

Travel Behavior of Low-Income Rural Residents: A Multi-dimensional Analysis Using Artificial Neural Network

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Abstract. Understanding the travel behavior of low-income rural residents is essential for effective transportation planning, particularly in urbanizing regions like Davao City, Philippines. Traditional transportation models often fail to capture the intersectionality of socioeconomic factors, such as income, sex, and age, which significantly influence mobility patterns. This study employs an Artificial Neural Network (ANN) approach to analyze the multi-dimensional characteristics of travel behavior among low-income residents in Barangay Angalan. Using household travel surveys, the study stratifies respondents into four groups: Male of Working Age, Female of Working Age, Elderly Male, and Elderly Female. Findings reveal distinct travel patterns across demographics. Working-age males primarily travel for employment, with motorcycles as their dominant mode of transport, whereas females utilize multi-modal transport, combining walking and tricycle rides. Elderly individuals, particularly women, exhibit lower trip frequencies, with a higher reliance on non-motorized travel. The ANN model demonstrates high predictive accuracy, effectively identifying trip purposes and mode choices, with F1-scores exceeding 0.7 for most classifications. The study highlights the importance of inclusive transport policies that consider gender and age disparities. Improved infrastructure, accessibility, and policy interventions tailored to the needs of marginalized populations can enhance mobility equity. The ANN approach provides a robust framework for predicting travel behavior, offering valuable insights for sustainable rural-urban mobility planning.

Keywords: travel behavior, artificial neural network, rural mobility, low-income residents, intersectionality

1. Introduction

It is important to understand the complexities of the travel behavior of low-income rural residents to plan effectively for regional planning, particularly in urbanizing cities like Davao City, Philippines. Conventional transportation models tend to overlook the complexities of travel patterns within such populations, where income, sex, age, and resource accessibility converge to produce distinct mobility complexities. The constraints of current infrastructure and the preference for engineering-based solutions may, at times, overlook the value of community-oriented knowledge in traffic management and transport planning [1]. Conducting travel behavior research in this particular population needs an integrated approach that takes into account the multifaceted interaction of socio-economic attributes [2]. Additionally, the growing urbanization, where two-thirds of the world's population is expected to live in cities by 2050, highlights the need to address mobility in both urban and rural peripheries. The development of transport infrastructure and services in rural areas can assist in decongesting urban areas by offering alternative mobility solutions for inhabitants of these areas, thus ensuring inclusive sustainable development for all strata of society [3]. Using sophisticated analytical methods such as Artificial Neural Networks, this study seeks to better understand these mobility patterns and inform the formulation of effective interventions. It is crucial to come up with effective transport policies and strategies that can address traffic problems and provide reliable, safe, and accessible mobility for the most disadvantaged groups. This research aims to bridge this gap by targeting low-income residents of rural Davao City, adding intersectionality with sex and age to reveal travel patterns.

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2. Related Literature

The intersectionality principle recognizes that social stratifications such as sex, age, socioeconomic status, and geography interact to shape experiences of privilege and disadvantage [4]. This framework moves beyond isolated identity factors to provide a holistic view of individual experiences [5]. In commuting analysis, mobility patterns are influenced not only by the built environment but also by social habits in households, workplaces, and society [6]. An intersectional approach reveals how sex and age interact with socioeconomic status to affect mode choice, trip-making, and transportation access [4]. Socio-demographic factors—including income, occupation, sex, and length of residence—alongside behaviors and attitudes significantly shape transportation decisions. Socioeconomic status directly impacts travel behavior, with low-income individuals often facing constraints such as limited vehicle access, leading to reliance on public transport, walking, or cycling [7]. While infrastructure affects mode choice, individual decisions still play a role. Age also shapes mobility needs, with older and younger individuals exhibiting different travel patterns. Creating age-friendly, accessible transportation is essential for improving older adults' quality of life [8]. Age differences must be considered in mobility policies [9], as accessibility declines with age [10]. Understanding variations in travel behavior between older and younger adults informs planning for aging populations [8], [10]. Despite reliance on public transit, older adults and low-income individuals still depend significantly on private vehicles [11].

Sex and age further complicate travel behavior, particularly for low-income rural residents. Women's mobility is shaped by caregiving duties, safety concerns, and societal roles, necessitating inclusive transport policies [4]. Women's labor force participation is increasing, but their commuting patterns differ from men's, often influenced by household and family responsibilities [12]. Job type and location are also affected by these obligations [12]. Addressing gender disparities in transportation infrastructure is crucial for fostering equitable mobility solutions [13].

3. Methodology

The study consisted of three main stages. The initial phase involved a review of relevant literature and household travel surveys to determine the factors impacting trips, with a focus on socioeconomic, demographic, and trip-related characteristics. The questionnaire design was informed by previous studies, particularly those conducted by the Japan International Cooperation Agency. The second phase entailed gathering data in the rural areas of Davao City through household travel surveys. These questionnaires collected socioeconomic information such as age, sex, and income levels. Travel diaries were distributed to all household members aged 7 and older, requesting them to document their weekday trip details, including origins, destinations, times, purposes, and transport modes used. The survey was conducted in Barangay Angalan, which had a recorded population of 2,741 in the 2020 census, but the survey yielded responses from 3,182 residents, indicating population growth in the area. The final phase involved the application of an artificial neural network to analyze the collected data, with the aim of predicting and deriving insights into the intersectional aspects of travel behavior. The analysis commenced with an examination of Barangay Angalan's socio-demographic and economic characteristics, including an assessment of age distribution, sex demographics, and income profiles derived from the survey data. This information was subsequently stratified into intersectional groupings based on factors such as age, sex, and income levels. Two age groups were classified in the study under the low-income category based on the Philippine Statistics Authority: the working age with a range from 18-64, and the elderly with an age of 65 and above. Hence, there are four stratification groups: Male of Working Age, Female of Working Age, Elderly Male, and Elderly Female. A person with an income less than PHP. 21,914 is considered low income as set by the Philippine government development studies for all areas [14].

3.1. Artificial Neural Network

The analysis in this study employed Artificial Neural Network Pattern Recognition in MATLAB, which was conducted for each four stratification groups [15]. The ANN architecture typically consists of three layers: an input layer, a hidden layer, and an output layer. The model utilized the socioeconomic characteristics (Age, Sex, and Income) of the respondents as input features, with the output variables representing trip purpose and mode choice. The accuracy of the developed model was evaluated by comparing the predicted outcomes with the actual observed data, utilizing metrics such as precision, recall, and F1-score to assess its performance. A

typical train-validation-test split was used since it can produce robust and unbiased performance estimates regardless of sample size [16]. Datasets are divided 80% for training, 10% for testing, and 10% for validation. The model was trained using a suitable optimization algorithm, such as backpropagation, to minimize the error between the predicted and actual outputs [17], [18].

Within pattern recognition, the effectiveness of an Artificial Neural Network (ANN) is determined by the use of a confusion matrix. The matrix offers an organized way of presenting the classification results, defining each of them in four categories: True Negatives (TN), True Positives (TP), False Negatives (FN), and False Positives (FP). More particularly, TP refers to a situation when the model makes a correct prediction of a positive class, and a TN refers to a correct prediction of a negative class. An FP occurs when the model predicts a positive tag incorrectly, while an FN occurs when a positive sample is predicted as negative. The accuracy of the model is measured through precision, recall, and F1-score. Recall measures the model's ability to correctly identify all actual positive instances; precision measures the model's accuracy when it predicts a positive class; and F1-score provides a balanced measure between precision and recall.

4. Results and Discussion

The socio-demographic characteristics of Barangay Angalan show that 43.92% of the population belongs to the Low-income category, 51.17% to the No-income Category, and only 3.37% and 1.54% belong to the Middle-income and High-income categories. The no-income population is comprised of students and the elderly who are dependent. This study considers the low-income population, aside from the majority of which are considered vulnerable, they contribute most of the daily trips in the community.

Artificial Neural Network pattern recognition was used to model both trip purpose and mode choice of the low-income rural residents with multi-dimensional characteristics, considering age and sex, to fully understand their holistic view of their trip characteristics.

4.1. Male and Female of Working Age

Male of Working Age is the dominant population in the low-income class, comprising 60.91%. ANN pattern recognition generates a confusion matrix to classify under these multi-dimensional criteria, which showed “work” as their main reason for travel.

As shown in Figure 1, the confusion matrix evaluates the model's performance in classifying trips as either work-related (1) or other types of trips (0). The model correctly identified 557 work trips (true positives) and 37 non-work trips (true negatives). However, it incorrectly classified 18 work trips as non-work trips (false negatives) and 193 non-work trips as work trips (false positives). This information allows us to calculate two key metrics: recall and precision. With a recall of 96.9%, the model demonstrates a strong ability to correctly identify actual work trips. However, the precision indicates that 74.3% of trips predicted as work trips are correctly predicted, suggesting good precision accuracy. Essentially, the model is good at finding most of the actual work trips but less accurate in confirming that the trips it flags as work are indeed work-related.

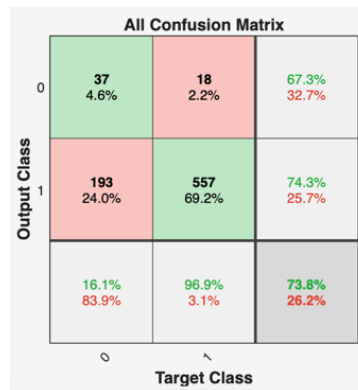


Fig. 1: Confusion Matrix for Male of Working Age Trip Purpose

The confusion matrix analysis presented in Table 1 indicates that the predominant mode of transportation for the low-income Male of Working Age group is the motorcycle. Furthermore, the results demonstrate that the model correctly classified 65.9% of the predicted work trips and was able to accurately identify 82.3% of

the actual work trips within this group. F1-score for trip purpose and mode choice showed 84.11% and 73.19%, respectively. In the case of Female of Working Age, the trip purpose showed high precision and recall for work trips, which implies that 66.5% are correctly predicted and 85.7% are correctly identified as actual work trips. On the other hand, female worker travel using multiple modes, a combination of walking and tricycle to get to their destination with a precision of 66.6%, a recall of 78.6%, and an F1-score of 72.10%.

Table 1: Confusion Matrix Result Accuracy

Multi-dimensional Characteristics	Trip Purpose				Mode Choice			
	TP	Precision	Recall	F1-score	MC	Precision	Recall	F1-score
Male of Working Age	Work	74.3%	96.9%	84.11%	Motorcycle	65.9%	82.3%	73.19%
Female of Working Age	Work	66.5%	85.7%	74.89%	Multi-modal (Walking, Tricycle)	66.6%	78.6%	72.10%
Elderly Male	None	83.1%	92.5%	87.55%	Multi-modal (Walking, Tricycle)	79.1%	66.7%	72.37%
Elderly Female	None	83.3%	69.5%	75.78%	Multi-modal (Walking, Tricycle)	61.2%	87.5%	72.02%

4.2. Elderly Male and Female

The results of the confusion matrix analysis, as presented in Table 1, for the elderly male and female populations of Davao City indicate differing patterns in the prediction of trip purpose and mode choice. In the case of the elderly males, the model exhibited high performance in predicting trips with no purpose ("NONE") with an 83.1% precision and 92.5% recall, leading to an F1-score of 87.55%. This reveals that the model was able to correctly identify No Trip Purpose, with high accuracy in its prediction. Multi-modal trips taking both walking and tricycles as modes was seen in elderly males. Whereas precision was generally high at 79.1%, recall had fallen to 66.7%, leading to an F1-score of 72.37%. In the case of elderly women, the model showed ("NONE") recorded trip purpose, with high precision (83.3%) and moderate recall (69.5%), resulting in an F1-score of 75.78%. This once more indicates the model's capacity to accurately detect trips without a specified purpose. But for mode choice, a reverse trend was observed. The model showed a lower precision of 61.2% but a higher recall of 87.5%, with an F1-score of 72.02% in predicting multi-modal trips. This means that although the model identified a high percentage of multi-modal trips taken by elderly women, it also incorrectly labeled a significant percentage of other trips as multi-modal. These results imply that although the model identifies trips with no stated purpose accurately for both elderly men and women, its accuracy in predicting multi-modal mode choice differs considerably between the two. The model is more conservative in estimating multi-modal trips for elderly males, resulting in higher precision and lower recall, whereas it is different for elderly females which has lower precision but higher recall. This inconsistency reflects real variations in travel patterns between elderly females and males.

4.3. ANN Comparison to Other Models

The comparative analysis of model performance in predicting TP and MC across various demographic segments revealed distinct strengths among the evaluated algorithms: ANN, Support Vector Machine (SVM), and Decision Tree. For Trip Purpose prediction (see Table 2), the ANN model consistently demonstrated superior performance, achieving the highest F1-scores across all four demographic groups: Male of Working Age (ANN: 84.11% vs. SVM: 71.43%, Decision Tree: 65.6%), Female of Working Age (ANN: 74.89% vs. SVM: 60%, Decision Tree: 57.3%), Elderly Male (ANN: 87.55% vs. SVM: 52.2%, Decision Tree: 53.3%), and Elderly Female (ANN: 75.78% vs. SVM: 61.7%, Decision Tree: 50.0%). This suggests that the ANN's capacity to model complex, non-linear relationships is particularly advantageous for identifying underlying trip purposes.

In contrast, the prediction of Mode Choice presented a more varied landscape. While the ANN model performed strongly, achieving the highest F1-score for Males of Working Age (73.19%) and Elderly Males

(72.37%), the SVM model showed good result and, in some instances, most accurate performance. Specifically, SVM outperformed ANN for Females of Working Age (SVM: 73.8% vs. ANN: 72.10%) and Elderly Females (SVM: 75.3% vs. ANN: 72.02%) in predicting multi-modal choices involving walking and tricycle. The Decision Tree model generally yielded the lowest F1-scores for both Trip Purpose and Mode Choice predictions across most segments, although it did surpass SVM for Elderly Male mode choice prediction (Decision Tree: 66.1% vs SVM: 62.7%). Despite the diverse results, ANN showed a small discrepancy with the SVM result, which showed the consistency of the model over other models. Overall, ANN highlighted its good prediction accuracy compared to other models [19].

Table 2: ANN vs SVM vs Decision Tree

Multi-dimensional Characteristics	F1-score				F1-score			
	TP	ANN	SVM	Decision Tree	MC	ANN	SVM	Decision Tree
Male of Working Age	Work	84.11%	71.43%	65.6%	Motorcycle	73.19%	59.3%	54.3%
Female of Working Age	Work	74.89%	60%	57.3%	Multi-modal (Walking, Tricycle)	72.10%	73.8%	68.2%
Elderly Male	None	87.55%	52.2%	53.3%	Multi-modal (Walking, Tricycle)	72.37%	62.7%	66.1%
Elderly Female	None	75.78%	61.7%	50.0%	Multi-modal (Walking, Tricycle)	72.02%	75.3%	56.7%

5. Conclusion

The research shows how Artificial Neural Networks can be used in analyzing and predicting the travel behavior of low-income groups while considering the intersectionality of gender and age. The ANN model was also able to achieve high precision and recall values. An F1-score above 0.7 indicates effective characterization of travel patterns for different demographics [20]. The application of intersectionality enabled the understanding of the complexity of the trip characteristics and how the combination of different forms of social attributes affects travel behaviours. In particular, the analysis revealed how age stands out as an important factor in determining the predominant trip purpose; the working age had a considerable amount of work trips, but elderly people had a much higher share of trips with no specific purpose [21], [22]. Furthermore, the study found distinct differences in mode choice between genders and age groups. The working male population predominantly utilized motorcycles, while women and the elderly demonstrated a higher reliance on multi-modal transportation, involving a combination of walking and tricycle use. This disparity is attributed to the rural, isolated nature of the low-income communities, characterized by poor road infrastructure and limited direct access, necessitating walking to reach the nearest main road where a tricycle is available. These insights underscore the value of employing ANN in understanding the nuanced travel behaviors of marginalized populations, particularly in the context of developing regions, where transportation accessibility and infrastructure play a crucial role in shaping mobility patterns.

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