# UNDERSTANDING TRAVEL BEHAVIOR THROUGH TRAVEL HAPPINESS

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**Word count:** 5946 words text + 3 tables x 250 words (each) = 6696

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**ABSTRACT**

The aim of this paper is to extend past research on travel behavior analysis by investigating traveler's emotions and perception of the system's performance. The perceived travel happiness as an extension of travel satisfaction is researched in the framework of the decision-making process during traveling. Socio-demographics, cognitive and affective data were collected from a questionnaire survey, which took place in Athens (Greece), the Netherlands and Barcelona and Salamanca (Spain). A Bayesian Network was developed in order to investigate the interrelations between travel happiness and parameters that affect travel behavior. Findings revealed that travel mode choice directly affects the level of happiness that someone experiences during everyday trips. Moreover, travel happiness is directly associated with the perception of the traveler on the occurrence of disruptions during everyday trips and the level of tolerance they have towards such disruptions. Results also indicated that further research should focus on understanding how each country's system's topology and performance affect travel related choices. Finally, a discussion of the most significant results is provided.

*Keywords:* travel happiness, mode choice, emotions, travel patterns, Bayesian Networks

## INTRODUCTION

The recent technological and communication advances in the transportation landscape with the plethora of travel mode alternatives offered to travelers' for their everyday trips result in a highly complex travel decision making process that, in order to make sensible predictions on the effects of interventions in transportation systems, should be understood and modeled (*1*). Previous research on analyzing how travel-related choices are made are usually based on the concept of a utility function that encapsulates the trade-offs travelers consider when making decisions. The factors in such utility functions may be predetermined for each individual (e.g., car ownership, driver license possession, location of work), or refer to each traveler's characteristics (e.g., gender, age, occupation, income) and emotions (e.g., anxiety, the perception of crowdedness). Moreover, trip-related attributes, such as cost and travel time, are also included in such functions. Subsequently, the sign and significance (or lack thereof) of these factors are derived from observed choices (decision utility) (*2*), either in a simulated environment (Stated Preferences (SP) surveys, travel simulators) (*3*) or from travel diaries (*4*).

Over the last decades, researchers have shown that *experienced* utility (i.e. the utility in hindsight) may differ from *decision* utility, due to traveler's emotions and feelings during traveling (*5*, *6*). To this end, researchers turn to investigate travelers' emotions and perceptions on the trip as well, by introducing the notion of travel satisfaction. According to (*7–9*), satisfaction with travel consists of two dimensions: one affective (emotional), which refers to emotions experienced during a trip and one cognitive (reasoned) dimension, which refers to the evaluation of the trip. Moreover, travelers' satisfaction can be seen as a measure of the extent to which a service matches the traveler's expectations (*10*). A significant portion of the research has addressed the cognitive dimension of travel satisfaction (*11*, *12*). In (*13*) researchers emphasize measuring both the cognitive and the affective component of travel satisfaction or well-being taking into consideration different emotions: whether the traveler feels bored, fed up, stressed, calm, enthusiastic or confident during the trip. Several studies (*14–16*) have examined the level of experienced stress during commuting trips. There is evidence that many other aspects of travel behavior, rather than just travel mode, are associated with travel satisfaction, which may include trip duration and in-vehicle activities (*17*, *18*). Furthermore, other studies show that travel choices are more likely to be motivated by the goal of enhancing happiness rather than by the traditionally studied concept of reducing travel cost (*19*, *20*). As highlighted by some researchers, travelers' attitudes and emotions are more important when planning to travel than objective travel quantities (costs, travel times, etc.) (*21*). In (*22*) a 5-level scale, the so-called Satisfaction with Travel Scale – STS, is proposed to examine whether emotional reasons affect travel choices. Results indicated that different activities (trip purpose) result in different level of satisfaction with travel. Some researchers have investigated travelers' satisfaction with different travel modes (*17*), while others focus on public transportation systems (*23*). It turns out that the use of specific modes is amongst the strongest differentiators in the level of travel satisfaction (*24*), (*25*). Furthermore, travelers' satisfaction is found to influence travel choices mainly for short distance and urban trips (*26*). Although these findings clearly point towards the relevance of the affective dimension in travel choice behavior, there still is a limited body of knowledge that conceptualizes and quantifies the role of this affective dimension. The gap of knowledge that arises from the literature concerns the importance of affective factors in the decision-making process of every day travelling and the relationship between them and other cognitive factors. Another interesting question is whether the perception of the traveler on the transportation system and the trip affects their travel decisions.

The scope of this paper is to investigate the existence of interrelationships between traditionally examined user and system-related factors that may affect travel behavior and affective factors under the umbrella concept of *Travel Happiness*. The differentiation from the more well-known notion of travel satisfaction lies in the fact that in this paper with travel happiness we aim to combine decision utility with (a) the satisfaction from the level of service and (b) two factors which express the perception of the user on the various aspects of their trip. This perception is described through two variables. The first one is the probability that the traveler assigns to the occurrence of a disruption or other unexpected event during their trip. The second one is the level of tolerance that the traveler has towards the occurrence of such unexpected events. The investigation of factors that affect travel behavior and the interrelations between various factors and travel happiness is performed through the analysis of data collected from a questionnaire survey using Bayesian networks.

The remainder of the paper is organized as follows: First, the methodological approach of the study is briefly discussed and the questionnaire used for the survey is presented. Then, the most meaningful statistics of the sample are analyzed and findings based on the Bayesian Network Structures are thoroughly presented. Finally, the most significant conclusions and suggestions for further research are presented.

## TRAVEL BEHAVIOR AND HAPPINESS

### A brief definition of travel happiness

Following research on the emotional aspects of travel choices, the concept of travel happiness has been gradually introduced as a broader term which includes travel satisfaction, placing emphasis on the "generalized" emotions a traveler experiences during a trip (*19*, *27*).

Firstly, we briefly place travel happiness in a broader context. Travel happiness can be considered as an attribute in the continuum of decision making in life (including mobility and transport), which may be perceived from two intertwined temporal dimensions: The first one is the medium-term dimension which aggregates the feelings of users about their overall mobility patterns. The second is the short-term dimension, which encapsulates the dynamically changing sense of happiness (constituted by affective factors during travel), which may, of course, vary in relation to the trip conditions (Figure 1). This long-term aspect of travel happiness is linked to life satisfaction, which, in this paper, is considered to relate to travel happiness as an *external mood* affected by a generalized perception of a traveler's life conditions. Life satisfaction measures how people evaluate their life as a whole, rather than their current feelings. Life satisfaction includes subjective data and personal evaluation of a person's health, education, income, personal fulfilment and social conditions. Based on the OECD report (*28*), the Greeks rate their life satisfaction equal to 5.2., way below the average of OECD countries which is 6.5, the Dutch 7.4 and Spanish people 6.4.

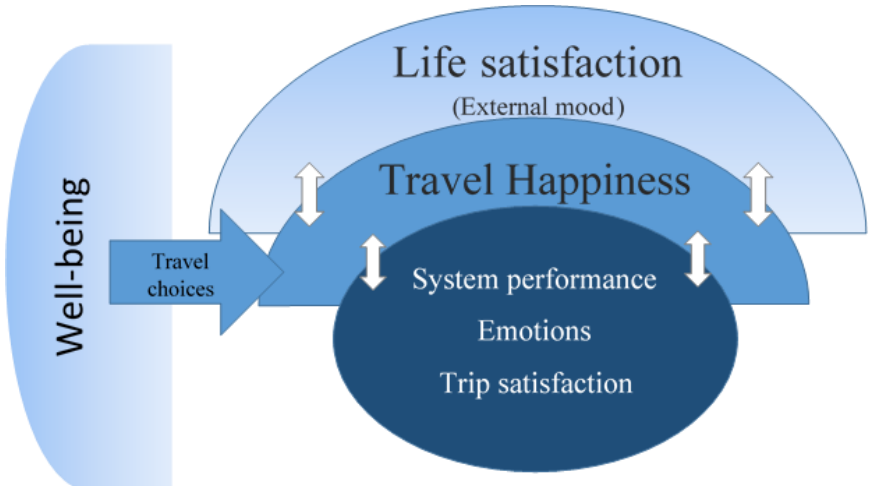


**FIGURE 1 Travel happiness in the continuum of decision-making in life.**

The short-term aspect of travel happiness is related to general macroscopically forming travel choices that are related to strategic factors and the well-being of a person, as well as user's perception of the services and system operation as well as the specifications of the transportation system. In some studies, happiness is used as a proxy for the notion of well-being as is considered to be the main subjective indicator of social system performance (*25*). The link between happiness and travel behavior has not been thoroughly studied. Nonetheless, there exists a small body of literature that investigates how trip attributes are associated with traveler's emotions, such as (*29*), which provides some evidence that travel happiness correlates with travel mode choice decisions, although Morris et al. suspect potential links also with other travel choices (*6*).

One of the challenges is that travel happiness, or any other variable which describes a person's feelings and emotions, is challenging to measure, especially in the case of travel behavior analysis (*30*). To this end, we assume that travel happiness can be measured in a 5-point Likert scale, which is a common and generally accepted way to measure opinions, perceptions, and behaviors. As noted, the concept of travel happiness has not yet been systematically quantified and assessed in terms of the factors that may influence it. To the authors' knowledge, the connection between travel behavior and happiness from a perspective of combining travel mode choice, trip purpose, users' perception of the trip and in the context of personal demographics and mobility profiles has not been extensively researched. In this paper we present an attempt to do so. A powerful tool to explore the relationship between these factors is a Bayesian network, which allows us to estimate the conditional probabilities between these factors in a structured way.

## Bayesian Networks

Bayesian Networks (BNs) are graphical representations for encoding the conditional probabilistic relationships among variables of interest. The nodes of the graph represent variables and the arcs between variables represent causal, influential, or correlated relationships. A BN for a set of variables consists of two parts: The qualitative part is a network structure *G* in the form of a Directed Acyclic Graph (DAG), in which nodes are in a one-to-one mapping with the random variables X and links characterize the dependence among connected variables. The quantitative part is a set of local probability distributions/tables $\Theta = \{P(X_1|\Pi_1), \ldots, P(X_n \,|\, \Pi_n)\}$ for each node/variable $X_i$, conditional on its parents $\Pi_i$. These conditional probability tables demonstrate the probability of $X_i$ with respect to each combination of its parent variables. In a BN, $X_j$ is referred to as a parent of $X_i$ if there exists a direct link from $X_j$ to $X_i$. $\Pi_i$ is used to denote the set of parent variables of $X_i$. If a variable has no parents, the local probability distribution collapses to its marginal $P(X)$.

In a BN model, $G$ is the model structure and $\Theta$ holds the model parameters. The DAG topology of a BN only asserts the conditional dependence of children given parents. Therefore, by integrating structure $G$ and parameter $\Theta$, the joint distribution for $X$ in a BN can be decomposed, by using the chain rule, into a factorized form with smaller and local probability distributions, each of which involves one node and its parents only:

$$P(X) = \prod_{i=1}^{n} P(X_i \,|\, x_{\Pi(i)}) \quad (1)$$

In other words, the joint probability distribution $P(X)$ can be exclusively encoded by the pair *(G, Θ)* (*31*). For discrete random variables, this conditional probability is often represented by a table, listing the local probability that a child node takes on each of the feasible values – for each combination of values of its parents. The joint distribution of a collection of variables can be determined uniquely by these local conditional probability tables (CPT) also referred to as parameters tables. Let the $n(x_i, x_{\Pi(i)})$ be the number of observations in which the variable $X_i$ has adopted the values $x_i$ and its parents $\Pi_i$ the values $x_{\Pi(i)}$.The standard estimate for a parameter $P(X_i \,|\, x_{\Pi(i)})$ is (*32*):

$$P\left(X_i | x_{\Pi(i)}\right) = \frac{n(x_i, x_{\Pi(i)})}{n(x_{\Pi(i)})} \quad (2)$$

The structure and the relationships in BNs can rely on both expert knowledge and relevant statistical data, meaning that they are well suited for enhanced decision-making (*33*). There are three methods to structure learning for a BN:

1. *Constraint-based algorithms*: These algorithms use conditional independences and dependences induced from the data, to detect the Markov blankets of the variables to recover the structure of a BN, e.g., PC, Max-Min Parents and Children and Grow-Shrink.
2. *Score-based algorithms*: These algorithms aim at maximizing a scoring function (Log-likelihood, AIC, BIC, e logarithm of the Bayesian Dirichlet equivalent score, etc.) by means of a heuristic search strategy (Search and Score), such as Hill-Climbing and Tabu Search. A scoring function used in structural learning in BNs is typically score-equivalent.
3. *Hybrid algorithms*: These algorithms combine constraints with search and score. The most common hybrid algorithm is the Max-Min Hill Climbing (MMHC), which starts with the constraint-based stage to develop the skeleton and then carries out a search and score based strategy, using the skeleton obtained as the candidate edge set (*34*).

In this paper, Tabu Search algorithm is implemented for the development of the BN which is a score-based algorithm moving from one solution to its neighboring solution while trying to maximize Log-likelihood. This algorithm was selected because it results in a DAG as opposed to hybrid algorithms and the structure of the graph is learned directly from the data.

Conditional Independence tests are functions of the Conditional Probability Tables implied by the graphical structure of the network through the observed frequencies for the random variables $\boldsymbol{X}$ and $\boldsymbol{Y}$ and all the configurations of the conditioning variables $\boldsymbol{Z}$. The conditional independence test used in this case was *Mutual Information*, an information-theoretic distance measure defined as follows:

$$MI(X,Y|Z) = \sum_{i=1}^{R}\sum_{j=1}^{C}\sum_{k=1}^{L}\frac{n_{ijk}}{n}log\frac{n_{ijk}n_{++k}}{n_{i+k}n_{+jk}} \quad (3)$$

It is proportional to the log-likelihood ratio test (they differ by a 2n factor, where n is the sample size), and it is related to the deviance of the tested models (*35*)

Regarding the evaluation of the trained models, the most common way to obtain unbiased estimates of the goodness of fit of a Bayesian structure is the k-fold Cross-validation technique (*36*). The goodness of fit of the true network (the one emerged from the Tabu algorithm) are compared with the performance of an empty and a random network.

In this project, structure learning was data-driven and performed by using the *bnlearn* package (*37*) of the R language (*38*).

## DATA COLLECTION

Data used for the analysis were collected through a questionnaire survey which took place in three European countries: Greece, the Netherlands and Spain. The questionnaire consists of 4 parts and 27 questions and is aimed at investigating factors that affect travel mode choice, identifying different mobility profiles as well as respondents' perception on the system they use. A comprehensive view on the content of each part is provided in Table 1.

**TABLE 1 Questionnaire's Parts Description**

| Questionnaire Part | Description | Questions Content |
|---|---|---|
| A | Travel profile | travel mode, trip purpose, number of trips per trip purpose, weekly travel cost, number of transfers, work time flexibility, PT pass possession |
| B | Perceived factors' importance for each type of choice | cost, travel time, reliability, cleanliness and comfort, flexibility, availability, safety, security, real-time information provision, in-vehicle activities, accessibility, weather conditions and parking availability |
| C | User assessment of travel mode | flexibility, availability, safety, security, accessibility, reliability, comfort |
| D | Socio-demographics | gender, age, income, occupation, car ownership, household size, home location |

In the first part, respondents are asked about their usual trip, namely for which purpose and by which mode they travel every day. This part also includes questions about the number of trips per trip purpose, number of transfers on the usual trip, work time flexibility and public transport pass possession. Furthermore, respondents are asked about their attitude towards Mobility as a Service (MaaS), namely whether they use or willing to use any MaaS service (Taxi, Uber, Car-sharing and Car-pooling). Respondents are asked to determine the level of happiness they experience during their usual trip using a 5-point scale, where 1 represents very unhappy and 5 represents very happy. Then, respondents are asked about their tolerance regarding changes of network and service conditions (e.g., traffic congestion, road accident, strike, etc.). Again, respondents answer using a 5-point scale, where 1 represents not tolerant and 5 represents very tolerant. Lastly, respondents are asked to state their estimation on the possibility of the occurrence of any unexpected event (PRE), such as road closure and vehicle damage, during their usual trip using a 5-point scale (1 represents not possible and 5 represents certain).

In the second part, respondents are asked about the importance of various factors that lead to choosing their usual travel mode. The importance of each factor is described in a 5-point scale from 1 (not important) to 5 (extremely important). Factors that are examined are: cost, travel time, reliability, cleanliness and comfort, flexibility, availability, safety, security, real-time information provision, in-vehicle activities, accessibility, weather conditions and parking availability. In the third part of the questionnaire, respondents are asked to assess the travel mode they use the most in terms of the same attributes in a 5-point scale from low to high. Finally, in the last part, demographic characteristics (gender, age, income, car ownership, etc.) of the sample are identified.

**Survey execution and sample size**

The questionnaire survey had a total duration of 10 weeks which was conducted both online and onsite. In the case of the Netherlands, survey was solely conducted via the internet and lasted 2 weeks. In Greece and Spain, the online platform was open for more than one month (January – February 2018) while the onsite survey had a total duration of 10 weeks. Onsite survey was carried out in metro stations and bus stations, which had connections with other travel modes, as well as in activity/leisure centers, especially in places where people were waiting and therefore had some time to consume for filling in the questionnaire.

The final sample size included a total number of 2199 valid responses and is representative for each country's population. The sample size per country, as well as the corresponding number of original responses, are presented in Table 2.

**TABLE 2 Sample Size per Country**

| Country | Original responses | Final sample size |
|---|---|---|
| Greece | 844 | 793 |
| Netherlands | 1065 | 699 |
| Spain | 736 | 707 |

**Analysis of responses**

The sample of the three countries is well distributed in terms of gender, age and income distribution. As shown in Table 3, the Greek sample includes younger ages with just the 4% of the sample being >65 years old. On the contrary, both Dutch and Spanish samples have a well distributed sample in terms of age. Having the largest group of unemployed and retired people, it is not surprising that the Dutch survey respondents have the smallest rate of high income. Moreover, income distribution for the Spanish sample is almost equally spread, while one would expect a more left-skewed distribution like the Greek population is showing.

**TABLE 3 Demographic Characteristics of the Sample**

| Variables | | Percentages | | |
|---|---|---|---|---|
| | | Greece | Netherlands | Spain |
| **Gender** | Male | 51.7% | 45.8% | 52.5% |
| | Female | 48.3% | 54.2% | 47.5% |
| **Age** | 18 – 24 | 21.8% | 10.0% | 15.1% |
| | 25 – 34 | 26.0% | 19.6% | 20.9% |
| | 35 – 44 | 19.2% | 18.6% | 21.1% |
| | 45 – 54 | 15.9% | 22.3% | 24.6% |
| | 55 – 64 | 12.9% | 18.2% | 11.7% |
| | > 65 | 3.7% | 11.3% | 6.5% |
| **Personal Income** | Low | 41.6% | 35.9% | 37.6% |
| | Medium | 47.7% | 60.7% | 30.6% |
| | High | 10.7% | 3.4% | 31.8% |
| **Car ownership** | Yes | 84.1% | 84.0% | 84.0% |
| | No | 15.9% | 16.0% | 16.0% |
| **Home location** | Urban | 64.1% | 43.6% | 63.2% |
| | Rural | 35.9% | 56.4% | 36.8% |

The sample includes different travel modes which are categorized in three categories: private vehicles (car and motorcycle), public transport and soft modes (cycling and walking). The majority (47%) of people in all countries perform their everyday trips by car, followed by metro (24%) in Greece, train (20%) in the Netherlands and bus (16%) in Spain. A further statistical analysis of the sample indicated that Dutch travelers prefer to use either car or bicycle when traveling for leisure. Moreover, they prefer to walk only when they perform trips for personal purposes, such as shopping, family visits etc. In the Greek sample, most of educational trips are performed with public transport, and especially by metro and bus. On the contrary, Spanish students either travel by bus or walk when traveling for educational purposes.

From the preliminary analysis of the responses, it is shown that Dutch travelers are in general happier during their everyday trips in contrast with the Greek travelers who appear to be the least happy among the three samples. In all three samples, travelers who usually use soft modes for their everyday trips are happier when compared to regular public transport users.

Figure 2 depicts the distribution of the level of tolerance with respect to changes of the network's conditions. Figure 3 shows the distribution of the perception of the respondents on the probability of the occurrence of any unexpected event during everyday trips. In terms of expecting disruptions during a trip, the Dutch respondents appear to be the most optimistic and the Greek ones the most apprehensive. Furthermore, in Greece roads are heavily congested, especially during rush hours, and frequent strikes negatively affect public transport services. This can be related to the low tolerance level of the Greek population. The Dutch respondents showed higher tolerance for disruptions in the network. Interestingly, in Spain, the level of tolerance of the travelers seems to follow a normal distribution. Concerning the perception of the travelers on the possibility of the occurrence of disruptions in the network, the majority of Spanish and Dutch respondents consider it as not possible (50% - 51% respectively), 27% of the Dutch assigned zero probability, in contrast to 10% of Spanish. In the case of Greece, 44% of respondents consider it as more than slightly possible.

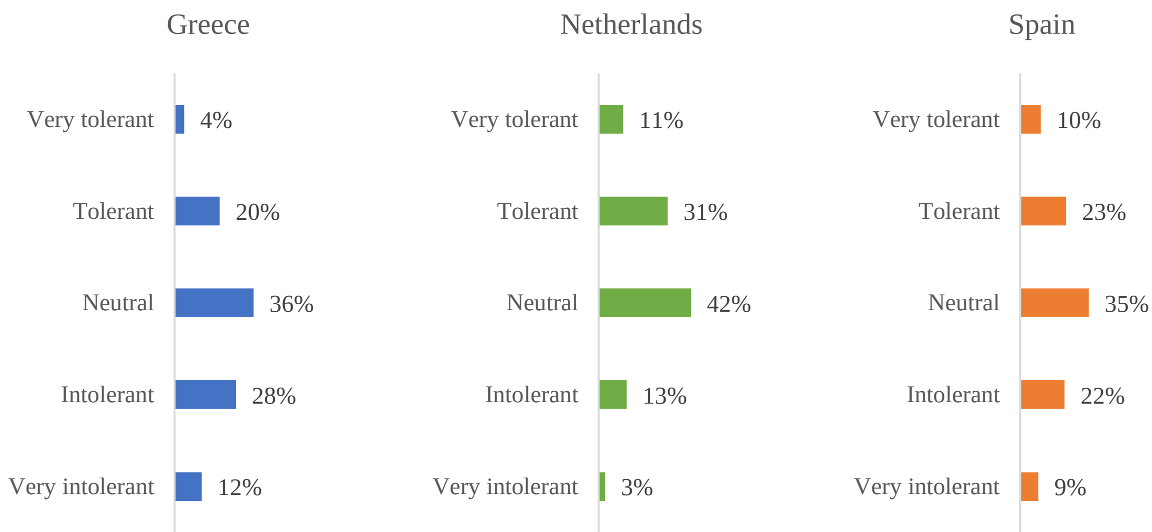


**FIGURE 2 Distribution of the level of tolerance with respect to changes of network's conditions.**

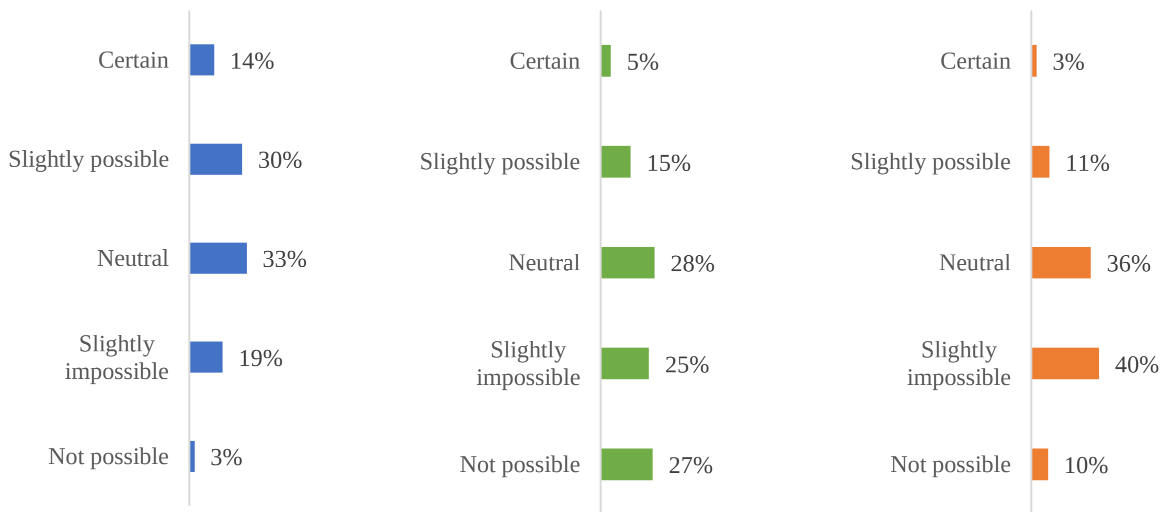


**FIGURE 3 Distribution of the perception of the respondents on the probability of the occurrence of any unexpected event during everyday trips.**

## RESULTS

This section provides the results of the Bayesian Network developed to assess the associations between travel mode choice, user's characteristics and feelings, as well as their perception on everyday trips. The Bayesian Network emerged from the analysis is depicted in Figure 4. The relations between variables are depicted by arcs which provide two measures: a) the strength of the association which takes values from 0 (weak association) to 1 (strong association) and b) the probability of the arc's direction depicting a causal relationship, that ranges from 0.5 (the direction is uncertain) to 1 (the direction depicted is the only possible one), written in brackets. It is very common for arc directions to change between different learning algorithms as a result of score equivalence.

The nodes in the graph represent user-related characteristics (age, gender, income, number of cars, work-time flexibility and home location), trip-related characteristics (trip purpose, cost and travel mode) and affective factors (travel happiness, PRE and level of tolerance). The relations among factors are represented by arcs. The log-likelihood ratio of the network was estimated: -28080.21 and the expected loss estimated after ten-fold cross-validation was: 12.88. Goodness of fit of this network (true network) was compared to an empty and a random graph. The expected loss ratio for the empty and random graph are 13.64 and 13.55 respectively, higher than the trained model, which means that the trained model fits better the data than the null and random model.

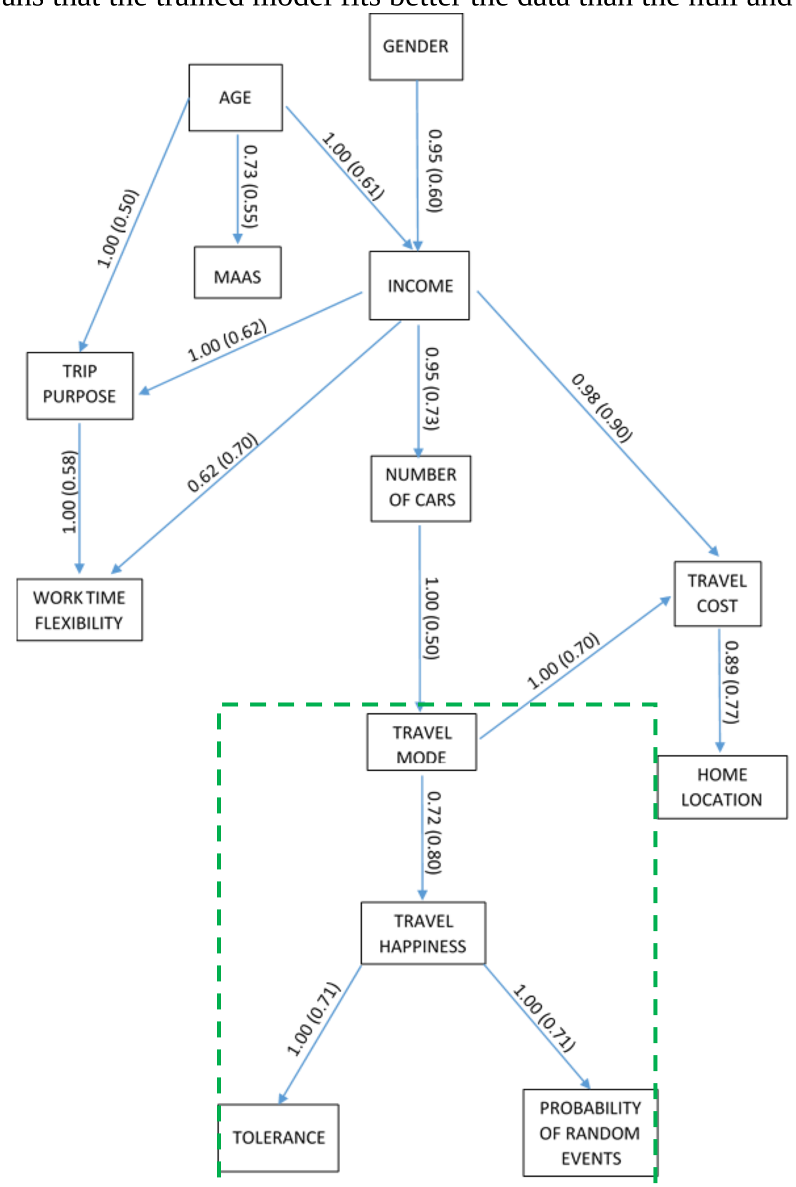


**FIGURE 4 Trained Bayesian Network for travel happiness and mode choice.**

Based on the structure of the Bayesian Network depicted in Figure 4 as well as the conditional probability tables that emerge from the analysis, some significant results are presented. Findings revealed significant interrelations among demographics of the user. More specifically, age and gender of the user stand as predictors of their total annual personal income. Furthermore, user's age appears to be highly associated with the intention to use Mobility as a Service. It is observed that the elderly (>55 years old) are more likely to use Taxi as an alternative mode for their everyday trips while the younger (< 34 years old) travelers may choose between a variety of services, such as car-pooling, car-sharing and Uber. This is reasonable, since younger people are more familiar with new services and technology in contrast with the elderly who prefer to use traditional and well-known services.

Moreover, age and income stand as predictors of the trip purpose. The age and the income of the traveler may reflect their occupation and therefore determine the usual purpose of everyday trips. Traveler's income also stands as a predictor of the number of cars that someone owns with higher income travelers being more likely to have more than one cars. Knowing the number of cars that someone owns or have access to together with their trip purpose makes it possible to predict travel mode. Although people who own a car are more likely to use it for every trip purpose, students who have access to or own a car will most likely not use it when traveling for educational purposes.

In addition, income and travel mode are highly associated with travel cost of everyday trips. Moreover, travel cost may be used as a predictor of travelers' home location. More specifically, people living in urban areas are more likely to spend less money on their everyday trip compared with those living in rural or suburban areas.

Furthermore, the trip purpose together with traveler's income may provide an insight about their work time flexibility. It appears that people with a high income are more likely to have flexible working hours.

Consequently, all trip-related and user-related predetermined factors are used for travel mode choice decisions. The Markov-Blanket of travel happiness, namely the subset of the network including travel happiness parents, its children and parents of its children (*39*), is identified by a green rectangle on the BN below. It is observed that travel mode choice is the only variable that directly affects the level of travel happiness experienced during everyday trips. Moreover, travel happiness is highly related with factors describing the perception of the user on the system they use the most, namely tolerance and probability of random events occurrence.

A further investigation on how each country's specific characteristics may affect travel happiness was conducted by developing a supplementary Bayesian Network which is depicted in Figure 5. This BN was developed based on the Markov blanket of travel happiness node as it emerged from the first analysis. Regarding the evaluation of the network's structure, the same approach was followed and results indicate that the network fits the data well. The trained network was compared with an empty and a random graph and assessed through the log-likelihood function, which showed that the expected loss was lower for the case of the trained network.

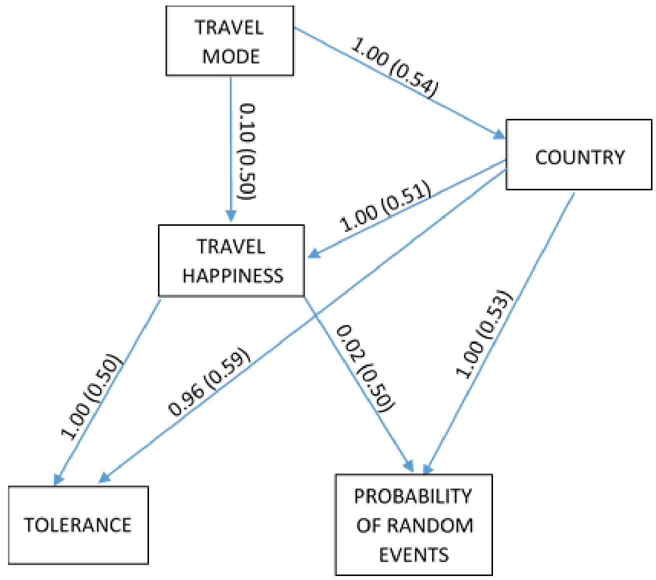


**FIGURE 5 Interrelations among country and the Markov blanket of travel happiness.**

According to the results, a strong association between country and all the affective factors that are taken into consideration is identified. Moreover, travel mode choice decisions are also strongly related to country. These preliminary results highlight the need for further investigation of how cultural differences may affect the perception of travelers' and their feelings during everyday trips. Finally, besides the cultural differences that are enclosed in the variable "country", differences on the transportation systems are also implied. Such differences both on the system's topology and performance at each country should not be ignored when analyzing travel behavior.

## CONCLUSIONS

This paper aimed at investigating relations among traveler's characteristics, perceptions and emotions during everyday trips. For this purpose, a questionnaire survey was conducted in three European countries (Greece, the Netherlands and Spain). The questionnaire consisted of four parts and 27 questions and aimed at identifying mobility profiles, factors that affect travel choices as well as travelers' perception on the system they use the most. The sample collected after 10 weeks of both on field and online survey was well distributed in terms of gender and age. Both private vehicle users and public transport users are included in the sample. Moreover, soft modes users are also included in the sample but they are underrepresented.

Data were used for the development of a Bayesian Network which allowed us to infer meaningful interrelations among traveler's choices, characteristics and perceptions. Results indicated that travel mode choice is the only variable which directly affects the level of travel happiness that the traveler experiences during their trip. Furthermore, user's perception on the occurrence of unexpected events and the level of tolerance they have towards such events are also directly associated with travel happiness.

The results emerged from the analysis of the Bayesian Network can be used in the framework of quantifying travel happiness in order to better understand how travel mode choices are made. To this end, the level of tolerance to system's non-recurrent disruptions and the perceived probability of an unexpected event occurrence in a specific mode can be exploited to measure the level of travel happiness. The identified associations between user's characteristics, travel choices and travel happiness can be exploited to create a personalized trip-based approach of quantifying travel happiness.

Modern research in transport and daily travel behavior, places particular emphasis on the needs and requirements of each traveler separately. In such systems and applications that seek to provide personalized information and recommendations, the findings of this research can be exploited by highlighting the importance of emotions in decision-making process of travelling. Moreover, the results can be exploited by policy makers in order to improve the conditions and services of modern transportation systems. Future research should further investigate the notion of travel happiness and examine possible interrelations between travel happiness and additional travel-related choices, such as route and time of departure decisions. Furthermore, research should emphasize in investigating supplementary variables that may affect the level of travel happiness that the traveler experiences during everyday trips. Finally, it would be interesting to deepen the analysis of the emotional state of the traveler by analyzing specific emotions such as boredom, excitement, anxiousness, pleasure, etc.

**ACKNOWLEDGMENTS**

This work is part of the My-TRAC (My-Travel Companion) project funded under the European Union's Horizon 2020 research and innovation program under grant agreement No 777640.

**AUTHOR CONTRIBUTION STATEMENT**

The authors confirm contribution to the paper as follows: study conception and design: E. Mantouka, E. Vlahogianni, A. Papacharalampous; data collection and initial discussions on the possible statistical inference: E. Vlahogianni, E. Mantouka, H. Van Lint, L. Heydenrijk-Ottens, S. Shelat, V. Degeler, A. Papacharalampous; analysis and interpretation of results: E. Mantouka, E. Vlahogianni, A. Papacharalampous, V. Degeler, H. Van Lint; draft manuscript preparation: E. Mantouka, E. Vlahogianni, V. Degeler, H. van Lint. All authors reviewed the results and approved the final version of the manuscript.

**REFERENCES**

1. De Palma, A., and D. Rochat. Understanding Individual Travel Decisions: Results from a Commuters Survey in Geneva. *Transportation*, 1999. 26: 263–281.
2. Sekhar, R. Mode Choice Analysis: The Data ,the Models and Future Ahead. *International Journal for Traffic & Transport Engineering*, 2014. 4(3): 269–285.
3. Kim, Y., T. Kim, and E. Heo. Bayesian Estimation of Multinomial Probit Models of Work Trip Choice.Pdf. *Transportation*, 2003. 30: 351–365.
4. Hagenauer, J., and M. Helbich. A Comparative Study of Machine Learning Classifiers for Modeling Travel Mode Choice. *Expert Systems with Applications*, 2017. 78: 273–282.
5. De Vos, J., T. Schwanen, and F. Witlox. The Road to Happiness: From Obtained Mood during Leisure Trips and Activities to Satisfaction with Life. Presented at 96th Annual Meeting of the Transportation Research Board, Washington, D.C., 2017.
6. Morris, E. A., and E. Guerra. Mood and Mode: Does How We Travel Affect How We Feel? *Transportation*, 2014. 42(1): 25–43.
7. Ellaway, A., S. Macintyre, R. Hiscock, and A. Kearns. In the Driving Seat: Psychosocial Benefits from Private Motor Vehicle Transport Compared to Public Transport. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2003. 6(3): 217–231.

8. Anable, J., and B. Gatersleben. All Work and No Play? The Role of Instrumental and Affective Factors in Work and Leisure Journeys by Different Travel Modes. *Transportation Research Part A: Policy and Practice*, 2005. 39: 163–181.
9. De Vos, J., P. L. Mokhtarian, T. Schwanen, V. Van Acker, and F. Witlox. Travel Mode Choice and Travel Satisfaction: Bridging the Gap between Decision Utility and Experienced Utility. *Transportation*, 2016. 43(5): 771–796.
10. Morfoulaki, M., Y. Tyrinopoulos, and G. Aifadopoulou. Estimation of Satisfied Customers in Public Transport Systems: A New Methodological Approach. *Journal of the Transportation Research Forum*, 2007 46(1): 63–72.
11. Jain, S., P. Aggarwal, P. Kumar, S. Singhal, and P. Sharma. Identifying Public Preferences Using Multi-Criteria Decision Making for Assessing the Shift of Urban Commuters from Private to Public Transport: A Case Study of Delhi. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2014. 24: 60–70.
12. Ponrahono, Z., S. Bachok, M. Ibrahim, and M. M. Osman. Assessing Passengers' Satisfaction Level on Bus Services in Selected Urban and Rural Centres of Peninsular Malaysia. *Procedia - Social and Behavioral Sciences*, 2016. 222: 837–844.
13. De Vos, J., T. Schwanen, V. Van Acker, and F. Witlox. How Satisfying Is the Scale for Travel Satisfaction? *Transportation Research Part F: Traffic Psychology and Behaviour*, 2015. 29: 121–130.
14. Lucas, J. L., and R. B. Heady. Flextime Commuters and Their Driver Stress, Feelings of Time Urgency, and Commute Satisfaction. *Journal of Business and Psychology*, 2002. 16(4): 565–571.
15. Healey, J. A., and R. W. Picard. Detecting Stress During Real-World Dring Tasks Using Physiological Sensors. *IEEE Transactions on Intelligent Transportation Systems*, 2005. 6(2): 156–166.
16. Legrain, A., N. Eluru, and A. M. El-Geneidy. Am Stressed, Must Travel: The Relationship between Mode Choice and Commuting Stress. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2015. 34: 141–151.
17. De Vos, J., T. Schwanen, V. van Acker, and F. Witlox. Travel and Subjective Well-Being: A Focus on Findings, Methods and Future Research Needs. *Transport Reviews*, 2013. 33(4): 421–442.
18. Ettema, D., T. Garling, L. E. Olsson, and M. Friman. Out-of-Home Activities, Daily Travel, and Subjective Well-Being. *Transportation Research Part A*, 2010. 44(9): 723–732.
19. Abou-Zeid, M., M. Ben-akiva, and M. Bierlaire. Happiness and Travel Behavior Modification, *European Transport Conference*, 2008.
20. Busseri, M. A., and S. W. Sadava. A Review of the Tripartite Structure of Subjective Well-Being: Implications for Conceptualization, Operationalization, Analysis, and Synthesis. *Personality and Social Psychology Review*, 2011. 15(3): 290–314.
21. Ory, D., and P. L. Mokhtarian. When Is Getting There Half of the Fun? Modelling the Liking for Travel. *Transportation Research Part A: Policy and Practice*, 2005. 39: 97–123.
22. Bergstad, C. J., A. Gamble, O. Hagman, M. Polk, D. Ettema, M. Friman, and L. E. Olsson. Subjective Well-Being Related to Satisfaction with Daily Travel. *Göteborg Psychological Reports*, 2009. 39(5)
23. van Lierop, D., M. G. Badami, and A. M. El-Geneidy. What Influences Satisfaction and Loyalty in Public Transport? A Review of the Literature. *Transport Reviews*, 2018. 38(1): 52–72. https://doi.org/10.1080/01441647.2017.1298683.

24. Zeid, M. A. Measuring and Modeling Activity and Travel Well-Being. *Doctoral Dissertation*, 2009.
25. Duarte, A., C. Garcia, G. Giannarakis, S. Limão, A. Polydoropoulou, and N. Litinas. New Approaches in Transportation Planning: Happiness and Transport Economics. *NETNOMICS: Economic Research and Electronic Networking*, 2010. 11(1): 5–32.
26. Olsson, L. E., T. Gärling, D. Ettema, M. Friman, and S. Fujii. Happiness and Satisfaction with Work Commute. *Social Indicators Research*, 2013. 111: 255–263.
27. Morris, E. A., and E. Guerra. Are We There yet? Trip Duration and Mood during Travel. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2015. 33: 38–47.
28. OECD. How's Life? 2017: Measuring Well-being, OECD Publishing, Paris, 2017. https://doi.org/10.1787/how_life-2017-en.
29. Cloutier, S., A. Karner, H. L. Breetz, P. Toufani, N. Onat, S. Patel, S. Paralkar, E. Berejnoi, B. A. Morrison, J. Papenfuss, A. D. Briggs, and C. Carlson. Measures of a Sustainable Commute as a Predictor of Happiness. *Sustainability (Switzerland)*, 2017. 9(7): 1–15.
30. Francois, S., P. Astegiano, and F. Viti. Analyzing the Correlation between Commuting Satisfaction and Travelling Utility. *Transportation Research Procedia*, 2017. 25: 2643–2652.
31. Sun, L., and A. Erath. A Bayesian Network Approach for Population Synthesis. *Transportation Research Part C: Emerging Technologies*, 2015. 61: 49–62.
32. Feelders, A., and L. C. van der Gaag. Learning Bayesian Network Parameters under Order Constraints. *International Journal of Approximate Reasoning*, 2006. 42: 37–53.
33. Constantinou, A. C., N. Fenton, W. Marsh, and L. Radlinski. From Complex Questionnaire and Interviewing Data to Intelligent Bayesian Network Models for Medical Decision Support. *Artificial Intelligence in Medicine*, 2016. 67: 75–93.
34. Tsamardinos, I., L. E. Brown, and C. F. Aliferis. The Max-Min Hill-Climbing Bayesian Network Structure Learning Algorithm. *Machine Learning*, 2006. 65(1): 31–78.
35. Nagarajan, R., M. Scutari, and S. Lèbre. *Bayesian Networks in R: With Applications in Systems Biology*. 2013.
36. Heckerman, D., D. Geiger, and D. M. Chickering. Learning Bayesian Networks: The Combination of Knowledge and Statistical Data. *Machine Learning*, 1995. 20(3): 197–243.
37. Scutari, M. Learning Bayesian Networks with the Bnlearn R Package. *Journal of Statistical Software*, 2009. arXiv preprint arXiv:0908.3817
38. R Development Core Team. R: A Language and Environment for Statistical Computing, [Computer Software].
39. Kulaga, T. The Markov Blanket Concept in Bayesian Networks and Dynamic Bayesian Networks and Convergence Assessment in Graphical Model Selection Problems. *Master thesis, Jagiellonian University*, 2006.