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School Mode Choice Classification Model Exploitation Though Artificial Intelligence Classification Application

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ABSTRACT

Human behavior pattern recognition exploited using Artificial Neural Networks (ANN) is at the core of Artificial Intelligence (AI) classification applications. School trip transport forecasting mode selection based upon ANN forecasting ability provided an easy-to-use scientific toolkit for sustainable urban policies designing and implementation. The paper capitalized acknowledged forecasting ability of ANN to recognize and classify behavior patterns leading to parental decisions of school mode choice. Main stages of this research included the conduction of an extended questionnaire survey in 512 parents of school students in Thessaloniki (northern Greece) and the investigation whether ANN forecasting model could classify school mode choice. Research provided promising results (forecasting ability ranging from 76% to 93%) on school mode parental selection forecasting models based on ANN classifier, providing a solid proof of concept for further investigation.

1. INTRODUCTION

1.1 Rationale

Travel activities are significant and crucial part of everyday life. People travel for business, education, vacation, or other activities. School trips are prominent for daily travel time of parents and their children, and cannot be ignored as it consists an integral and important parameter of students' social activities, ensuring the right to education and contributing to knowledge acquisition, socialization and adoption of mobility behavioural patterns [1]. The design, organization and general functioning of a school transportation system, is a research subject which gained ground only within the last decades among the global scientific community. Earlier studies have extensively examined school mobility in regards to socio-economic and demographic dimensions. However, school travel patterns adopted by parents' personal perceptions and attitudes as well as school trips modelling, have so far received scant attention [2]. From one hand, the investigation and recognition of factors seem to influence parents in the school mode choice process and the understanding of the importance they attribute to these factors is particularly important for transport planning and for shaping the appropriate strategic directions towards an overall improvement of a school transportation system. On the other hand, the ability of communities to forecast school mode choice can act as a good asset in the hands of policy and decision makers, taking advantage of possible opportunities, avoiding threads and proposing groundbreaking actions to bring out the best possible result in the school transportation system operation.

1.2 Research objectives

The scope of this paper was to deliver pragmatic proof for ANN application efficiency and usefulness in modeling and identification of parental school mode choice. The paper focused on the following research topics:

- Evaluate and assess forecasting ability of suggested ANN topology and architecture.
- Examine whether ANN classifying applications could model sufficiently and provide solid and robust forecasting ability for parental school mode choice.

2. LITERATURE REVIEW

In recent years, human behavior pattern recognition has been at the core of AI applications. ANN applications have proved their ability to forecast human behavior characteristics, which are described by complexity, non-linearity and high noise, main features that ANN applications can handle successfully [3].

Relevant research of different scientific fields (medicine, psychology, transportation, etc.) have applied ANN in order to arise useful conclusions from questionnaire research. Skin response has been forecasted through the development of ANN based on data collected from questionnaire research [4]. This new forecasting approach contributed to human skin properties testing, which reduced the considerable amount of time and cost required to conduct cosmetology experiments, as ANN approach resulted in satisfactory forecasting ability, compared to experimental data.

The issue of whether stressful factors accelerate the mental and physical disorders of adults, have also been examined through a questionnaire survey conducted in 4,569 adults aged between 18 and 85 years forecasting the percentage of participants who may be mentally or physically ill and those who are not at risk [5].

Another research developed a forecasting model for breast cancer risk based on questionnaire survey data using 15,148 samples of healthy women aged 35 to 74 in Shanghai's Minhang District [6]. The results highlighted the importance of ANN based questionnaire research prognostic value in breast cancer fight.

Regarding the transportation field, traffic forecasting models based on ANN applications is an innovative and hi-tech approach [7-14] that, could mitigate the risk in planning and designing of future transport infrastructure and investments [15, 16], and alleviate traffic congestion and transportation network issues [17].

However, questionnaire survey-based ANN applications is a method of a rather limited research, as only a few studies have been found to follow such a methodological approach. The possibility of forecasting the perceived quality of public transport services provided by users has been investigated, based on ANN models trained using data collected from questionnaire survey, regarding the users' perceptions of Dhaka (capital and largest city of Bangladesh) urban bus services [18]. Among twenty-two selected service quality features, the most important features were ranked according to their impact on the user decision-making process for the use of public transport. The trained ANN models forecasted that punctuality, reliability, service frequency, seat availability, and travel experience were the most important characteristics.

An ANN model was also developed for public transport services quality forecasting, provided in rural areas, based on users' perceptions [19]. Data were collected through a questionnaire survey, and a total of thirteen indicators were taken into consideration, while the results invoked satisfactory forecasting ability for user dissatisfaction level, regarding the public transport system's reliability and seats' availability.

Through an ANN application, the forecasting ability of modal shift from private vehicle to public transport was investigated [20], after the introduction of smart transport services provided to commuters of Mersin city (southern Turkey). Using the data collected from two questionnaire surveys (total sample of 606 participants) and as output the shortest route calculated using an algorithmic procedure, the researchers determined the characteristics of trips to forecast the percentage of transport mode shift after the smart service introduction. The researchers concluded that the use of ANN was suitable for modeling dynamic transport systems and that can be used for modal shift forecasting.

Factors that determined school trip mode choice was investigated in Kandy, Sri Lanka [21]. Results indicated that gender, age, household income, school type and distance play a significant role in determining the school transport mode. Nonetheless, the ability to generalize on other case studies or forecast was identified as limitation of the study, due to different socio-economic and weather conditions.

Literature review pointed rather limited research on school mode choice models, more over on AI applications. Thus, primary research objectives established a logical framework for better understanding human behavior pattern recognition on school mode choice, engaging ANN applications. This framework emphasized on initiating a scientific toolkit on designing and implementation sustainable urban policies.

In this concept, the school mode choice prediction based on quantitate and qualitative data collected through a dedicated to students' parents questionnaire survey paves the way for exploring new abilities of computational intelligence and provides new directions for the future school transportation system overall optimization.

3. CASE STUDY

3.1 Primary research

For the primary research and data collection, a questionnaire was designed based on an in-depth literature review analysis conducted to identify the factors affecting parents in the school mode choice process.

The questionnaire had a structured character of a clear and predefined sequence of consecutive questions and statements. It consisted of three sections: the first one included questions regarding the socioeconomic characteristics of respondents, the second part included questions regarding the school trips completion, while the third part consisted of three subsections: in the first one, eighteen crucial factors that motivated parents in mode choice decision process were given in order to defined the significance level. For that purpose, a typical 5-point Likert scale was used (1 corresponds to very significant, 5 corresponds to not significant at all). Following, in the second section, the role of the structure environment in which students were traveling was examined. Parents were asked to declare their level of agreement or disagreement regarding thirteen statements describing the environment that included the route from the residence to the school unit. Similarly, a 5-point Likert scale was used for that purpose (1 corresponds to strongly agree, 5 corresponds to strongly disagree). The questionnaire was completed in the third section, where fifteen statements related to parents' travel habits were examined to identify the impact of their perception regarding the different transport modes used on the school trips mode choice process. Their responses were given in 5-point Likert scale.

3.2 Sampling method

The survey took place in the second largest Greek city, Thessaloniki (Northern Greece), numbering approximately one million residents and 100,000 primary and secondary school students. It was conducted from May to June and from September to November 2019. The minimum sample size was defined based on the following statistical method [22-24]:

$$n \geq N \cdot \left[1 + \frac{N-1}{p \cdot (1-p)} \cdot \left(\frac{d}{z_{\alpha/2}}\right)^2\right]^{-1} \tag{1}$$

For N =100,000 school students, p =50%, d =±5% and $z_{\alpha/2}$ =1.96 for confidence level 95%.

Based on Eq. (1) and for the case examined, were required at least 383 questionnaires to be completed. However, in total 512 questionnaires were collected, of which 496 fully and correctly completed questionnaires were finally used for ANN training and modeling. The questionnaire's completion followed a two-fold process. in person interviews were conducted while also parents were invited to complete the questionnaire online by using a google docs format file received in their e-mails.

4. ARTIFICIAL NEURAL NETWORKS FOR SCHOOL MODE CHOICE FORECASTING

4.1 Training method, learning rule and algorithm

The training method used for the ANN assessment was the supervised learning method, as the desirable output result (dependent variable/transport mode) for each input was already known and predefined through the questionnaire survey and concern the categories of transport modes examined; use of private car, use of (public or private) bus, and use of non-motorized modes; on foot/bicycle.

Feedforward ANN were developed for the research needs, while perceptron was the learning rule agreed to be used as the ANN weights in each iteration were modified in relation to the difference between the target value (which is available through the questionnaire survey respondents' answers) and the value calculated by the ANN.

Finally, Levenberg-Marquardt algorithm was selected, as it was distinguished for its high-speed training, its excellent adaptability to different problems and its wide range of applications [3, 23, 25-27].

4.2 Artificial Neural Networks inputs and outputs

Machine learning classification problems classify data instances into two or more classes. In our case, ANN trained included thirty-eight inputs (independent variables/ questionnaire items) and 1 output (dependent variable/the school mode choice: use of private vehicle (M_1), use of (public or private) bus (M_2) and use of non-motorized (on foot or bicycle) modes (M_3)). Input variables were the parental responses to questionnaires regarding the factors that motivate them in the school mode choice process, and their shaped perceptions regarding the use of the transport modes examined.

The output variable depicted the school mode choice and concerned two case studies:

(1) First case study, classifier with three output classes – three different school mode choices: use of private vehicle (M_1), use of (public or private) bus (M_2) and use of non-motorized (on foot or bicycle) modes (M_3), or
(2) Second case study, classifier with two output classes – two different school mode choices: use of motorized modes (private car and public or private bus, M_1) and use of non-motorized modes (on foot or bicycle, M_2).

Table 1. Independent variables used as inputs for the ANN training process

Question / Input variable for the ANN	
Q_1	Student's age
Q_2	There is someone to help
Q_3	Working hours
Q_4	Driving license possession
Q_5	Car ownership
Q_6	Limitations on parking
Q_7	Distance from school
Q_8	Time spent on trip
Q_9	Student's comfort
Q_{10}	Student's safety
Q_{11}	Environmental sensitivities
Q_{12}	Student's health
Q_{13}	School luggage (heavy or not)
Q_{14}	Socializing with friends
Q_{15}	Spending quality time with my child
Q_{16}	Traffic conditions are not dangerous
Q_{17}	There are safe intersections
Q_{18}	I find it unlikely my child to be abducted/injured by a stranger
Q_{19}	I find it unlikely my child to be harassed by others
Q_{20}	The route from residence to school is safe
Q_{21}	Thera are sidewalks of adequate width
Q_{22}	Sidewalks are clean
Q_{23}	Sidewalks are separated by traffic with trees
Q_{24}	There are no obstacles on sidewalks (rubbish bins, cars, etc.)
Q_{25}	Residents in the neighborhood are in good condition
Q_{26}	Thera are no vandalism traces in our neighborhood
Q_{27}	There is adequate lighting on the route from residence to school
Q_{28}	Travelling to school on foot/bike is a good way my child to become familiar with the neighborhood
Q_{29}	I would like my child to travel to school on foot or by bike under the appropriate circumstances
Q_{30}	Travelling to school on foot/by bike is a way to increase my child's physical activity
Q_{31}	Driving is more comfortable than walking/cycling
Q_{32}	I like driving within the city
Q_{33}	Owing a car makes my life more comfortable
Q_{34}	I use my car even for short distances
Q_{35}	I like to use urban bus for travelling within the city
Q_{36}	The urban bus is a very reliable transport mode
Q_{37}	I am satisfied with the comfort of the urban bus
Q_{38}	I am satisfied with the punctuality of the urban bus

Output variable of school mode choices was filled from parents three times, according to the:

(1) Preferable transport mode for every day school trips.
(2) Selected transport mode used during the morning school trip (from residence to school unit).
(3) Selected transport mode used during the afternoon school

trip (from school unit to residence).

Table 1 described the thirty-eight questionnaire items which were included in the ANN development and training.

4.3 Artificial neural network architecture

The selection of node's number and hidden layers were based on some heuristics that have been proposed by researchers in the past. Table 2 described the results of such heuristics.

The definition of the ANN architecture was based on:

- the selection of an appropriate number of neurons that would lead to a stable ANN of which the forecasting ability may not be optimal per case but overall (including all simulations);
- the selection of an ANN structure in terms of one or two hidden layers.

Table 2. The heuristics proposed for the number of neurons to be used in hidden layer(s) (N_i: number of input variables, N_o: number of output variables, n: number of training data)

Heuristic for the definition of hidden layers and nodes	Researcher	Number of nodes
$3 \cdot N_i$	Hush (1989), [28]	114
$2 \cdot N_i + 1$ (ANN with one hidden layer)	Hecht-Nielsen (1987), [29]	77
$2 \cdot N_i / 3$	Ripley (1993), [30]	19 or 20
$\dfrac{2 + N_i \cdot N_o + \frac{1}{2} \cdot N_o \cdot (N_i^2 + N_i) - 3}{N_i + N_o}$	Paola (1994), [31]	20
Total nodes: $2 \cdot \sqrt{(N_o + 2) \cdot n}$		67
First layer: $\sqrt{(N_o + 2) \cdot n} + 2 \cdot \sqrt{n / (N_o + 2)}$	Huang (2003), [32]	56
Second layer: $N_o \cdot \sqrt{n / (N_o + 2)}$		11
Total nodes: $N_i + N_o$		39
1^{st} layer: $(2/3) \cdot (N_i + N_o)$	Gupta (2015), [33]	26
2^{nd} layer: $(1/3) \cdot (N_i + N_o)$		13

The current research proposed three different ANN architectures that were further examined:

(1) Architecture A (Figure 1), including thirty-eight inputs, fifty nodes in a hidden layers and 1 output (38–50–1).
(2) Architecture B (Figure 2), including 38 inputs, 55 + 10 nodes on two hidden layers and 1 output (38–55–10–1).
(3) Architecture C (Figure 3), including 38 inputs, 65 + 15 nodes on two hidden layers and 1 output (38–65–15–1).

Each ANN architecture training process was applied on each output case (preferable school transport mode, selected transport mode used for the residence to the school unit trip, and selected transport mode used for the school unit to residence trip). Thus, for every ANN architecture three different output cases were examined.

To confirm classifier stability, ten experimental simulations were executed per ANN architecture (three different architectures), per each output case (three cases), resulting ninety simulations.

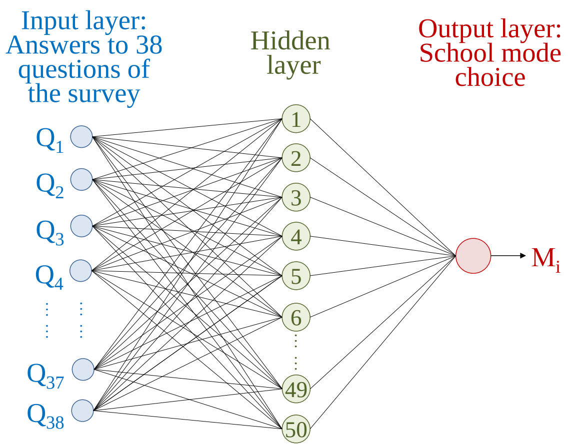

Figure 1. Artificial Neural Network Architectures – Architecture A: 38–50–1

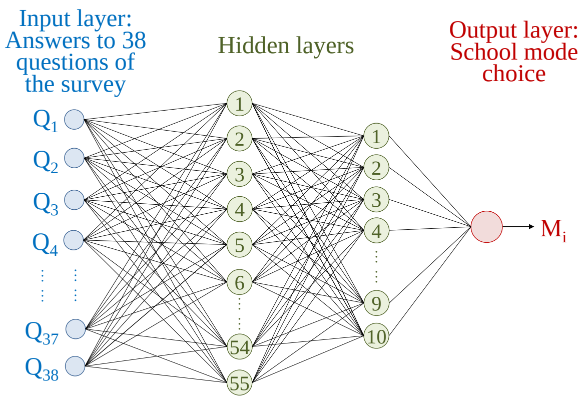

Figure 2. Artificial Neural Network Architectures – Architecture B: 38–55–10–1

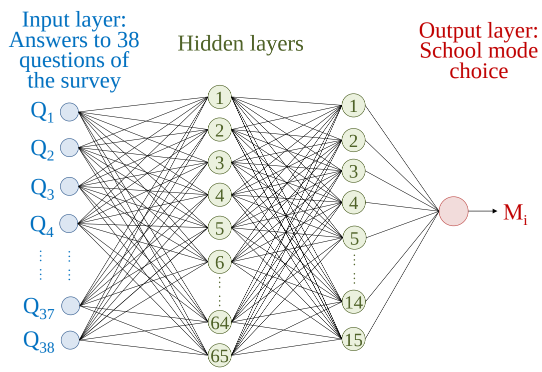

Figure 3. Artificial Neural Network Architectures – Architecture C: 38–65–15–1

The above-mentioned process was applied for two different study cases (classifier with three and two output classes). In total, 180 different ANN architectures were finally trained and modeled.

5. ANN CLASSIFICATION PERFORMANCE ANALYSIS FOR SCHOOL MODE CHOICE FORECASTING

5.1 Performance analysis metrics

Confusion matrix is commonly used for performance evaluation of classification models [27, 28, 34]. All the diagonal elements denote correctly classified outcomes. The misclassified outcomes are represented on confusion matrix off diagonals. Thus, the best classifier will have a confusion matrix with only diagonal elements and the rest of the elements set to zero. From confusion matrix, the following metrics need to be calculated [35, 36]:

- True Positive (*TP*), which stands for forecasted values that were classified as actual values and positive cases.
- False Positive (*FP*), which stands for forecasted values that were misclassified as actual values.
- True Negative (*TN*): which stands for forecasted values that were classified as actual values and negative cases.
- False Negative (*FN*): which stands for forecasted values that were misclassified as negative cases.

Once confusion matrix is established and the relevant metrics were calculated, performance of classification model was determined through the following classification parameters.

Accuracy is a classifier's efficiency metrics that calculates the fraction of total correct forecasted values made by classifier (*TP* + *TN*) divided to total number of test examples (*TP* + *TN* + *FP* + *FN*):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

Precision of class is an efficiency metrics that calculates the fraction of negative forecasted values (*TN*), divided to total predicted positive instances and represents the purity of class, that is the classifier ability to prevent wrong forecasts and is determined as:

$$\text{Precision} = \frac{TN}{TN + FN} \tag{3}$$

Weighted average precision is a classifier's efficiency metrics that calculates the overall precision of the classifier and is calculated as:

$$\text{Weighted average precision} = \sum_{k=1}^{G} n_k \cdot Precision_k \tag{4}$$

where, G is the number of classes, g is the number of each class, and $n_g = \sum_{k=1}^{G} c_{gk}$ is the number of samples belonging to the g-th class (n_g) and it corresponds to the sum of the g-th row elements of confusion matrix.

Sensitivity or *Recall* of class is an efficiency metrics that calculates the fraction of positive forecasted values be classifier (*TP*), divided to total positive instances and defines the classifier's ability to correctly identify the class samples:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5}$$

Weighted average recall is a classifier's efficiency metrics that calculates the overall precision of the classifier and is calculated as:

$$\text{Weighted average recall} = \sum_{i=1}^{G} n'_k \cdot \mathrm{Re}call_k \tag{6}$$

where, $n'_g = \sum_{k=1}^{G} c_{gk}$ is the number of samples predicted in the g-th class (n'_g) corresponds to the sum of the g-th column elements of confusion matrix.

F1 Score is a classifier's efficiency metrics that calculates the fraction of harmonic mean of precision and sensitivity and ranges between 0 to 1:

$$\text{F1 Score} = 2 \cdot \frac{\text{Sensitivity} \cdot \text{Precision}}{\text{Sensitivity} + \text{Precision}} \tag{7}$$

5.2 First case-study classifier with three output classes: Private car (M_1), bus (M_2) and non-motorized transport modes (M_3) – Performance evaluation

First case-study classifier with three output classes (private car (M1), bus (M2) and non-motorized modes (M3)) was modeled and simulated and results in form of confusion matrix are presented for ANN topology 38–50–1 at Table 3, for ANN 38–55–10–1 at Table 4 and for ANN 38–65–15–1 at Table 5

Table 3. ANN 38–50–1 confusion matrix regarding the preferable and the used transport mode for the school trip – Case of choice between private car (M_1), public or private bus (M_2), and non-motorized modes (M_3)

Preferable mode for school transport		**Forecasted transport mode**			
		Private car	Bus	Non-motorized	
Actually used transport mode	Private car	**5.7%**	0.8%	3.6%	
	Bus	0.8%	**16.5%**	6.5%	
	Non-motorized	1.3%	3.4%	**61.4%**	
				Accuracy:	**83.6%**
Route from the residence to the school unit		**Forecasted transport mode**			
		Private car	Bus	Non-motorized	
Actually used transport mode	Private car	**35.1%**	1.1%	7.2%	
	Bus	4.0%	**3.1%**	1.7%	
	Non-motorized	7.0%	0.7%	**40.1%**	
				Accuracy:	**78.3%**
Route from the school unit to the residence		**Forecasted transport mode**			
		Private car	Bus	Non-motorized	
Actually used transport mode	Private car	**9.9%**	2.0%	7.3%	
	Bus	2.4%	**11.5%**	6.6%	
	Non-motorized	3.3%	2.5%	**54.5%**	
				Accuracy:	**75.9%**

Table 4. ANN 38–55–10–1 confusion matrix regarding the preferable and the used transport mode for the school trip – Case of choice between private car (M_1), public or private bus (M_2), and non-motorized modes (M_3)

Preferable mode for school transport		**Forecasted transport mode**		
		Private car	Bus	Non-motorized
Actually used transport mode	Private car	**3.5%**	1.2%	5.4%
	Bus	0.2%	**15.8%**	7.8%
	Non-motorized	0.9%	3.4%	**61.8%**
			Accuracy:	**81.1%**
Route from the residence to the school unit		**Forecasted transport mode**		
		Private car	Bus	Non-motorized
Actually used transport mode	Private car	**35.0%**	0.7%	7.6%
	Bus	4.5%	**2.1%**	2.3%
	Non-motorized	7.1%	0.3%	**40.4%**
			Accuracy:	**77.5%**
Route from the school unit to the residence		**Forecasted transport mode**		
		Private car	Bus	Non-motorized
Actually used transport mode	Private car	**11.0%**	2.2%	6.1%
	Bus	2.6%	**13.3%**	4.4%
	Non-motorized	2.0%	2.8%	**55.6%**
			Accuracy:	**79.9%**

Table 5. ANN 38–65–15–1 confusion matrix regarding the preferable and the used transport mode for the school trip – Case of choice between private car (M_1), public or private bus (M_2), and non-motorized modes (M_3)

Preferable mode for school transport		**Forecasted transport mode**		
		Private car	Bus	Non-motorized
Actually used transport mode	Private car	**5.0%**	1.2%	3.9%
	Bus	0.7%	**17.6%**	5.4%
	Non-motorized	1.1%	3.7%	**61.3%**
			Accuracy:	**83.9%**
Route from the residence to the school unit		**Forecasted transport mode**		
		Private car	Bus	Non-motorized
Actually used transport mode	Private car	**35.6%**	0.3%	7.4%
	Bus	5.0%	**1.9%**	2.0%
	Non-motorized	6.7%	0.1%	**41.0%**
			Accuracy:	**78.5%**
Route from the school unit to the residence		**Forecasted transport mode**		
		Private car	Bus	Non-motorized
Actually used transport mode	Private car	**10.3%**	2.0%	6.9%
	Bus	1.8%	**12.7%**	5.9%
	Non-motorized	2.6%	2.4%	**55.4%**
			Accuracy:	**78.4%**

According to Tables 3, 4 and 5, the predictive ability of all ANN topologies is better in the case of the preferable transport mode than the other two cases representing the transport mode finally selected for the school trip completion. This can be justified by the fact that machine learning algorithm was trained on the basis of parents' responses to the questionnaire survey. As a result, ANN seem to interpret in a large degree their behavioral patterns, leading to more accurately predictions regarding the transport mode they would prefer for the school trip in relation to the mode actually selected, due to factors that seem to have a negative effect on the realization of their preference and which ultimately lead them to safer choices (e.g., selection of private vehicle or bus instead of non-motorized transport, such as walking and bicycling). For example, an unsafe built environment could act inhibitory in selecting walking or bicycling for the school trip completion. Furthermore, potential time constraints due to parents' working hours may turn them towards the use of private vehicle during the morning trip (combining both school and work trip) instead of walking them to school, while in the case the afternoon school trip, parents may be turned towards the use of other modes than the ones preferred (e.g., school bus) due to the fact that they are still working and are not therefore available for any other choice.

Thus, in a major degree, it can be well supported that the ANN process followed, allowed the decoding of parents' profile characteristics and behavioral travel patterns, leading to a robust forecasting model, regarding the mode preferred for the school trip in relation to the one finally selected.

Within Tables 6, 7 and 8, the forecasting ability of each ANN classifier architecture for the cases i) "Preferable mode for school transport", ii) "Route from the residence to the school unit" and iii) "Route from the residence to the school unit" are depicted. More specifically:

- Forecasting ability of each ANN classifier architecture for the case "Preferable mode for school transport" is displayed at Table 6. In case of ANN 38–50–1 classifier topology, forecasting accuracy was 83.6%, while forecasting accuracy for topology ANN 38–55–10–1 and ANN 38–65–15–1 was 81.1% and 83.9%, respectively.
- Table 7 presents the forecasting ability of each ANN classifier architecture considering the case "Route from the residence to the school unit". In case of ANN 38–50–1 classifier topology, forecasting accuracy was 78.3%,

while forecasting accuracy for topology ANN 38–55–10–1 and ANN 38–65–15–1 was 77.5% and 78.5% respectively.

- Finally, for the case “Route from the residence to the school unit” as depicted in Table 8, the higher accuracy is noticed in the case ANN 38–55–10–1 classifier topology, reaching 79.9% with lower rates to follow for the topologies ANN 38–50–1 and ANN 38–65–10–15 75.9% and 78.4%, respectively.

Table 6. Classifier’s performance metrics for case “Preferable mode for school transport”

ANN topology	Accuracy	F1 Score	Weighted average precision	Weighted average recall
38–50–1	83.6%	84.1%	83.1%	85.1%
38–55–10–1	81.1%	80.7%	78.8%	82.6%
38–65–15–1	83.9%	80.4%	79.1%	81.7%

Table 7. Classifier’s performance metrics for case “Route from the residence to the school unit”

ANN topology	Accuracy	F1 Score	Weighted average precision	Weighted average recall
38–50–1	78.3%	78.9%	77.7%	80.1%
38–55–10–1	77.2%	78.8%	76.9%	80.9%
38–65–15–1	78.5%	76.8%	74.9%	81.1%

Table 8. Classifier’s performance metrics for case “Route from the school unit to the residence”

ANN topology	Accuracy	F1 Score	Weighted average precision	Weighted average recall
38–50–1	75.9%	76.8%	74.9%	78.8%
38–55–10–1	79.8%	78.9%	77.7%	80.1%
38–65–15–1	78.4%	79.4%	77.7%	78.8%

According to the Tables’ 6, 7, and 8 results, the ANN 38–65–15–1 topology is identified as the best performance classifier among two others regarding the preferable school transport mode and the selected transport mode used for the residence to the school unit trip output cases, while for the case of selected transport mode used for the school unit to residence trip, ANN 38–55–10–1 topology seems to perform slight better. Thus, it can be well supported that all ANN topology performances examined in the current research would be acceptable as a real-life classifier.

5.3 Second case-study classifier with two output classes: motorized (M_1) and non-motorized transport modes (M_2) – Performance evaluation

Second case-study classifier with two output classes, (motorized transport modes (M_1) and non-motorized transport modes (M_2) was modeled and simulated, and results in form of confusion matrix are presented for ANN topology 38–50–1 at Table 9, for ANN 38–55–10–1 at Table 10 and for ANN 38–65–15–1 at Table 11.

Table 9. ANN 38–50–1 confusion matrix regarding the preferable and the used transport mode for the school trip – Case of choice between motorized (M_1: private car, public or private bus) and non-motorized (M_2: on foot or bicycle) modes

Preferable mode for school transport		**Forecasted transport mode**		
		Motorized	Non-motorized	
Actually used transport mode	Motorized	**4.8%**	5.3%	
	Non-motorized	1.4%	**88.5%**	
			Accuracy:	**93.3%**
Route from the residence to the school unit		**Forecasted transport mode**		
		Motorized	Non-motorized	
Actually used transport mode	Motorized	**32.0%**	11.0%	
	Non-motorized	9.6%	**47.4%**	
			Accuracy:	**79.4%**
Route from the school unit to the residence		**Forecasted transport mode**		
		Motorized	Non-motorized	
Actually used transport mode	Motorized	**7.7%**	11.6%	
	Non-motorized	3.3%	**77.4%**	
			Accuracy:	**85.1%**

According to Tables 9, 10 and 11, the predictive ability of all ANN topologies is remarkably better in the case of the preferable transport mode than the other two cases representing the transport mode finally selected for the school trip completion. As already mentioned in the first case-study classifier, this finding also applies in this case, highlighting the fact that the parents’ preferences as regards the school trip can be more easily predicted in relation to the final transport mode selection, as there are additional factors that seem to influence the decision-making process and sometimes even force them to select a different transport mode of the one actually preferred.

Within the Tables 12, 13 and 14, the forecasting ability of each ANN classifier architecture for the cases i) “Preferable mode for school transport”, ii) “Route from the residence to the school unit” and iii) “Route from the residence to the school unit” are depicted.

Moreover, Table 12 depicted the forecasting ability of each ANN classifier architecture considering the case “Preferable mode for school transport”. In case of ANN 38–50–1 classifier topology, the forecasting accuracy expands 93%, while the corresponding forecasting accuracy for topology ANN 38–55–10–1 and ANN 38–65–15–1is noticed a bit lower (92.2% and 92.5% respectively.

Table 13 presented the forecasting ability of each ANN classifier architecture considering the case “Route from the residence to the school unit”. The higher forecasting ability is depicted in the ANN 38-65-15-1 classifier topology (85.8%) while ANN 38–50–1 and ANN 38–55–10–1 seem to significantly reduce as the respective percentages are noticed under 80% (79.4% and 79.7% respectively).

Forecasting ability of each ANN classifier architecture for case "Route from the residence to the school unit" is displayed at Table 14. In case of ANN 38–50–1 classifier topology, forecasting accuracy is the lowest (85.1%), while forecasting accuracy for topology ANN 38–55–10–1 and ANN 38–65–15–1 was 88.8% and 88.3%, respectively.

According to the Tables' 12, 13 and 14 results, topology ANN 38–50–1 identified as the best performance classifier only for the preferable school transport mode output case. For the other two output cases (selected transport mode used for the residence to the school unit trip and selected transport mode used for the school unit to residence trip) ANN 38–55–10–1 and ANN 38–65–15–1 performance metrics are found similar and higher than the ANN 38–50–1 topology. This finding, in relation to the one derived from the first case-study classifier which examined three output classes, indicates that the increase of hidden levels in ANN architectures, might affect in a larger degree the optimization of the predictive ability of ANN, in the case of examining less ones output classes. However, the fluctuations noticed are particularly low, allowing the specific ANN topology performances examined in the research to be considered as real-life classifiers.

Table 10. ANN 38–55–10–1 confusion matrix regarding the preferable and the used transport mode for the school trip – Case of choice between motorized (M_1: private car, public or private bus) and non-motorized (M_2: on foot or bicycle) modes

Preferable mode for school transport		**Forecasted transport mode**		
		Motorized	Non-motorized	
Actually used transport mode	Motorized	**3.6%**	6.5%	
	Non-motorized	1.3%	**88.6%**	
			Accuracy:	**92.2%**
Route from the residence to the school unit		**Forecasted transport mode**		
		Motorized	Non-motorized	
Actually used transport mode	Motorized	**34.0%**	9.3%	
	Non-motorized	10.9%	**45.7%**	
			Accuracy:	**79.7%**
Route from the school unit to the residence		**Forecasted transport mode**		
		Motorized	Non-motorized	
Actually used transport mode	Motorized	**10.8%**	8.5%	
	Non-motorized	2.7%	**78.0%**	
			Accuracy:	**88.8%**

Table 11. ANN 38–65–15–1 confusion matrix regarding the preferable and the used transport mode for the school trip – Case of choice between motorized (M_1: private car, public or private bus) and non-motorized (M_2: on foot or bicycle) modes

Preferable mode for school transport		**Forecasted transport mode**		
		Motorized	Non-motorized	
Actually used transport mode	Motorized	**4.1%**	6.0%	
	Non-motorized	1.5%	**88.4%**	
			Accuracy:	**92.5%**
Route from the residence to the school unit		**Forecasted transport mode**		
		Motorized	Non-motorized	
Actually used transport mode	Motorized	**36.2%**	7.1%	
	Non-motorized	7.1%	**49.6%**	
			Accuracy:	**85.8%**
Route from the school unit to the residence		**Forecasted transport mode**		
		Motorized	Non-motorized	
Actually used transport mode	Motorized	**10.4%**	9.0%	
	Non-motorized	2.8%	**77.9%**	
			Accuracy:	**88.3%**

Table 12. Classifier's performance metrics for case "Preferable mode for school transport"

ANN topology	Accuracy	F1 Score	Weighted average precision	Weighted average recall
38–50–1	93.3%	67.9%	52.7%	95.3%
38–55–10–1	92.2%	85.5%	85.3%	85.8%
38–65–15–1	92.5%	74.6%	63.5%	92.0%

Table 13. Classifier's performance metrics for case "Route from the residence to the school unit"

ANN topology	Accuracy	F1 Score	Weighted average precision	Weighted average recall
38–50–1	79.4%	58.3%	42.0%	95.4%
38–55–10–1	79.7%	79.5%	79.4%	79.7%
38–65–15–1	85.8%	73.8%	62.3%	91.1%

Table 14. Classifier's performance metrics for case "Route from the school unit to the residence"

ANN topology	Accuracy	F1 Score	Weighted average precision	Weighted average recall
38–50–1	85.1%	62.4%	46.4%	95.1%
38–55–10–1	88.8%	78.8%	78.2%	79.5%
38–65–15–1	88.3%	64.8%	50.7%	89.7%

6. CONCLUSIONS

ANN application on human travel behavior interpretation is a relatively recent methodology that authors applied to forecast the school transport mode parents prefer and select for their children. Based on parents' responses to a number of questions and statements, a variety of ANN architecture forecasting classification models were engaged to investigate the forecasting ability for parent's preference of transport mode and finally selection of residence to the school unit route and vice versa, in case of different circumstances (e.g., enhanced road and pedestrian infrastructures, reliable provided public bus services, etc.). A total of 180 ANN of different architecture were trained, shaped by one or two hidden layers and two case-study classifiers were considered including two and three output classes respectively. The first case examined private car (M_1), bus (M_2) and non-motorized transport modes (M_3), while the second case merged M_1 and M_2 under the motorized (M_1) category and kept the non-motorize category (M_2) as such. The results compared to parents' real choices or desires proved a high forecasting accuracy of the proposed AI classification models, varying between 75.9% and 93.3%.

Regarding the forecasting ability of the ANN topologies examined, this was found better in the case of the preferable transport mode than the other two cases representing the transport mode finally selected for the school trip completion. This could be justified by the fact that machine learning algorithm was trained on the basis of parents' responses to the questionnaire survey. As a result, ANN seem to interpret in a large degree their behavioral patterns, leading to more accurately predictions regarding the transport mode they would prefer for the school trip in relation to the mode actually selected, due to factors that seem to have a negative effect on the realization of their preference and which ultimately lead them to safer choices (e.g., selection of private vehicle or bus instead of non-motorized transport such as walking and bicycling). Thus, in a major degree, it can be well supported that the ANN process followed, allowed the decoding of parents' profile characteristics and behavioral travel patterns, leading to a robust forecasting model, regarding the mode preferred for the school trip in relation to the one finally selected.

Regarding to the results derived from the comparison of all topologies examined for both case studies, a general finding, indicates that the increase of hidden levels in ANN architectures, might affect in a larger degree the optimization of the predictive ability of ANN, in the case of examining less ones output classes. However, the fluctuations noticed are particularly low, allowing all the ANN topology performances examined in the research to be considered as real-life classifiers.

Accurate forecast of school mode transportation mode is essential for utilities, regulatory authorities, decision makers, local and national authorities, and transportation system engineers and will guide on safer conclusions and proposals for transportation systems maintenance and expanding. The present paper incorporated a computational intelligence classification methodological approach and proposed a useful toolkit for research and analysis of school travel decisions, creating the necessary background to be used in similar future research. It will be extremely challenging to investigate forecasting robustness and the applicability of deep learning algorithms on similar transportation problems. Additionally, an extended application of proposed methodology on different case studies would be extremely useful since it could prove generalization ability of this approach and empower the establishment as a solid and acknowledged scientific approach in the planning and implementation of sustainable urban transport policies.

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