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Quantifying the Impact of Individual Characteristics on Driving Speed – Elasticity Insights from Taxi Drivers' Education and Personality Traits

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ABSTRACT

This study investigates the impact of individual characteristics on taxi drivers' speed choices based on a survey of 102 valid responses. The drivers' speed behaviour was categorised into four intervals, considering age, driving experience, personality traits and vision correction. A model based on disaggregated theory was developed to measure the impact of these factors on driving speed. Using elasticity theory, the sensitivity of these factors was analysed. The results indicated that the absolute values of the elasticity coefficients for age, vision correction and passenger presence were all below 1.000, implying that these factors have a relatively inelastic influence on the selection of speed intervals. In contrast, in the four speed intervals, the elasticity values of education are -6.194, -4.108, -5.011 and -2.972, and those of personality are 7.228, 7.602, 10.753 and 9.298; all of them have an absolute value greater than 1.000. These findings suggest that education level and personality traits significantly impact taxi drivers' capacity to drive safely. For the benefit of passenger safety, the qualification and daily management of taxi drivers must consider their individual characteristics.

KEYWORDS

taxi driver; driving speed; elasticity; disaggregated theory.

1. INTRODUCTION

With the rising demand for urban travel, public attention has increasingly shifted toward the safety and efficiency of transportation, particularly in the context of taxi services. While safety and efficiency are both essential to passenger satisfaction, they can often be in conflict. Driving speed lies at the heart of this contradiction: it is a key factor in ensuring travel efficiency but also closely associated with the risk of traffic accidents. In this regard, taxi drivers' individual characteristics play a significant role, as they influence how drivers perceive and balance safety and efficiency. Differences in personal traits lead to considerable variation in speed preferences and risk-taking behaviour among drivers. In particular, professional ethics education has emerged as a potentially effective tool to strengthen drivers' awareness of safety. To strike a better balance between safety and efficiency in taxi operations, this study aims to examine how individual characteristics and professional ethics education jointly affect taxi drivers' speed choices, thereby identifying behavioural traits conducive to safe and efficient driving. The results will provide a theoretical and empirical foundation for improving driver selection and ethics training programs.

Previous research has explored various aspects of taxi drivers' behaviour, including risk-taking tendencies [1-2], accident involvement [3] and speed selection [4]. Cheng et al. [5], for example, investigated impulsive risk-taking behaviour among taxi drivers in Hong Kong by comparing neural responses in those with and without traffic violation records. Their findings suggested that drivers with infractions focus more on potential rewards than consequences. Wu et al. [6] used a driving simulator to compare professional and non-professional drivers and found that professional drivers, despite being more prone to red-light running, demonstrated better collision avoidance skills. La et al. [7] studied accident prevalence among taxi drivers in Hanoi and identified several key contributing factors, such as age, licence type, employment status, safety awareness and income. Notably, 22.7% of drivers reported being involved in traffic accidents, with 18.1% having experienced two to four incidents.

Other scholars have focused on driving behaviours and crash propensity. Peng et al. developed a Bayesian network (BN) model to explore taxi crashes' contributing effects [8]. Ming et al. [9] examined speeding behaviour among female taxi drivers in Taiwan and found that age, education and mileage significantly influenced speed choices. Yuan and Sun [10] argued that the psychological state of taxi drivers, shaped by the pursuit of profit, is a major determinant of driving safety. Ahmed et al. [11] characterised lane-changing behaviour of drivers under differing congestion levels and identified extreme lane-changing traits using high-resolution trajectory data. Similarly, Si and Guan [12] discovered that taxi drivers' behaviour in seeking passengers aligns with the theory of planned behaviour, with a preference for residential areas. Zhang and Mao [13] revealed a discrepancy between drivers' self-reported safety awareness and their actual traffic violations.

Although recent years have seen growing interest in driving ethics, particularly in relation to autonomous vehicles, the ethics of human drivers have received less attention. Husak [14] emphasised the need for more serious discussions around ethical dilemmas in private vehicle use. The burgeoning literature on autonomous vehicle ethics [15–18] contrasts with the relative neglect of human drivers' professional ethics. However, the moral foundations of human driving behaviour remain critical. Cociu et al. [19] argued that drivers have a moral responsibility to comply with traffic regulations, while Evans [20] examined moral issues related to speeding, drunk driving and policy enforcement. Ori [21] provided a normative analysis of speeding behaviour, highlighting the importance of road ethics. Charlton [22] explored how speed preferences are shaped by drivers' subjective beliefs about speed limits. Meanwhile, Chen et al. [23] used stated preference methods to evaluate how punishment and enforcement measures deter speeding, and suggested that ethics-based driver education could reduce repeat violations.

Despite this extensive body of research, there remains a notable gap regarding how individual traits and ethics education jointly shape driving speed decisions, especially among taxi drivers. Few studies quantitatively assess how responsive speed choice is to personal characteristics, and even fewer consider ethics education as a variable of interest. To address this gap, the present study builds on previous research by systematically analysing how various factors, such as age, gender, education, personality type, ethics training, vision correction and mobile phone use, affect taxi drivers' speed choices. By employing an elasticity-based measurement model, this study quantifies the influence of each factor on speed interval selection. The findings are expected to inform policy decisions regarding driver recruitment, ethics training and safety management in the taxi industry.

2. METHODOLOGY

In this paper, a disaggregated model is employed to analyse the traffic behaviour of taxi drivers, utilising personal data obtained through an on-site sampling survey. In the field of road transport, the disaggregated model has been widely used to describe individual decision-making behaviour more accurately and comprehensively, and has produced a wealth of research results [24-29]. The model is grounded in the theory of utility maximisation, which posits that taxi drivers select the most efficient option for achieving utility-optimal decision-making. The utility function comprises two components: a systematic part and a stochastic part, typically represented as

$$U_{in} = V_{in} + \varepsilon_{in} \tag{1}$$

$$V_{in} = \sum_{k=1}^{k} \beta_k X_{ink} \tag{2}$$

where V_{in} represents the systematic part of U_{in}; U_{in} represents the i-th scheme's utility function for the n-th driver; K represents the number of explanatory variables; ε_{in} represents the stochastic (unobservable) component of U_{in}, assumed to be independently and identically distributed following a Gumbel distribution; β_k is the parameter to be estimated; X_{ink} is the i-th scheme's k-th variable value for the n-th driver.

As the primary participants in the road traffic system, drivers constitute the most volatile traffic factor. Their individual traffic behaviour varies significantly based on their personal characteristics, leading to a certain degree of randomness in their driving speeds within the road traffic system. While the traffic environment also influences drivers' speed choices, this impact is relatively uniform and generally stable across all drivers. Consequently, the primary cause of variability and dispersion in drivers' speed choices stems from differences in their perception of the traffic environment, which is contingent upon their personal characteristics. Personal characteristics are the key influencing factor of driving speed because drivers with different personal characteristics perceive even the same traffic environment differently and choose different speed intervals. The disaggregated model utilised in this paper effectively captures the discreteness and nonlinearity of drivers' speed choice behaviour, which is attributed to variations in their personal characteristics. This model demonstrates robust generality and adaptability. Furthermore, a driver's choice of a speed interval is made by the principle of maximum utility, considering the combined influence of various circumstances and aligning with their own maximum expectations. This aligns with the fundamental premises of the disaggregated theory. The disaggregated model is adopted in this work to investigate how taxi drivers' personal traits affect their speed choice behaviour.

The multinomial logit (MNL) model [30] is a foundational form of discrete choice model that assumes individuals make decisions among a finite set of mutually exclusive alternatives by maximising their utility. It is widely recognised as a classic representative of disaggregate behavioural modelling frameworks [31-34]. According to the basic form of the MNL model, the probability of the n-th driver choosing the i-th speed choice behaviour can be expressed as

$$P_{in} = \frac{e^{V_{in}}}{\sum_{j=1}^{J} e^{V_{jn}}} \tag{3}$$

where J is the total number of available alternatives.

The specific process of establishing the influence measurement model of taxi drivers' speed choice behaviour is shown in *Figure 1*, where t is the t-test value of each influencing factor and R^2 represents the correlation coefficient. It begins with defining the utility function, which captures drivers' preferences for different speed options. The choice limbs are then identified, followed by the selection of key influencing factors such as age, personality traits, driving experience, education level and professional ethics training. Collected data undergoes processing to ensure quality and suitability. Model parameters are estimated, and the significance of each factor is assessed by testing whether its t-value exceeds 1.960, indicating 95% confidence. If the condition is met, the coefficient of determination (R^2) is calculated to evaluate the model. If the condition is satisfied, the final results are output, revealing the influence of individual factors on drivers' speed choices.

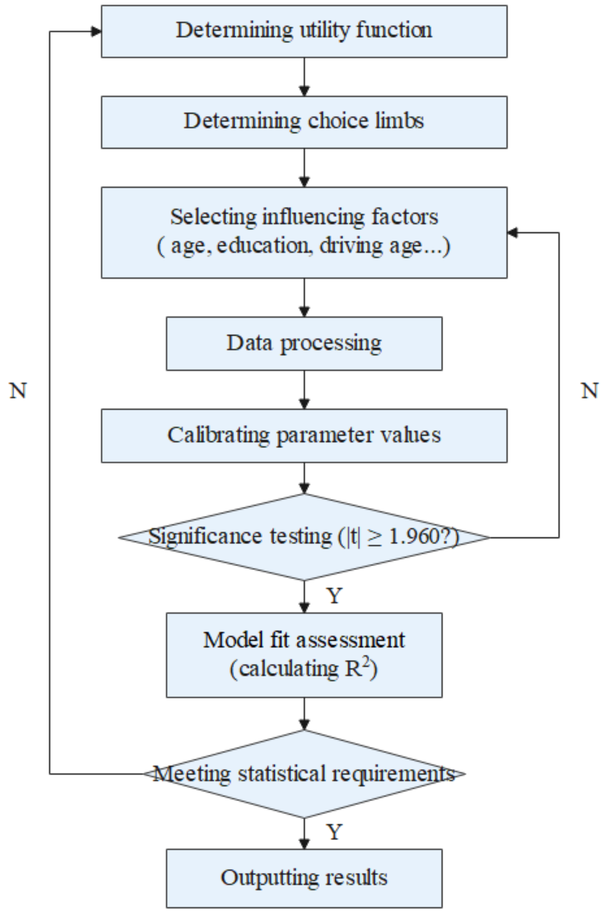

Figure 1 – Process of the model

3. ESTABLISHING THE SPEED CHOICE BEHAVIOUR MODEL

3.1 Main elements

A questionnaire was developed to assess the personal characteristics of taxi drivers and their speed choice behaviour. It included nine items: gender, age, education, driving age, personality, professional ethics education, vision correction, mobile phone use while driving and passenger presence.

Among these, personality was classified based on the classical four temperament theory in psychology, which has been widely used in behavioural and occupational research. This model divides personality into four types: melancholic, sanguine, phlegmatic and choleric, each representing a distinct set of emotional and behavioural traits.

— Melancholic temperament (sensitive, easily frustrated, withdrawn, oligarchic, slow to recover from fatigue, slow to react);

— Sanguine temperament (calm, tolerant, focused and conscientious, patient and hardworking, but inflexible and lacking in enthusiasm);

— Phlegmatic temperament (enthusiastic and capable, but witty and flexible, not focused enough, moody and lacking in patience);

— Choleric temperament (easily excited, short-tempered, outspoken, depressed when exhausted).

Each driver was asked to self-assess their behavioural tendencies based on these definitions. This classification enabled the study to explore the correlation between personality traits and speed choice behaviour from a psychological perspective.

In addition, using a mobile phone while driving involves the utilisation of mobile phone software for purposes such as receiving business orders or communicating with colleagues, potentially impacting driving safety and speed. Professional ethics education was included mainly to compare the driving behaviour of drivers with different levels of professional ethics education. The inclusion of passenger presence in the study is attributed to the influence of passengers' demands concerning travel time and drivers' pursuit of business volume, which may affect driving speed.

Data were obtained through on-site sampling conducted in Wuhan, China, from 10 to 15 June 2024, during weekday daytime hours (9:00–17:00) to capture typical urban traffic conditions. The speed choice behaviour of taxi drivers was investigated under their normal working conditions without experimental manipulation. The survey site was selected to avoid bus stops and intersections, ensuring smooth traffic flow and minimising the impact of other traffic elements on the behaviour of taxi drivers. The chosen route was a six-lane road with separate lanes for motor and non-motor traffic.

A total of 107 taxi drivers were randomly approached for the survey, and after removing invalid or disturbed samples, 102 valid responses were retained for analysis, resulting in a 95.33% effective response rate. Among the 102 valid responses, 100 drivers (98%) were male and 2 drivers (2%) were female. The statistical distribution of individual taxi driver characteristics, obtained through the processing of survey data statistics, is presented in *Figures 2 – 5* below.

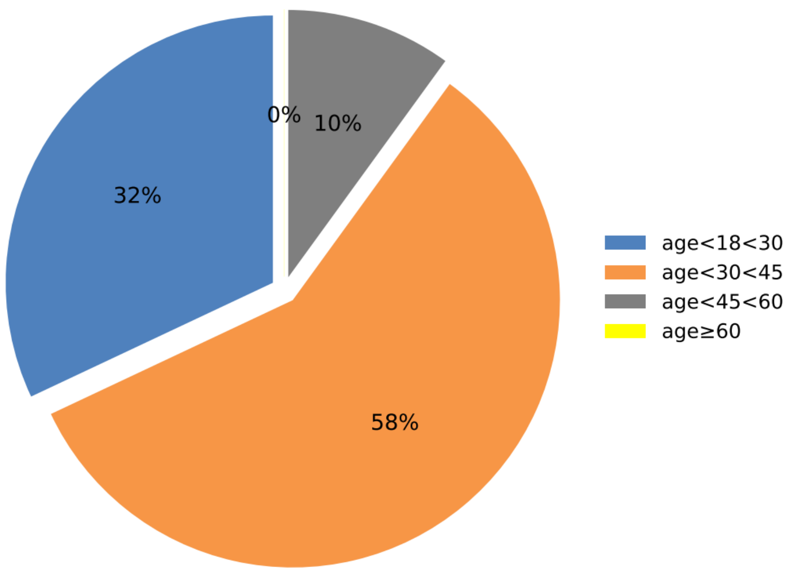

Figure 2 – Age distribution of taxi drivers

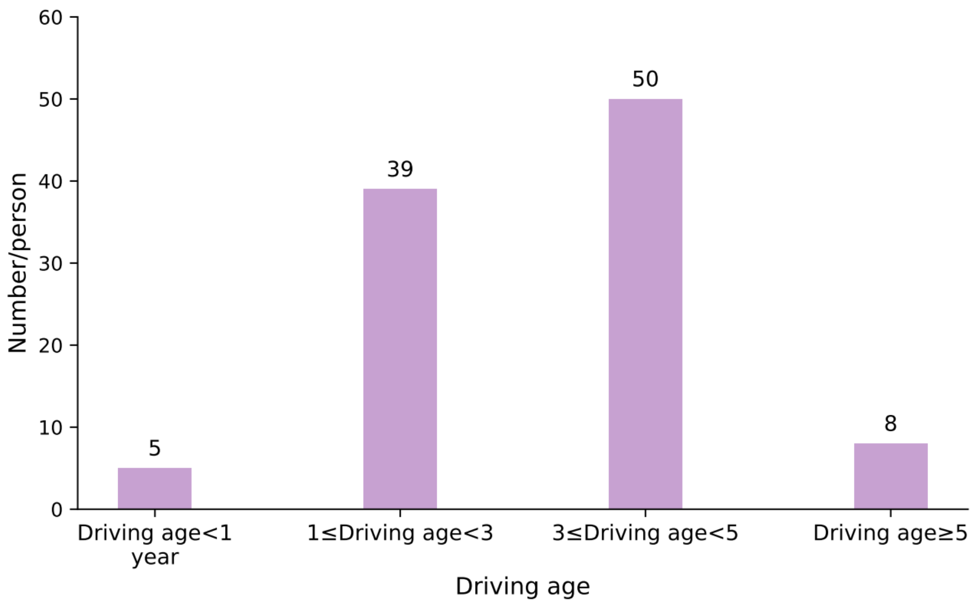

Figure 3 – The driving age distribution of taxi drivers

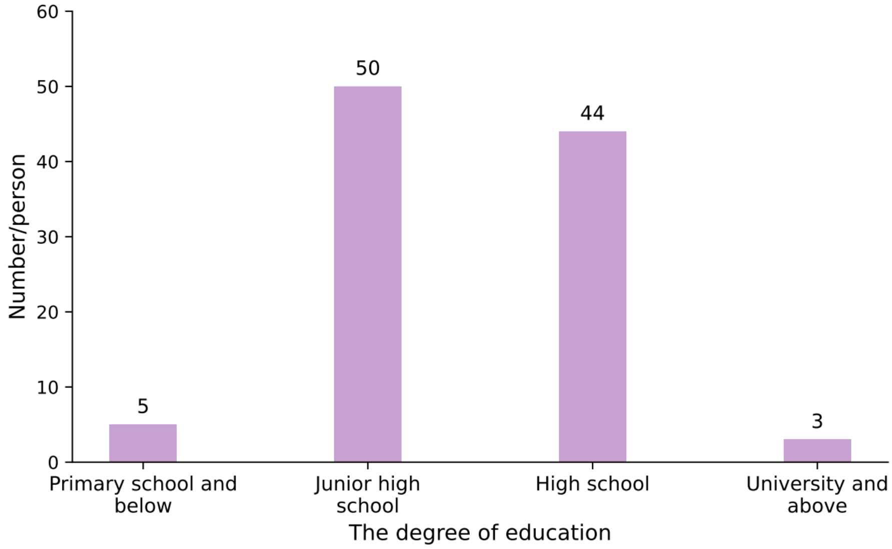

Figure 4 – Education level distribution of taxi drivers

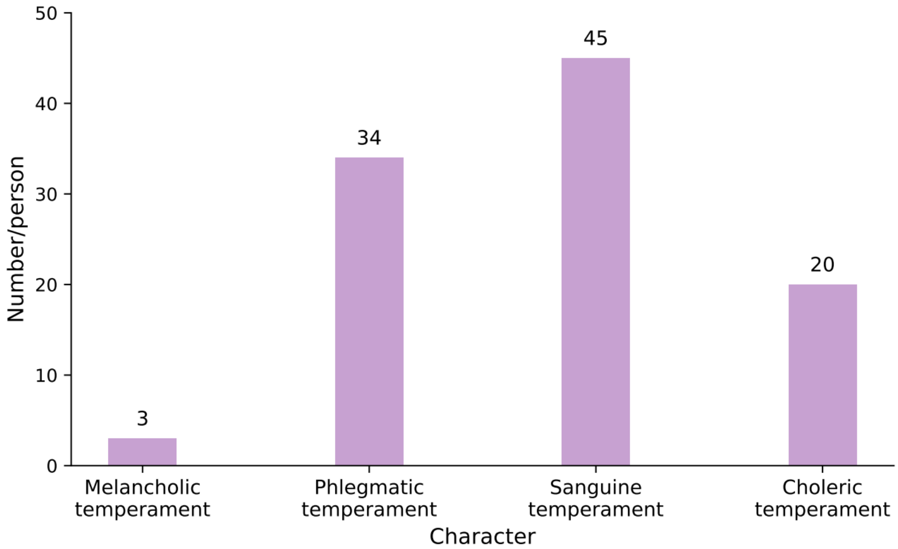

Figure 5 – The character distribution of taxi drivers

Statistically, all drivers were 26-54 years old, with 58% of them aged 30-45; all of them had one year or more driving experience; 92.16% of them had junior high school or high school education; most of them were phlegmatic temperament or sanguine temperament, and only 2.94% of them were melancholic temperament.

To investigate the influence of taxi drivers' individual characteristics on their driving speed and to make more informed use of the survey data, while considering the permissible range of motor vehicle driving speeds on urban roads and the recommended speeds for safe driving on actual on-site roads, we utilised A, B, C and D to represent four speed intervals for taxis, namely: 0-50 km/h, 51-60 km/h, 61-70 km/h and above 71 km/h. We counted the number of taxi drivers, the average speed, the maximum and the minimum value for each speed interval. The data pertaining to taxi drivers' speed choice behaviour is presented in *Table 1*.

Table 1 – Taxi speed

Speed interval	A	B	C	D
Number of drivers	29	29	31	13
Average speed	44.508	54.430	64.693	76.933
Maximum value	49.291	59.120	69.758	90.000
Minimum value	39.725	49.74	59.628	63.866

Table 1 displays the average speeds of taxi drivers corresponding to the four defined speed intervals. Subsequently, an analysis will be conducted on the elasticity values of taxi drivers' personal characteristics corresponding to the four speed intervals, in order to determine the speed interval and average speed associated with those characteristics exhibiting higher elasticity values. Taxi drivers possessing diverse characteristics demonstrate varying speed intervals in their driving behaviour. The maximum speed required of taxi drivers varies based on the lane they select, ensuring passenger safety.

Based on valid survey data regarding taxi drivers' personal characteristics and guided by disaggregated theory, an analysis of taxi drivers' speed selection behaviour was carried out through the development of a disaggregated model.

3.2 Reliability and validity tests

The questionnaire data were evaluated in terms of reliability and validity [35-37]. Reliability, referring to the internal consistency of the items, was assessed using Cronbach's alpha coefficients in SPSS 19.0. The results showed that all five prospective variables (age, education, personality, professional ethics education and passenger presence) exhibited Cronbach's alpha values exceeding 0.73. The overall reliability of the nine variables included in the questionnaire (gender, age, education, driving experience, personality, vision correction, mobile phone use while driving, professional ethics education and passenger presence) is 0.704. This indicates that the questionnaire has acceptable reliability. The Kaiser-Meyer-Olkin (KMO) test and Bartlett's test were employed to evaluate the questionnaire's validity and determine if factor analysis was appropriate. The results confirmed the suitability of the factor analysis, with a significance level (Sig) of 0.014 (less than 0.05) and a Kaiser-Meyer-Olkin value of 0.502 (greater than 0.50).

3.3 Determining choice limbs and influencing factors

By the disaggregated theory, the four intervals A, B, C and D, which represent the taxi drivers' driving speeds, were chosen as the four choice limbs of the suggested model and were assigned the values 1, 2, 3 and 4. The influencing factors were determined according to the influence of taxi drivers' individual characteristics on their choice of speed interval, the details of which are shown in *Table 2*.

Table 2 – Influencing factors

Influencing factor	Variable	Remark
Gender	X_1	1 for male, 0 for female
Age	X_2	4 levels: 18-30 years, 30-45 years, 45-60 years and 60 years and above; the values are 0, 1, 2 and 3, respectively
Education	X_3	4 levels: primary school and below, middle school, high school, university and above; the values are 0, 1, 2 and 3, respectively
Driving age	X_4	4 levels: 1 year or less, 1 - 3 years, 3 - 5 years and 5 years and above; the values are 0, 1, 2 and 3
Personality	X_5	4 levels: melancholic temperament, sanguine temperament, phlegmatic temperament and choleric temperament; the values are 0, 1, 2 and 3, respectively
Vision correction	X_6	Dummy variable is 1 if vision is corrected and 0 otherwise
Mobile phone use	X_7	Dummy variable is 1 if a mobile phone is used while driving and 0 otherwise
Professional ethics education	X_8	3 levels: regularly, occasionally, never; the values are 1, 2, 3, respectively
Passenger presence	X_9	Dummy variable is 1 if the taxi carries passengers and 0 otherwise

4. RESULTS AND DISCUSSION

4.1 Calibration of influencing factors

As stated in *Table 3*, the affecting factors were calibrated and chosen using SPSS. The t-minimum test's result, 2.282, is higher than 1.960, indicating that the nine factors can have a sizable impact on the taxi drivers' speed choice behaviour.

Table 3 – Influencing factor correction results

Influencing factor	Variable	Parameter value	Standard deviation	*t*-test value
Gender	X_1	0.972	0.139	12.784
Age	X_2	-1.788	0.612	22.804
Education	X_3	-4.289	0.638	22.820
Driving age	X_4	0.652	0.707	23.238
Personality	X_5	6.289	0.784	2.282
Vision correction	X_6	1.324	0.217	3.841
Mobile phone use	X_7	-3.258	0.335	30.483
Professional ethics education	X_8	2.826	0.299	24.121
Passenger presence	X_9	1.800	0.776	12.784

Table 4 – Calibration model fitting

Model	*R*	R^2	Adjusted R^2	Error in standard estimates
1	0.749	0.561	0.519	9.9089

The fitness of the model is judged by R^2, a coefficient of determination, where $R^2 \in (0,1)$. Thus, the more closely the linear regression connection resembles reality, the closer the R^2 number is to 1. In our situation, R^2 is 0.561, and the corrected R^2 is 0.519, indicating that the created model performs satisfactorily.

4.2 Utility function

When determining the utility function model, SPSS 19.0 statistical analysis software was used in this paper. According to the value properties of multiple variables, the logistic model was applied to take the last category of a variable as the reference category and compare it with the first several categories to get the final model.

In this study, the utility function is constructed based on several factors that are hypothesised to influence the taxi drivers' speed choice. The utility function V_i for each speed interval is a linear combination of these factors, and each influencing factor has an associated coefficient. *Table 5* presents the parameter values for each of the influencing factors corresponding to the four speed choice intervals. The utility functions for intervals A, B, C and D, which represent the utility of choosing a specific speed interval for each driver, are as follows:

$$V_0=0.972\ X_1-4.289\ X_3+6.289\ X_5+1.324\ X_6\ \mathrm{V}+2.826\ X_8+1.800\ X_9$$

$$V_1=-1.788\ X_2-4.289\ X_3+0.652\ X_4+6.289\ X_5-3.258\ X_7+1.800\ X_9$$

$$V_2=0.972\ X_1-4.289\ X_3+0.652\ X_4+6.289\ X_5+1.324\ X_6+2.826\ X_8$$

$$V_3=0.972\ X_1-1.788\ X_2+6.289\ X_5-3.258\ X_7+2.826\ X_8+1.800\ X_9$$

where X_1 to X_9 represent various influencing factors, including gender, age, education level, driving experience, personality, mobile phone use, vision correction, passenger presence and professional ethics education.

Table 5 – Influencing factors and parameter values

Influencing factor	Variable	Interval			
		A	B	C	D
Gender	X_1	0.972		0.972	0.972
Age	X_2		-1.788		-1.788
Education	X_3	-4.289	-4.289	-4.289	
Driving age	X_4		0.652	0.652	
Personality	X_5	6.289	6.289	6.289	6.289

Influencing factor	Variable	Interval			
		A	B	C	D
Vision correction	X_6	1.324		1.324	
Mobile phone use	X_7		-3.258		-3.258
Professional ethics education	X_8	2.826		2.826	2.826
Passenger presence	X_9	1.800	1.800		1.800

In order to obtain the correlation between each influencing factor and taxi drivers' speed, a sensitivity analysis was conducted on each influencing factor, and driving speed and elasticity values were used to express the degree of sensitivity. In the disaggregated theory, the elastic value E of the change in the selection probability of the scheme i can be described as follows when a specific influencing factor changes:

$$E = \theta_k X_{ink} (1 - P_{in}) \tag{4}$$

where θ_k is a parameter representing the effect of the influencing factor k on the choice behaviour. X_{ink} is the value of the k-th influencing factor for the n-th driver choosing the i-th speed choice behaviour. P_{in} is the probability of a taxi driver's speed-selection behaviour.

The elasticity value can be divided into positive and negative; the value is positive when the two variables have a positive correlation, and vice versa. If the absolute value of the elasticity for each of the four speed intervals exceeds 1.000, the influencing factor is considered elastic in relation to the choice of the speed interval; conversely, if the absolute value is below 1, it indicates a lack of elasticity.

According to the survey data of taxi drivers' individual characteristics and speed interval selection behaviour, the average value of the speed interval matched by each driver's individual features is calculated through (1), to determine the elastic value of each influencing element on the probability of drivers' speed interval selection behaviour, (2) calculating the probability of the taxi driver's speed interval choice behaviour by entering the parameter values from *Table 4* into Formula (3), and (3) using the elastic value calculation Formula (4), the elastic value of each influencing element on the likelihood that the driver will select a speed interval may be calculated.

4.3 Analysis of calculation results

Gender and age

Based on the utility function described in Section 3.3 above, the choice probability, parameter value, sample average of each influencing factor and elasticity value of the taxi driver's gender and age can be computed in different selection intervals. The values for other influencing factors discussed below were calculated using the same method. As shown in *Table 6* below, the changes of gender average values in each speed interval were relatively stable, with an average value of 0.972, indicating that there are more males than females in the taxi driver occupation. The choice probability of speed interval D reaches 0.399, indicating that male drivers are more likely than female drivers to choose to drive at high speeds. The elasticity value for speed interval C is 0.859, which is the largest, indicating that gender has the greatest influence on the choice of high speeds, but has no significant influence on the choice of other speed intervals.

Table 6 – Gender and age results

Speed interval	Choice probability	Gender			Age		
		Parameter value	Average value	Elasticity value	Parameter value	Average value	Elasticity value
A	0.145	0.972	0.966	0.802	-1.788	0.897	-1.370
B	0.339	0.972	1.000	0.643	-1.788	0.552	-0.652
C	0.117	0.972	1.000	0.859	-1.788	0.871	-1.376
D	0.399	0.972	0.923	0.539	-1.788	0.769	-0.826

The average age remains relatively stable, ranging from 0.5 to 0.9. The average value for interval B is the smallest, at 0.552, suggesting that younger taxi drivers tend to select speeds within this interval. The average value for interval A is the highest, at 0.897, indicating that as taxi drivers age, they generally opt for lower driving speeds. The average absolute value of age elasticity across the four intervals is less than 1.000, indicating that age does not definitively determine the choice of speed interval. Besides, the elasticity of age is negative, indicating that as the age of taxi drivers increases, they usually choose to drive at lower speeds. This suggests that, with greater driving experience, taxi drivers are more inclined to select lower speed intervals, owing to their heightened safety awareness and increased caution when assessing traffic conditions.

Education and driving age

As shown in *Table 7*, the drivers' education average, which corresponds to the four speed intervals, has a decreasing trend and stands at 1.404. Interval A exhibits the highest average, suggesting that as the education level of taxi drivers increases, they are more likely to select lower speed intervals. Education is elastic for drivers' speed choice behaviour, as shown by the fact that the elasticity values for the drivers' education are all negative and the absolute values are all more than 1.000. In other words, the higher the taxi drivers' education, the more safety conscious they are, and the lower the speed interval they choose. The absolute elasticity value for interval A is 6.194, greater than those for the other three intervals, indicating that education has the greatest influence on the taxi drivers' choice of low speeds. However, drivers are less inclined to select speeds within interval A, with 51.6% preferring higher speeds within intervals C and D. This correlation can be attributed to the road conditions chosen by taxi drivers: roads with good motor vehicle access may encourage taxi drivers who typically drive at lower speeds to increase their driving speed. *Figure 6* depicts the association between a particular taxi driver's education level and driving speed.

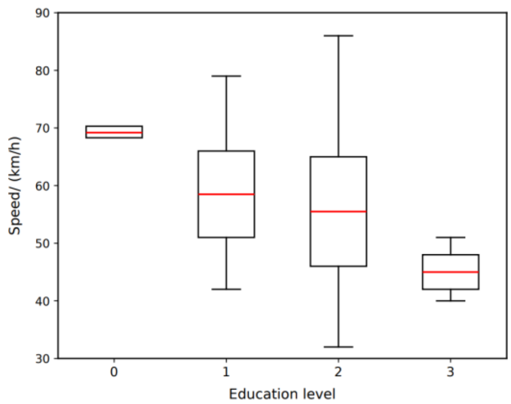

Figure 6 – Association between education level and driving speed

It is evident from *Figure 6* that an increase in a driver's education level leads to a decrease in the average driving speed (as indicated by the red line in the graph), thereby confirming the negative correlation between education level and driving speed. This indicates that taxi drivers with higher education levels have higher safety awareness and are better able to ensure the safety of their passengers in terms of driving speed.

Table 7 – Education and driving age results

Speed interval	Choice probability	Education			Driving age		
		Parameter value	Average value	Elasticity value	Parameter value	Average value	Elasticity value
A	0.145	-4.289	1.670	-6.194	0.652	1.552	0.865
B	0.339	-4.289	1.448	-4.108	0.652	1.621	0.699
C	0.117	-4.289	1.323	-5.011	0.652	1.549	0.892
D	0.399	-4.289	1.154	-2.972	0.652	1.770	0.693

Table 7 demonstrates that as the average driving age increases, taxi drivers are more inclined to prefer higher speed intervals. Specifically, the average driving age for interval A is the highest, at 1.770, suggesting that

older and more experienced drivers are more familiar with and tend to choose higher speeds. Driving age is inelastic to the choice of speed interval, as shown by the fact that the elasticity values for all four speed intervals are lower than 1.000. As a result, the choice of high speeds is not significantly affected by changes in driving age. The range of elasticity values varies from 0.693 to 0.892, with an average of 0.787, indicating that drivers' age has a greater influence on their preference for slower and more stable driving speeds.

Personality and vision correction

The average personality values of taxi drivers across the four speed intervals, as presented in *Table 8*, demonstrate an ascending trend. As taxi drivers' personalities transition from melancholic to choleric, there is a gradual increase in the selected driving speed range, indicating that taxi drivers who exhibit a more irritable disposition tend to drive at faster speeds. All four intervals exhibited elasticity values exceeding 1.000, indicating that taxi drivers' personalities are responsive to their choice of speed interval. The elasticity values for intervals C and D are notably higher, at 10.753 and 9.298, respectively, suggesting that taxi drivers' personality has a more pronounced impact on their choice of high speeds. The specific relationship between taxi driver personality and driving speed is shown in *Figure 7*.

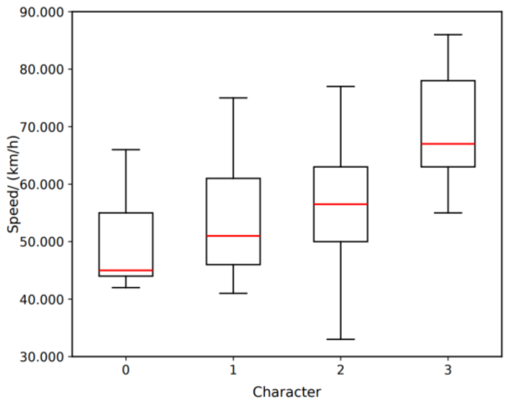

Figure 7 – Relationship between taxi driver personality and driving speed

Figure 7 illustrates that as taxi drivers' personalities transition from melancholic to choleric temperament, there is a corresponding increase in driving speed with the augmentation of character strength. Taxi drivers who are choleric have an average speed of around 70 km/h, and their minimum speeds are higher than those of drivers with the other three personalities. This indicates that these drivers have the highest pursuit of speed and are prone to high-speed or speeding behaviour. While these drivers may ensure a certain level of journey efficiency expected by passengers, it is detrimental to ensuring safety and comfort.

Table 8 – Results for personality and vision correction

Speed interval	Choice probability	Personality			Vision correction		
		Parameter value	Average value	Elasticity value	Parameter value	Average value	Elasticity value
A	0.1453	6.289	1.3448	7.228	1.324	0.0690	0.078
B	0.3386	6.289	1.8276	7.602	1.324	0.0690	0.060
C	0.1166	6.289	1.9355	10.753	1.324	0.0323	0.038
D	0.3994	6.289	2.4615	9.298	1.324	0.0000	0.000

Information about the road environment, the basis for the perception of and judgment about the driving environment, is mainly obtained visually by taxi drivers. While corrective vision can assist taxi drivers in obtaining certain dynamic information with greater detail, it does not compare favourably to normal vision. This is especially noticeable when driving at high speeds, as the lens curvature worsens the effect of vision correction on driving ability. As shown in *Table 8*, the average vision correction value across the four periods is below 0.500, indicating that most taxi drivers fall into this category. This suggests that the choice of speed range is not affected by whether or not vision is corrected. The elasticity values of vision correction for all four intervals are less than 1.000, indicating that vision correction exhibits inelasticity towards taxi drivers' choice of speed interval, thereby exerting a minimal influence on it. In addition, the elasticity value decreases as the speed increases, which suggests that among those choosing high speeds, there are more taxi drivers with normal vision than with corrective vision.

Mobile phone use while driving, professional ethics education and passenger presence

Given the unique characteristics of the taxi driver profession and the prevalent use of communication and ride-hailing software, taxi drivers need to access timely business information through mobile phones while driving. However, this significantly impacts driving safety. *Table 9*'s average value of mobile phone use, which is 0.121 on average, demonstrates a tendency toward decline. With a value of 0.172, interval A's average is the highest, indicating that taxi drivers' driving speed decreases as the frequency of mobile phone use increases. The elasticity values of mobile phone use across the four intervals are all below 1.000, indicating that mobile phone use exhibits inelastic behaviour with respect to the choice of speed interval. Furthermore, as driving speed increases, the elasticity value decreases, implying a reduction in the utilisation of mobile devices by taxi drivers while driving. These findings underscore the significance of enhancing taxi drivers' professional ethics education to elevate their safety awareness.

Table 9 – Results for mobile phone use, professional ethics education and passenger presence

Speed interval	Choice probability	Mobile phone use while driving			Professional ethics education			Passenger presence		
		Parameter value	Average value	Elasticity value	Parameter value	Average value	Elasticity value	Parameter value	Average value	Elasticity value
A	0.145	3.258	0.172	0.480	2.826	1.759	4.248	1.800	0.862	0.807
B	0.339	3.258	0.138	0.297	2.826	1.759	3.287	1.800	0.966	1.221
C	0.117	3.258	0.097	0.279	2.826	2.032	5.073	1.800	0.903	1.173
D	0.399	3.258	0.077	0.151	2.826	1.846	3.133	1.800	0.846	1.294

From *Table 9*, the average level of professional ethics education is 1.849, and the four intervals show a relatively stable trend. Interval C has the largest average value, indicating that professional ethics education has the greatest influence on the choice of high-speed intervals. All four intervals' professional ethics education elasticity values are larger than 1.000, suggesting that professional ethics education is elastic to the choice of speed interval. Interval C has the highest elasticity value of 5.073, which means that professional ethics education has the greatest influence on the choice of high-speed intervals. Consequently, professional ethics education exerts a significant influence on taxi drivers' speed choice behaviour. The specific relationship between them is shown in *Figure 8* below.

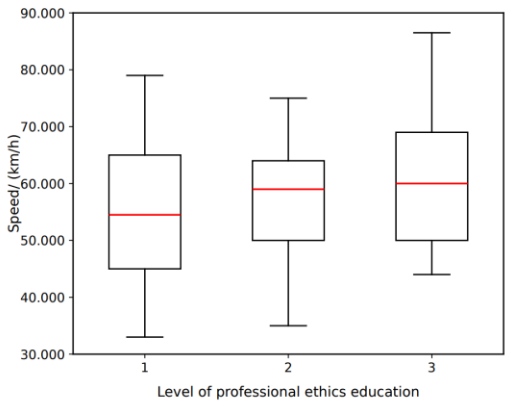

Figure 8 – Relationship between professional ethics education and driving speed

Figure 8 demonstrates that a lower level of professional ethics education is associated with a higher driving speed, affirming a robust correlation between professional ethics education and driving speed.

Regarding passenger presence, *Table 9* demonstrates a steady change in its average value, with a mean of 0.894. Interval B has the largest average value of 0.966, indicating that more drivers choose to travel at a relatively low speed when carrying passengers to ensure passenger safety and comfort. The average elasticity value is greater than 1.000, which means that passenger presence has a strong elasticity on the choice of speed interval. Interval D exhibits the highest elasticity value of 1.294, suggesting that the presence of passengers has the most significant influence on high-speed driving behaviour. This is closely related to passenger demand: when passengers demand a short travel time, taxi drivers will be more likely to choose high-speed driving.

4.4 Discussion

The results of this study highlight key factors influencing taxi drivers' speed choice behaviour. Age, emotional tendency and educational level are significant determinants of driving speed, which is consistent with previous research results. Younger drivers are more prone to choose higher speeds due to lower risk aversion and limited driving experience [8-9]. The negative elasticity values for age across all intervals, especially the minimum average age observed in interval B (0.552), reaffirm this trend. Conversely, older drivers tended to opt for lower speed ranges, reflecting heightened safety awareness.

Personality traits also influenced speed choices, with more choleric personalities driving faster, as seen in the high elasticity values for intervals C and D (10.753 and 9.298, respectively). This is consistent with the previous view that emotional instability can lead to dangerous driving behaviour [38-39]. In addition, male drivers are more inclined to choose higher speeds, especially in interval D, where the elasticity value is 0.859.

Drivers with higher education levels showed a clear tendency to choose lower speeds [9, 39-40], with elasticity values all being negative and exceeding 1 in magnitude, particularly in interval A. This finding reflects stronger safety consciousness and rule compliance among more educated drivers. Vision correction and mobile phone use were found to have weak effects on speed choice. Elasticity values for both factors were less than 1.000, suggesting low sensitivity. Although drivers with corrected vision may perceive dynamic environments slightly differently, especially at higher speeds, the impact was not substantial.

This article focuses on professional ethics education as a factor of interest and quantitatively assesses how personal traits and moral education jointly influence the decision on driving speed. Lower level of professional ethics education is associated with a higher driving speed, affirming a robust correlation between professional ethics education and driving speed. Passenger presence also strongly influenced speed, with drivers opting for lower speeds to ensure passenger safety and comfort. The elasticity value for passenger presence was above 1.000, indicating a strong effect, particularly on high-speed choices.

By incorporating factors such as personality and education into the model, this paper provides a more comprehensive understanding of driver decision-making. Practically, the findings highlight the need for driver training programs focused on education and ethics to improve safety.

5. CONCLUSION AND PROSPECT

To measure the impact of fundamental characteristics and professional ethics education of taxi drivers on driving speed, a model was established in this study. The t-test results demonstrate that the model exhibits robust applicability and practicability, as it aligns closely with real-world scenarios and is capable of quantifying the correlation between taxi drivers' driving speed choices and their personal characteristics. Then, the sensitivity of each influencing factor to taxi drivers' speed choice behaviour was analysed using elasticity theory. Finally, the influence of the taxi drivers' individual characteristics on their choice of speed interval was analysed. The results demonstrate that all three elasticity values, related to education, personality and professional ethics education, exceed 1.000, indicating that these factors are elastic concerning speed choice behaviour, thereby suggesting a high sensitivity between these factors and speed choice behaviour. A strong correlation exists between professional ethics education and driving speed, thereby highlighting the significance of professional ethics education in enhancing taxi driving safety. In practice, the results can be applied by municipal transport authorities and taxi fleet operators to enhance driver selection and training processes. For instance, driver recruitment can incorporate psychological assessments and education level screening, while ethics-focused training programs can be customised for drivers with a higher propensity toward risky speed behaviour.

In the actual survey, the study of taxi drivers' use of mobile phones during driving was limited due to the limitations in obtaining sample data. Hence, future studies can delve deeper into this aspect to identify the key elements that should be prioritised in the professional ethics education of taxi drivers. In addition, by constantly revising the parameter values of the model's influencing factors, the sensitivity analysis's findings can be improved in accuracy and alignment with actual driving conditions.

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