Accelerating building decarbonization: Houseowner's adoption behaviours analysis towards Residential Photovoltaic (RPV) systems in Singapore

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Abstract
Residential photovoltaic (RPV) systems are one type of building-integrated photovoltaics (BIPV) specialized for residential buildings, demonstrating a significant positive impact on reducing carbon emissions. The Singapore government targets to install at least two gigawatts of solar energy by 2030, but the development of RPV is slow. RPV adoption analysis is critical for RPV development as it helps understand the market and identify the driving factors. However, the existing study ignored the non-linear relationships due to the limitations of conventional data analysis approaches. On the other hand, Artificial Neural Networks (ANNs) are robust in dealing with non-linear relationships, but they lack interpretation capability, making ANNs unsuitable for adoption analysis. This study proposed a hybrid-ANN by integrating the behavior theory and the network weight-based method, aiming to find the key drivers of RPV adoption in Singapore by considering non-linear relationships in raw data. The proposed model was trained and tested by a survey study of RPV adoption in Singapore. The results show that the hybrid-ANN outperformed existing models in predicting and explaining adoption behaviors. Furthermore, this study reveals that consumers' pro-environmental, economic attitudes and social obligation are driving factors in determining consumers' intention to adopt RPV. The study contributes the methodology in RPV adoption analysis by developing a novel way to construct the behavioral theory hybrid-ANN, which can be extended to analyse the adoption of other Renewable Energy Technologies (RETs) across the globe.

Keywords
Adoption behaviors; Artificial Neutral Networks (ANNs); Residential Photovoltaic (RPV)

1 Introduction

Residential Photovoltaic (RPV) systems are solar energy technologies installed on the rooftop of residential buildings. Unlike large-scale PV systems in industrial or commercial buildings, RPV is scalable and distributed, demonstrating a significant positive impact on reducing carbon emissions in residential buildings. Residential buildings account for roughly 20% of greenhouse gas (GHG) emissions due to energy consumption, which usually takes around 20% of total energy usages in developed countries and more than 35% in developing countries (Kelly 2012, Goldstein *et al.* 2020). In Singapore, residential buildings consume more than 15% of the nation's electricity use (Hwang and Tan 2012). To reduce the carbon footprint, the Singapore government launches the Green Plan 2030, aiming to install at least two gigawatt-peak solar energy. However, RPV adoption is relatively slow. By the end of Q1 2020, the installed RPV capacity is 13.1 MWp, less than 4% of the total installed PV capacity after launching PV products for 12 years (EMA 2020). To further promote the RPV market expansion, an in-depth RPV adoption analysis for understanding the RPV market, driving factors, and potential barriers is necessary (Wolske *et al.* 2017, Palm 2018).

RPV adoption analysis results help policymakers identify policy implications to leverage RPV's development. Behavioural factors are prevalent in recent RPV studies because individuals' behavioural factors play a significant role in individual decision-making (Centola 2010, Masini and Menichetti 2012). Researchers exploited behavioural factors in explaining RPV adoption decisions by applying different psychological theories based on raw data from the futuristic or retrospective survey of household owners and processed with statistical analysis approaches (Bollinger and Gillingham 2012, Korcaj *et al.* 2015, Wolske *et al.* 2017). Korcaj et al.(2015) applied the Theory of Planned Behaviour (TPB) to predict consumers' intentions to purchase RPV in German with high accuracy. The results showed that consumers' positive attitudes are strongly influenced by beliefs that RPV would enhance social status, energy independence, and financial gain. Besides, many other psychological or social factors are analysed with outstanding findings, such as peer effect (Bollinger and Gillingham 2012), consumer's pro-environmental attitude (Wolske et al. 2017) and network structure (Zhang et al. 2018).

Current statistical analysis approaches in RPV adoption analysis ignored the non-linear relationships in the raw data when evaluating the impact of testing factors (e.g., age, education, income) on the dependent variable (e.g., adoption decision). The statistical analysis approaches, according to Alipour et al.'s (2021) review, consist of conventional regressions (linear regression, multivariable regression, logit regression), descriptive statistics, structural equation modelling (SEM) and various correlation tests (e.g., Analysis of Variance, T-test, F-test). An apparent drawback for the above statistical approaches is their incapable to consider non-linear relationships in RPV adoption (Walters *et al.* 2018). Artificial Neural Networks (ANNs) are good at finding hidden patterns in complex and non-linear problems, but they suffer from weak model interpretability (Partridge 2016). ANNs are made of several layers of interconnected neurons, including one input layer, one output layer and several hidden layers, similar to the human nervous system (**see Figure 1a**) (Mellit and Kalogirou 2008). ANNs have not been applied to RPV adoption analysis because researchers need to know the importance of factors to RPV adoption decisions, but the use of ANNs as "black models" makes it challenging to identify directly driving factors. In addition, a well-performing ANN model requires a large amount of raw data, which is not suitable for survey-based RPV adoption analysis with a small amount of data (typically less than 500). Moreover, the small amount of data and low data dimension may lead to the performance of ANNs being lower than other conventional techniques, such as linear regression (Kanungo *et al.* 2006).

This study proposes a TPB-ANN model associated with factors' explaining method to resolve the difficulties of applying ANNs in RPV adoption analysis. Herein, TPB, a classic psychological theory developed by Ajzen (2003), provides a practical consumer behaviour analytic framework with a three-hierarchy structure. The first layer consists of three direct components that are involved in consumers' rational decision-making process: (1) one's attitude towards the behaviour, (2) perceived social pressure to perform the behaviour (subjective norms), (3) one's assessment about the ability to perform it (perceived behavioural control). The second layer uses the intention of the behaviour to connect three components in the first layer. The last layer involves the consumer behaviour under the intention in the second layer and perceived behavioural control in the first layer (**see Figure 1b**). In addition, many researchers successfully applied TPB in their analysis of pro-environmental behaviours (Harland *et al.* 1999, Heath and Gifford 2002, Han *et al.* 2010). The TPB-ANN model uses the TPB's theoretical structure to build the ANNs layers' architecture (topology) by segregating and connecting specific neurons in different layers following TPB's components interactive relationships (**see Figure 1c**).

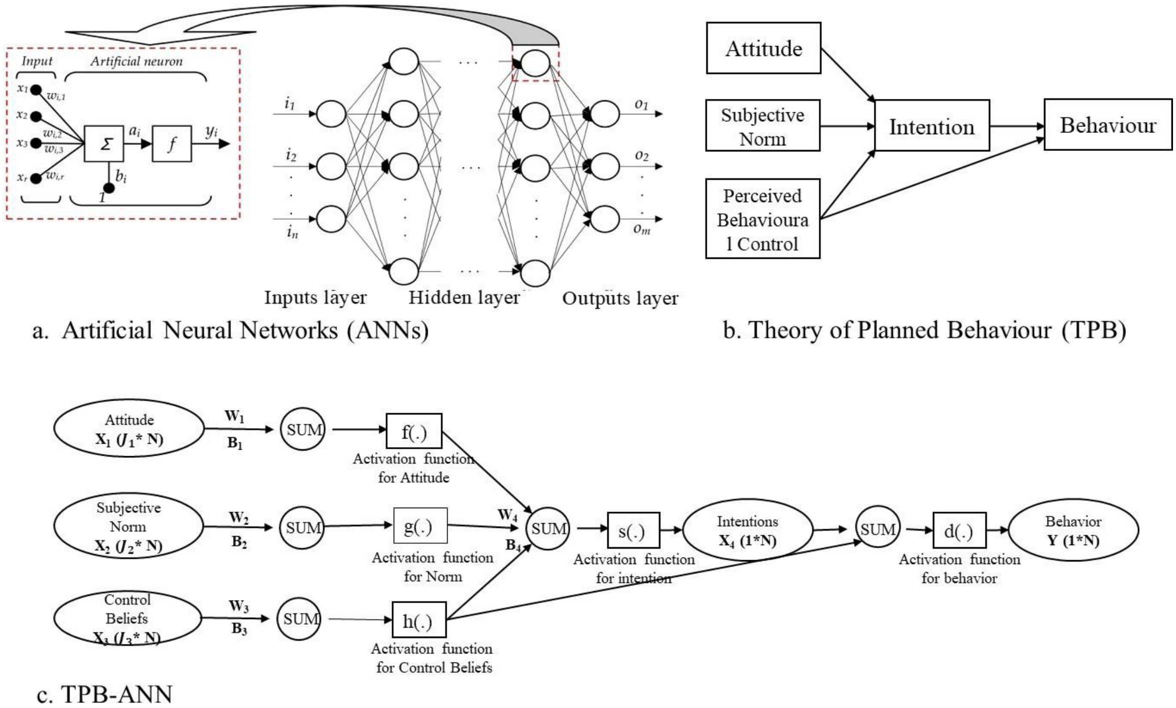


Figure 1. Illustration of TPB, ANNs and TPB-ANN

The Connection Weights (CWs) approach is selected to calculate factors' importance because its assumption aligns with the proposed TPB-ANN, which assumes that rationality can be learned and inherited by the topology of ANN through model training (Olden *et al.* 2004). CWs approach calculates factors' importance by multiplying weights of the trained ANNs backwards. To illustrate the non-linear capability and factors explanation ability of the proposed approach, a survey data with 293 valid responses measuring RPV adoption in Singapore was utilized for training and testing the proposed model. Model's prediction performance is compared with conventional regression models, such as linear regression (LR) and multilayer perceptron (MLP). In addition, the factors' importance is compared with path analysis result from structural equation modelling (SEM). LR is the most straightforward and cost-saving data analysing approach by fitting a linear plot with the lowest errors, and relationships between predictors and dependent variables are reflected by models' weights (Schmidt and Finan 2018). The MLP is a fully connected feed-forward ANN. Each neuron in one layer is connected to all neurons in the next layer, consisting of at least one hidden layer. SEM analysis utilizes the correlation matrix to analyse the structural relationship between measured variables and latent constructs, but it requires linear and normal assumptions in raw data, making it incapable of dealing with non-linear relationships in raw data (Schmidt and Finan 2018, Nam *et al.* 2020).

The study demonstrates the suitability of adopting ANNs in decision analysis through the development of a novel way to construct the TPB-ANN to solve the small data impact and "black-box" issue, which can be applied to analyse the factors driving the adoption of other Renewable Energy Technologies (RETs) across different geographical locations. In practice, the study analysed the non-linear relationships of RPV adoptions in Singapore and proposed instructive policy implications based on identified driving factors, which may help policymakers design the tailored energy policy to leverage RPV adoption.

2 Literature Review

2.1 Artificial Neural Networks in Adoption Analysis

ANNs have various applications in decision-making areas and usually are applied to forecast the human's judgment, based on factors that a person would use (Hill *et al.* 1994). Researchers in the early stage mainly applied ANNs in finance and investment. For example, Dutta and Shekhar (Dutta and Shekhar 1988) used different models to predict the ratings of corporate bonds and found that ANNs outperformed the linear regression. Later researchers applied ANNs in fault detection, which is proven effective because it can capture the hidden non-linear relationships in the raw data. With the tremendous increment of computing power in recent decades, more complex ANNs are invented to achieve more challenging tasks. For example, Convolutional Neural Network (CNN) implemented the convolution and pooling layer in the topology, making it superior in analysing visual imagery (Valueva *et al.* 2020). The Recurrent Neural Network (RNN) constructs the connections between nodes and forms a directed graph along a temporal sequence, making it applicable to sequence data (time-series, text, audio) (Sak *et al.* 2014, Valueva *et al.* 2020). However, it should be noted that the above-mentioned tasks generally place more weight on ANNs' forecast capability rather than its interpretability.

Using ANNs to illustrate and explain the adoption behaviours is complex, and existing researchers have chosen to implement other technologies or theories to help achieve the goal. Sim et al. (2014) utilized the sensitivity analysis to identify motivators from the trained ANNs in the study of mobile music acceptance in Malaysia and they compared the performance with Multiple Regression Analysis (MRA). They found that ANNs outperformed the MRA with smaller prediction Mean Square Error (MSE) because their ANNs captured the non-linear relationships in the survey data. Another interesting integration combines the SEM with ANNs to generate a hybrid SEM-Neural Networks approach (Tan *et al.* 2014). Tan et al. tried to identify drivers of behavioural intention to use mobile learning by applying a behavioural theory, the ANNs, and the SEM analysis. Firstly, they extended the behavioural theory with some hypotheses and collected survey data based on extended theory. Secondly, the SEM analysis was conducted to identify the causal relationships from the raw data. Finally, ANN associated with sensitivity analysis was utilized as a supplementary method to capture the non-linear relationships based on determined inputs and outputs from SEM results.

Current works explaining adoption behaviours with ANNs did not try to open the "black box" to illustrate the learned relationships from inside. Instead, they designed the sensitivity analysis to illustrate relationships between inputs and outputs by running the trained ANNs iteratively. Such practice may lead to a partial understanding of relationships or longer analysis time. Nevertheless, ANNs have some limitations besides low interpretability, such as slow convergence speed, arriving at the local minimum, over-fitting problems and relying on large data amounts and data dimensions (Kanungo *et al.* 2006).

2.2 ANNs' Connection Weights Approach

To address the "black-box" issue, some studies have been conducted on the factors' importance analysis, aiming to assess the variables' contributions in ANNs. Olden et al. (2004) conducted a robust comparison among the existing factors' importance assessment methods in ANNs. They concluded that the CWs approach outperformed the others in terms of similarity between identified importance and real ranked importance. The CWs approach is an ANN specified factor importance approach and calculates the importance of each input based on the weights in trained ANNs (Olden and Jackson 2002). **Figure 2** utilizes a simplified ANN model to illustrate the CWs calculation progress. Herein, the ANN consists of three predictors (inputs) and one hidden layer with two neural cells. Each predictor is fully connected with the cells in the hidden layer, and hence there are two input-hidden weights and one hidden-output weight for each predictor. The factor's importance is calculated by first multiplying corresponding hidden-output weight and input-hidden weight, and then sum the products, which is shown as **Figure 2**. CWs approach's performance depends on the distribution of the ANNs' weights and the topology. The CWs approach is implemented in this study for the factors importance assessment because its assumption is consistent with the proposed TPB-ANN.

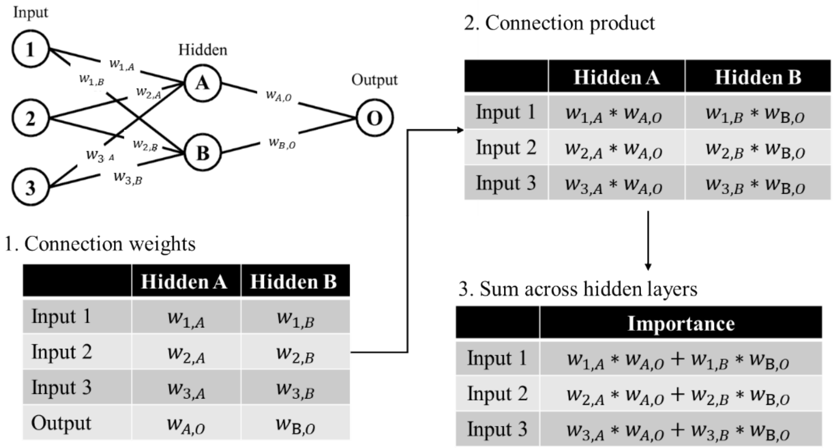


Figure 2. Example of Connection Weights for assessing predictors importance in ANNs

3 Research Methodology

The TPB-ANN is trained and tested based on the survey data, which is designed based on the TPB framework. **Figure 3a** shows the determined survey questions, and there are 18 questions (7-point Likert-scale from extremely disagree to extremely agree) with the extension of familiarity about RPV. Familiarity is essential in determining consumers' adoption behaviours, and some effective policy recommendations are proposed to increase the consumer's familiarity (Rebane and Barham 2011). Herein, the intention to adopt RPV was measured because there are few households adopted RPV in Singapore. The survey was sent via email, posted on social media, and distributed in train stations randomly to household owners in Singapore. The survey collections took three months, starting from December of 2019. There are in total, 314 responses were received, and 293 valid responses were left after verification. Given the determined data structure, the TPB-ANN model can be established by building the ANN's topology based on TPB's structure, which is shown in **Figure .3b**. Inputs are separated into four parts to feed in respective components in the input layer. The matrix X is used to denote the set of input vectors with $X.shape = (J, N)$. The sample size is N and the number of factors for each sample is J. Based on the TPB structure, input matrix X can be expressed as a matrix with $(\mathrm{J}_1 + \mathrm{J}_2 + \mathrm{J}_3 + \mathrm{J}_4) * N$ shape, while J_i $i \in (1,2,3,4)$ represents the number of factors in each TPB component defined in **Figure 3a**. There are two hidden layers followed by the input layer. The first hidden layer separates the neurons into four groups to match the input component i. Each group has m_i neurons, the independent active function, and a unique set of weights ($W_{Ji,mi}$) and bias (B_{Ji}). The first hidden layer of the proposed model can be expressed as Equation (1).

$$a_i = \sigma_i\left(W_{Ji,mi}^T * X_i + B_{Ji}\right),\ i = (1,2,3,4) \tag{1}$$

where, σ_i and a_i are the activate function and outputs for each input component i in first hidden layer. The size of output a_i is (m_i, N). Afterward, perspective outputs of the first layer components combined and fully connected to the second hidden layer with k neurons and weights set $W_{m,k}$. The "concat" function is applied, which simply full out join the four outputs matrix from the first hidden layer ($\bigcup_{i\in(1,2,3,4)} a_i$). The output layer is also fully connected with the second hidden layer with weight set $W_{k,I}$ and output vector Y ($Y.shape = (I, N)$). I measures different levels of RPV adoption intention respondents appeared in the survey data. Consumers' adoption intention can be normalized to a single value between -1 to 1 by averaging the scores of three intention questions. Afterwards, the intention value is categorized into I groups by doing the distribution fit because the value is not continuous and repeated. Hence, this is a multilabel classification problem.

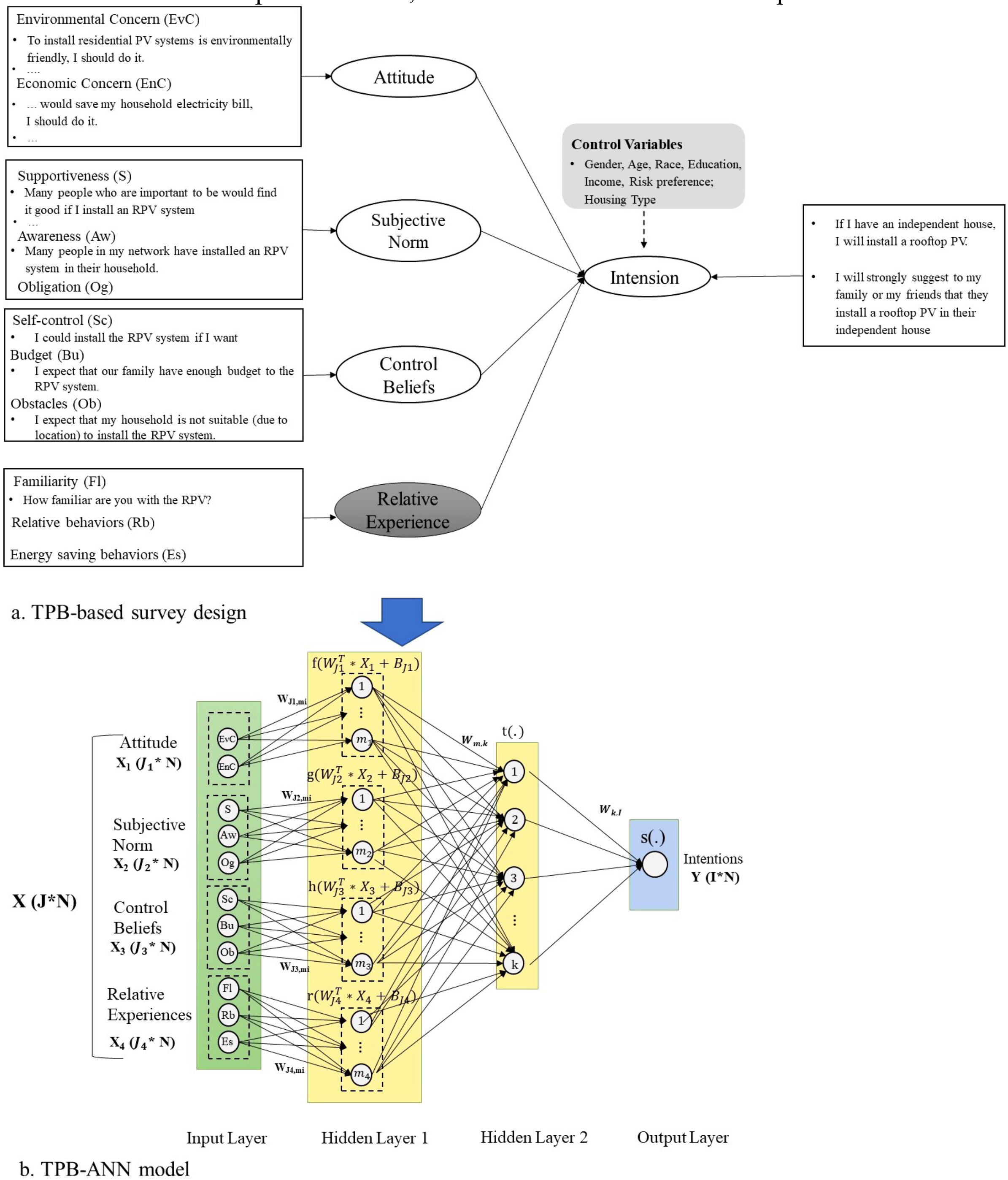


Figure 3 TPB based survey and TPB-ANN prediction model

After the model construction, this model needs to be tuned and trained. In this study, "relu" function is chosen as the active functions in hidden layers. "relu" function can significantly increase the model training speed by projecting the outputs into a piece function, which indicates the good "non-linear" process capability. For the output layer, the "softmax" function is applied to the final output matrix, which is the default active function for the classification problem. The number of the neurons of each input component and the second hidden layer are determined to be $m_i = 16\ i \in (1,2,3,4)$ and $k = 32$, respectively after balancing the training time and forecast accuracy. The loss function is calculated based on the cross-entropy loss function, which measures the degree of similarity between predicted results and actual values and its value will turn to zero if the prediction is the same as the actual. The "SGD" optimizer with a learning rate of 0.001 and decay of 0.0001 achieved the highest prediction accuracy. This study set up the pre-defined epoch numbers ($n_{iter} = 200$) to determine when to stop.

CWs approach helps identify the factor importance by backward calculating the product of the weights in the network. When calculating the CWs for TPB-ANN, the backward calculation needs to stop at the first hidden layer, split the weight product into four and then continue to calculate the weight for each factor. Suppose the CWs for input component i is denoted by CW_{Ji} ($CW_{Ji}.shape = (1, Ji)$). The trained weight set for component i in the first hidden layer is $W_{Ji,mi}$ ($W_{Ji,mi}.shape = (Ji, mi)$) and trained weight sets for the second hidden and output layers are $W_{m,k}$ ($W_{m,k}.shape = (m, k)$) and $W_{k,I}$ ($W_{k,I}.shape = (k, I)$) respectively. The $CW_{j,i}$ can be formulated shown as Equation (2) by referring to Olden and Jackson's (2002) work.

$$\bigcup_{i\in(1,2,3,4)} CW_{Ji} \cdot W_{Ji,mi} = W_{k,I}^T \cdot W_{m,k}^T \tag{2}$$

Where the notation "·" represents the dot product between two matrixes. $W_{k,I}^T \cdot W_{m,k}^T$ generate the weights product with shape = (I , m), which is consistent with the left side of the equation because $m = m_1 + m_2 + m_3 + m_4$. Therefore, the weights product $W_{I,m} = W_{k,I}^T \cdot W_{m,k}^T$ needs to be split into four weight sets ($W_{I,mi}$) based on the mi distribution before calculating the specific Connection Weights for factor j. The ultimate CWs for factor j is then calculated as follows.

$$CW_j \in \sum_I (W_{I,mi} \cdot W_{Ji,mi}^T),\ \ j \in (1, .. J_i)\ and\ i \in (1,2,3,4) \tag{3}$$

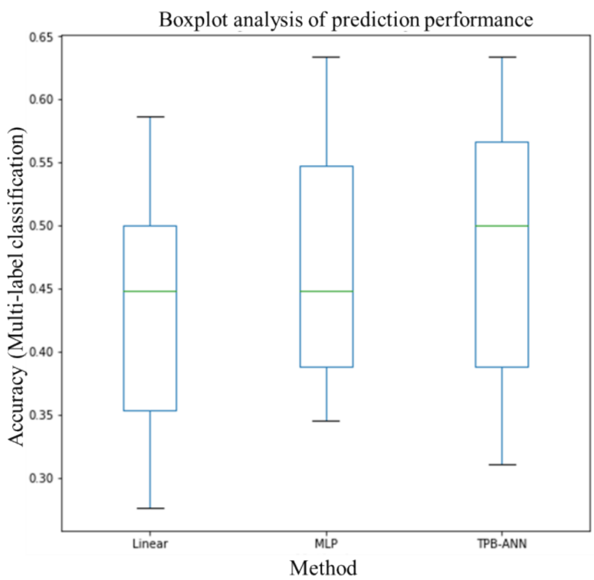
Where $\sum_I (W_{I,mi} \cdot W_{Ji,mi}^T)$ generates the set of weight connections for factors in input component i with size (1, J_i)

4 Findings and Discussion

In this study, three models (LR, MLP, TPB-ANN) were tested using the same ten sets of training and testing data, and their prediction results were recorded and displayed in **Figure 4**. Accuracy in this study is calculated using the number of correct classifications dividing the total test. ANN models (MLP, TPB-ANN) outperformed the linear regression model in 8 out of 10 cases. The TPB-ANN model appeared to have dominant performance among three candidate methods in 7 out of 10 cases. The average and median value of TPB-ANN's accuracy is also the highest among the three models. This indicates that ANNs have better model forecast accuracy than linear models because ANNs can discover the non-linear relationship in the data. Compared with MLP, the TPB-ANN's forecast accuracy is higher, which may due to TPB-ANN model can effectively prevent the over-fitting issue because it made the "intended drop-out" operation.

Factors' importance in TPB-ANN is calculated based on the CWs approach and summarized across five intention groups in ten folds, which is shown in **Table 1**. To illustrate the effectiveness of the proposed factors' importance method, SEM was implemented to do the cross-validation. After conducting a series of rigorous data normality checking and cleaning the out of limit points, the SEM identified that "Attitude" and "SubNorm" are two significant components impacting the intention for RPV adoption directly. In addition, factors inside the two main components are significant to the corresponding component, which is shown in **Table 1**. TPB-ANN is able to identify the importance of each factor without any pre-processing, and the results revealed that TPB-ANN identified driving factors are consistent with the result from SEM. Besides, CWs approach can rank the factors according to their absolute importance to differentiate which factors are more impactful, while SEM cannot. The comparison shows the conveniences and feasibility of applying the CWs approach to explain factors' importance in the TPB-ANN model.

This study found that "Attitude" and "Subjective Norms" were two drivers that significantly influence the respondents' intention to adopt RPV in Singapore. The results reflected respondents who care more about RPV's possible environmental and economic improvements show more interest in RPV adoption, which is consistent with finding from Wolske et al. (2017) in their analysis of RPV adoption in the U.S. Inside the "Subjective Norms," the research shed light on the respondents' "Obligation," and "Supportiveness". Precisely, the obligation reflects respondents' sense of social responsibility, which was identified to play an essential positive role in promoting RPV adoption intentions. Respondents' obligation of RPV reflects the awareness of the consequences of RPV adoption, which was found to play a significant positive effect (Wolske et al., 2017). Consistent with past research, the research also concluded that the potential adopters were found to tend to install RPVs because of the peer's support because friends or relatives' support can help respondents gain confidence in RPV adoption.



Fold	Linear	MLP	TPB-ANN
1	0.50	**0.57**	**0.57**
2	0.50	**0.63**	**0.63**
3	0.50	0.53	**0.57**
4	0.41	0.55	**0.59**
5	0.38	0.45	**0.52**
6	**0.59**	0.34	0.34
7	**0.48**	0.41	0.41
8	0.28	**0.38**	**0.38**
9	0.34	**0.38**	0.31
10	0.34	0.45	**0.48**

	Linear	MLP	TPB-ANN
count	10	10	10
mean	0.43	0.47	**0.48**
std	0.10	0.10	0.11
min	0.28	0.34	0.31
max	0.59	0.63	0.63

Figure 4 Prediction accuracy results and boxplot in ten folds experiment

Table 1. Factors importance comparison between TPB-ANN and SEM

Method	lval	op	rval	Estimate	Std. Err	z-value	Count	p-value
SEM	Intention	~	Attitute	0.206	0.095	2.164	/	**0.0305***
	Intention	~	SubNorm	0.374	0.126	2.965	/	**0.003****
	EnC	~	Attitude	0.935	0.081	11.531	/	0
	EvC	~	Attitude	1	-	-	/	-
	Og	~	SubNorm	0.757	0.097	7.798	/	0
	Aw	~	SubNorm	0.797	0.106	7.542	/	0
	Sup	~	SubNorm	1	-	-	/	-
TPB-ANN	Intention	~	EvC2	0.14	0.34	/	50	/
	Intention	~	EvC1	0.17	0.28	/	40	/
	Intention	~	S2	0.19	0.25	/	30	/
	Intention	~	EnC2	0.11	0.24	/	20	/
	Intention	~	Og	0.18	0.23	/	50	/
	Intention	~	S1	0.15	0.23	/	30	/
	Intention	~	EnC1	0.11	0.22	/	20	/

* $P < 0.05$; ** $p < 0.01$

Based on the findings, this study proposes several policy implications to promote RPV adoption in Singapore. Firstly, attitude can help to categorize the target consumer types in different RPV development and diffusion phases. For example, our findings show that targeting environmentally conscious households in the initial adoption phase will help to grow the market. Secondly, the results emphasize the social supports in promoting RPV adoption, as highlighted by many researchers (Bollinger and Gillingham 2012, Zhang *et al.* 2018). The finding shows that the consumers' referral programs and word-of-mouth would be the most effective marketing strategies for innovations, especially in the initial adoption phase when most consumers know little about the product. Policymakers are suggested to display the role models in the relevant residential communities or encourage adopters to share their experiences in their networks by setting up various incentives.

5 Conclusions and Further Research

This study proposes a TPB-ANN associated with the CWs approach to analyse non-linear relationships in RPV adoption. The case study of RPV adoption in Singapore was applied to test the proposed approach's performance by comparing it with existing models (LR, MLP, SEM). The TPB-ANN showed outstanding performance in the intention forecasting and driving factors explanation. In addition, environmental concerns and social support are identified as the top two components impacting the consumer's RPV adoption in Singapore and corresponding tailored policy implications such as consumers' referral programs and role models, are suggested to promote RPV development.

Future research should focus more on the more profound analysis of the trained TPB-ANN model with various scenario analyses to discover more interesting findings from the model. In addition, the complete structure of TPB was not implemented and tested in this study due to the difficulty in measuring actual RPV adoption decisions in the survey study. ANNs' training process is time-consuming, and currently, there is no automated way to tune hyperparameters for better performance ANNs. Future works focusing on testing the complete set of TPB and developing the intuitive hybrid-ANN integrated data analytical platform will further support the outcomes of this study.

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