller et al., 2024).

Nevertheless, evidence remains weighted toward urban systems, technical prototypes, and institutional case studies. Research on isolated communities shows that resilience depends on residents' knowledge, local platforms, resource capacity, learning, and collaboration as much as on the technology itself (Lin et al., 2025). Longitudinal community-resilience research likewise highlights human, social, physical, natural, and financial capacities (Yang et al., 2024), while comparative work stresses that resilience measures must be localized rather than transferred mechanically across communities (Zhai & Lee, 2024).

This study addressed that gap by examining how residents and local stakeholders in Marinduque perceived the prospective contribution of AI to five dimensions of sustainable island living. It also tested whether demographic characteristics were associated with those perceptions. Its contribution lies in providing place-based evidence for a climate-vulnerable island province while explicitly separating perceived potential from measured AI impact.

1.1. Research Questions

The study asked three questions: (1) What were the respondents' demographic and digital-access characteristics? (2) How did respondents assess AI's prospective impact on environmental conditions, socio-economic conditions, technological infrastructure, institutional and policy context, and community participation and awareness? (3) Were demographic factors significantly associated with the five perceived-impact dimensions?

2. Methods

2.1. Study Design and Setting

A quantitative, cross-sectional descriptive-correlational survey design was used. The study was conducted across the six municipalities of Marinduque—Boac, Buenavista, Gasan, Mogpog, Santa Cruz, and Torrijos. The design was appropriate for describing perceptions at one point in time and examining statistical associations; it did not permit causal inference or measurement of the actual performance of implemented AI systems. The retained study documentation did not specify the exact fieldwork dates.

2.2. Participants and Sampling

The achieved sample comprised 365 respondents. Participant groups included local government personnel, community members from livelihood and vulnerable sectors, technical and information-technology practitioners, environmental and sustainability personnel, educators and researchers, and development or policy stakeholders. Purposive selection was used for role-specific participants, stratified procedures were used to broaden representation across demographic and livelihood groups, and snowball referrals were used to reach specialized participants. Because the available records did not retain a complete sampling frame, municipality-by-municipality allocation, invitation denominator, or response rate, the sample should not be treated as statistically representative of all Marinduque residents.

2.3. Instrument and Measures

Data were collected using a researcher-developed questionnaire. The first part recorded age, sex, educational attainment, occupation or livelihood, primary access to technology, income category, length of island residence, community role, and self-rated digital literacy. The second part contained five-item scales for environmental factors, socio-economic factors, technological infrastructure, institutional and policy context, and community participation and awareness. Items were presented in English with Filipino equivalents. Responses used a five-point scale interpreted as very small (1.00–1.79), small (1.80–2.59), moderate (2.60–3.39), large (3.40–4.19), and very large (4.20–5.00).

The source manuscript documented expert review, alignment of items with the research objectives, and pilot testing for clarity. However, it did not retain the number of validators or pilot participants, scale-specific reliability coefficients, or factor-analytic results. Unverified coefficients were therefore not reconstructed or reported, and the five measures were treated as researcher-developed perception scales.

2.4. Data Collection and Ethics

Questionnaires were distributed in digital and paper formats to accommodate differences in internet access. Participation was voluntary, informed consent was obtained, and responses were handled confidentially. No personal identifiers are reported in this article. The available manuscript record did not include the name of an approving ethics committee or an approval reference number; consequently, no institutional approval number is claimed here.

2.5. Data Processing and Analysis

Frequencies and percentages summarized respondent characteristics. Item means and scale-level means and standard deviations summarized perceived AI impact. Five simultaneous multiple linear regression models were then estimated, one for each sustainability dimension, using the nine demographic variables as predictors. Statistical significance was evaluated at $\alpha = .05$. The available output did not retain the software name and version, missing-data protocol, or diagnostic statistics. Moreover, multilevel nominal predictors were represented by single numerical codes rather than complete sets of indicator variables. Their coefficients are therefore reported for transparency but interpreted only as coding-dependent associations.

3. Results

3.1. Respondent Characteristics

The sample was nearly balanced by sex and included all adult age groups. College graduates formed the largest educational group (43.01%), while government employees represented the largest occupational group (21.92%) and government personnel accounted for almost half of reported community roles (48.22%). Smartphones were the most frequently reported primary form of technology access (41.92%), whereas 12.33% reported no access. Most respondents had lived on the island since birth (80.28%), and 82.99% rated their digital capability as basic, proficient, or very proficient.

Table 1. Demographic and digital characteristics of respondents (N = 365).

Variable	Categories	n (%)
Age	18–24; 25–34; 35–44; 45–54; 55–64; ≥65	70 (19.18); 73 (20.00); 75 (20.55); 55 (15.07); 50 (13.70); 42 (11.51)
Sex	Male; Female	180 (49.30); 185 (50.70)
Educational attainment	Elementary; High school; Vocational/technical; College; Postgraduate	39 (10.68); 65 (17.81); 64 (17.53); 157 (43.01); 40 (10.96)
Occupation/livelihood	Student; Farmer/fisherfolk; Government; Private sector; Self-employed; Unemployed	75 (20.55); 60 (16.44); 80 (21.92); 76 (20.82); 48 (13.15); 26 (7.12)
Primary technology access	Smartphone; Computer/laptop; Home internet; None	153 (41.92); 85 (23.29); 82 (22.47); 45 (12.33)
Monthly household income (PHP)	<10,000; 10,001–20,000; 20,001–30,000; 30,001–40,000; >40,000; Prefer not to say	94 (25.75); 140 (38.35); 60 (16.44); 30 (8.22); 31 (8.49); 10 (2.74)
Length of island residence	1–5 years; 6–10 years; 11–20 years; >20 years; Since birth	5 (1.37); 5 (1.37); 25 (6.85); 37 (10.14); 293 (80.28)
Community role	Resident; Leader; Organization member; Educator; Government employee; Business owner; Farmer/fisherfolk; Student	32 (8.76); 23 (6.30); 18 (4.93); 25 (6.85); 176 (48.22); 26 (7.12); 27 (7.40); 38 (10.41)
Digital literacy	Very proficient; Proficient; Basic; Limited; Not proficient	43 (11.78); 146 (40.00); 114 (31.23); 42 (11.51); 20 (5.48)

Note. Percentages may not total 100 because of rounding. PHP = Philippine peso.

3.2. Perceived Impact of AI on Sustainable Island Living

All five dimensions received a large overall rating. The socio-economic dimension had the highest overall mean (M = 3.72), followed by technological infrastructure (M = 3.69), community participation and awareness (M = 3.67), environmental factors (M = 3.60), and institutional and policy context (M = 3.58).

3.2.1. Environmental factors

Respondents generally perceived AI as having a large prospective impact across all environmental indicators (Table 2). Among the five items, AI-enhanced early-warning systems for typhoons and floods received the highest rating (M = 3.82), whereas AI-supported waste management received the lowest rating (M = 3.51). The overall environmental dimension was rated as large (M = 3.60, SD = 0.13).

Table 2. Perceived prospective impact of AI on environmental factors.

Survey item	Mean	Interpretation
AI technologies for environmental monitoring, including coastal erosion and deforestation	3.59	Large
AI for managing natural resources such as water and fisheries	3.55	Large
AI-enhanced early-warning systems for typhoons and floods	3.82	Large
AI-assisted decisions for environmental-protection initiatives	3.53	Large
AI-supported waste management	3.51	Large
Overall mean	3.60	Large
Standard deviation	0.13	—

Note. English item wording is shown; Filipino equivalents were included in the questionnaire.

3.2.2. Socio-economic factors

Perceptions of AI's prospective socio-economic contribution were consistently favorable across all five indicators (Table 3). AI-based tools for sustainable tourism received the highest mean rating (M = 3.81), followed by employment opportunities associated with skills training and innovation (M = 3.78) and AI applications in agriculture and fishing (M = 3.75). The overall socio-economic dimension recorded the highest mean among the five sustainability dimensions examined (M = 3.72, SD = 0.09).

Table 3. Perceived prospective impact of AI on socio-economic factors.

Survey item	Mean	Interpretation
Local employment opportunities through skills training and innovation	3.78	Large
AI-based tools for sustainable tourism	3.81	Large
AI in agriculture and fishing for productivity and economic gains	3.75	Large
AI-enabled access to services and opportunities	3.61	Large
AI-enabled services for island economic development	3.64	Large
Overall mean	3.72	Large
Standard deviation	0.09	—

Note. English item wording is shown; Filipino equivalents were included in the questionnaire.

3.2.3. Technological infrastructure

Ratings for technological infrastructure also indicated a large perceived prospective impact of AI (Table 4). The highest-rated item concerned the capacity of local organizations to integrate AI tools (M = 3.75), followed by prioritizing AI applications in infrastructure development (M = 3.73) and investment in AI technology for sustainable development (M = 3.72). Existing digital infrastructure (M = 3.62) and reliable electricity (M = 3.61) received slightly lower, although still large, ratings. The overall mean for this dimension was 3.69 (SD = 0.07).

Table 4. Perceived prospective impact of AI on technological infrastructure.

Survey item	Mean	Interpretation
Existing digital infrastructure for AI adoption	3.62	Large
Reliable electricity for AI-powered systems	3.61	Large
Investment in AI technology for sustainable development	3.72	Large
Local organizations' capacity to integrate AI tools	3.75	Large
Priority for AI applications in infrastructure development	3.73	Large
Overall mean	3.69	Large
Standard deviation	0.07	—

Note. English item wording is shown; Filipino equivalents were included in the questionnaire.

3.2.4. Institutional and policy context

The institutional and policy dimension was also assessed positively, with all five indicators falling within the large-impact category (Table 5). Institutional collaboration with AI experts and organizations received the highest mean rating (M = 3.64), followed by strategic action planning for AI adoption (M = 3.61). Existing policies and the need for policy reforms received identical mean scores (M = 3.54). Although this dimension had the lowest overall mean among the five dimensions examined, it was still classified as large (M = 3.58, SD = 0.04).

Table 5. Perceived prospective impact of AI on institutional and policy context.

Survey item	Mean	Interpretation
Local-government support for AI integration	3.58	Large
Existing policies promoting digital technologies and AI	3.54	Large
Policy reforms for AI-driven sustainability	3.54	Large
Institutional collaboration with AI experts and organizations	3.64	Large
Strategic action planning for AI adoption	3.61	Large
Overall mean	3.58	Large
Standard deviation	0.04	—

Note. English item wording is shown; Filipino equivalents were included in the questionnaire.

3.2.5. Community participation and awareness

Respondents also reported a large perceived prospective role for AI in community participation and awareness (Table 6). Community-awareness campaigns concerning AI's environmental and social roles received the highest rating (M = 3.73), followed by opportunities for residents to provide ideas and feedback (M = 3.69) and awareness of AI applications for sustainable practices (M = 3.67). The overall mean for this dimension was 3.67 (SD = 0.04), indicating consistently favorable perceptions across the five items.

Table 6. Perceived prospective impact of AI on community participation and awareness.

Survey item	Mean	Interpretation
Participation in sustainability projects using AI	3.62	Large
Awareness of AI applications for sustainable practices	3.67	Large
Opportunities for residents to provide ideas and feedback	3.69	Large
Community-awareness campaigns on AI's environmental and social roles	3.73	Large
Community engagement in AI-driven sustainability initiatives	3.63	Large
Overall mean	3.67	Large
Standard deviation	0.04	—

Note. English item wording is shown; Filipino equivalents were included in the questionnaire.

3.3. Associations Between Demographic Factors and Perceived Impact

Each of the five regression models was statistically significant. Demographic variables explained 17.8% of variance in environmental ratings, 12.7% in socio-economic ratings, 14.0% in technological-infrastructure ratings, 6.6% in institutional-policy ratings, and 11.5% in community-participation ratings. These values indicate modest explanatory power.

Table 7. Multiple regression model fit for the five perceived-impact dimensions.

Outcome	R	R^2	Adjusted R^2	$F(9, 355)$	p
Environmental factors	0.422	0.178	0.157	8.536	< 0.001
Socio-economic factors	0.357	0.127	0.105	5.750	< 0.001
Technological infrastructure	0.374	0.140	0.118	6.416	< 0.001
Institutional and policy context	0.257	0.066	0.042	2.789	0.004
Community participation and awareness	0.340	0.115	0.093	5.149	< 0.001

Note. N = 365. Values reported as 0.000 in the source output are presented as $p < 0.001$.

Age had significant negative coefficients for environmental, socio-economic, technological-infrastructure, and community-participation ratings. Educational attainment was significant in the environmental model, while income was significant in the community-participation model. Technology access was significant in the environmental, socio-economic, and institutional-policy models. Occupation was significant in the socio-economic, technological, and community-participation models; sex was significant only in the community-participation model; and community role was significant only in the environmental model. Because coding documentation for categorical predictors was not retained, the direction of those categorical coefficients is not given a substantive category-to-category meaning.

Table 8. Predictors with statistically significant coefficients in the simultaneous regression models.

Outcome	Predictor	B	β	t	p
Environmental	Age	−0.125	−0.209	−3.761	< 0.001
Environmental	Educational attainment	0.156	0.217	3.876	< 0.001
Environmental	Technology access	0.068	0.143	2.463	0.014
Environmental	Community role	−0.048	−.142	−20.669	0.008
Socio-economic	Age	−0.161	−0.294	−5.127	< 0.001
Socio-economic	Occupation/livelihood	0.108	0.193	3.223	0.001
Socio-economic	Technology access	0.052	0.119	1.990	0.047
Technological infrastructure	Age	−0.148	−0.257	−4.517	< 0.001
Technological infrastructure	Occupation/livelihood	0.090	0.153	2.581	0.010
Institutional-policy	Technology access	0.069	0.150	2.421	0.016
Community participation	Age	−0.084	−0.142	−2.459	0.014
Community participation	Sex	0.194	0.117	2.307	0.022
Community participation	Occupation/livelihood	0.073	0.121	2.003	0.046
Community participation	Income	0.071	0.147	2.747	0.006

Note. Full coefficient estimates, including non-significant predictors, are reported in Appendix A.

4. Discussion

4.1. Brief Summary of Key Findings

Respondents expressed broadly favorable perceptions of AI's prospective contribution to all five sustainability dimensions. The strongest individual ratings concerned early warning, sustainable tourism, local organizational capacity, infrastructure prioritization, and community-awareness campaigns. Demographic models were significant but explained only 6.6%–17.8% of outcome variance, indicating that perceptions were shaped largely by factors not captured in the demographic profile.

4.2. Interpretation and Explanatory Mechanisms

The prominence of early warning is plausible in a province exposed to typhoons, flooding, drought, coastal hazards, and geographically uneven service access. Residents may recognize AI most readily when it is linked to visible, time-sensitive public benefits. At the same time, high perception scores do not establish that AI systems are already available, accurate, trusted, or effective in Marinduque. They indicate receptiveness to proposed uses.

Technology access was the only significant predictor in the institutional-policy model. A reasonable interpretation is that connectivity increases exposure to digital services, online information, and government communication, which may make AI-enabled governance more imaginable. However, the small R^2 for that model shows that access alone is insufficient. Trust, service quality, perceived fairness, institutional openness, and actual experience with local programs are likely to matter.

The recurring negative age coefficients suggest an age-related perception gap. This may reflect differences in digital exposure, confidence, perceived relevance, or accessibility. The pattern supports age-sensitive design and assisted access, but it should not be read as evidence that older residents oppose innovation or are incapable of using digital systems.

4.3. Comparison With Existing Literature

The results align with research describing disaster resilience as a combination of social, institutional, infrastructural, and learning capacities rather than a purely technical capability (Lv et al., 2024). They also support calls to localize community-resilience indicators because the usefulness of a technology depends on local resources, governance arrangements, and patterns of vulnerability (Milenković et al., 2026).

The observed importance of access and community participation is consistent with evidence that AI benefits in marginalized communities depend on infrastructure, institutional support, affordability, and trust safeguards (Karmaker & Cvetković, 2026). It also parallels findings that mobile and social-media systems can strengthen disaster communication when information is timely, understandable, and accessible (Yamah & Folorunsho, 2026). Digital platforms can extend ecological learning and collaboration, but equity and governance must be designed into the platform rather than added later (Gajović et al., 2025).

For the Philippine context, GIS-based analysis of evacuation-center safety and accessibility illustrates the value of combining data tools with locally specific hazard and access criteria (Aniñon & Oreta, 2026). The present study extends this line of inquiry by showing that Marinduque residents perceive comparable value in AI-assisted warning, monitoring, and planning, while also revealing demographic and access-related differences that technical studies alone may not capture.

4.4. Theoretical Implications

The findings support a socio-technical view of sustainable island innovation. Perceived AI value emerged across environmental, economic, infrastructural, institutional, and participatory dimensions, suggesting that adoption is not a single-technology decision. It is a relationship among tools, users, organizations, policies, and local ecological conditions. The modest R^2 values further imply that demographic characteristics are background conditions rather than a complete explanation of readiness or acceptance.

4.5. Practical and Policy Implications

A prudent implementation pathway would begin with bounded, publicly accountable pilots. Provincial and municipal governments could prioritize early-warning augmentation, environmental monitoring, and decision-support dashboards that use validated local data and preserve human oversight. Each pilot should publish its purpose, data sources, accuracy limits, responsible office, complaint channel, and evaluation criteria.

Digital inclusion should be treated as core infrastructure. Assisted-access points, offline or low-bandwidth modes, age-sensitive training, Filipino-language interfaces, and non-digital alternatives are necessary so that residents without reliable devices or internet are not excluded. Community representatives—including farmers, fisherfolk, older adults, youth, women, and persons in remote barangays—should participate in problem definition, testing, and review.

Finally, Marinduque State University, local governments, civil-society groups, and sectoral organizations could establish a shared island data and AI governance forum. Its functions should include data-quality standards, privacy and cybersecurity safeguards, skills development, procurement review, impact evaluation, and public reporting.

4.6. Limitations and Potential Biases

The study measured perceptions of prospective AI impact rather than outcomes from operational AI systems. Its cross-sectional design cannot establish causation. Mixed purposive, stratified, and snowball procedures, together with the absence of a complete sampling frame and response denominator, limit representativeness. Government-affiliated respondents were prominent, which may have elevated institutional viewpoints.

The instrument was researcher-developed, and retained documentation did not include scale-specific reliability coefficients or construct-validity evidence. Common-method, acquiescence, and social-desirability biases are possible. The regression output did not preserve full coding specifications, diagnostic tests, software information, or a missing-data protocol. In particular, single-code treatment of multilevel nominal variables means that several coefficients are coding-dependent. These limitations narrow the conclusions to exploratory associations and policy signals rather than validated causal determinants.

4.7. Directions for Future Research

Future studies should use probability-based municipal samples, document response rates and fieldwork dates, validate the five scales through factor analysis and reliability testing, and pre-register predictor coding and diagnostics. Mixed-methods work could examine why residents differ in perceived value, trust, and willingness to participate. Longitudinal or quasi-experimental evaluations should then assess actual pilots using accuracy, response time, service reach, equity, environmental outcomes, and user trust rather than perceptions alone.

5. Conclusions

This study examined residents' perceptions of AI's prospective role in sustainable island living and their associations with demographic characteristics. Respondents rated all five sustainability dimensions as having a large potential impact, while demographic models explained only a modest share of variation.

The study contributes place-based evidence from Marinduque and clarifies that favorable perceptions of AI are not equivalent to proof of implemented impact. It identifies digital access, age-related differences, institutional conditions, and community participation as important considerations for locally appropriate innovation.

AI initiatives should begin with transparent, limited pilots; pair digital systems with assisted and non-digital access; and involve communities in design, oversight, and evaluation. Early warning, environmental monitoring, and public decision support are plausible starting points if they use validated local data and maintain human accountability.

Because the evidence is cross-sectional, perception-based, and affected by sampling and measurement limitations, the findings should be treated as exploratory. Representative sampling, validated measures, correctly specified categorical models, and evaluation of operational systems are needed.

For island communities, responsible AI will be sustainable only when technological capability is matched by inclusion, trustworthy governance, local knowledge, and measurable public benefit.

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Appendix A

The following tables reproduce the complete coefficient estimates retained in the source statistical output. Coefficients for multilevel nominal predictors are coding-dependent because complete indicator coding was not retained.

Table A1. Complete simultaneous regression coefficients for environmental factors.

Predictor	B	SE	β	t	p
Age	−0.125	0.033	−0.209	−3.761	< 0.001
Sex	0.041	0.082	0.025	0.504	0.614
Educational attainment	0.156	0.040	0.217	3.876	< 0.001
Occupation/livelihood	0.011	0.035	0.017	0.301	0.763
Technology access	0.068	0.028	0.143	2.463	0.014
Income	0.008	0.025	0.017	0.325	0.745
Length of residence	−0.026	0.036	−0.036	−0.713	0.476
Community role	−0.048	0.018	−0.142	−2.669	0.008
Digital literacy	0.020	0.051	0.021	0.389	0.698

Note. N = 365. The intercept is omitted for compact presentation.

Table A2. Complete simultaneous regression coefficients for socio-economic factors.

Predictor	B	SE	β	t	p
Age	−0.161	0.031	−0.294	−50.127	< 0.001
Sex	−0.018	0.078	−0.012	−0.230	0.818
Educational attainment	0.012	0.038	0.018	0.313	0.754
Occupation/livelihood	0.108	0.034	0.193	3.223	0.001
Technology access	0.052	0.026	0.119	1.990	0.047
Income	−0.006	0.024	−0.013	−0.251	0.802

Predictor	B	SE	β	t	p
Length of residence	−0.004	0.034	−0.005	−0.105	0.917
Community role	−0.026	0.017	−0.083	−1.508	0.132
Digital literacy	0.021	0.048	0.025	0.441	0.659

Note. N = 365. The intercept is omitted for compact presentation.

Table A3. Complete simultaneous regression coefficients for technological infrastructure.

Predictor	B	SE	β	t	p
Age	−0.148	0.033	−0.257	−4.517	< 0.001
Sex	0.037	0.081	0.023	.454	0.650
Educational attainment	0.054	0.040	0.078	1.355	0.176
Occupation/livelihood	0.090	0.035	0.153	2.581	0.010
Technology access	0.053	0.027	0.115	1.936	0.054
Income	0.047	0.025	0.099	1.875	0.062
Length of residence	−0.033	0.036	−0.047	−.922	0.357
Community role	−0.030	0.018	−0.091	−1.675	0.095
Digital literacy	0.046	0.050	0.051	.914	0.361

Note. N = 365. The intercept is omitted for compact presentation.

Table A4. Complete simultaneous regression coefficients for institutional and policy context.

Predictor	B	SE	β	t	p
Age	−0.050	0.034	−0.086	−1.457	0.146
Sex	0.070	0.085	0.043	.829	0.408
Educational attainment	0.044	0.041	0.064	1.063	0.289
Occupation/livelihood	−0.019	0.037	−0.031	−.508	0.612
Technology access	0.069	0.029	0.150	2.421	0.016
Income	0.011	0.026	0.024	.429	0.668
Length of residence	−0.042	0.038	−0.059	−1.111	0.267
Community role	−0.019	0.019	−0.057	−1.006	0.315
Digital literacy	−0.027	0.052	−0.030	−.525	0.600

Note. N = 365. The intercept is omitted for compact presentation.

Table A5. Complete simultaneous regression coefficients for community participation and awareness.

Predictor	B	SE	β	t	p
Age	−0.084	0.034	−0.142	−2.459	0.014
Sex	0.194	0.084	0.117	2.307	0.022
Educational attainment	0.056	0.041	0.080	1.374	0.170
Occupation/livelihood	0.073	0.036	0.121	2.003	0.046
Technology access	0.037	0.028	0.078	1.295	0.196
Income	0.071	0.026	0.147	2.747	0.006
Length of residence	−0.068	0.037	−0.095	−1.826	0.069
Community role	−0.033	0.019	−0.099	−1.799	0.073
Digital literacy	0.084	0.052	0.091	1.623	0.106

Note. N = 365. The intercept is omitted for compact presentation.

6. References

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