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# Autonomous Vehicles Probability-to-Choose and Public Usage Behavior Study in Developing Countries; Case Study: Port Said City

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## ABSTRACT

The rapid development of transportation technology has had a significant impact on human life, with Autonomous Vehicle Systems (AVs) emerging as one of the most popular and intriguing products in recent years. This study aims to capture user perspectives on AV usage by estimating a utility function using the Multinomial Logit (MNL) model, and comparing it with other conventional modes of transportation, such as ordinary vehicles (OVs). The second part of the study focuses on predicting the probability of AV usage, specifically in the context of Port Said City, an urban area characterized by heterogeneous mixed traffic and users. The usage probability is influenced by network capacity and assists decision-makers in determining the appropriate course of action for AVs in three different scenarios: "perfectly-need," "limited-need," and "no-need". The study findings indicate that AVs can be a viable solution when the capacity ratio exceeds 50%, as predicted by the usage function study. While the MNL modeling using Stated Preference (SP) surveys can estimate the number of trips, it alone is insufficient for making well-informed decisions. In summary, this research underscores the potential of AVs in transportation systems and provides valuable insights for policymakers and urban planners.

**Keywords**: Autonomous vehicle, Capacity ratio, Developing countries, Usage probability, Traffic performance

## 1 INTRODUCTION

Extensive research and development efforts have been undertaken in the field of partially or fully automated car manufacturing. The development of fully automated cars is expected to bring significant benefits to society, such as more efficient use of road capacity, reduced energy consumption and emissions, and fewer accidents (Fagnant and Kockelman, 2015). The use of autonomous transport is rapidly evolving, and there are five levels of vehicle autonomy in the transportation system, which depends on the degree of automation of the vehicle (Khan M. A. et al., 2022). The Society of Automotive Engineers (SAE, 2014) defines Level 4 (high automation) and Level 5 (full automation) as the only levels of autonomy that allow drivers to devote their attention to other activities while driving. One innovative application of autonomous vehicles is the Autonomous Vehicle System (AVs), which can coexist with human-driven vehicles and improve mobility and accessibility (Bagloee S., 2016). However, this system may cause traffic congestion if it continues to drive at full speed when the traffic is congested.

Connected Autonomous Vehicles (CAVs) are another type of automated system that uses smart technology to connect vehicles. When the leading vehicle decelerates, all other connected vehicles will also decelerate and then accelerate in turn (Sharma and Zheng, 2021). This reduces the safe following distance between vehicles, shortening the perception time and reducing congestion (Stanek D. et al., 2017). Parking buffers are provided to assist interchanges and allow vehicles to change their routes. Motamedidehkordi visualized a descriptive year-basis forecast for the expected share of automated vehicles in Germany. They predicted that the share of automated vehicles would begin to increase in 2020, but it would be less than 25% of the total number of vehicles by 2030, and would rise to 82% by 2050 in developed countries. These predictions have spurred researchers to pay close attention to the rapid innovations in this field (Motamedidehkordi et al., 2017).

Although many previous types of research have been conducted to study or predict the impact of AVs on traffic performance with any infrastructure management or the travel patterns of AV users in future scenarios, there is a lack of studies on its effect on public behavior, particularly with heterogeneous households with different or low income that affect willingness to choose such a new policy (Othman k., 2022). Also, it influences the choice of public policies for vehicle automation from an operations management standpoint. Shortly, because of these essential benefits, more than 55 cities have committed to installing AVs, and another 27 cities are preparing for automation by undertaking surveys of authoritarian, planning, and governance issues raised by AVs (Bloomberg, 2017). There are many studies concerning the innovative AVs preference issues. So, the literature review relied on a combination of sources in a search of Research Gate and Science Direct using "automated*", "usage probability", "utility", "autonomous vehicles", "preference functions" and "willingness-to-choose" keywords of papers to reach a brief acknowledgment of the studied issue.

About the estimation of utility preference function, Multinomial Logit MNL, Mixed Multinomial Logit MMNL, and modern tools had been effetely used. Zhao X. examined the multinomial and machine learning models and estimated the accuracy of models. He used the multinomial model, which has a significantly better model fit, underperformed the MNL model in terms of its out-of-sample predictive power (Zhao X., 2020). Some used a MMNL model with different types of sensitivity analysis for choosing AVs (Cherchi and Cirillo, 2010). They suggested that the mixed logit model may have over fitted the data with the introduction of random parameters, and such over fitting resulted in greater out-of-sample prediction error. They proved that the MNL model resulted in higher aggregate-level predictive accuracy than the mixed logit model. Other studies go into using probit model such as Bansal who used it with descriptive statistics and verified that male groups with high education levels and high-income individuals have higher acceptance and interest in using AVs (Bansal P., 2016). Selected characteristics differ from one to another depending on the characteristics of people and cities. Most previous studies confirm the effect of AVs existence on capacity because they reduce travel time. But it may increase the number of trips per day, which may increase congestion (Wagner, 2016).

The usage function is a way to choose the new strategy or not. Here, the need for such implementation is the key. Aside from the unusual congestion, the primary goal of the usage function is to improve the social welfare of AVs (Conceicao et al., 2018).The usage model depends on simplifying the analysis of the impact of AVs on utility by optimizing the capacity instead of utility. So, a usage probability model has been chosen in this study to enrich findings. As the capacity ratio changes, the need for such a strategy similarly changes. It is expected to help decision makers by suggesting suitable policies/strategies, such as the introduction of automotive vehicles into their transport systems, especially for developing countries with limited funds (Jing P., 2020).

This study aims to achieve two objectives in order to illustrate the impact of automotive technology when applied to the transport system of Port Said City. Firstly, it aims to model the preference/choice probabilities of all alternatives, including the expected usage of Autonomous Vehicles (AVs) for long trips. Secondly, it analyzes the impact of capacity ratios on the usage probability and travel times, considering them as indicators of public behavior. The structure of the study is shown in **Figure 1**. This study's work plan is completed as follows:

1. Estimating the expected utility function parameters for trips of Autonomous Vehicles AVs or other Ordinary Vehicles OVs; such as cars, minibuses, and taxis
2. Preparing a manual survey with the Stated Preference SP questionnaire to collect SP data
3. Estimating the usage utility and the probability for the three proposed scenarios of AVs needs, which are "perfectly big need", "limited-need", and "perfectly no- need"
4. Using the usage utility with a capacity model to expect the usage probability according to AVs/OVs capacity ratio with several scenarios
5. Studying the effect of utilities on public choice behavior and the decisions needed for each scenario
6. Analyzing the results from the proposed MNL model and the usage probability model
7. Estimating the predicted travel time for all the expected scenarios using Bureau of Public Roads (BPR) function

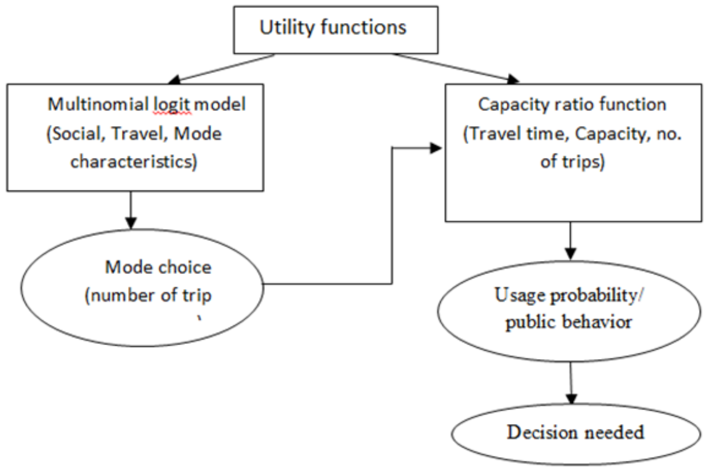


**Figure 1: the structure of the study**

## 2 DATA COLLECTION

The process of collecting data is influenced by various factors that may impact user choices. Therefore, selecting appropriate factors is a crucial step. It is widely recognized that personal characteristics such as gender, age, and income can affect utility functions. Additionally, there may be a reciprocal effect among factors, such as car ownership, which may affect users' choices based on other personal characteristics. For example, elderly people with disabilities related to driving may choose AVs despite owning a car users are becoming more aware of autonomous driving technology and its potential as the future of transportation (Lenz, 2020).. However, they may still have concerns regarding the safety and reliability of self-driving cars. Thus, it is necessary to create an awareness sheet to explain how and why to use upcoming vehicles in our survey (refer to **Appendix 1**). Furthermore, people may alter their travel behavior after gaining more knowledge about AVs.

### 2.1 Study area, survey, and sample characteristics

Port Said city is an urban city with heterogeneous traffic network. It is located in the north of Egypt. Its importance as a trade position with its important ports and freight transportation activities and give it's the priority in using any innovative transport strategies to transport goods and people with a low travel time and high mobility (Elbany M. at el., 2014). People's preferences tend to favour the most recent and comfortable accessibilities. For this reason, the preference for using autonomous vehicles has been studied. In this study, data is collected from respondents' surveys in Port Said city. Different scenarios are prepared for the revealed data (RP) and stated preference (SP) questionnaires. Such questionnaires are distributed to the potential respondents in five separate household groups, with a 10% sample size for each group from several administrative areas. The data was collected for three months (from August to October, 2021). Each respondent considered many scenarios and was asked a small set of questions (see **Appendix 2**). Two- wheelers, three- wheelers, and walking are excluded from study because they are not suitable for making a long trip. 490 persons were interviewed explaining their personal characteristics such as age, gender, car ownership, and awareness level, with a total of 425 valid responses. Each trip scenario consisted of the mode and the reason for choosing it for only long trips (see **Appendix 3**). Also, the purpose of the trip and the transport modes of each trip segment are included. Manual method is used to distribute the awareness sheet and questionnaires and re-collect them to construct an excel data sheet. The results of the analysis in terms of cross-classification tables are constructed in order to use them in the modeling process.

### 2.2 Choosing factors for MNL model

To estimate a utility function for any mode, it is important to propose factors affecting the choice behavior among AVs and OVs including cars, taxis, and minibuses. These factors are classified into two groups: the personal characteristics (education level, gender, age, and car ownership), and the trip characteristics (trip purpose, travel time, travel cost, waiting time, walking distance) with other travel features such as comfort, availability, and safety. **Table 1** shows the frequency numbers of respondents for the four age groups (<18, 18-35, 36-65, and >65 years old) and the two gender groups (males and females). Table 2 depicts the description of each factor along with its percentage of the sample.

**Table 1. Frequencies across age and gender groups**

| *Age(years old)* | < 18 | 18-35 | 36-56 | > 65 |
|---|---|---|---|---|
| Female | 78 | 35 | 24 | 51 |
| Males | 70 | 63 | 45 | 23 |

**Table 2. The selected personal and travel data characteristics**

| Factors | Ranges | Percent (%) |
|---|---|---|
| *Personal data (group1)* | | |
| Age | <18, 18-35, 36-65, >65 | 11 %,44 %,36 %,9 % |
| Gender | Male, female | 71 %,29 % |
| Car ownership (car or AVs) | No car, one car or more | 21 %,79 % |
| Awareness level | Low, medium, high | 28 %,43 %,29 % |
| *Travel data (group 2)* | | |
| *Trip purpose (travel behavioral)* | Working, education, shopping, social | 23 %,12 %,61,4 % |
| *Trip data* | | |
| OVTD (walking distance) | 0, 50, 100, 150, 200 | |
| OVTT(waiting time) | 0, 2,4,5,6,7,9,10 | |
| IVTT (travel time) | 15,20,25,30 | |
| TC (travel cost) | 2,3,4,5,10,15,20 | |
| *Travel features* | | |
| Comfort | Low, medium, high | |
| Availability | Available all time (100 %), part of time (<100 %) | |
| Safety | Medium safety, high safety | |

The aim of the survey is to explore user perspectives on autonomous driving by asking users of the transportation system about their attitudes towards autonomous driving and their prospects for individual behavioral change once they have access to autonomous/self-driving cars in the future. The survey examines trip purposes (shopping, education, working, and social). Comfort has three levels (low, medium, and high), which indicate the physical strain with high or low crowds, as it is a personalized mode of travel with air conditioning facilities and an easy-to-use application, though other aspects are similar to Careem applications. Safety has two levels (medium or high), indicating the probability of crashes and safety from criminals. Safety levels are classified into high safety (cars, AVs) and medium safety (taxi, minibus). Availability implies that the mode is available whenever and wherever users require it. It is categorized as anywhere all the time and anywhere part of the time. Candidate factors of choice for the generation model have been chosen, such as gender, age, awareness, and income. Additionally, trip characteristics (time, distance, and cost) are added to the model for trip purposes to compare responses from all trip purpose cases (social, educational, working, and shopping).

### 2.3 Design of the Survey SP Questionnaire

The goal of this research section is to gather data on the demand and preferences for both autonomous vehicles (AVs) and ordinary vehicles (OVs) such as cars, taxis, and minibuses. The data collected will be used to estimate the expected number of trips for each type of vehicle based on respondents' preferences and using effective utility factors. The SP questionnaire and awareness sheet used in the survey are provided in Appendixes 1 and 2. The primary survey for trip purposes has already been conducted, with two scenarios - one for OVs and the other for AVs with different expected values. The survey is divided into two parts: personal information and chosen scenarios. If needed, the assistant provides an awareness sheet to individuals who require further information or assistance in filling out the survey. Additionally, a Revealed Preference (RP) data questionnaire has been conducted to determine the percentage preference for existing modes of transportation, transport behavior factors, and technological interests.

### 2.3 Respondents results

Port Said city is an urban area that offers various transport modes, including personal cars with a high ownership rate of 78%, as well as taxis, minibuses, bikes, and motorbikes. While walking is another means of travel, it has been neglected in the questionnaire due to the expected substitution of hardware travel modes by AVs. Only long-distance travel trips were considered in the questionnaire to match the expected use of AVs, so walk, bike, and motorbike modes were excluded. Following the RP questionnaire, the collected data includes the distribution of trips according to different modes, as illustrated in **Figure 2**.

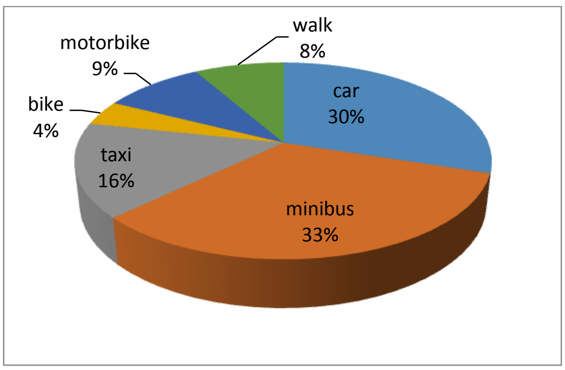


**Figure 2: RP data of modal split**

A primary study of transport behavior was conducted in Port Said city, incorporating mode characteristics such as short distance, comfort, accessibility, and safety into the model. The study confirmed that respondents placed high importance on availability, comfort, and safety, which were thus selected as the three factors to include in the proposed model. **Figure 3** displays respondents' technological interests and awareness about AVs, while **Figure 4** shows their responses to questions regarding AVs.

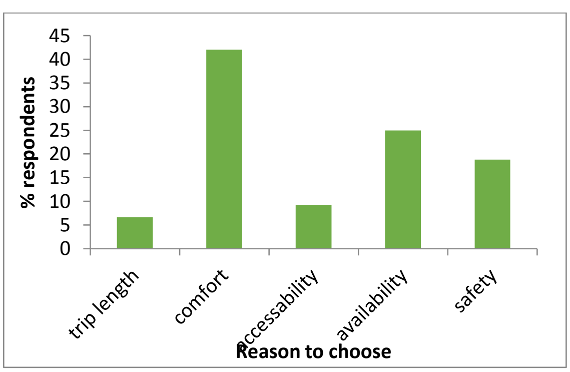


**Figure 3: Responses of reason to choose transport mode**

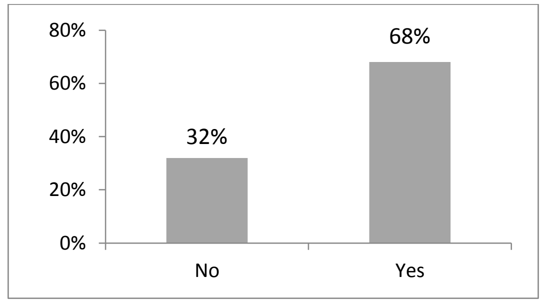


**Figure 4: Technological interests of AVs**

Data on trip purposes was collected through a Stated Preference (SP) questionnaire administered to respondents. **Figure 5** displays the results, indicating that respondents who were interested in new technology were more inclined to use AVs for social and shopping trips compared to other types of trips. This may be due to the perception that AVs are a more comfortable mode of travel. On the other hand, respondents showed the least interest in using AVs for education trips, as they were already accustomed to using minibuses and taxis for this purpose. Furthermore, given the high car ownership level in the city, respondents tended to use their own cars when making working trips. A previous study that focused on mobile app car services showed that InDrive and Careem were preferred by 65% and 52% of respondents, respectively. Respondents cited reliability and safety as the main reasons for preferring mobile applications over conventional public transportation, and these preferences have been incorporated into the taxi mode.

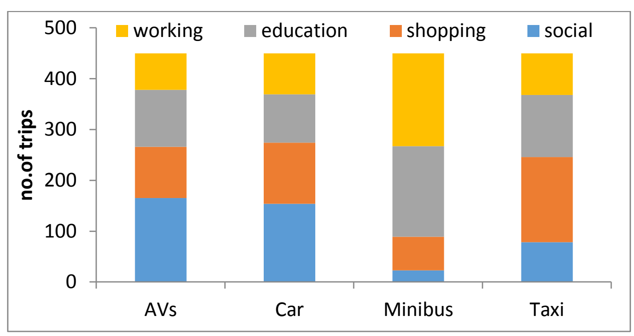


**Figure 5: Awareness of AVs**

## 3 MULTINOMIAL LOGIT MODEL

This utility model is estimated for expecting the number of trips per day as it called the mode choice modeling process. Multinomial Logit Model MNL has been used to interpret and calibrate the predicted utility function. It indicates the individual preference (Ben-Akeva, 1985). In the MNL model, the utility function is:

$$Uin,m = Vin,m + \varepsilon_i n,m \qquad (1)$$

It is classified into two elements; the systematic utility and the random error. *Uin* is the overall utility of the user $i$ , $\varepsilon_{in}$ is the error component, and $Vin$ is the systematic utility function. The linear equation of the utility for AVs will be as follows:

$$V_{AVs} = Vin,m = a_{0\ av} + (\text{ß}_{1m}*v_{1m}+ \text{ß}_{2m}*v_{2m}+ \ldots\ldots) + (\text{ß}_{1n}*v_{1n}+ \text{ß}_{2n}*v_{2n} \ldots\ldots\ldots) \quad (2)$$

Where, $a_0$ is the constant of the function. It indicates the value of the utility when the variable is zero. Data is classified into two groups; travel data and personal data. $\beta in$ are the parameters of alternative-specific attributes for variable group n and $\beta\ im$ are the parameters of individual-related variables of group m. $v$ is the explanatory variable. The probability-to-chose when user choosing alternative i from a set of alternatives $j$ ($j = 1, 2, \ldots, J$) can be estimated by:

$$P_{in,m} = \frac{exp(Vin,m)}{\sum_{j=1}^{j} exp(Vin,m)} \quad (3)$$

The proposed model aims to forecast the process of mode choice after introducing AVs. $P_{av}$ represents the probability of using an autonomous vehicle, while the total probability of all modes equals 1. The transport modes prevalent in the study area include cars, taxis, minibuses, and AVs. To capture the mode choice behavior of the commuters, the study considered several influential variables, such as travel time, travel cost, waiting time, and walking time as input variables. The total time spent in the vehicle during the trip is considered as in-vehicle travel time, and it is assumed that comfort is a factor that affects the mode choice process. To account for this factor, random numbers were generated within the specified range for all samples (refer to Appendix 2).

The study used the MNL model, assuming that all four modes of transportation were available to all travelers. The results are briefly presented in the analysis section (see section 5) and include the number of daily trips for AVs and OVs as well as the value of time. The utility model was used to estimate the expected number of trips per day for each alternative, providing an indication of reference behavior. However, it is still unclear how individuals will decide to use the new mode considering other factors not included in the MNL utility function, such as the AVs ratio and capacity. Thus, the second part of the study aims to include these factors, along with travel time, to facilitate decision making in light of various area facilities.

# 4 USAGE PROBABILITY AND THE NEED TO APPLY AVS (UTILITY FORM OTHER SIDE DEPENDING ON CAPACITY)

In less than a decade, autonomous vehicles are predicted to become available for consumers. However, there is currently no consensus on whether their presence will have a positive impact on users and society. Some studies suggest that the introduction of AVs may lead to increased congestion, while others believe it could result in smoother traffic, shorter travel times, and increased capacity. Most studies confirm that there is a problem of increasing volume with the increasing penetration of AVs (Opher, 2018).

Another factor that may impact public behavior is the capacity of AVs when they enter the market (Hartmann M., 2017). This capacity can affect utility, depending on the combination of AVs and traditional vehicles. Decision makers can use estimates of demand (number of trips) and utility to determine appropriate policies. The suitability of different policies for various traffic patterns has been assessed. In Port Said city, three decisions can be considered: full AVs penetration, partial AVs penetration, or no AVs at all.

The previous part of the study in Port Said city focused on obtaining usage preference and demand for AVs (number of trips) to help policymakers determine how and when to support autonomous vehicles. The impact of policies that can sustain sufficient usage of AVs was also investigated. The primary source of heterogeneity in this study is a multinomial logit model used for choosing vehicle types, as discussed in Part 1. One question that arises is whether changes in network capacity can affect AV usage behavior, which has been addressed by estimating the probability of AV usage based on capacity changes. Using a numerical example, four scenarios of usage probabilities have been evaluated. Consider a study area with $n$ users distributed into *autonomous vehicles user* ($A_n$) and ordinary vehicle users ($A_o$) users with number of trips per day ($X_o$), the total ordinary vehicle trip volume ($V_o$) is calculated by:

$$V_O = Ao\ .\ Xo \quad (4)$$

From $n$ users there is $m$ percent use AVs that will give a huge number of trips. The offset in number of trips has been neglected. In the network, the number of trips ($Xo$) is assumed to be increased by a transferring trip function of factors group by $l_{n,m} = L(m, n)$ per trip which is fixed and known to reduce conflicts of trips in case of sharing behavior. In this study, the transferring trip function is changes to get several scenarios. So, the AVs vehicle trip volume is calculated as:

$$V_a = A_n.\ Xa\ \ [1+ L(m, n)\ ] \quad (5)$$

### 4.1 The capacity of the transportation network

It is expected that AVs have a faster reaction time than OVs because of their automated decision-making (Levin and Boyles, 2016). When AVs increases, the overall traffic turns out to be smoother which can be taken to mean as having a network with a larger capacity (Asakura and Seo, 2017). The capacity of the mixed traffic depends on the ratio of the AVs volume to the total trip volume ($k$). So, the capacity $c = C(k)$ increases with the increasing of AVs ratio $k$ in a linear and equal to 0 and 1 for OVs and AVs; respectively as shown in equation 6. The capacity function is a convex combination of $c_r$ and $c_a$ where the weights are the number trips of the ordinary users $A_o$ and AVs users $A_n$ $(1 + l)$ adjusted by the added transferring trips $l$.

$$C = \frac{c_o \cdot A_o + c_a \cdot A_n\,(1+l)}{A_n\,(1+l) + A_o} \qquad (6)$$

Capacity function is a combination of AVs and OVs capacities that $A_o$ and $A_n$ $(1 + l)$ are the weights after adjusted by the added transferring trips $l$. so, the adjusted capacity $\acute{C}$ is depended on $A_n$. The *adjusted capacity* $\acute{C}$ is calculated by:

$$\acute{C} = \frac{c_o\,(1- A_n) + c_a \cdot A_n\,(1+l)}{[(1+l) \cdot A_n]^2} \qquad (7)$$

As usual, the travel time depends on the number of AVs trips, OVs trips, and capacity. Once the capacity is obtained, the travel time of trip can be calculated using *Bureau of Public Roads* (BPR) function (Chen et al., 2016):

$$T = T_0 + \left[\frac{Va+VO}{\acute{C}}\right]^b \qquad (8)$$

*Where,*

$T$ to refer to the value of the function when no confusions get up,

$T_0$ is the free-flow travel time (when the road has no trips), and

$b$ is a parameter often equal to 3 or 4 (Berman, 2018)

**4.2 Usage probability or public behavior Utility functions of AVs and OVs**

To assign trips, travel time is required, and the value of time is assessed for all users. In the analysis, AV usage has been estimated using the estimated number of trips and value of time. The probability of usage reflects public behavior (Baron, 2018). The utility function is computed to determine the preferred behavior, which is influenced by time and cost variables. Since AVs can travel at higher speeds, they can cover longer distances in less time. From the first part of study, AVs users have a lower value-of-time $\beta ix$ compared to the ordinary users. The utility can be estimated as:

$$Ui = u(x)\,\mathrm{d}x - \beta ix.\,T \qquad (9)$$

The impact of the number of trips on the utility can be estimated when maximizing the utility and adjusted capacity, the probability of using AVs (usage probability $P_a$, for three thresholds of AVs and OVs capacity ratios which reflects the travel demand impact of entering new autonomous vehicles, is estimated by:

$$P_a = \begin{cases} 0 & \frac{1}{1-l} \le r \\ \frac{(c_a - c_o)(1+l) - c_o.l}{(c_a - c_o)l + c_a\, l^2} & \frac{1}{1-l} < r \le \frac{1}{1+l} \\ 1 & 1 + \frac{1}{1-l} < r \end{cases} \qquad (10)$$

Here, "$r$" represents the capacity ratio and "l" represents the extra transferring function. The perfectly needed AVs value is calculated as $\acute{C} = c_a / (1 + l)$, while the perfectly no-need AVs value is calculated as $\acute{C} = c_a$. The equilibrium between these two cases occurs at $r \ge 1 + l$ or $r < 1 + l$, as described in Berman's capacity analysis for AVs.

The four scenarios confirm the impact of using AVs on utility based on the capacity ratio. Therefore, the policy required depends on the ratio of AVs capacity to ordinary vehicle capacity, which changes as the utility of using AVs changes. The case study focuses on the residents of Port Said city and network capacity. The usage probability results for the four decision scenarios are presented in sections *5.2*, *5.3*, and *5.4* of the result.

## 5 Analyses and results

### 5.1 Generic Variables and Goodness-of-Fit of the Models' Results

For data analysis and calibration, discrete choice models were utilized. The BIOGEME software was used for estimating model parameters and testing goodness-of-fit. The MNL model was analyzed, as it is simpler and easier to interpret. Variables found to be significant at a 90% level ($p < 0.10$) were included in the final model.

**Table 3** provides a summary of the results, including coefficients of input variables and constants. Evaluation was based on McFadden pseudo $R^2$ and log-likelihood value. Since the sum of all probabilities is equal to 1, it is not necessary to calculate the probability of using taxis, as it can be estimated using the following equation:

$$P_{taxi} = 1 - (P_{av} + P_{car} + P_{minibus}) \qquad (11)$$

**Table 3.Calibration results of MNL model**

| Coefficients *a, ß* | AVs | Car | Minibus | Taxi |
|---|---|---|---|---|
| $a_i$ | -0.123 | -0.245 | -0.231 | - |
| ***Group1(m)*** | | | | |
| $ß_{gen}$ | 0.153 | 0.234 | 0.087 | - |
| $Z_{value}$ | 0.78 | 2.11** | 0.49 | - |
| $ß_{age}$ | 0.176 | 0.265 | 0.344 | |
| $Z_{value}$ | 0.84 | 1.45* | 1.22* | |
| $ß_{awr}$ | 0.224 | 0.211 | 0.093 | - |
| $Z_{value}$ | 0.66 | 1.31* | 0.82 | |
| $ß_{inc}$ | 0.787 | 0.321 | 0.534 | - |
| $Z_{value}$ | 4.97*** | 0.11 | 2.78** | |
| $ß_{own}$ | -0.014 | 0.323 | -0.401 | - |
| $Z_{value}$ | 1.86* | 0.43 | 0.13 | |
| ***Group2(n)*** | | | | |
| $ß_{com}$ | 0.222 | 0.093 | 0.112 | - |
| $Z_{value}$ | 1.3* | 0.33 | 0.42 | |
| $ß_{av}$ | 0.623 | 0.911 | 0.082 | - |
| $Z_{value}$ | 1.98* | 2.32** | 0.93 | |
| $ß_{saf}$ | 0.034 | 0.053 | 0.012 | - |
| $Z_{value}$ | 0.84 | 1.93* | 0.83 | |
| $ß_{OVTD}$ | $-2.65x10^{-3}$ | $-0.23x10^{-3}$ | $-0.72x10^{-2}$ | - |
| $ß_{OVTT}$ | $-2.99\ x10^{-2}$ | $-1.51x10^{-2}$ | $-3.97x10^{-2}$ | - |
| $ß_{IVTT}$ | $-\ 4.56x10^{-2}$ | $-2.11x10^{-2}$ | $-0.03x10^{-3}$ | - |
| $ß_{TC}$ | $-2.27x10^{-2}$ | $-1.07x10^{-3}$ | $-0.97x10^{-2}$ | - |
| ***No. of observations*** | *425* | | | |
| ***Log-likelihood*** | *-948.012* | | | |
| ***Null log-likelihood*** | *-1921* | | | |
| ***McFadden $R^2$*** | *0.543* | | | |

**p<0.1,**p<0.001,***p<0.00*

Based on the estimated coefficients, it can be inferred that the awareness level, availability level, travel time, and travel cost are the most influential factors in mode choice. The comfort and safety parameter is observed to be less influential than availability, indicating that users prioritize having access to a vehicle over the comfort or safety features it provides. The negative sign of the coefficients for in-vehicle travel time and travel cost suggests that the utility of a mode decreases as these variables increase, which is expected. Travel time was found to have the highest effect on mode choice. By applying the estimated MNL choice model, modal split was calculated, and the overall prediction accuracy was estimated to be about 42%. The estimated group factor was 36% and 72% for coefficients groups m and n, respectively. This indicates that travel characteristics have a greater effect on mode preference than personal characteristics.

Some personal characteristics, such as awareness level, have a significant effect on mode choice, particularly for modern policies. The study, though conducted in a developing area, reflects similar findings to studies conducted in developed countries, where people with access to mobiles and social media have a higher level of knowledge and awareness of AVs even in the absence of actual policies, indicating a pre-awareness process. After a meeting with respondents to explain AVs transportation and its potential benefits for long-distance trips, most respondents were encouraged to choose AVs, while some only wanted to fill out the questionnaire by looking at the brochure presented with it and were excluded from the data.

For long-distance trips, AVs were found to be around 6% less negatively perceived than other modes of transportation, with a small difference between AVs and personal cars. Minibus preference had a small effect of 18% more than AVs, likely due to the expectation of longer travel times with lower costs. Car ownership was insignificant in AVs utility preference, likely because people who have cars tend to use them regardless of other transportation options. Income had a significant positive effect on AVs preference, particularly for those with high income and a high level of awareness, who have nearly the same preference until they distinguish the mode and try it. (Zhong Wang, 2021).

Value of time is calculated from dividing the coefficient of cost $ß_{IVTT}$ by the coefficient of time $ß_{TC}$ in the estimated utility function of AVs ( Hess S., 2010). The travel cost of AVs by multiply *βIVTT by T (*L.E. per trip). The average travel cost of AVs is expected to be 21.43 L.E/trip. The number of trips can be calculated by multiply $P_{av}$ by total households. From the estimated model, the number of expected AVs trips in Port Said city are 3200, 1690, 2000, and 930 trips/day for working, education, shopping, social trips; respectively. After modeling the preference according to the utility of each alternative, the value of time is needed to complete demand and welfare study analysis.

### 5.2 Trip purpose preference, No. of trips (collected and estimated from model) for each trip purpose

After modeling the mode choice MNL models, the demand is the number of trips *X* is calculated as shown in **Figure 6**. For AVs, the estimated daily trips are nearly to the collected data from survey with average error 12%. In general, it is noticed that the highly trips will be which aims at a welfare, such as shopping and social trips that user can bay more money for having more comfort and safety.

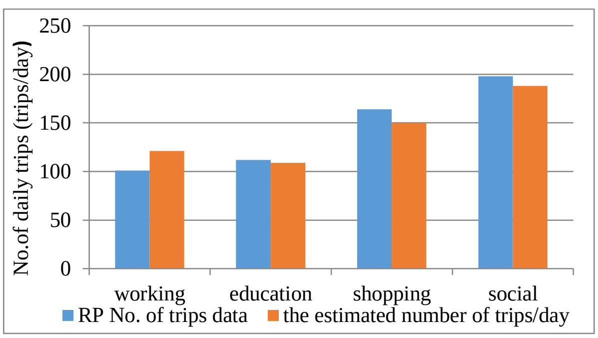


**Figure 6: the estimated AVs daily trips with the collected daily trips**

### 5.3 Capacity impact on usage probability with its thresholds

The user of AVs should be aware of their surrounding environments. Usually, they perform variety sensing to obtain information from pre-stage interviews. In this process, four scenarios of utilities explained above are proposed. **Figure 7** shows the presented utilities according to capacity ratio (*r*) and transferring trips function (*l* ).

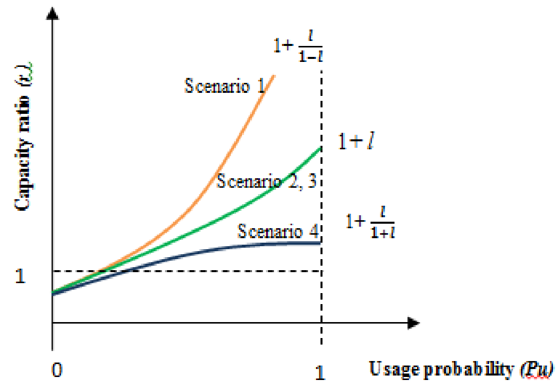


**Figure 7: the effect of capacity ratio on the usage probability for all expected scenarios**

*In **scenarios 1, 2, and 3***, the usage probability increases with the increase of the capacity ratio with no probability to decrease. This means that using new mode is important or preferred. Only *scenario 4* shows that the usage probability may be decreased. In this case, the ordinary vehicles achieve high utilities and it is not recommended to use AVs.

### 5.4 Decision needed of automation penetration

There are three possible cases for the utility function according to the capacity ratio *r* and the extra transferring function *L*(*m; n*) (see section *4.1*). As the capacity is an important variable in the utility of any innovative transport system, four scenarios are obtained with description of utility and policy needed as illustrated in **Table 4**. Figures illustrated the relationship between number of autonomous vehicle $A_n$ and utility values $P_{av}$. The following table illustrated the policy needed for each of utility cases. As the capacity ratios and the load function change, the utility changes to assist a policy confirmation.

**Table 4. Utility and $P_U$ scenarios with decision needed**

| Scenarios | cases of capacity ratio r | Utility description | Decision needed |
|---|---|---|---|
| 1 | $r > 1/(1 - l)$ | *Utility* increases with the increasing of *r* | There is a big need to have AVs "perfectly-need" with $A_n = 1$ to increase $P_U$ |
| 2 | $(1 + l) < r \leq 1/(1 - l)$ | *Utility* is lower at $A_n = 1$ compared to $A_n = 0$ | Using AVs-penetration is better than using OVs "limited-need" |
| 3 | $1/(1 + l) < r \leq (1 + l)$ | *Utility* is highest at $A_n = 0$ compared to $A_n = 0$, | using AVs-penetration is worse than using OVs "limited-need" |
| 4 | $r \geq 1/(1 + l)$ | *Utility decreases with the increasing of r* | It is "no-need" (refuse AVs) |

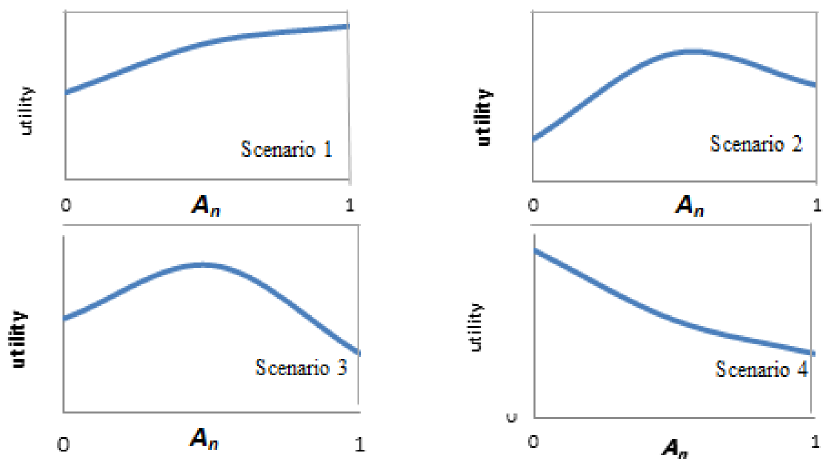


**Figure 8: the expected utility for AVs need scenarios**

The previous figures describe needing to such new system and help decision makers in choosing the suitable policy. For elder people with high income, the estimated utility strictly increases with the AVs existence $A_n$. Hence, it is ideal to have AVs with $A_n = 1$, because the capacity ratio is large enough to take up any extra trips. The following scenarios indicate the way to confirm policy:

- **Scenario 1** *utility* always increases at $A_n = 1$ compared to $A_n = 0$, hence, using AVs is a precise solution than using OVs which is "perfectly-need" for AVs. Moreover, the optimal $A_n$ is between 0 and 1. Therefore, the AVs penetration is constantly useful if the capacity of AVs increases to be more than 50%.
- **Scenario 2** using AVs is better than ordinary vehicles because the relocation load is substantial which is considered as a "limited-need" case but preferred. Also, when *utility* has the highest value at $A_n = 0$, hence, the autonomous vehicle is little preferred because of the low relocation load and high AVs capacity
- **Scenario 3** *utility* increases then decreases at $A_n = 1$ than it value at $A_n = 0$, hence, using AVs is worse than ordinary vehicles because the relocation load is substantial which is considered as a "limited-need" case but not preferred. Also, when *utility* has the highest value at $A_n = 0$, hence, the ordinary vehicles is preferred because of the high relocation load and low *AVs capacity* will give nearly the same distribution of utility which make it nearly to scenario 2 for decision makers.
- **Scenario 4** the utility is maximum at $A_n = 0$ and reduces *even* $A_n = 1$, "no-need" is preferred because the increasing of capacity causes reduction in utility. It is happened when the load function equal to 1 and the capacity equal to 1.5.

The probability of using AVs ($P_{av}$) and the usage probability ($P_u$) are estimated to be 56% and 62%; respectively. This indicates the nearest prediction of the public behavior towards using autonomous transport vehicles with mainly two prediction tools. There is a big need to use both methods because the limitations of the first one to help in answer the question; is it a suitable time to use AVs or not concerning environment affects?. But the usage probability can easily help to predict it.

**5.5 Results of the expected travel times in Port Said city**

In case of Port Said city, the calculations are assessed to confirm the impact of automation on the expected travel time assuming that *co* = 5; the extra transferring trips percent *l* = 0.2; $\beta_a$ = 0:012; $\beta_o$ = 0:005 (see table3); $T_0$ = 0; parameter *b* is assumed to be 2; the estimated value of network AVs capacities for the main roadways are 6, 8, 10.6 for the “perfectly-need”, ‘limited-need’, and ‘no-need”, for several AVs penetration levels, from 0 (no AVs) to 1 (perfectly-need). The travel time for all scenarios are estimated using equation (8) and shown in **Figures 9 a, b, c, and d**.

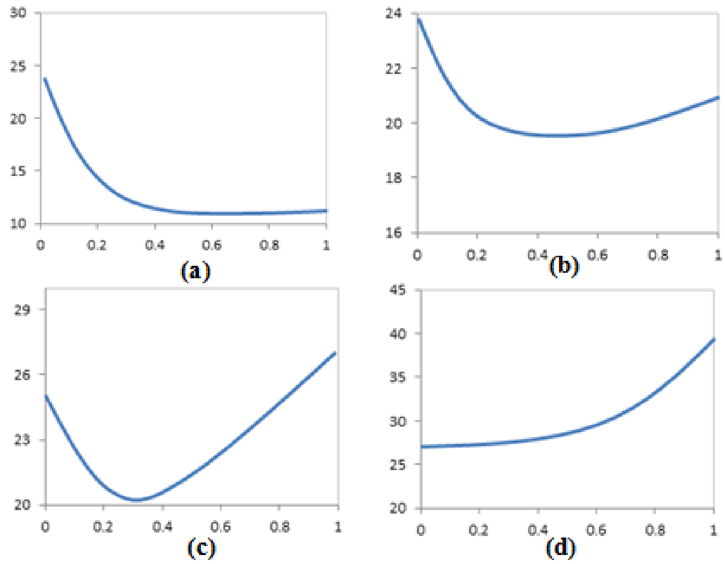


**Figure 9: Results of the expected travel time (min.) for different scenarios (a) scenario 1,(b) scenario 2 , (c) scenario 3, and (d) scenario**

The figure shows that the penetration of AVs increases its household trip volumes $V_a$. regardless of this increase, the expected travel time decreases in the first scenario as shown in Figure 9-a. In scenarios 2 and 3, the expected travel time may be decrease, even if traffic growth with using autonomous transport. So, travel time can’t take as an indicator of the transport performance when using usage and capacity ratio model. In both first and fourth scenarios, the direction of inclination either positive or negative is clearly proven. In the case of “no-need”, the capacity improvement is not sufficient and AVs cause longer travel times. As a result of calculations, transport decision makers will prefer to use AVs or don’t use it without confusions. But, in scenarios 2 and 3, there is a doubt of AVs system effectiveness. It is preferred to use the proposed study methodology to take the suitable decision if the decision limited to “perfectly-need” or “no-need”. If there is limited-need, it will be in a risk because travel time that it can’t be estimated as an indicator of the strategy success.

## 6 CONCLUSIONS

There is doubt surrounding the integration of autonomous vehicles into developing countries' transportation systems due to lack of awareness, fear of user reactions, and insufficient infrastructure. However, by studying predicted and Multi-Nominal Logit (MNL)

utility functions, user preferences, usage probability, and demand, a clear vision can be formed regarding how and when new technologies can be implemented. The following results were obtained:

(i) Users under 18 years old tend to prefer AVs, while users up to 65 years old do not.

(ii) Elders tend to travel more frequently than other people because they can engage in alternative activities while in the vehicle.

(iii) Travel time still has the highest effect on users' choice of regular vehicles due to its high coefficient and its value when converted into monetary terms (known as the value of time). Travel cost has a greater effect on choosing AVs compared to other modes.

(iv) While traffic increases with automation, travel times may decrease due to the positive impact of AVs on network capacity. However, traffic may increase in cases of "limited-need", but travel times may decrease due to significant improvements in traffic flow caused by automation.

(v) Autonomous vehicle owners can engage in alternative activities, such as reading, while traveling, which results in more travel than regular vehicle owners.

(vi) For scenarios 2 and 3, travel time cannot be considered as an indicator of transport performance. This means that implementation is in doubt, and "no-need" is the preferred option.

(vii) MNL models aid in predicting choice behavior without considering environmental factors. Therefore, it is important to predict usage probability and travel time based on capacity to make the appropriate decision.

(viii) In cases of "no-need" infrastructure, AVs do not provide sufficient capacity improvement and result in longer travel times.

(ix) AV penetration is consistently useful if AV capacity exceeds 50%

In Port Said city, the study concludes results as:

- Using the ordinary policy investigates bad impacts on utility functions for disabled and older people with high income level but may be useful for low income people because its great costs.
- It proves the positive impact of AVs on network capacity. Also, It gives higher social welfare than the ordinary vehicles

Future studies, trip length, as a demand factor, will be examined to determine its equilibrium with supply in developing countries. If revealed preference (RP) data is available for Autonomous Vehicles (AVs), they will be incorporated as additional groups in the utility preference function. Additionally, different scenarios of capacity ratios or penetration ratios can be tested using simulation tools to assess the network's performance. This evaluation will include analyzing the number of trips and origin-destination matrices based on usage preferences.

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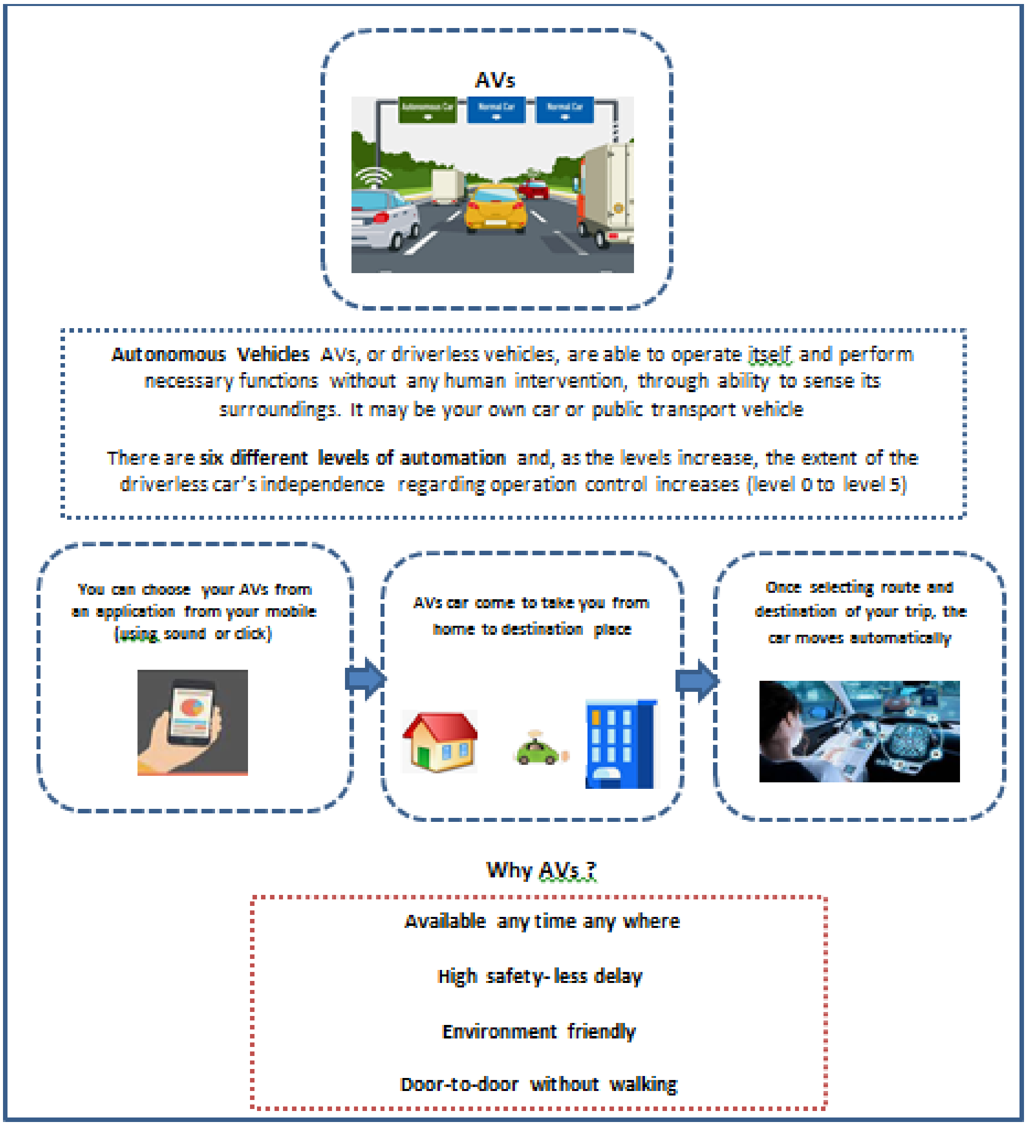
## Appendix 1: Awareness sheet of the survey




## Appendix 2: The proposed data

| | variables | | | |
|---|---|---|---|---|
| **alternatives** | walking distance(m) | waiting time (min.) | travel tme(min.) | travel cost (L.E.) |
| **Personal car** | 0 | 0 | 15,20,25 | 5,10,15 |
| **taxi (including indrive and Care** | 0,50,100 | 5,8,10 | 15,20,25 | 10,15,20 |
| **mini-bus** | 100,150,200 | 5,7,9 | 20,25.30 | 2,3,4 |
| **Avs** | 0 | 2,4,6 | 15,20,25 | 10,15,20 |
| 0 :not applicable | | | | |

## Appendix 3: An example of preference scenarios

| **alternatives** | **walking distance(m)** | **waiting time (min.)** | **travel tme(min.)** | **travel cost (L.E)** | choose |
|---|---|---|---|---|---|
| **Personal car** | 0 | 0 | 15 | 5 | |
| **taxi** | 50 | 5 | 15 | 10 | |
| **mini-bus** | 100 | 5 | 20 | 2 | |
| **Avs** | 0 | 2 | 15 | 10 | |
| note that taxi (including indrive and Careem) | | | | | |