Artificial Intelligence-Assisted Community Needs Assessment and Extension Planning: Evidence from Wesleyan University-Philippines Partner Communities

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***Abstract*—This study conducted an Artificial Intelligence-assisted community needs assessment of partner-community respondents of Wesleyan University-Philippines, with emphasis on the Tricycle Operators and Drivers Association. Using a descriptive-quantitative design, five objectives were addressed: to describe the socioeconomic profile of the respondents; to determine livelihood and income conditions; to identify health, educational, and public-service needs; to rank priority community needs; and to develop a transparent, data-driven Artificial Intelligence-assisted framework. A cleaned dataset of 151 respondents was analyzed, of whom 46 were formally affiliated with tricycle operator and driver associations. Frequency, percentage, mean, and a proportion-based priority score summarized the data, while an Artificial Intelligence-assisted workflow supported response coding, respondent clustering, pattern detection, and need-to-intervention matching. Results showed that the transport subgroup consisted entirely of male drivers with lower average income, stronger income-expenditure pressure, greater reliance on borrowing and relatives, and recurring health concerns, including respiratory illness, hypertension, dental problems, and diabetes. Educational needs centered on books and learning materials. Ranked priorities were transport-oriented support, public-service linkage, health and wellness, educational assistance, livelihood and financial stability, skills training, and environmental support. The study concludes that pairing descriptive statistics with a reproducible Artificial Intelligence-assisted procedure produces more targeted, equitable, and responsive extension planning, and offers a practical template for other higher-education institutions.**

Keywords*—Artificial Intelligence; Community Needs Assessment; data-driven extension program; tricycle drivers; needs prioritization; decision support

I. Introduction

Community needs assessment is a critical process for identifying the social, economic, health, livelihood, and service-related concerns of a target population. In university extension work, it provides an empirical basis for designing programs that respond to the actual conditions of partner communities rather than to assumptions or generalized interventions. Prior studies have shown the value of structured surveys for determining industry and community priorities, building extension programs, and identifying future research and service needs [1]–[6]. These studies indicate that systematic data collection can help institutions align their programs with the needs of specific beneficiary groups.

At Wesleyan University-Philippines, the Tricycle Operators and Drivers Association represents an important community sector. Tricycle drivers contribute directly to local mobility, campus access, and everyday transportation. Like other transport-dependent and underserved groups, they may face income instability, high household expenses, limited access to public services, unmet health needs, and gaps in skills development. Transportation research has emphasized that mobility systems are closely connected to social equity, public participation, and access to opportunities [7]–[11]. Assessing the needs of these members is therefore not only a question of livelihood analysis but also one of inclusive community planning and equitable service delivery.

Public participation is also essential to identifying community priorities. Arnstein’s framework on citizen participation stresses the importance of moving beyond token consultation toward meaningful involvement in decision-making [12]. Later work similarly argues that effective planning requires participatory approaches that let affected groups express their needs and lived experiences [13]–[17]. For transport workers, participatory needs assessment can help ensure that university extension initiatives address genuine concerns such as livelihood support, financial literacy, health services, skills training, and access to institutional assistance.

Traditional needs assessment, however, often produces large amounts of survey data that require careful interpretation. Artificial Intelligence offers a way to improve this analysis by assisting in pattern detection, classification, prioritization, and decision support. Applied responsibly, it can help identify which needs are most urgent, which respondent groups are most vulnerable, and which interventions are most appropriate for a given community profile. This direction is consistent with survey-based studies that used structured instruments and quantitative analysis to evaluate community or industry needs [5], [18], [19], and with a growing body of work that applies machine learning to community and poverty data [26]–[31].

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Equity-oriented planning literature further supports examining communities that may be disadvantaged, underrepresented, or underserved in formal decision-making [20]–[23], [9], [11]. Studies on transportation equity and public engagement show that vulnerable communities are often affected by planning decisions yet have limited influence over the programs intended to serve them [24], [9]–[11], [25]. An Artificial Intelligence-assisted needs assessment can provide a more systematic way to prioritize interventions and ground extension programs in evidence, equity, and participation.

This study analyzed all 151 respondents in the dataset, while giving particular emphasis to the 46 respondents who were formally affiliated with tricycle operator and driver associations. The emphasis is justified because these members form a coherent transport-sector subgroup that shares an occupation, an income structure, and a set of road-related exposures; retaining the full sample allows their conditions to be benchmarked against the broader partner community. Accordingly, the study addressed five objectives: 1) to describe the socioeconomic profile of the respondents; 2) to determine their livelihood and income conditions; 3) to identify their health, educational, and public-service needs; 4) to rank their priority community needs; and 5) to develop a data-driven, Artificial Intelligence-assisted community extension framework.

The contribution of the study is threefold. First, it documents a transparent and reproducible Artificial Intelligence-assisted workflow—covering response coding, clustering, pattern detection, proportion-based prioritization, and need-to-intervention matching—rather than treating Artificial Intelligence as a black box. Second, it shows how this workflow adds value beyond conventional frequency-and-percentage reporting by isolating a vulnerable subgroup and linking each surfaced need to a concrete extension response. Third, it provides a deployable framework that a university can reuse for planning, implementation, monitoring, and evaluation of extension programs for transport and other partner communities.

II. Related Work

A. Community Needs Assessment and University Extension

Structured surveys have long been used to characterize the needs of specific industries and communities and to translate those needs into extension programs [1]–[6]. This literature established that descriptive instruments, careful coding, and ranking can yield actionable priorities, and that ongoing evaluation is needed to keep programs aligned with beneficiaries [3]. Community-engaged health-needs assessments similarly combine closed and open-ended items with descriptive and thematic analysis to direct concrete public-health initiatives [28]. The present study builds on this tradition but extends it to a transport-sector partner community of a university.

B. Transportation Communities, Equity, and Informal Transport Workers

Transportation scholarship frames mobility as a matter of social equity and meaningful participation, noting that underserved communities are frequently shaped by decisions they have little power to influence [7]–[11], [24], [25]. Within this literature, informal transport workers are a distinctly vulnerable group. Drivers of tricycles, pedicabs, and similar vehicles face poverty risks linked to low educational attainment, prolonged participation in the informal economy, and limited social protection, as recent machine-learning and econometric analyses of informal transportation in the Philippines demonstrate [26], [27]. These conditions motivate a needs assessment that treats tricycle operators and drivers as a priority sector rather than as an undifferentiated part of the population.

C. Artificial Intelligence Needs Assessment and Decision Support

A rapidly expanding body of work applies machine learning to survey and administrative data for social purposes. Studies have used supervised and tree-based models to predict healthcare needs and access barriers from community surveys [28], and to predict and target poverty across localities, often finding ensemble methods such as random forests effective [27], [29], [30]. For unstructured responses, topic modeling, embedding-based clustering, and few-shot classification with language models now support faster and more consistent coding of open-ended items, while still requiring human interpretation of the resulting clusters [31]. Collectively, this literature positions Artificial Intelligence as a decision-support layer that augments, rather than replaces, descriptive analysis and expert judgment.

D. Research Gap and Positioning of the Study

Two gaps remain. First, machine-learning poverty and needs studies typically operate at a regional or national scale and rarely target a single university partner community, such as a campus-serving tricycle association. Second, many "Artificial Intelligence-assisted" community studies describe the technology only in general terms, without specifying the workflow, inputs, and outputs. This study addresses both gaps by focusing on a defined transport-sector partner community and by documenting an explicit, reproducible Artificial Intelligence-assisted procedure that maps surfaced needs to specific extension responses. In doing so, it differs from conventional survey-based assessment, which usually stops at frequency, percentage, mean, and ranking, by adding respondent grouping, pattern detection, and need-to-intervention matching that can be carried into program monitoring.

III. Methodology

A. Research Design

This study employed a descriptive-quantitative research design integrated with Artificial Intelligence-assisted data analysis to assess and prioritize the needs of members of the Tricycle Operators and Drivers Association of Wesleyan University-Philippines and of the broader partner community. The descriptive component determined the demographic, socioeconomic, livelihood, health, educational, skills-development, and public-service profile of the respondents. The Artificial Intelligence-assisted component supported response coding, clustering, pattern recognition, and prioritization of needs.

The design is appropriate because community needs assessment studies commonly use structured survey data to identify priority concerns and guide extension programs [1]–[6]. Here, Artificial Intelligence served as a decision-support tool that helped organize and interpret patterns in the dataset. The overall methodological flow is shown in Table I.

TABLE I. RESEARCH DESIGN MATRIX

Component	Description	Purpose	Expected Output
Research Design	Descriptive-quantitative with Artificial Intelligence-assisted analysis	To describe and analyze the needs of the respondents.	Community needs profile
Data Source	Community Needs Assessment Survey	To gather demographic, socioeconomic, health, livelihood, and service-related data.	Encoded dataset
Statistical Analysis	Frequency, percentage, mean, and proportion-based priority score	To identify dominant respondent characteristics and priority needs.	Summary tables and ranked needs
Artificial Intelligence-Assisted Analysis	Coding, clustering, pattern recognition, and prioritization	To group respondents and determine high-priority intervention areas.	Needs-priority model
Final Output	Data-driven extension program framework	To guide university extension planning.	Proposed extension program

The overall methodological flow of the study is presented in Fig. 1.

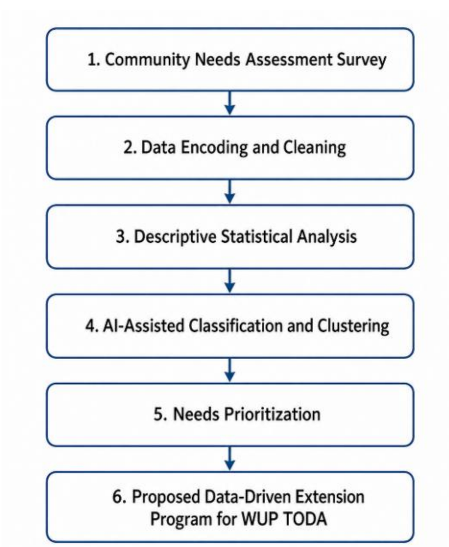

Fig. 1. Methodological flow of the AI-assisted community needs assessment.

B. Research Locale

The study was conducted at Wesleyan University-Philippines, with emphasis on tricycle operators and drivers working within and around the university premises. The dataset included respondents associated with WUP TODA, WUP Main Gate TODA, TODA WUP, and other tricycle associations near the university. The locale was selected because these members provide daily transportation to students, employees, and nearby residents, which makes them a relevant partner community for university-based extension services.

C. Respondents of the Study

The study used secondary data from an existing Community Needs Assessment, so no new sampling was performed by the researchers during analysis. The dataset was treated as a complete enumeration of the available respondents: all 151 records that passed data screening were analyzed rather than a probability sample drawn from them. Within this total enumeration, a purposive emphasis was placed on the 46 respondents who were formally affiliated with tricycle operator and driver associations, because they constitute the priority transport sector for the university's extension work. The combined approach is therefore a complete enumeration of an available, non-probability dataset with a purposively defined subgroup. This choice is consistent with the descriptive aim of the study, but it limits statistical generalization beyond the participating community, a point revisited in the limitations.

The respondents were members of the partner community of Wesleyan University-Philippines, including tricycle drivers, operators, and household representatives recorded in the Community Needs Assessment dataset. They were described according to demographic and socioeconomic variables such as age, sex, civil status, educational attainment, occupation, household size, monthly income, expenses, skills, health condition, access to services, and identified priority needs (Table II).

TABLE II. PROFILE VARIABLES OF THE RESPONDENTS

Variable Category	Specific Variables	Purpose of Analysis
Demographic Profile	Age, sex, civil status, household size	Described the general characteristics of partner community respondents.
Educational Profile	Highest educational attainment and school-age dependents	Identified education-related needs and possible learning support programs.
Economic Profile	Occupation, monthly income, and household expenses	Assessed income stability and financial vulnerability.
Livelihood Profile	Main source of income, additional livelihood, and skills	Determined livelihood and skills-training needs.
Health Profile	Health concerns and access to health services	Identified possible medical, wellness, or health-extension needs.
Public Service Access	Access to government or community services	Determined gaps in service delivery.
Priority Needs	Stated household and community needs	Ranked intervention areas for extension planning.

D. Research Instrument

The primary instrument was the Community Needs Assessment Survey Form. It contained items on respondent profile, socioeconomic condition, livelihood status, educational background, health concerns, available skills, access to services, environmental concerns, and priority community needs. Scaled or selection-type responses were interpreted using proportion-based scoring and ranking, consistent with structured measurement in survey research [18]. The survey results also served as the input dataset for the Artificial Intelligence-assisted analysis.

E. Data Gathering Procedure

The study used the existing Community Needs Assessment data collected from respondents of Wesleyan University-Philippines. The data were reviewed, encoded, cleaned, and organized prior to statistical and Artificial Intelligence-assisted analysis. The procedure followed seven steps: responses were collected and organized; reviewed for completeness, consistency, and relevance; checked and corrected for duplicate, unclear, or inconsistent entries; coded into analyzable categories for categorical and text-based items; prepared for descriptive and Artificial Intelligence-assisted processing; summarized into tables, patterns, clusters, and rankings; and finally translated into a proposed data-driven extension program.

F. Data Preparation, Coding, and Reliability

Before analysis, the dataset was preprocessed to improve accuracy and consistency. Missing values, inconsistent entries, duplicate responses, and unclear categories were checked. Categorical responses were standardized, and open-ended responses were grouped into common themes (Table III). For the Artificial Intelligence-assisted analysis, categorical variables were converted into coded values, and multiple-response items such as skills, services needed, and priority concerns were transformed into binary indicators.

To strengthen the thematic grouping of open-ended responses, a documented coding protocol was applied. A draft codebook of recurring themes was first prepared from an initial read of the responses. A language-model assistant proposed candidate theme labels for each response, and two researchers independently reviewed and assigned the final codes against the codebook. Disagreements were resolved by discussion and consensus, and a sample of coded responses was re-checked for consistency. In this way, the Artificial Intelligence output was used as a suggestion that researchers verified, not as a final categorization, which preserves human control over interpretation.

TABLE III. DATA PREPROCESSING AND CODING PLAN

Data Type	*Example Variables*	*Preprocessing Procedure*	*Output*
Numeric Data	Age, income, expenses, household size	Missing values and outliers were checked.	Clean numeric dataset
Categorical Data	Sex, civil status, occupation, educational attainment	Responses were standardized and coded.	Coded variables
Text-Based Data	Skills, stated needs, livelihood concerns	Similar responses were grouped into themes.	Thematic categories
Multiple-Response Data	Priority needs, services needed, training interests	Responses were converted into binary or frequency indicators.	Needs matrix
Incomplete Entries	Blank or inconsistent responses	Entries were validated, corrected, or excluded when necessary.	Final cleaned dataset

G. Statistical Treatment of Data

Descriptive statistics summarized the profile and needs of the respondents. Frequencies and percentages were used for categorical variables, and the mean was used for continuous variables such as age, income, and expenditure. The percentage for category i was computed as $\%_i = (f_i / n) \times 100$, where f_i is the frequency of category i and n is the number of valid responses. The arithmetic mean was computed as $\bar{x} = (\Sigma x_i) / n$.

For multiple-response and binary-coded needs, a proportion-based priority score (endorsement rate) was used. For need j, the score was $ER_j = (\Sigma_i b_{ij}) / n$, where $b_{ij} = 1$ if respondent i endorsed need j and 0 otherwise, and n is the relevant denominator (151 for all respondents and 46 for the transport subgroup). The score ranges from 0 to 1 and equals the proportion of respondents who indicated the need; needs were then ranked in descending order of ER_j. This formulation is reported transparently because the values in Table IV are endorsement rates, and the column is labeled accordingly. Computational tools were used to organize and process the dataset, consistent with survey-based studies that applied statistical software [19].

TABLE IV. STATISTICAL TREATMENT OF DATA

Research Objective	*Data Required*	*Statistical Tool*	*Interpretation*
Describe the profile of respondents	Demographic and socioeconomic variables	Frequency and percentage	Identified dominant respondent characteristics.
Determine livelihood and income conditions	Income, occupation, expenses, livelihood source	Frequency, percentage, and mean	Showed economic status and livelihood vulnerability.
Identify health, education, and service needs	Health concerns, educational needs, public-service access	Frequency and ranking	Determined common social-service needs.
Rank priority community needs	Stated needs and intervention preferences	Endorsement rate (proportion) and rank	Identified the most urgent areas for extension.
Develop an Artificial Intelligence-assisted framework	Ranked needs, cleaned and coded dataset, profile and livelihood indicators	Coding, normalization, pattern identification, proportion-based prioritization, framework mapping	Produced a framework identifying priority intervention areas.

H. Artificial Intelligence-Assisted Data Analysis

Artificial Intelligence was integrated to support deeper interpretation of the dataset, focusing on coding, clustering, pattern recognition, and needs prioritization. To make the procedure transparent and reproducible, the specific tools and workflow are described here. A general-purpose large language model assistant was used for assisted thematic coding of open-ended responses, and a Python environment with the pandas and scikit-learn libraries was used for the quantitative steps.

The workflow proceeded in seven steps: 1) The cleaned and coded dataset was ingested. 2) Open-ended responses were thematically coded with language-model assistance and researcher review, as described in Section III G. 3) Categorical and multiple-response items were converted into numeric and binary features. 4) Respondents were grouped using k-means clustering on standardized socioeconomic features, while text needs were grouped using term-frequency representations and similarity-based clustering. 5) Patterns were detected through cross-tabulation and association checks, for example, between income level and livelihood needs, household size and financial difficulty, or occupational exposure and health concerns. 6) Needs were prioritized using the endorsement-rate score defined above. 7) Each high-priority need was matched to a candidate extension response through a rule-based mapping that researchers reviewed. The input variables and expected outputs of each procedure are summarized in Table V, and the prioritization logic is illustrated in Fig. 2.

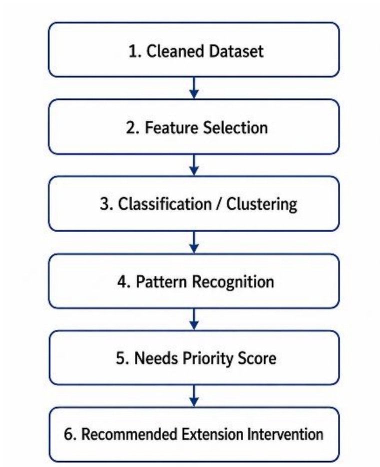

Fig. 2. AI-assisted needs prioritization framework.

TABLE V. AI-ASSISTED ANALYSIS PLAN

AI Procedure	*Purpose*	*Possible Input Variables*	*Expected Output*
Classification / Coding	Categorized respondents and responses by dominant need	Income, occupation, skills, health and education needs	Respondent and response need categories
Clustering	Grouped respondents with similar conditions	Socioeconomic and household variables	Clusters of similar respondents
Pattern Recognition	Detected relationships among variables	Income, expenses, household size, livelihood, needs	Identified trends and associations
Priority Modeling	Determined urgent intervention areas	Endorsement rate of needs, respondent profile	Ranked community priorities
Decision Support	Guided extension program design	Artificial Intelligence and statistical results	Proposed intervention framework

The Artificial Intelligence-assisted analysis was not a replacement for the researcher's interpretation. It functioned as a decision-support mechanism that revealed patterns and priority areas. Its value beyond conventional descriptive statistics is summarized as follows: whereas frequency, percentage, mean, and ranking describe the dataset one variable at a time, the assisted workflow additionally grouped respondents into comparable clusters, detected co-occurring needs across variables, isolated the more vulnerable transport subgroup, and linked each surfaced need to a specific intervention. These capabilities turn a set of summary tables into a reusable decision-support layer for planning, implementation, and monitoring.

I. Needs Prioritization Procedure

Priority needs were determined using both the endorsement-rate ranking and the Artificial Intelligence-assisted analysis. Needs that appeared frequently across respondents were identified and ranked, then examined in relation to profile variables such as income, household expenses, occupation, health status, household size, and available skills. A prioritization matrix connected each identified need with a possible university extension response (Table VI).

TABLE VI. NEEDS PRIORITIZATION MATRIX

Priority Area	*Basis for Ranking*	*Possible Extension Response*
Livelihood and Income Support	Low income, high expenses, and unstable livelihood	Livelihood training and income-generating projects
Skills Development	Existing skills and training interests	Technical, vocational, or entrepreneurial training
Health and Wellness	Reported health concerns or limited access to health services	Medical mission, health education, and wellness programs
Financial Literacy	Income-expense gap and household financial difficulty	Budgeting seminar, savings orientation, and microenterprise training
Educational Support	Education-related household needs	Scholarship orientation, tutorial support, and learning assistance
Public Service Access	Limited access to government or community services	Linkage with local government units and social-service agencies

J. Validation of Results

The statistical and Artificial Intelligence-assisted results were reviewed to ensure that the generated priorities were reasonable, interpretable, and aligned with the actual responses. Validation compared the assisted outputs with the descriptive statistical results and the stated needs of the respondents. The interpretation also considered the importance of meaningful community participation in planning, because participatory approaches strengthen the relevance of community-based programs by allowing affected groups to express their actual needs and priorities [13]–[17], [24], [25].

K. Ethical Considerations

The study observed ethical standards in handling community data. Respondent information was treated confidentially, and personal identifiers were removed before analysis. The dataset was used only for academic and extension-planning purposes. Because the study involved Artificial Intelligence-assisted analysis, the generated outputs were reviewed carefully before interpretation. The researchers ensured that findings were presented in a respectful, community-centered, and equity-oriented manner, and that results were used to identify appropriate support programs rather than to stigmatize respondents.

IV. Results and Discussions

A. Data Screening and Scope of Analysis

The Community Needs Assessment dataset contained 151 respondents, and the analysis covered all of them. Because the study prioritized tricycle operators and drivers of Wesleyan University-Philippines, a transport-focused comparison was also made. Of the 151 respondents, 46 (30.5%) were formally affiliated with tricycle associations, including WUP TODA, WUP Main Gate TODA, TODA WUP, Mabini Ext TODA, and a senior-citizen WUP TODA entry; among them, 36 (23.8%) were directly linked to WUP-related groups. Multiple-response items were treated as selected when the corresponding cell contained an entry, so percentages in some tables may exceed 100%.

This emphasis on the transport subgroup is methodologically defensible: the 46 members share an occupation, an income structure, and a set of road-related exposures, which makes them a coherent unit for targeted planning, while the full sample provides a comparison baseline. The framing as a transport-focused study therefore reflects the analytical priority rather than an overstatement of the subgroup's share, and the title has been revised to make the broader respondent base explicit.

B. Profile of the Respondents

Frequency and percentage were used to identify dominant respondent characteristics (Table VII). The general respondent group was predominantly male, with 110 male respondents (72.8%). This pattern was stronger in the transport subgroup, where all 46 members (100.0%) were male, indicating that transport-related livelihood in the dataset was male-dominated.

By age, the largest group among all respondents was 40–49 years (63; 41.7%), and the same pattern held for the transport subgroup (14; 30.4%). The mean age was 45.78 years overall and 46.91 years for the transport subgroup, indicating a middle-adult population for whom household, livelihood, health, and educational responsibilities are typically high. For occupation, 80 respondents (53.0%) were in transport or driver-related work; among the transport subgroup, 45 of 46 (97.8%) were transport workers, confirming a clearly defined transport-sector community within the larger dataset.

TABLE VII. Profile of all Respondents with TODA Emphasis

Profile Variable	Category	All f	All %	TODA f	TODA %
Sex	Male	110	72.8	46	100.0
	Female	41	27.2	0	0.0
Age Group	Below 30	5	3.3	2	4.3
	30–39	37	24.5	13	28.3
	40–49	63	41.7	14	30.4
	50–59	31	20.5	7	15.2
	60 and above	14	9.3	9	19.6
	Not reported	1	0.7	1	2.2
Occupation	Transport/driver-related	80	53.0	45	97.8
	Other / not reported	71	47.0	1	2.2

C. Livelihood and Income Conditions

Frequency, percentage, and mean were used to show economic status and livelihood vulnerability (Table VIII). Valid monthly income data were available for 100 respondents. The mean monthly income of all respondents was ₱8,945.20 and the median was ₱9,250.00. For the transport subgroup, valid income data were available for 41 respondents, with a lower mean of ₱7,682.93 and a median of ₱9,000.00.

Income was concentrated at the lower ranges. In the full sample, 52 respondents (34.4%) earned below ₱10,000 per month; among the transport subgroup, the share rose to 26 of 46 (56.5%). This greater concentration of low income is consistent with machine-learning and econometric findings that informal transport workers in the Philippines face elevated poverty risk tied to low educational attainment and prolonged informal-sector participation [26], [27].

TABLE VIII. Monthly Income Distribution

Monthly Income Range	All f	All %	TODA f	TODA %
Below ₱5,000	24	15.9	14	30.4
₱5,000–₱9,999	28	18.5	12	26.1
₱10,000–₱14,999	31	20.5	12	26.1
₱15,000–₱19,999	16	10.6	3	6.5
₱20,000 and above	1	0.7	0	0.0
Not reported / non-numeric	51	33.8	5	10.9

Household expenditure patterns reinforced this picture (Table IX). Food was the most frequently reported expense overall, followed by electricity or gas, education, water, and cooking fuel. Among the transport subgroup, food, electricity or gas, and water were equally common, each reported by 18 respondents (39.1%). Valid total monthly expenditure was available for 48 respondents, with a mean of ₱11,044.17 and a median of ₱9,275.00; for the transport subgroup (12 respondents), the mean was ₱8,438.33 and the median ₱8,300.00.

TABLE IX. Common Household Expenditure Categories

Expenditure Category	All f	All %	TODA f	TODA %
Food	63	41.7	18	39.1
Electricity / Gas	57	37.7	18	39.1
Education	51	33.8	12	26.1
Water	46	30.5	18	39.1
Cooking Fuel	40	26.5	13	28.3
Soap	27	17.9	13	28.3
Clothing	26	17.2	14	30.4

Among respondents with both valid income and expenditure data, 20 of 39 (51.3%) had expenses exceeding income; among the transport subgroup, 8 of 12 (66.7%) did. This stronger income-expenditure pressure helps explain the coping strategies reported (Table X). The most common strategy overall was borrowing money (73; 48.3%), whereas in the transport subgroup the most common was asking relatives for help (25; 54.3%).

These findings indicate heavy dependence on informal support networks. While family assistance can cushion financial difficulty, reliance on borrowing and on relatives also signals economic instability, echoing accounts of the financial precarity of Filipino tricycle drivers in the informal economy [26]. They support the need for financial literacy, savings orientation, debt management, and livelihood support programs.

TABLE X. COPING STRATEGIES

Coping Strategy	All f	All %	TODA f	TODA %
Borrow money	73	48.3	20	43.5
Ask relatives for help	46	30.5	25	54.3
Endure without resources	11	7.3	6	13.0
Keep children from school	4	2.6	0	0.0
Others	11	7.3	1	2.2

D. Health, Education, and Service Needs

The third objective was to identify health, education, and service needs. Frequency and ranking were used to determine the common social service needs of respondents.

1) Health needs: Frequency and ranking were used to determine common social-service needs (Table XI). The leading health concern in both groups was cough, colds, or fever (106; 70.2% overall and 30; 65.2% in the transport subgroup). High blood pressure was more pronounced among transport members (12; 26.1%) than in the full sample (21.2%). This is notable because tricycle drivers are routinely exposed to heat, road dust, pollution, fatigue, and long hours, conditions that plausibly elevate cardiovascular and respiratory risk. The results support preventive services such as blood-pressure monitoring, respiratory-health education, dental check-ups, diabetes screening, and wellness activities.

TABLE XI. REPORTED HEALTH CONCERNS

Rank	Health Concern	All f	All %	TODA f	TODA %
1	Cough, colds, or fever	106	70.2	30	65.2
2	Toothache	34	22.5	9	19.6
3	High blood pressure	32	21.2	12	26.1
4	Diabetes	13	8.6	5	10.9
5	Others	7	4.6	3	6.5
6	Skin disease	5	3.3	1	2.2
7	Lung disease	3	2.0	1	2.2

2) Educational needs: Books were the most common educational need in both groups (84; 55.6% overall and 27; 58.7% in the transport subgroup), as shown in Table XII. Educational support thus remained a relevant household concern, and especially so for transport households whose income was generally low and unstable. Assistance may include book donation, school supplies, tutorial assistance, digital-literacy orientation, and scholarship information drives.

TABLE XII. EDUCATIONAL SUPPORT NEEDS

Rank	Educational Need	All f	All %	TODA f	TODA %
1	Books	84	55.6	27	58.7
2	Others	26	17.2	9	19.6
3	Radio	18	11.9	4	8.7
4	Reading materials	5	3.3	0	0.0
4	Educational toys	5	3.3	2	4.3
6	Computer	4	2.6	4	8.7
6	Video camera	4	2.6	1	2.2

3) Public service access: The most frequently identified services overall were elementary education, day-care center, tanod patrol, health center, and cemented road (Table XIII). For the transport subgroup, day-care center, tanod patrol, elementary education, police monitoring, cemented road, and curfew were highly reported. Awareness of existing services did not eliminate household-level needs in health, education, livelihood, and income. The university can therefore act as a linkage institution, connecting members to barangay services, health centers, road-safety programs, livelihood agencies, and social-welfare offices, an approach aligned with calls for meaningful public involvement of underserved transport communities [9], [24], [25].

TABLE XIII. COMMON PUBLIC SERVICES AND FACILITIES IDENTIFIED

Rank	Public Service / Facility	All f	All %	TODA f	TODA %
1	Elementary education	120	79.5	39	84.8
2	Day-care center	115	76.2	44	95.7
3	Tanod patrol	93	61.6	40	87.0
4	Health center	87	57.6	24	52.2
5	Cemented road	77	51.0	38	82.6
6	Basketball court	73	48.3	13	28.3
7	Supplemental feeding	67	44.4	24	52.2
8	Trained community health workers	64	42.4	22	47.8
9	Curfew	63	41.7	38	82.6
10	Police monitoring	61	40.4	39	84.8

E. Ranked Priority Community Needs

Because the dataset used multiple-response and binary-coded items, the priority of each need was measured by the endorsement rate (the proportion of respondents who indicated it), with denominators of 151 for all respondents and 46 for the transport subgroup (Table XIV). The highest-ranked area for the full sample was transport-oriented support (0.894), driven by the many respondents linked to transport work, tricycle use, road-related indicators, or formal membership; among the transport subgroup this reached 1.000.

TABLE XIV. RANKED PRIORITY COMMUNITY NEEDS

Rank (All)	Priority Area	All f	Endorsement Rate (All)	Rank (TODA)	TODA f	Endorsement Rate (TODA)
1	Transport-oriented support	135	0.894	1	46	1.000
2	Public-service linkage / access	133	0.881	1	46	1.000
3	Health and wellness support	126	0.834	4	39	0.848
4	Educational support	121	0.801	3	40	0.870
5	Livelihood and financial stability	120	0.795	4	39	0.848
6	Skills training and diversification	108	0.715	7	30	0.652
7	Environmental and climate-related support	94	0.623	6	36	0.783

Public-service linkage also ranked highly (0.881 overall; 1.000 for the transport subgroup). Because these items reflected services and facilities identified by respondents, the result should be read as an opportunity for stronger linkage rather than as evidence that all services were absent. Health and wellness ranked third overall and remained important for the transport subgroup, consistent with the high frequency of respiratory illness, hypertension, dental problems, and diabetes.

Educational support ranked fourth overall but higher within the transport subgroup, indicating strong education-related needs—especially for books and learning materials—among lower-income transport households; this mirrors community-survey evidence that educational access is a recurrent social-determinant need [28]. Livelihood and financial stability also emerged as a major priority, supported by low income, borrowing, reliance on relatives, lack of capital, and negative income-expenditure gaps, with the transport subgroup showing stronger vulnerability than the full sample. Skills training and environmental support ranked lower but remained relevant; environmental and climate-related support was especially salient for the transport subgroup, whose members work outdoors and are directly exposed to extreme heat and changing weather.

F. *Artificial Intelligence-Assisted Framework and Decision Support*

The fifth objective was to translate the cleaned and coded dataset into an Artificial Intelligence-assisted framework. The resulting framework (Fig. 3) shows how technology can support a more responsive extension program. Instead of using survey results only for manual reporting, the workflow transforms the dataset into a decision-support layer that can identify which respondents need livelihood assistance, which households require educational support, which health concerns to prioritize, and which transport-related issues require targeted intervention.

For the transport subgroup, the assisted analysis is especially useful because members share common conditions as transport workers. It distinguishes their needs from the general population by detecting patterns in income, occupation, coping strategies, health risks, road-related concerns, and environmental exposure, allowing the university to design interventions specifically for them. The framework also extends into implementation: it can support a beneficiary database, recommend training modules, identify priority households, monitor participation, and evaluate whether the program improved income, health awareness, skills, or access to services. In this sense, Artificial Intelligence becomes a continuing tool for planning, implementation, monitoring, and evaluation.

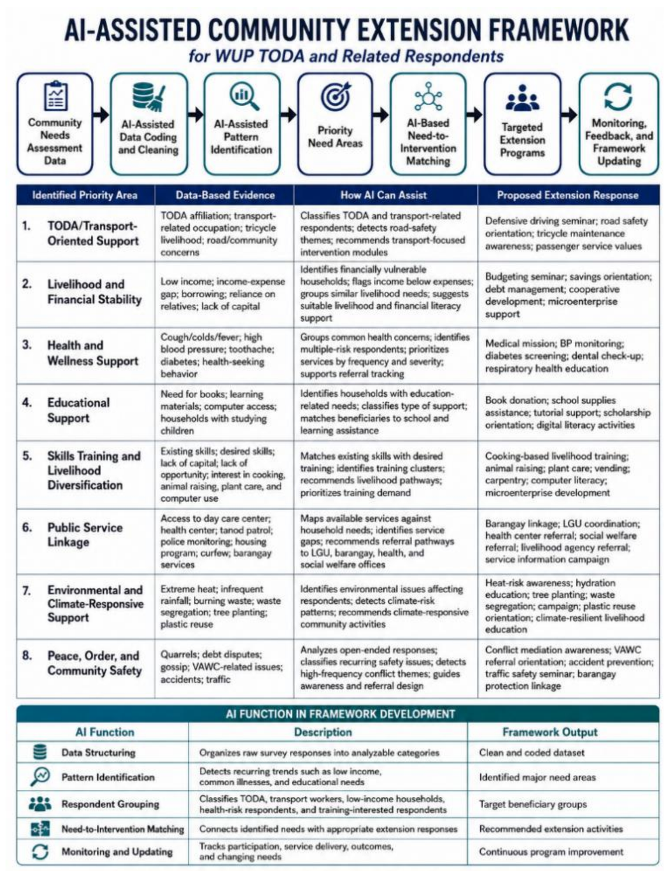

Fig. 3. Artificial Intelligence-assisted community extension framework for the partner community and transport subgroup.

V. Conclusion

The Community Needs Assessment dataset of 151 respondents revealed substantial needs in livelihood, health, education, public-service access, transportation support, skills development, and environmental awareness. While all respondents were analyzed, the results emphasized the transport subgroup, which formed a distinct priority sector composed entirely of male tricycle drivers with lower average income and higher livelihood vulnerability.

Profile results showed a largely middle-aged population with household and income responsibilities, and tricycle driving as the dominant livelihood within the transport subgroup. Income and expenditure results indicated financial pressure, particularly for transport members, whose average income was lower than the overall sample. Borrowing and reliance on relatives were common coping strategies, pointing to the need for financial literacy, savings orientation, cooperative development, and livelihood assistance. Health and education were also major concerns, supporting regular medical missions, blood-pressure monitoring, diabetes screening, dental check-ups, respiratory-health education, wellness programs, and educational assistance such as book donations, school supplies, tutorial support, scholarship orientation, and digital-literacy activities.

The ranked priorities indicated that the most important extension areas were transport-oriented support, public-service linkage, health and wellness, educational support, livelihood and financial stability, skills training, and environmental support. Wesleyan University-Philippines should therefore develop an integrated, data-driven extension program for its transport and related partner communities, potentially including defensive-driving seminars, road-safety orientation, tricycle-maintenance awareness, livelihood training, financial literacy, health services, educational assistance, skills development, and barangay or local-government referral support.

Several limitations should be acknowledged. First, the study was confined to a single university partner community, so the findings describe that community and are not statistically generalizable to other settings. Second, the sample was modest (151 respondents, of whom 46 belonged to the transport subgroup), which limits subgroup-level statistical power and the stability of some estimates. Third, the analysis relied on self-reported survey data, which are subject to recall and social-desirability biases, and several income and expenditure fields were incomplete, reducing the number of valid cases for those computations. Fourth, the design was descriptive and cross-sectional; it characterizes needs at one point in time and does not establish causal relationships or change over time. Finally, the Artificial Intelligence component was assistive rather than fully automated, and its clustering and coding outputs depended on researcher review and on the chosen features and parameters.

These limitations point to several directions for future research. Larger and, where feasible, probability-based or multi-community samples would improve representativeness and allow stronger subgroup comparisons. Longitudinal designs could track whether interventions improve income, health awareness, skills, or service access over time. Mixed methods—interviews and focus group discussions—could validate and enrich the quantitative findings. Methodologically, supervised predictive models and more advanced text-embedding or language-model pipelines could be benchmarked against the present descriptive approach, and a full Artificial Intelligence-based decision-support system could be developed and validated for community needs assessment and extension planning.

Finally, the study concludes that Artificial Intelligence can strengthen community extension planning by organizing raw survey data, identifying patterns, grouping respondent populations, ranking priority needs, matching needs with suitable interventions, and supporting monitoring and evaluation. The originality of the work lies in documenting this assistive workflow transparently and showing how it adds value beyond conventional descriptive reporting. It is recommended that the university adopt the proposed framework to make extension programs more targeted, evidence-based, and responsive, and that future researchers validate the findings through interviews, focus group discussions, and the development of an Artificial Intelligence-based decision-support system.

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