Proceedings of the 11th World Congress on New Technologies (NewTech'25)
Paris, France - August, 2025
Paper No. ICCEIA 120
DOI: 10.11159/icceia25.120

Decision Factors to Walk from House to a Park in Housing Estate Projects: Case of Chiang Mai, Thailand

Kriangkrai Arunotayanun[1], Padej Sukpattanacharoen[1], Sattaya Manokeaw[1], Panupong Khankham[1], Damrongsak Rinchumphu[1]
[1]Department of Civil Engineering, Faculty of Engineering, Chiang Mai University, Chiang Mai, Thailand
kriangkrai.a@cmu.ac.th; padej_suk@cmu.ac.th; sattaya.manok@cmu.ac.th; panupongearth24@gmail.com; damrongsak.r@cmu.ac.th

Abstract **-** Walking distance is an essential factor for the service design of any public park, including the park within the housing estate projects. This study aims to determine the resident's walking distance from the house to the nearest park through the artificial neural networks model. The model was formulated on 554 data sets collected from housing estate projects in Chiang Mai, Thailand. The dependent variable was the binomial variable which represented the potential to walk. In contrast, the independent variable is the distance from the house to the nearest and the personal data such as gender, age, and insurance. The study finds that individuals in various age ranges who earn an income exceeding 50,000 baht and age 35 years, a proportion of 50%, display a limited acceptable distance of no more than 445 meters, representing the minimum walking distance compared to other age groups. Hence, it is crucial to adopt a deliberate approach in designing park locations within housing estates to ensure that no more than 445 meters separate 50% of the residential area from the public park. The results provide a proper guideline for the service area planning of the park, which will support use efficiently for the housing estates' residents.

Keywords**:** Walk distance, Park, Urban planning, Subdivision, Housing estate, Artificial neural network, Chiang Mai

1. Introduction

The issue of abandoned parks has become a pervasive concern, particularly within numerous housing estates, leading to an unfavorable environment. The preliminary study revealed that the lack of park utilization stemmed from an unsuitable park location that posed challenges in accessing its amenities due to a considerable walking distance. Specifically, the distance of 300 meters was deemed excessively far for potential visitors to conveniently avail themselves of the park services [1]. Meanwhile, a Chiang Mai housing estate has an 800-meter distance between the farthest house and the park. Liao et al. [2] research demonstrates that an increase in distance is associated with a decline in walking frequency, revealing the impact on walking behavior. While park visits primarily involve exercise activities like running and walking, there is a difference between recreational and utilitarian walks from one's residence to access park services due to safety, convenience, and other pertinent factors. The initial survey revealed divergent distance perceptions and walking preferences among residents of the same house or neighboring individuals, despite the shared external factors.

The problem of park abandonment arises from the inappropriate positioning of public parks within housing estates, typically at the project's center. This location poses difficulties for residents to access the parks on foot. Furthermore, these parks often feature rectangular or free-form layouts with similar diameters. This issue can be solved by strategically positioning and designing the park to align with the needs and preferences of the housing estate project's target residents. However, assessing the walkable distance for residents is a complex task due to the influence of various factors, including environmental conditions and socio-economic characteristics, which play a role in residents' decision-making processes. Environmental factors can be regenerated in response to the residents' requirements later. Nonetheless, a crucial determinant in selecting a green area location is the factors of the economic and social characteristics of the residents.

This research aims to study the decision factors to walk from a house to the nearest park in a housing estate to examine the relationship between factors influencing the residents' walking decisions. It emphasizes the socio-economic characteristics, including age, gender, health insurance, income, and distance from the house to the park within the village.

The results can offer valuable guidance for planning park spaces, thereby facilitating the efficient utilization of public parks within housing estates

2. Literature review

2.1. Key Concepts and Relevant Factors

The concept of housing estates revolves around addressing the primary needs of residents. According to Krungsri Guru [3] analysis, housing estates can be distinguished from general villages through three main aspects. Firstly, housing estates facilitate convenient cost determination for housing, allowing buyers to establish a budget without the concern of escalating expenses due to the complexity involved in every step of the house construction process, which may encounter deliberate or unintentional issues from contractors. Additionally, when purchasing a housing estate, most banks offer full loan guarantees, thereby expanding the options available to buyers. Secondly, housing estates offer the convenience of selecting desired house styles. With a wide range of housing service providers available, buyers can choose from various house designs, village structures, and compatible neighbors that align with their budgetary considerations and personal preferences. Thirdly, housing estates prioritize the comfort of living for residents. It is a common practice for housing estates to offer comprehensive central services following the completion of the sale. These services include ensuring residential area security, maintaining cleanliness on communal thoroughfares, providing central club facilities, and incorporating green spaces within the village.

As green spaces or gardens, public parks are essential hubs for community gatherings and recreational activities within nearby residential areas. They provide opportunities for social interaction and serve as relaxing spaces for families seeking large open areas. Consequently, constructing well-designed parks that cater to the housing community is pivotal in enticing residents to utilize these amenities while promoting convenience within short walking distances within residential neighborhoods.

An ideal park should embody the concept of "Dynamic Parks" which refers to vibrant and interactive park spaces designed to cater to the recreational needs of its users. This concept emphasizes inclusivity, disregarding age, income, or education when providing park amenities. Public parks should offer a wide range of activities and facilities to accommodate the diverse needs of a broad demographic without favoring any specific group. Moreover, these parks should feature well-planned and aesthetically pleasing designs, ensuring that the layout and arrangement of facilities do not hinder the users' activities [4].

Walkability is a term that lacks a precise definition, but it is commonly used to assess the spatial walking ability within an area. It encompasses various aspects, including the frequency of walking [2]. Spatial walking capacity is often considered an indicator of a pedestrian-friendly environment [5], including factors like safe road crossings and accessible pathways [6]. While limited research focuses explicitly on individual spatial walking ability, personal preferences strongly influence walking decisions. Negative perceptions of the environment can diminish one's inclination to engage in spatial walking [7].

This research will concentrate on the concept of "Walkability" regarding individual walking ability. Specifically, it refers to the distance individuals can walk under similar external environmental conditions. In travel decision-making, travelers need to consider two interconnected factors. The first pertains to external factors independent of the traveler, such as pavement width, pavement condition, lighting, and safety. The second part encompasses internal factors directly associated with the traveler, including age, gender, occupation, income, and education level. It is important to note that all these factors from both parts are consistently correlated. For instance, women often have a lower sense of security than men in similar situations, leading to a decreased likelihood of female travelers choosing walking as their mode of transportation compared to male travelers [8]. This research focuses solely on the internal factors of travelers, as the inclusion of external factors could introduce complexity to the study (Table 1).

Table 1: Decision Factors to Walkability.

Factor	Relevant research
Distance	Access to green space has the opposite relationship. The short distance has the accessibility of travelers will be higher. On the contrary, the distance that can reach the area is reduced [2, 9]. However, the pavement infrastructure's quality is important because it can help promote walking and the decision to walk [10, 11].
Health insurance	Income is directly variable to health insurance. Health insurance is another factor that affects the demand for traveling on foot. Insured people will need to walk less than those who are not insured. Carthy et al. [12] studied walking accessibility for the elderly (over 50 years old) was conducted to examine the relationship of walking accessibility with body mass index (BMI) as a health profile of individuals and used to classify obesity in adults according to the standards set by the World Health Organization (WHO).
Income	Members from low-income families are more likely to walk than those from high-income families. It shows that household income affects family members' walking ability [12, 13]. However, Su [14] studied the trend of walking to school among students with different household incomes. Therefore, it cannot be concluded that low-income households will have the ability to walk higher than high-income households Because other factors affect the decision to walk for children, such as distance from home to school walking route safety as well as alternative forms of travel.
Age	Walking distance is correlated with age, such as children tend to travel for fun purposes and to do outdoor activities. Elders often have the purpose of relaxing in the park [2, 12, 13]. Sugiyama [15] studied only the effects of age and walking distance were analyzed. It was found that people aged 18 to 34 had an average walking distance of 620 meters; people aged 35 to 49 had an average walking distance of 670 meters; people aged 50 to 64 had an average walking distance of 790 meters; Those aged 65 to 84 years had an average walking distance of 720 meters and an average walking distance of 680 meters, indicating that the youngest did not need to walk for considerable distances. Other factors should be further analyzed as well.

2.2. Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) are vital to artificial intelligence (AI). ANN aims to simulate and understand the structure and functionality of the processing systems found in living organisms. These networks revolutionize cognitive processes, enabling distinct thinking, analysis, and decision-making modes through learning rules. In the case of complex organisms like humans, the brain consists of many interconnected neurons. Research by Shanmugamani [16] suggests that ANN has been developed to mimic the functioning of the human brain. The processing occurs at individual units called nodes, which emulate neurons in biological brains. Each node comprises five key components: 2.2.1 Input data, 2.2.2 weight values, 2.2.3 summation function, 2.2.4 activation function, and 2.2.5 output data. These components will be elaborated upon in the subsequent section (Fig 1).

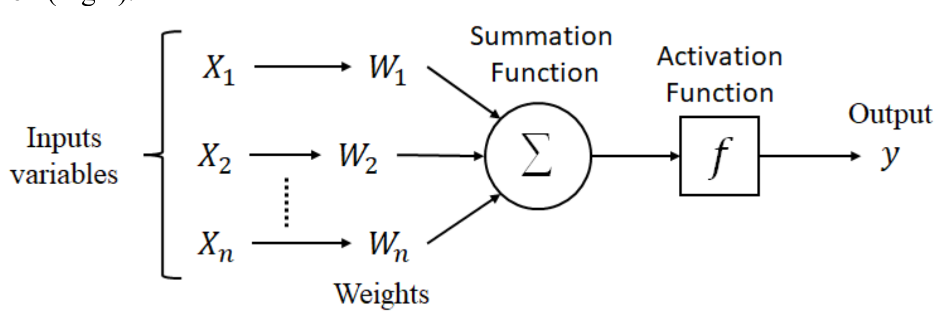

Fig. 1: Structural model of the subunits in ANN.

2.2.1 Input Data (x)

Importing data is the initial step in initiating a neural network. The data under analysis can generally be categorized into two types: qualitative data and quantitative data. Qualitative data comprises non-comparable information, such as gender, phone number, and dates, which cannot undergo mathematical manipulation. On the other hand, quantitative data refers to information that can be compared, usually expressed in numerical forms, such as numbers, periods, heights, and ages, enabling mathematical operations. Nevertheless, the classification of data can be flexible depending on the objectives of the data analysis. For instance, if a question offers options like "satisfied" or "unsatisfied," the obtained information would be regarded as qualitative data. However, if the available choices are "very satisfied," "satisfied," "neutral," and "dissatisfied," the resulting information would be considered quantitative data since a comparison can be made. Similar considerations apply when employing ANN for analysis. However, all imported data must be in a format acceptable and processable by the network, meaning it must be in numerical form. In cases where qualitative data cannot be quantified, it is necessary to assign codes to the dataset to facilitate comprehension and processing by the computer.

2.2.2 Weights Values (W)

The weight or importance of data is acquired through the neural network's learning process, known as knowledge value. It is typically generated from past experiences encoded within the network. However, the weights are initialized with random values and then iteratively adjusted during the network's calculation process. These weights serve as the model's learned results and can be used to analyze other datasets using the same

2.2.3 Summation Function

The summation function is a mathematical function used to calculate the weighted sum of input data (x) and their corresponding weights (W). It produces the summation value, denoted as z, which is passed through the activation function. Mathematically, the summation function can be expressed as Eq. (1).

$$z^j = \sum_{i=0}^{n} W_i^j x_i^j \qquad (1)$$

2.2.4 Activation Function

The activation function, also called the transfer function, is a crucial component in determining the output format of data obtained from the summation function within a neural network. The system designer makes a design choice based on the desired outcomes of the input data set analysis. The selection of an activation function depends on system characteristics and the data type to be processed by the artificial neural network. Various forms of activation functions exist, with some commonly used formats including Sigmoid, Rectified Linear Unit (ReLU), Hyperbolic Tangent (tanh), Leaky Rectified Linear Unit (Leaky ReLU), Exponential Linear Unit (ELU) [17].

Neural network models are commonly employed for analyzing decision data, where the model's output, representing the dependent variable, corresponds to binary alternatives: 1 for a decision and 0 for no decision. In this regard, the activation function selection can be achieved by utilizing the sigmoid function, as illustrated in Eq. (2).

$$Sigmoid(z) = \frac{1}{1 + e^{-z}} \qquad (2)$$

The Sigmoid function is a continuous function well-suited for representing probability values and can be further transformed into a classification value. However, a challenge associated with this function is that the variation in the output (Y) impacts the input (X) value, causing it (X) to diminish significantly during the gradient computation [16]. Consequently, it is primarily employed as a function for analyzing variable data in the final stage of the model.

2.2.5 Output Data (Y)

The output data (Y) represents the actual outcomes of the neural network analysis. In a simple network, the final response (y) is typically defined as a binary choice, indicating information that results in either 0 or 1. Such choices include yes/no, use/quit, and travel/not travel. However, if a broader range of responses is desired, designers must carefully select a more intricate Activation Function that creates suitable conditions for generating the desired calculation results.

In the work process of artificial neural networks, in addition to analyzing variable data within a single Node, a hidden layer component exists. This component involves the analysis of multiple layers of variable data before obtaining the result. This multi-layer structure enables a complex data analysis process that considers the influence of weight values associated with each variable. Notably, most predictor variables used in the model are of the nominal scale, meaning they are organized into distinct groups without a clear prioritization between them. Hence, the Rectified Linear Unit (ReLU) is commonly employed as the Activation Function in the hidden layer. This choice ensures that the data values are preserved and not lost during calculation, as illustrated in Eq. (3).

The Rectified Linear Unit (ReLU) is an activation function that effectively reduces the computational burden of neural networks. It operates by setting any input value less than or equal to zero. It means that data points with values below zero that are not engaging in the analysis are excluded from the network calculation. The Rectified Linear Unit function yields a result value greater than or equal to zero, as expressed in Eq. (3).

$$ReLU(z) = \begin{cases} 0 \text{ } when \text{ } z \leq 0 \\ z \text{ } when \text{ } z > 0 \end{cases} \tag{3}$$

A comprehensive literature review has identified several key variables that are crucial in analyzing the decision-making process of walking from a residential area to a park or green space. These variables include distance, health insurance coverage, income, and age [18]. The significance of these variables will be further elucidated in the subsequent section, which outlines the neural network model's data collection and analysis process.

3. Methodology

3.1. Data Collection

This study employed a data survey approach, targeting residents residing in housing estates in Chiang Mai, the second-largest province in Thailand, which boasts a population of approximately 1.76 million individuals and is situated in the northern part of the country. The local climate and environment make it an ideal setting for recreational walking activities. The survey was conducted utilizing a sample size of 400 participants. A comprehensive questionnaire was administered to investigate individuals' travel behavior from their residences to the village park. Online and offline distribution methods were employed, ensuring a diverse representation of respondents. The questionnaire comprised two main sections: the initial section encompassed general inquiries and solicited travel-related information, while the subsequent section delved into various walking options presented in different scenarios.

This study involved conducting a comprehensive survey of medium-sized housing projects that met specific criteria. The criteria included projects with an area larger than 19 rai but not exceeding 100 rai, or projects offering a range of 100 to 499 plots for sale, as they are projects with a single park that could not be divided into smaller sections. Furthermore, the project size contains enough houses to examine variations in the distances between houses and the park.

In the data analysis phase, the survey data underwent a meticulous process known as data cleansing. This process involved segregating high-quality questionnaires from those that could be effectively utilized for analysis. Subsequently, various information was extracted from the dataset, encompassing socio-economic characteristics and attitudes towards walking among the sample group. These variables were analyzed and distributed to elucidate the relationship between the factors and the decision-making behavior of the sample group. The data analysis outcomes served as a foundation for recommending optimal designs for the layout of housing estate projects, aiming to facilitate efficient walking from residences to the park. Furthermore, variables displaying discernible differences in the utilization of park services among the sample group were subjected to a correlation analysis using appropriate models.

3.2. Artificial Neural Networks Model

The process of creating a model involves dividing the data into two parts. The first part, known as Training, is used for data analysis, while the second part serves as testing to assess the accuracy of the model. A neural network model is constructed by splitting the data in a ratio of 80/20 (following the Pareto Principle), with 80 percent of the data utilized for analysis and 20 percent reserved for testing. Although the specific ratio for data splitting is not universally defined, common choices include 80/20, 70/30, or 50/50, depending on the available raw data and desired model effectiveness. This study, a 70/30 ratio was employed, resulting in 338 data sets for model creation and 166 data sets for prognostic testing out of a total of 554 data sets. When selecting between the activation or transfer functions, there is no formal method, and decisions are typically based on experiential knowledge. In this study, the model's dependent variable pertained to the ability to walk, involving a binary classification of walking or not walking. Thus, the sigmoid function was chosen as the activation function, as it is well-suited for this type of binary classification task.

The data utilized for model development and prediction testing needs to be appropriately classified and categorized to align with the data analysis requirements of the neural network model. This point involves converting qualitative variables into numerical representations that the model can effectively analyze, as depicted in Table 2.

Table 2: Types and categories of input data.

Variable	Type	Class	
Walkability	Binominal	Nominal	(1) walk (0) not walk
Distance	Integer	Continuous	Distance (m)
Health insurance	Binominal	Nominal	(1) have (0)do not have
Income	Integer	Ordinal	(1) Less than 10,000 baht (2) 10,001 to 20,000 Baht (3) 20,001 to 30,000 Baht (4) 30,001 to 40,000 Baht (5) 40,001 to 50,000 Baht (6) 50,001 to 60,000 Baht (7)More than 60,001 Baht
Age	Integer	Continuous	Age (years)

The dataset is divided into two distinct parts for analysis. The first part, known as the training data, comprises 338 data sets utilized in the neural network process to examine and assess the variables' weights and influences. These results are expressed as equations, which are subsequently employed in accuracy analysis. The second part of the data, referred to as the testing data, consists of 166 data sets that validate the model's predictions. The researcher performs accuracy checks as the accuracy of the network can vary with each analysis iteration. Several factors can contribute to low or high accuracy, such as low data quality and limited data diversity, leading to suboptimal analysis outcomes. In cases where the dataset is insufficient to establish transparent relationships, the accuracy of the analysis network cannot be definitively determined. Consequently, analysts need to manually evaluate the displayed accuracy value against acceptable benchmarks to determine the completion of the analysis and usability of the model.

To assess the accuracy of the model, the Confusion Matrix principle is employed to present the prediction outcomes of the two models. The fusion matrix table comprehensively displays values, including accuracy and precision (Table 3).

Table 3: Confusion matrix.

<table>
<tr><th colspan="2" rowspan="2">Confusion matrix</th><th colspan="2">Actual value</th></tr>
<tr><td>Walk</td><td>Not walk</td></tr>
<tr><td rowspan="2">Predicted value</td><td>Walk</td><td>TP[a]</td><td>FP[b]</td></tr>
<tr><td>Not walk</td><td>FN[d]</td><td>TN[c]</td></tr>
<tr><td colspan="2">Accuracy</td><td>94%</td><td>Precision (P)</td></tr>
</table>

Upon data analysis and validation, the model that aligns with the intended objectives can be utilized. The output data generated from this network consists of two components. Firstly, a tabular representation displaying the weights assigned to factors influencing the decision to walk to the park. Secondly, a chart illustrates these factors' comparative significance in influencing the choice to walk to the park within the housing estate.

In applying the model, the initial step involves identifying the target group for the housing estate project based on the key factors influencing the decision to walk, as determined through data analysis using the model. Subsequently, the walking distance from the farthest house to the nearest neighborhood park area is determined and assessed using the model to ascertain whether all residents will have convenient access to the park. If the analysis indicates that walking is feasible, it implies that all residents can utilize the park. Conversely, suppose the analysis suggests that walking is not feasible. In that case, alternative measures must be taken, such as identifying a specific target audience or establishing a service period for the park based on the project owner's requirements.

4. Result and Discussion

4.1. Result of data collection

The objective of this study is to examine the accessibility of green areas within medium-sized housing estates and small communities that have designated green spaces and recreational areas. A total of 554 participants were surveyed, with a majority being female (61%) and falling within the age range of 21 to 40 years (57%). Participants were selected based on their ability to perceive and physically access the park, contributing to a healthier lifestyle. Classification based on body mass index revealed that most respondents exhibited good health (39%). Furthermore, over 40% of the participants reported an income exceeding 20,000 baht. Analysis of the occupation distribution indicated that a significant portion of the respondents were employed in the private sector (29%), aligning with the educational background of the sample group. Notably, 79% of the participants possessed a bachelor's degree or higher. A correlation was observed between private health insurance coverage and income level, as respondents with incomes below 20,000 baht displayed lower rates of private health insurance. Conversely, a more significant proportion of those earning above 20,000 baht were in the stage of starting a family. The data further revealed that over 70% of married or cohabiting respondents had children.

4.2. Result of Artificial Neural Networks Model

Data analysis using an artificial neural network model exhibits characteristics that differentiate it from conventional statistical computations. While it is rooted in statistical calculations, it involves complex computations that simulate critical thinking following an organism's model. As a result, each instance of analysis is likely to yield different results to previous or subsequent analyses. This variability does not imply that the outcomes of each analysis are fundamentally different. Instead, it suggests that the relative importance of factors influencing predictions may vary across different iterations.

Nonetheless, consistent trends can be observed with each repetition of the analysis. Notably, all factors or variables consistently demonstrate a negative impact on walking behavior. This study employed the same dataset and processes to perform 20 iterations of neural network modeling.

The results obtained from the 20 conducted analyses and forecasts revealed variations across all instances. Among these, the model exhibiting the highest prediction and forecasting accuracy highlighted the distance variable as the most influential factor in determining walking choices. Income, health insurance, and age were found to have diminishing levels of impact, respectively, as presented in Table 4. Notably, this model achieved an accuracy rate of 92.17 percent, accurately predicting walking decisions in 94 percent of cases and non-walking decisions in 83 percent of cases. For every 100 individuals who chose not to walk, the model correctly predicted this decision for 83 individuals while incorrectly predicting that 17 individuals would opt to walk, as demonstrated in Table 5

Table 4: Weights values form the best model.

Variables	**Weights**
Distance	1.000
Income	0.899
Health Insurance	0.841
Age	0.742

Table 5: Result of the confusion matrix.

Confusion matrix		**Actual value**	
		Walk	Not walk
Predicted value	Walk	134	4
	Not walk	9	19
Accuracy		94%	83%

The forecast test results revealed a negative influence of all factors or variables on walking choices. Higher values of these factors indicate a more excellent resistance to walking. Younger individuals tend to have more opportunities for walking and cover greater distances than older individuals. Moreover, individuals with higher incomes exhibit a lower propensity to walk than those with lower incomes. Additionally, the presence of health insurance is associated with a reduced likelihood of choosing to walk.

The application of the artificial neural network model extends to planning park design within housing estates. A critical aspect of this design process is determining the optimal distance between residences and parks, as highlighted in the analysis of data weights in the artificial neural network. Furthermore, income and age emerge as influential factors in decision-making regarding the distance for area design. Fig 2 illustrates an example of analyzing the suitable distance for area design based on the impact of income, while Fig 3 showcases the influence of age on the same aspect.

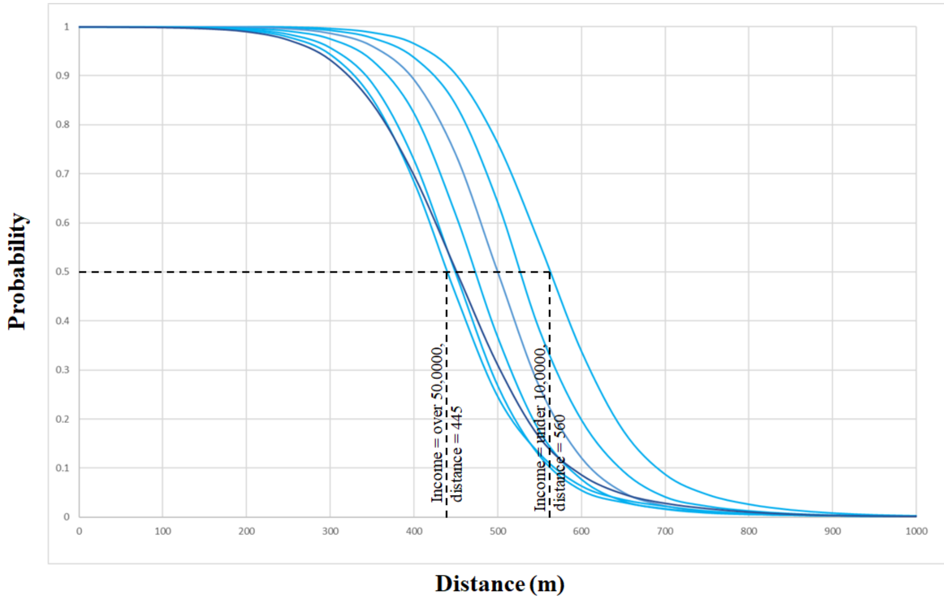

Fig. 2: The relationship between the probability of choosing to walk and the distance, classified by income.

A discernible trend emerges when examining the correlation between the probability of choosing walking and distance based on income using the neural network model. At a probability of 50% for choosing to walk and individuals with an income below 10,000 baht, the artificial neural network model can predict a maximum walking distance of 560 meters. Conversely, for those with an income exceeding 50,000 baht, the model indicates a maximum walking distance of 445 meters. This finding suggests that individuals with lower incomes have a greater inclination towards walking, as evidenced by the 115-meter disparity in walking distance compared to their higher-income counterparts. Notably, this correlation was established by fixing the age variable at 35 years (Fig 2).

When considering the relationship between the probability of choosing to walk and the distance, categorized by age according to the neural network model, the finding indicates that at the age of 15 years with a 50% probability of choosing to walk, the model predicts a maximum walking distance of 537 meters. Conversely, at the age of 55 years, the model predicts a maximum walking distance of 490 meters. The results indicate that younger individuals are more inclined to walk than older individuals, with a difference in walking distance of 47 meters. This relationship is established by manipulating the income variable within the 20,000-to-30,000-baht range (Fig 3).

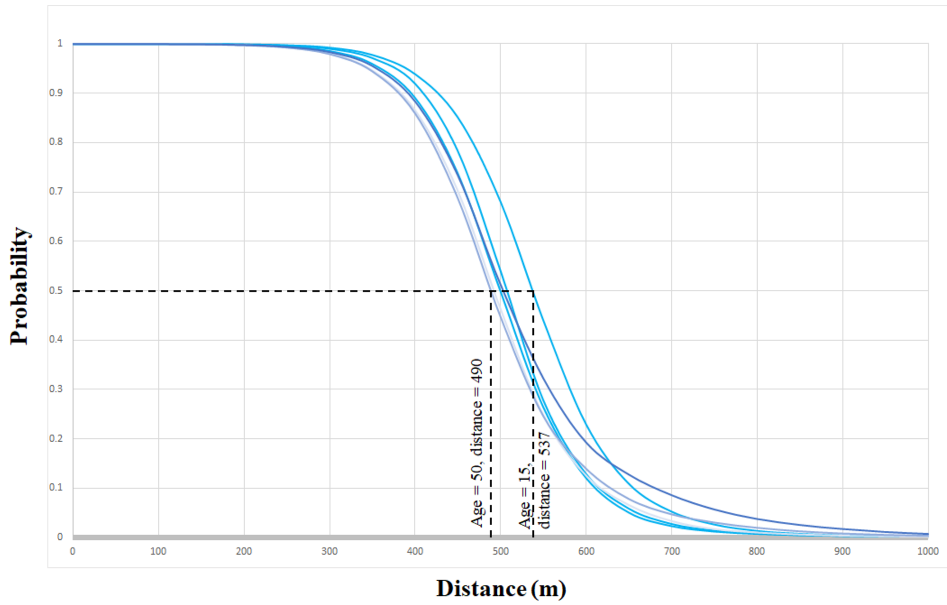

Fig. 3: The relationship between the probability of choosing to walk and the distance, classified by age.

Table 6: Walking distances at a 50 percent probability of choosing to walk with health insurance factor.

Health insurance	Age	Income	Distances (m)
Have the health insurance	15	less than 10,000 baht	617
Have the health insurance	15	20,001 to 30,000 baht	537
Have the health insurance	15	more than 50,001 baht	462
Have the health insurance	25	less than 10,000 baht	580
Have the health insurance	25	20,001 to 30,000 baht	507
Have the health insurance	25	more than 50,001 baht	455
Have the health insurance	35	less than 10,000 baht	560
Have the health insurance	35	20,001 to 30,000 baht	500
Have the health insurance	35	more than 50,001 baht	445
Have the health insurance	45	less than 10,000 baht	570
Have the health insurance	45	20,001 to 30,000 baht	490
Have the health insurance	45	more than 50,001 baht	455
Have the health insurance	55	less than 10,000 baht	575
Have the health insurance	55	20,001 to 30,000 baht	490
Have the health insurance	55	more than 50,001 baht	500
Have the health insurance	65	less than 10,000 baht	592
Have the health insurance	65	20,001 to 30,000 baht	500
Have the health insurance	65	more than 50,001 baht	550

In addition to analyzing the appropriate distance based on the influence of income and age, the presence of health insurance is another factor that impacts the decision to walk. This relationship is illustrated in Table 6. According to the analysis of data considering income and age among individuals with health insurance, there are variations in walking distances at a 50 percent probability of choosing to walk. Notably, the minimum walking distance of 445 meters was observed for those with an income exceeding 50,000 baht and aged 35 years, indicating the negative influence of each variable in the model. These findings contribute to the design considerations for determining the distance from the residential area to the park within the housing estate.

5. Conclusion

The analysis conducted using an artificial neural network model to examine the factors impacting the decision to walk and utilize public park services determined that all variables influenced the tendency to choose walking. Among these variables, walking distance emerged as the most influential factor, displaying a negative impact. Consequently, an increase in walking distance leads to a decrease in the likelihood of choosing to walk. Income was identified as the subsequent variable influencing the decision, with a higher income level correlating with a reduced propensity for walking. Individuals with higher incomes tend to opt for walking less frequently compared to those with lower incomes.

Moreover, the variable of health insurance also exerted a negative effect, indicating that having health insurance diminishes the likelihood of walking. Lastly, age was found to have the least significant influence. As individuals grow older, their inclination to walk decreases, and thus elderly individuals are less likely to choose walking compared to teenagers.

Analyzing these variables yields valuable insights that can be utilized in the design of housing estates. Most homebuyers in housing estates are those with higher incomes, considering the relationship between income levels and housing affordability (over a 30-year period). Current housing estates in Chiang Mai have prices exceeding 3 million baht, with a maximum allowable monthly payment of less than 50,000 baht and no additional financial obligations such as car loans. When examining individuals with incomes surpassing 50,000 baht across various age groups, it is observed that 50 percent of those aged 35 years have a maximum distance of 445 meters. This distance serves as the minimum threshold among other age groups. Consequently, the design of the housing estate should ensure that 50 percent of the project's residential area is located within 445 meters or less from the public park.

The obtained results offer valuable insights into the spatial planning of parks, facilitating the efficient utilization of public park areas within housing estates. Additionally, several other intriguing factors that are worthy of investigation influence decision-making, such as the temporal aspect and the availability of park facilities. Exploring these factors further has the potential to enhance the model's predictive accuracy regarding decision-making trends in the future.

Acknowledgements

This project was supported by Chiang Mai University, Thailand. The authors also wish to thank the Faculty of Engineering, Chiang Mai University to their help and support.

References

[1] Khonthachai Rochanasmita, "The utilization comparison study of centralized and decentralized recreation park in large housing estate in BMA," Master of Housing Management, Department of Housing, Faculty of Architecture, Chulalongkorn University, 2000.

[2] Bojing Liao, Pauline E. W. van den Berg, Pieter J. V. van Wesemael, and Theo A. Arentze, "How Does Walkability Change Behavior? A Comparison between Different Age Groups in the Netherlands," *International Journal of Environmental Research and Public Health*, vol. 17, no. 2, doi: https://doi.org/10.3390/ijerph17020540.

[3] Krungsri Guru. "The difference between housing estates and general villages." https://www.krungsri.com/th/plearn-plearn/home (accessed May 25, 2023).

[4] Decha Boonkham, *On landscape architecture: selected essays in 3 decades*. The Association of Siamese Architects under Royal Patronage, 2020.

[5] Antoine de Courrèges, Florent Occelli, Manon Muntaner, Philippe Amouyel, Aline Meirhaeghe, and Luc Dauchet, "The relationship between neighbourhood walkability and cardiovascular risk factors in northern France," *Science of The Total Environment*, vol. 772, p. 144877doi: https://doi.org/10.1016/j.scitotenv.2020.144877.

[6] Shanna Trichês Lucchesi, Ana Margarita Larranaga, Helena Beatriz Bettella Cybis, João António de Abreu e Silva, and Julian Alberto Arellana, "Are people willing to pay more to live in a walking environment? A multigroup

analysis of the impact of walkability on real estate values and their moderation effects in two Global South cities," *Research in Transportation Economics*, vol. 86, no. C, doi: https://doi.org/10.1016/j.retrec.2020.100976.
[7] Giovanna Fancello, Tanja Congiu, and Alexis Tsoukiàs, "Mapping walkability. A subjective value theory approach," *Socio-Economic Planning Sciences*, vol. 72, p. 100923doi: https://doi.org/10.1016/j.seps.2020.100923.
[8] Katarína Rišová, "Walkability research: concept, methods and a critical review of post-socialist studies," *Geografický časopis,* vol. 72, pp. 219-242, 2020, doi: https://doi.org/10.31577/geogrcas.2020.72.3.11.
[9] Yage Cui, Wenhao Tan, Linli Cheng, Tingting Chen, Liang Lv, and Hui Pan, "Analysis of Walking Accessibility of Park Green Space in Weidu District of Xuchang City Based on GIS," in *E3S Web of Conferences*, 2020, vol. 165: EDP Sciences, p. 04017.
[10] Katie Perumbeti. "Walk-a-what? What Walkability Means, and Why It's So Important." https://www.empowerline.org/walk-a-what-what-walkability-means-and-why-its-so-important/ (accessed August 26, 2020).
[11] James Leather, Herbert Fabian, Sudhir Gota, and Alvin Mejia, *Walkability and pedestrian facilities in Asian cities state and issues*. © Asian Development Bank., 2011.
[12] Philip Carthy, Sean Lyons, and Anne Nolan, "Characterising urban green space density and footpath-accessibility in models of BMI," *BMC Public Health*, vol. 20, no. 1, p. 760doi: https://doi.org/10.1186/s12889-020-08853-9.
[13] Fariba Sotoudehnia and Lex Comber, "Measuring perceived accessibility to urban green space: an integration of GIS and participatory map," in *14th AGILE Conference on Geographic Information: Advancing Geoinformation Science for a Changing World*, 2011.
[14] Jason G. Su, Michael Jerrett, Rob McConnell, Kiros Berhane, Genevieve Dunton, Ketan Shankardass, Kim Reynolds, Roger Chang, and Jennifer Wolch, "Factors influencing whether children walk to school," *Health & Place,* vol. 22, pp. 153-161, 2013/07/01/ 2013, doi: https://doi.org/10.1016/j.healthplace.2013.03.011.
[15] Takemi Sugiyama, Akio Kubota, Masaaki Sugiyama, Rachel Cole, and Neville Owen, "Distances walked to and from local destinations: Age-related variations and implications for determining buffer sizes," *Journal of Transport & Health*, vol. 15, p. 100621doi: https://doi.org/10.1016/j.jth.2019.100621.
[16] Rajalingappaa Shanmugamani, *Deep Learning for Computer Vision: Expert techniques to train advanced neural networks using TensorFlow and Keras*. Packt Publishing Ltd, 2018.
[17] Himanshu Sharma. "Activation functions: Sigmoid, ReLU, Leaky ReLU and Softmax basics for neural networks and deep learning." https://shorturl.asia/EO4Uo (accessed).
[18] Padej Sukpattanacharoen, "Walkability Analysis for Accessing Public Parks Within Housing Estates " Master of Civil Engineering, Department of Civil Engineering, Faculty of Engineering, Chiang Mai University, 2023.