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Effects of Aging on Taxi Service Performance: A Comparative Study Based on Different Age Groups

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Abstract: Rapid population aging has significantly impacted labor supply and posed substantial challenges for the taxi industry, which have not yet been fully comprehended. Here, for the first time, we employ a large-scale dataset of taxi driver operations from China, establishing a comprehensive indicator system of taxi service performance, encompassing economic, environmental, and safety aspects. Through the application of multivariate regression models and other statistical analysis techniques, we have thoroughly investigated the mechanisms through which aging influences taxi service performance. Our research reveals that older drivers, despite exhibiting higher operational efficiency and greater inclination towards stability, underperform in time efficiency metrics, such as income per hour worked, owing to a more conservative working style. Furthermore, aging manifests negative effects on safety and environmental performance. Adjusting the driving strategies of older taxi drivers, such as regulating daily working hours and refining passenger-searching area preferences, can help mitigate these adverse impacts.

Keywords: aging; taxi driver; taxi service performance; multiple regression analysis; statistical modeling

1. Introduction

The taxi industry is recognized as a sector with substantial potential for sustainable development, involving key stakeholders such as policymakers, regulatory agencies, companies, drivers, and customers [1]. Among these roles, drivers are pivotal as direct service providers and major contributors to the overall performance of taxi services. Nevertheless, over time, the taxi industry has confronted an undeniable challenge: an aging workforce among its drivers [2–9].

In recent years, the aging trend within the taxi industry has garnered widespread attention. It is widely acknowledged that as the driver workforce ages gradually, a range of new issues and opportunities arise. On the one hand, some argue that an aging driver workforce may face challenges related to declining physical and cognitive abilities [10], which could adversely affect their driving safety [4,11–14] and job motivation [11,15]. On the other hand, there is the viewpoint that aging could bring about some positive aspects. Older drivers may possess richer driving experience, potentially leading to higher driving skills [16], greater earnings, and a reduced likelihood of engaging in risky driving compared to younger drivers [17–21]. These controversial viewpoints may be attributed to a reliance on certain data sources. Given that studying how aging affects taxi service performance requires data derived from driver privacy, previous research has often relied on self-reported information provided by drivers, which poses challenges for conducting

comprehensive and nuanced research in this area. This type of data source not only tends to have a limited sample size but also is susceptible to social desirability bias, as noted in previous studies [22]. Although researchers can mitigate this bias, it cannot be entirely eliminated. To attain a more comprehensive understanding of how aging impacts taxi service performance, it is imperative to surmount the constraints associated with prior data sources and leverage more expansive and objective datasets that are inclusive of driver privacy. The advent of the big data era has rendered this endeavor feasible. By aligning official driver privacy data with extensive taxi operational datasets, we have been able to ascribe human attributes to the taxi operational data. This metamorphosis has facilitated the conversion of taxi operational data into driver-centric operational data, culminating in a comprehensive and unbiased dataset of taxi driver operations. Notably, our dataset not only entirely circumvents the limitations of previous self-reported driver data but also enables a more thorough investigation of taxi performance.

Besides the research data, careful attention to the research methodology is crucial. To thoroughly understand how driver aging affects taxi service performance, it is imperative to utilize precise and practical research methodologies. At present, in the specific operation of causal analysis using objective big data on taxis, it is possible to combine the treatment of various variable biases by using methods such as simple linear regression [23], propensity score matching [24], instrumental variables [25], etc. It is also possible to combine the control of experimental scenarios and use methods such as regression discontinuity design [26], difference in differences [27], etc. But inevitably, the core of these methods is still multivariate regression, in order to quantify the impact of independent variables on the dependent variable. In summary, the core of these methods is still multivariate regression analysis, with the goal of quantifying the effect of independent variables on the dependent variable. Consequently, we will employ a multivariate regression model as the core research method to delve into how aging impacts taxi service performance.

In conclusion, driver aging is a significant issue within the taxi industry, but the comprehensive and profound discussion of the impact of aging on taxi service performance has been limited by constraints in available research data. To address this issue, our research utilizes unprecedented data, breaking free from the constraints of previous research data. Through the integration of driver personal information with extensive operational data from taxi orders, we have acquired a substantial and unbiased research dataset. Using this dataset, we developed a comprehensive indicator system for taxi service performance. We applied multiple regression models (MRMs) to examine the influence of aging on taxi service performance. Additionally, we utilized structural equation models (SEMs) to explore the pathways of influence and suggest mitigation strategies. Our research addresses the gap in the literature concerning the impact of aging on taxi service performance.

This paper is organized as follows: Section 2 focuses on a comprehensive review of the relevant literature regarding the impact of aging in the transportation sector, extending from non-professional drivers to professional drivers and ultimately to taxi drivers. Section 3 presents the taxi operational order data and driver personal data from Ningbo, China, in 2022, as well as the data-processing methods and the taxi operational performance indicator system established based on the data. In addition, Section 3 elaborates on the statistical analysis methods, primarily using MRMs. Section 4 demonstrates the results of the statistical analyses and provides detailed discussions. Section 5 concludes the paper.

2. Literature Review

Population aging presents a significant challenge with the aging workforce, potentially impacting the development of various industries. Researchers across diverse fields have been dedicated to comprehending the implications of aging on industry sustainability and growth, as well as devising potential solutions [28–32]. In transportation, researchers have also dedicated considerable efforts to address safety concerns related to driver aging. Using non-professional driver data, Reason et al. [33] found a decline in violations with age based on multiple regressions. Blockey et al. and Rimmö [34,35] reached consistent

conclusions. On the contrary, Khan M T. [36] conducted an evaluation of the impact of aging on driving abilities. They categorized drivers into two groups, the young group (under 40) and the elderly group (over 60), and performed various tests that correlated neuropsychological outcomes with driving performance. Their findings indicated a decline in driving performance within the elderly group. However, Hakamies-Blomqvist et al. [37] present a differing perspective. Utilizing survey data from Finland, they compared accident rates between older drivers (aged 65 and above) and younger drivers (aged 26–40). Innovatively, they introduced an additional control to account for low mileage bias across all age groups. Their research, for the first time, revealed that age does not lead to an increase in accidents per kilometer driven. For professional drivers, Dorn and Af Wåhlberg [38] employed two different methodologies, direct calculations and the indirect method of quasi-induced exposure, to investigate the influence of age and experience on bus driver accident involvement. Their research revealed that both young and old drivers had a higher frequency of accidents, which became more evident when their experience was held constant. In a separate study, Hamido et al. [39] conducted a statistical analysis of experiential data from Japanese truck transportation companies. Their findings indicated that, in comparison to younger drivers, age had a significantly reduced impact on older drivers.

There is also significant research on how aging affects taxi driver safety, often making comparisons between older and younger drivers. In earlier years, some viewpoints asserted that younger drivers lacked experience and were more prone to being unsafe [40,41]. Conversely, in recent years, numerous studies have taken a contrasting stance, suggesting that older drivers should be more focused on safety concerns. Vahedi et al. [42] used linear regression models and data from the Driver Behavior Questionnaire (DBQ) to suggest that older drivers may be more susceptible to traffic accidents due to their declining physical abilities. Peng et al. [12] collected self-report questionnaires from 2391 drivers in China and employed a set of comparative analyses and three structural equation models to analyze samples from specific age groups. The results indicated that elderly taxi drivers engage in risky behaviors and traffic accidents more frequently. Sun et al. [8] utilized independent sample *t*-tests to analyze data from 550 taxi drivers aged between 25 and 59. Their findings revealed that older drivers with greater driving experience tended to exhibit slower responses to hazards in video clips and were more inclined to adopt maladaptive driving styles.

However, although there is a significant amount of research on taxi services [43–46], the relationship between driver age and various aspects of the taxi service has been surprisingly understudied. While Koh et al. [47] compared physical health, working hours, driving distances, and accident rates between older and younger drivers, research into other performance factors is limited. More recently, Meng et al. [15] identified age as the only demographic predictor of self-reported fatigue among taxi drivers. Their findings revealed a complex dynamic in which younger drivers earn higher incomes but report greater work intensity and fatigue. Further investigation into the nuanced impacts of aging on additional dimensions of taxi service performance, such as customer satisfaction, driving skills, and earnings, is needed.

In summary, population aging has evidently exerted pressure on workforce sustainability across various industries. Scholars in many fields have comprehensively and profoundly discussed aging's impacts within their respective disciplines. However, there has been limited research thoroughly examining how aging influences taxi service performance. The existing literature on aging's effects in the taxi industry primarily focuses on safety aspects. There remains an inadequate understanding of how aging affects other dimensions of taxi performance such as economic, environmental, and overall metrics. While some initial insights have been gained, it is important to recognize that the relationship between aging and taxi service performance is both nuanced and complex. More empirical research is needed to investigate the multifaceted effects of aging on the economic, safety, environmental, and holistic performance of taxi services. This study aims to help address this gap by

utilizing robust statistical models and a rich dataset to examine how driver age influences various performance metrics. The findings will provide evidence to inform policies on leveraging aging drivers' strengths while mitigating risks.

3. Methodology

3.1. Data Preparation

We employed 14,066,815 trips of single-vehicle operational data from the Ningbo urban area in 2022, where a single vehicle refers to a taxi driven by a sole driver. The urban area includes districts such as Haishu, Jiangbei, Yinzhou, Zhenhai, and Beilun (Figure 1). It covers an area of approximately 2446 square kilometers, with a permanent population of about 4.62 million. The raw data we used were provided by the Bureau of Transportation in Ningbo as part of a taxi performance monitoring program. The operation data of traditional taxis was collected through a dedicated taxi management system of Ningbo, whilst the operational data of ride-hailing taxis was provided through platforms who run the ride-hailing fleet. The operational data consisted of taxi operational order information, including taxi license plates, mileage, earnings, pick-up and drop-off times, and GPS coordinates. Driver profile data, including personal age, gender, birthplace, and the condition of the taxi vehicles they operate, was also provided by the taxi management system of Ningbo. Data cleaning was conducted on the original taxi operational order data to remove the following types of orders: (1) those originating outside the city limits; (2) orders with missing pick-up or drop-off times; (3) trips with a passenger duration of less than 1 min; (4) and trip earnings less than the initial taxi fare.
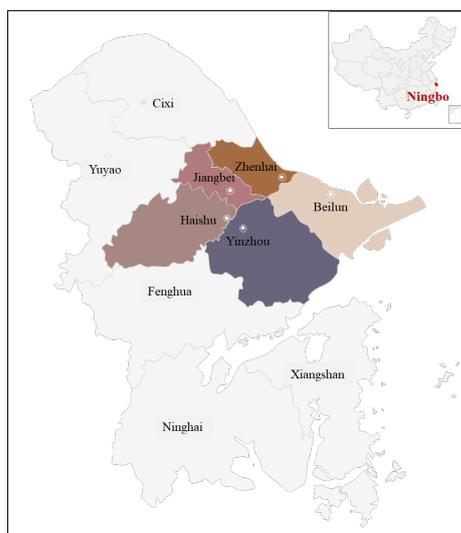
Figure 1. Location of the study area.

3.2. Quantifying Taxi Service Performance

To quantify taxi service performance, the preprocessed taxi operational order data, which has undergone cleaning and adjustments, necessitates further preprocessing. This additional preprocessing encompasses two key steps: computing the total business time for each taxicab and establishing the taxi service performance indicator system.

3.2.1. Calculating the Total Business Time of Each Taxicab

The total business time, denoted as T_{bus}, is the sum of two distinct components: the total trip time (T_{trip}) and the total seek time (T_{seek}). The trip time includes the time from when a passenger is picked up to the time they are dropped off. Each trip duration is logged, and the aggregate of these durations within a given period gives us the total trip time for a taxicab.

$$T_{bus} = T_{seek} + T_{trip} \tag{1}$$

The calculation of the total seeking time (T_{seek}) is intricate because the total seeking time for different drivers varies. To compute the total seeking time, we systematically examined all intervals between consecutive trips in the dataset. Subsequently, we introduce a methodology to differentiate these intervals into categories: seeking time, short idle time, and long idle time.

A short idle time refers to a brief interval typically lasting about 30 min, during which a taxi driver is not actively engaged in transporting passengers. This idle time may arise from a temporary lack of passenger demand, platform order dispatch intervals, or the driver's choice to momentarily cease operations after a continuous period of activity. During a short idle time, drivers usually find a suitable place to park, which slightly prolongs the duration beyond the time spent actively seeking passengers. The term "idle" here reflects the possibility that the taxi is available for service. Similarly, "long idle time" refers to significantly longer periods when the taxi is not in service, often lasting around 120 min or more. This period may include the driver's off-duty time or long intervals of low demand or platform inactivity.

We employ the k-means algorithm to categorize the gaps between service orders for each driver into three clusters, namely seek time, short idle time, and long idle time. A typical clustering result is shown in Figure 2, where the brown cluster represents seeking times, the green cluster represents short idle times, and the blue cluster represents long idle times.
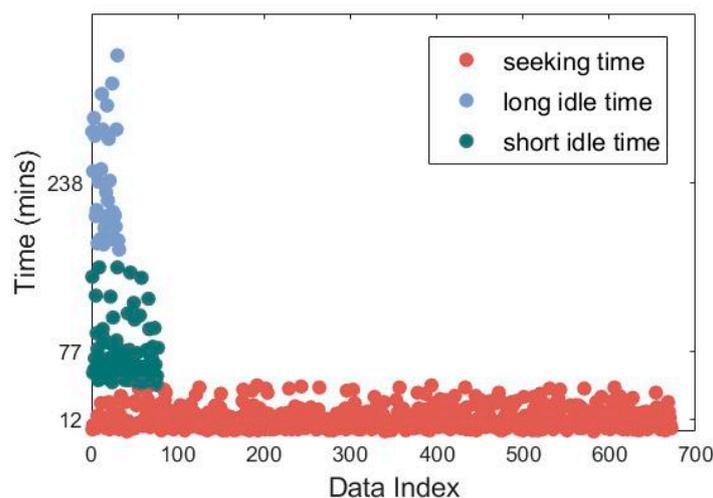
Figure 2. The k-means clustering results of the gaps between service orders for a typical driver.

3.2.2. Establishing a Taxi Service Performance Indicator System

Numerous studies have explored how to quantify taxi service performance. In the realm of economics, researchers often employ variables related to income or net income [1,48,49]. These indicators clearly reflect the economic performance of taxi operations and variables related to workload, such as the cumulative distance traveled by taxis [50], and variables related to operational efficiency [51,52] also shed light on the economic characteristics of taxi operations to some extent. In terms of safety, Alavi et al. [53] defined risky driving behaviors, including intentional violations, unintentional errors, deliberate errors, intentional errors, unintentional violations, and unintentional errors. Risky driving behaviors are often used to quantify the safety performance of taxi operations [12,54,55]. Notably, driving speed stands out as a common indicator for the evaluation of taxi driver safety performance, as previously documented [14]. As a result, we have incorporated speed-related metrics into our assessment of safety performance. In the environmental aspect, pollutants primarily consisting of carbon dioxide emissions and the energy types of existing vehicles have long been a focal point for scholars [56,57].

Drawing inspiration from these prior studies and leveraging our own research data, we have constructed a comprehensive taxi service performance indicator system that

encompasses economic, environmental, and safety performance (Table 1). It is important to note that while we categorize taxi operational performance into these three aspects, it does not imply their independence from one another. For instance, operational efficiency is a key focus in taxi operation. On the one hand, improving operational efficiency can increase drivers' income while reducing gas emissions and fuel consumption [58]. On the other hand, the profit-oriented nature of taxi drivers exposes them to risks when driving on public roads [42], and operational efficiency is closely tied to their earnings. This suggests that operational efficiency is closely linked to performance in economic, safety, and environmental dimensions. Therefore, the taxi operation performance indicators we establish are complementary and closely interconnected.

Table 1. Taxi service performance indicators.

Category	Indicator	Indicator Nature	Indicators Used in Refs	Refs
Economic performance	The total operating revenue	Direct	Total revenue, average daily income, income difference	Zhang et al. [1]
	Average net income per operating hour	Direct	The average net profit per unit time	Qu et al. and Tang et al. [48,49]
	The total occupied travel distance	Indirect	The accumulated distance	Li et al. [50]
	The total operating order volume	Indirect	Daily taxi passenger demand, passenger waiting time, taxi availability, taxi utilization, and average taxi waiting time	Yang et al. [59]
	Average number of orders per operating hour	Indirect	The number of active days, the average number of daily orders	Xiong et al. [60]
	The total operating cost	Indirect	Operation cost, vehicle purchase cost, vehicle contract fee	Li et al. [61]
	Ratio of occupied travel time	Indirect	Time capacity utilization rate and mileage capacity utilization rate	Dong et al. [52]
	Ratio of occupied travel distance	Indirect	Time capacity utilization rate and mileage capacity utilization rate	Dong et al. [52]
	The total number of complaints	Indirect	Complaints	Ahmed et al. [62]
Safety performance	The total number of traffic rule violations	Direct	Risky behaviors	Peng et al., Hassen et al., and Zhao et al. [12,54,55]
	Average occupied travel speed	Indirect	Average occupied trip speed, the average empty time and pick-ups	Tang et al. [63]
Environmental performance	New-energy taxi	Indirect	The vehicle energy use and GHG emissions	Gawron et al. [56]
	The total CO_2 emissions	Direct	The tons of carbon dioxide equivalent and the incurred cost	Mingolla et al. [57]

Detailed explanations and calculation methods for each indicator are shown as follows:

- The total operating revenue (*TOR*)

The total operating revenue (unit: RMB) refers to the sum of all revenue generated by taxi operations. This indicator directly reflects the economic performance of taxis and follows the calculation method as follows:

$$TOR = \sum_{i}^{n} tkinc_i \tag{2}$$

where *TOR* is the total operating revenue and $tkinc_i$ is the revenue of trip *i*.

- The total occupied travel distance (*TOTD*)

The total occupied travel distance (unit: km) refers to the sum of passenger travel distances for taxi operations. This indicator reflects the workload of taxi drivers and indirectly reflects the economic performance of taxis. It follows the calculation method as follows:

$$TOTD = \sum_{i}^{n} tktrip_i \tag{3}$$

where $TOTD$ is the total occupied travel distance and $tktrip_i$ the passenger travel distance of trip i.

- The total operating order volume ($TOOV$)

The total operating order volume (unit: units) refers to the total number of taxi orders for operations. This indicator reflects the workload of taxi drivers and indirectly reflects the economic performance of taxis.

- Average occupied travel speed ($AOTS$)

The average occupied travel speed (unit: km/h) refers to the average passenger-carrying speed of taxi drivers. This metric indirectly reflects the safety of taxis driving, and the calculation method is as follows:

$$AOTS = \frac{\sum_{i}^{n} \frac{tktrip_i}{tkt_i}}{n} \tag{4}$$

where $AOTS$ is the average driving speed, $tktrip_i$ is the occupied travel distance of trip i, tkt_i represents the occupied travel time for trip i, and n is the total number of trips.

- The total operating cost (TOC)

The total operating cost (unit: RMB) refers to the total operational costs for taxis. This indicator reflects the investment costs of taxi drivers and indirectly reflects the economic performance of taxis. The calculation of this indicator involves important variables such as fuel costs, vehicle maintenance expenses, vehicle leasing expenses, and insurance fees. Among these, the calculation of fuel costs is related to a crucial variable, the total driving distance.

The total driving distance (unit: km) includes two components: the total occupied travel distance and the total seeking distance. Before defining the total seeking distance, it is necessary to determine the seeking speed. We reference the study by Wang et al. [64] and introduce the speed coefficient (denoted as SC), representing the ratio of the average empty trip speed to the average occupied trip speed. For each driver, the calculation of seeking speed and seeking distance is as follows:

$$TSD = SC \times AOTS \times T_{seek} \tag{5}$$

$$TDD = TOTD + TSD \tag{6}$$

where TDD stands for the total driving distance. $AOTS$ is the average driving speed, T_{seek} is the driver's total seeking time, $TOTD$ is the total occupied travel distance, and TSD is the total seeking distance.

Based on this, the total operating cost follows the calculation method as follows:

$$TOC = FC_{p.y} \times TDD + VMC_{p,y} + VRC_{p,y} \tag{7}$$

where TOC represents the total operating cost. $FC_{p.y}$ refers to the fuel cost per kilometer for renting taxis of brand p within the age range y (in yuan per kilometer). TDD stands for the total driving distance (in kilometers). $VMC_{p,y}$ refers to the maintenance expenses (in yuan) for brand p taxis within the age range y (in yuan per year). $VRC_{p,y}$ represents the average yearly leasing and insurance fees (in yuan per year) for brand p taxis within the

age range y. The variables $FC_{p.y}$, $VMC_{p,y}$, and $VRC_{p,y}$ are collected by taxi companies, and the range y is defined as a one-year period.

- Average net income per operating hour (*ANIOH*)

The average net income per operating hour (unit: RMB/hour) refers to the average net income per operating hour for taxis. This indicator directly reflects the economic performance of taxis and follows the calculation method as follows:

$$ANIOH = \frac{TOR - TOC}{T_{trip}} \tag{8}$$

where *ANIOH* is the average net income per operating hour. *TOR* is the total operating revenue, *TOC* represents the total operating cost, and T_{trip} is the total trip time.

- Average number of orders per operating hour (*ANOOH*)

The average number of orders per operating hour (unit: units/hour) refers to the average number of orders per operating hour for taxis. This indicator can be used to measure the relative workload and work intensity of drivers, and indirectly reflects the economic performance of taxi services. It follows the calculation method as follows:

$$ANOOH = \frac{TOOV}{T_{trip}} \tag{9}$$

where *ANOOH* is the average number of orders per operating hour. *TOOV* is the total operating order volume and T_{trip} is the total trip time.

- Ratio of occupied travel time (*ROTT*)

The ratio of occupied travel time refers to the utilization rate of effective time for taxis. This indicator is one of the intuitive indicators of taxi operational efficiency and can indirectly reflect the economic performance of taxis. It follows the calculation method as follows:

$$ROTT = \frac{T_{trip}}{T_{bus}} \tag{10}$$

where *ROTT* is the ratio of occupied travel time. T_{trip} is the total trip time and T_{bus} is the total business time.

- Ratio of occupied travel distance (*ROTD*)

The ratio of occupied travel distance refers to the utilization rate of effective mileage for taxis. This indicator is one of the intuitive indicators of taxi operational efficiency and can indirectly reflect the economic performance of taxis. It follows the calculation method as follows:

$$ROTD = \frac{TOTD}{TDD} \tag{11}$$

where *ROTD* is the ratio of occupied travel distance. *TDD* stands for the total driving distance and *TOTD* is the total occupied travel distance.

- The total number of complaints (*TNC*)

The total number of complaints (unit: occurrences) refers to the total number of complaints lodged and processed against taxis. This indicator intuitively reflects the service quality of taxi drivers and can indirectly reflect the economic performance of taxis.

- The total number of traffic rule violations (*TRV*)
- The total number of traffic rule violations (unit: occurrences) refers to the total number of traffic rule violations committed by taxi drivers and processed under the traffic rules of the People's Republic of China. This indicator intuitively reflects the safety performance of taxi drivers.
- New-energy taxi (*NE*)

New-energy taxi is a binary variable indicating whether the taxis driven by drivers belong to the category of new-energy taxis. New-energy taxis include pure electric taxis and plug-in hybrid electric taxis. This indicator indirectly reflects the environmental performance of taxis.

- The total CO_2 emissions (*TCO2*)

The total carbon dioxide emissions (unit: kg) are mainly influenced by the driving distance and the energy type, which is calculated as follows:

$$TCO2 = EF \times TDD \tag{12}$$

where *TCO*2 represents the total CO_2 emissions and *EF* is the carbon dioxide emission factor corresponding to the taxi's energy type (e.g., diesel, gasoline, electric power, CNG, etc.); the values were taken from references [65–67]. *TDD* is the total driving distance.

3.3. Statistical Analysis

3.3.1. Multiple Regression Model

Existing research on how aging affects taxi service performance has not provided us with sufficiently detailed hypotheses to support our study. To enhance the reliability of our research findings, it is essential to conduct a preliminary investigation into the variations in taxi service performance between different age groups, based on existing data. To achieve this goal, we utilized the method of independent-sample *t*-tests to compare the overall taxi service performance between two age groups (the older group and the younger group).

Prior to conducting the analysis, it is imperative to establish clear age group definitions. Upon reviewing the existing literature, we have observed that the age of 50 is frequently utilized to distinguish between non-elderly and elderly taxi drivers [68,69]. Therefore, we categorize drivers into two groups based on the age of 50 as the dividing point: the older group (above 50) and the younger group (under 49).

Subsequently, we intend to employ the MRM to delve deeper into the impact of aging on taxi service performance. Drawing from prior research on the effects of aging, it is evident that age serves as a crucial quantitative measure of aging. Therefore, our study incorporates driver age as a fundamental explanatory variable, while controlling for other relevant variables. We will establish a comprehensive multiple regression equation to thoroughly investigate how aging influences taxi service performance, quantifying this impact.

Our quantification of aging primarily relies on the driver's age. Additionally, we take into consideration various control variables. The personal behaviors of taxi drivers, also referred to as driving strategies, have long been recognized as significant factors influencing the performance of taxi services. We will examine drivers' driving strategies during their work from two dimensions: spatial and temporal.

In the temporal dimension, we will consider the use of the daily average work time, which is calculated as follows:

$$T_{work} = T_{bus} + T_{si} \tag{13}$$

$$dt = \frac{T_{work}}{days} \tag{14}$$

where dt is the daily average work time. T_{work} is the total work time, T_{si} is the total short idle time defined in Section 3.2.1., T_{bus} is the total business time, and *days* represents the number of operational days with recorded taxi service.

In the spatial dimension, we will take into account the average pick-up point (drop-off point) demand intensity. Demand intensity, as defined by Wang [70], follows the calculation method below.

We adopt a grid generation method to divide the study area into 1 km × 1 km grids and calculate the demand intensity of taxis based on spatial grid units. The mathematical expression for this is as follows:

$$DI = \frac{AN_{cell-i}^{pick-up}}{\sum\limits_{i=1}^{N} AN_{cell-i}^{pick-up}} \tag{15}$$

where DI represents the demand intensity of taxis for the spatial unit to which the drop-off point (or pick-up point) belongs. AN represents the number of taxi pick-up points in the spatial unit and $i(= 1, 2, \cdots, N)$ represents the spatial unit number.

The demand intensity of proximate taxis at the drop-off point upon completion of a prior trip serves as a reflection of the prospective success in securing the subsequent passenger, thereby exerting a direct influence on the driver's inaugural cruising determination and, by extension, impacting their work arrangement. Furthermore, the demand intensity at pick-up locations is duly accounted for. The demand intensity at the drop-off (or pick-up) point is delineated as the proportion of taxi pick-up points situated within the spatial unit corresponding to the drop-off (or pick-up) point, relative to the aggregate count of taxi pick-up points encompassing all spatial units. And the average pick-up point (drop-off point) demand intensity refers to the average demand intensity at each pick-up point (drop-off point) per trip.

Based on the preceding content, the description of the selected variables is shown in Table 2.

Table 2. Description of the variables (N = 3137).

Variable	Symbol	Mean	S.D.	Min	Max
Log—driver's age	ln*age*	3.842	0.169	3.091	4.431
An elderly driver (0–1 variable)	*old*	0.431	0.495	0	1
Average drop-off point demand intensity	*offdi*	0.582	0.187	0	0.992
Average pick-up point demand intensity	*ondi*	0.759	0.321	0	1.755
Log—daily average work time	ln*dt*	2.649	0.340	0.326	3.155
Log—the total operating cost	ln*TOC*	11.02	0.612	8.155	11.96
Log—average number of orders per operating hour	ln*ANOOH*	1.011	0.250	−2.179	2.319
Log—the total CO_2 emissions	ln*TCO2*	8.992	0.859	3.800	10.41
Log—the total occupied travel distance	ln*TOTD*	10.51	0.800	5.400	11.82
Log—the total operating revenue	ln*TOR*	11.47	0.780	6.578	12.88
Log—the total operating order volume	ln*TOOV*	8.133	0.852	2.773	9.585
Log—average number of orders per operating hour	ln*ANIOH*	2.620	0.864	0.00277	6.580
Ratio of occupied travel time	*ROTT*	0.667	0.0784	0.315	1.000
Ratio of occupied travel distance	*ROTD*	0.721	0.0670	0.351	0.992
The total number of complaints	*TNC*	1.018	1.583	0	17
The total number of traffic rule violations	*TRV*	2.886	2.832	0	43
Log—average occupied travel speed	ln*AOTS*	3.903	0.104	2.940	4.787
New-energy taxi (0–1 variable)	*NE*	0.182	0.386	0	1

S.D.—standard deviation.

- Multiple Linear Regression Model

To investigate the impact of aging on driver performance, we first conducted an analysis using the multiple linear regression model. We estimated the following equation using taxi driver operational data from 2022:

$$Taxi = \alpha + \beta \times \ln age + \gamma \times offdi + \delta \times ondi + \lambda \times \ln dt + \theta \times X + \varepsilon \tag{16}$$

where α is the constant, representing the intercept term of the model, while β, γ, δ, λ, and θ are the estimated coefficient. *Taxi* is the performance indicator in continuous variable form, $\ln age$ is the logarithmic form of the driver's age, $offdi$ represents the average drop-off

point demand intensity, *ondi* represents the average pick-up point demand intensity, and ln *dt* stands for the daily average work time. *X* represents other potentially controllable variables and *ε* is the error term.

- Multiple Logit Regression Model

The dependent variables, whether driving a new-energy taxi (*NE*), are binary variables, for which we propose a multiple logit model. We estimated the following equation using taxi driver operational data from 2022:

$$\log it\{P(NE = 1)\} = \alpha + \beta \times \ln age + \gamma \times offdi + \delta \times ondi + \lambda \times \ln dt + \theta \times X + \varepsilon \quad (17)$$

where *P* represents the probability of the occurrence of *NE* (*NE* = 1 indicates that the event occurred, *NE* = 0 indicates that the event did not occur). *α* is the constant, representing the intercept term of the model, while *β*, *γ*, *δ*, *λ*, and *θ* are the estimated coefficient. ln *age* is the logarithmic form of the driver's age, *offdi* represents the average drop-off point demand intensity, *ondi* represents the average pick-up point demand intensity, and ln *dt* stands for the daily average work time. *X* represents other potentially controllable variables and *ε* is the error term.

- Tobit Model

The variables for the total number of complaints (TNC) and the total number of traffic rule violations (TRV) contain a small portion of values as 0, but are continuously distributed among positive values. We estimated the following equation using taxi driver operational data from 2022:

$$\begin{cases} y = y^* \text{ if } y^* > 0 \\ y = 0 \text{ if } y^* \leq 0 \end{cases} \quad (18)$$

Based on the following equation, the Tobit regression model is employed to examine the relationship between these variables and aging:

$$y^* = \alpha + \beta \times \ln age + \gamma \times offdi + \delta \times ondi + \lambda \times \ln dt + \theta \times X + \varepsilon \quad (19)$$

where y^* represents the variables for the total number of complaints and the total number of traffic rule violations. *α* is the constant, representing the intercept term of the model, while *β*, *γ*, *δ*, *λ*, and *θ* are the estimated coefficient. ln *age* is the logarithmic form of the driver's age, *offdi* represents the average drop-off point demand intensity, *ondi* represents the average pick-up point demand intensity, and ln *dt* stands for the daily average work time. *X* represents other potentially controllable variables and *ε* is the error term.

3.3.2. Structural Equation Model

To further explore the direct and indirect impacts of aging on performance indicators, we have employed the SEM. While the MRM can only relate to a single dependent variable, providing direct effects with other conditions held constant by handling multiple independent variables, one of its drawbacks is its inability to derive indirect effects by comparing results from different MRMs. Furthermore, due to the multiple control variables we have incorporated into our model, calculating the direct and indirect effects of aging through the MRM would be complex and impractical.

In contrast, the SEM allows us to deduce comparable effects by consolidating the multiple relationships among variables using standardized coefficients. The SEM enables us to immediately reveal the direct and indirect impacts of aging on each performance indicator of taxi services. Additionally, the SEM addresses the issue of partial correlations, such as the partial correlation between the total occupied travel distance and the total operating order volume. Therefore, in our study, we have utilized both the SEM and MRM simultaneously.

4. Results

4.1. Statistical Analysis Results

4.1.1. Results of MRM Analysis

We conducted an analysis of the mean values of all taxi service performance indicators across two different age groups using a two-sample *t*-test (Figure 3). A significant divergence was observed in all other performance indicators when comparing the two age groups. The two-sample *t*-test results suggest that, from an economic performance perspective, the older age group outperformed the younger cohort across several indicators. However, when evaluating environmental and safety performance, the trend was noticeably inverted.
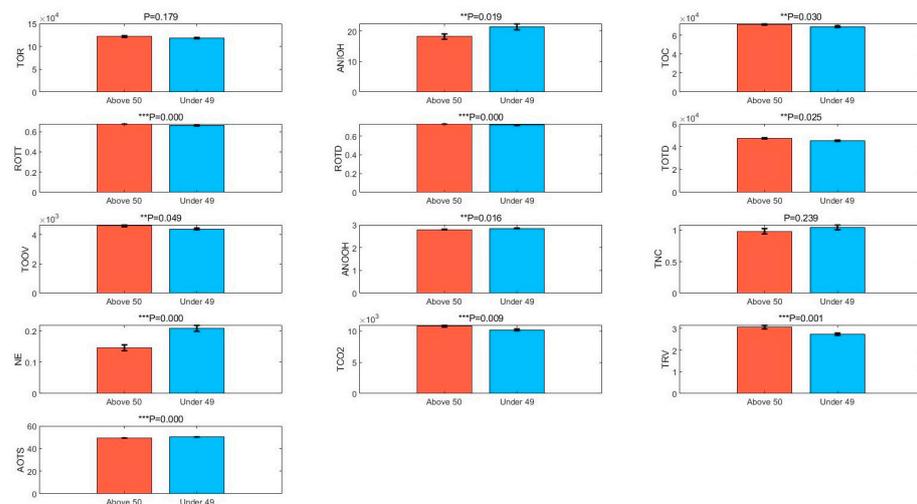
Figure 3. Comparison of taxi service performance indicators across two age groups. (Note: ** *p* < 0.05, *** *p* < 0.01, indicating the significance levels of differences in means of taxi performance indicators among two age groups. Error bars are standard errors.)

Based on the aforementioned preparatory work, we developed a series of MRMs, the results of which are presented in Table 3. To ensure the robustness of the models, the heteroskedasticity test was conducted by grouping the drivers based on their age and replacing the core explanatory variable "*age*" with the binary variable "*old*". For all models, we utilized robust standard errors to control potential heteroskedastic effects.

Previously, drivers had been classified according to age. In the process of evaluating model robustness, we used the young driver group as the baseline reference and introduced a binary variable, "*old*", for the older driver group. Table 4 presents the results of our robustness tests, which demonstrate that the sign and significance of the "*old*" variable are consistent with the "*age*" variable in the MRM, ensuring the model's stability.

According to the results of the MRM, significant correlations are observed between all the performance indicators and the key explanatory variable "*age*". The multivariate regression analysis indicates that as the age of drivers increases, they become more experienced but also more conservative. Specifically, older drivers are likely to have richer road experience and a better understanding of passenger needs, enabling them to complete tasks for passengers more efficiently. As a result, they perform better on operational efficiency-related metrics (*ROTT* and *ROTD*) and demonstrate better service attitudes, as reflected in fewer customer complaints (*TNC*). In addition, compared to younger drivers, older drivers may pursue more job stability by treating taxi driving as their career rather than a part-time job. This stable working pattern leads to higher cumulative workload metrics (e.g., *TOTD*, *TOOV*, and *TOR*) for older drivers compared to younger ones. The total operating costs also exhibit a significant positive correlation with driver age, likely due to its close relation with the above metrics. However, as the age of drivers increases, the "average net income per operating hour" (*ANIOH*) and "average number of orders per

operating hour" (*ANOOH*) metrics decrease significantly. This trend may be attributed to older drivers' preference for a more relaxed working pace, which could involve more rest periods or extended waiting times, thus diminishing their average net income and average order number per hour. In general, older drivers demonstrate superior performance in most economic metrics.

Table 3. MRM determining the effect of age on performance indicators.

Variables	(1) lnTOR	(2) lnANIOH	(3) lnANOOH	(4) lnTOTD	(5) lnTOOV	(6) lnTOC	(7) ROTT	(8) ROTD	(9) TNC	(10) lnTCO2	(11) NE	(12) TRV	(13) lnAOTS
ln*age*	0.275 ***	−0.178 ***	−0.104 ***	0.368 ***	0.360 ***	0.223 ***	0.024 ***	0.020 ***	−0.778 **	0.478 ***	−1.923 ***	1.245 ***	−0.073 ***
	(3.83)	(−2.68)	(−5.13)	(4.89)	(4.94)	(3.65)	(3.54)	(3.39)	(−2.50)	(5.86)	(−7.28)	(3.42)	(−7.41)
offdi	3.001 ***	−0.516 ***	0.092	2.940 ***	3.723 ***	2.351 ***	0.116 ***	0.092 ***	−2.625 ***	2.650 ***	2.308 ***	−0.270	−0.485 ***
	(24.08)	(−3.68)	(1.50)	(23.26)	(35.07)	(24.42)	(10.23)	(9.23)	(−4.11)	(20.67)	(4.88)	(−0.44)	(−23.25)
ondi	−0.969 ***	−0.050	0.009	−0.970 ***	−1.358 ***	−0.626 ***	−0.044 ***	−0.030 ***	3.579 ***	−0.869 ***	−0.838 ***	0.392	0.215 ***
	(−12.92)	(−0.66)	(0.29)	(−12.52)	(−20.17)	(−10.41)	(−6.95)	(−5.23)	(10.05)	(−10.77)	(−2.91)	(1.00)	(18.81)
ln*dt*	1.070 ***	0.705 ***	−0.067 ***	1.058 ***	1.323 ***	0.458 ***	−0.155 ***	−0.136 ***	−1.159 ***	1.244 ***	−0.022	1.840 ***	−0.024 ***
	(25.43)	(13.83)	(−3.28)	(24.54)	(36.06)	(14.93)	(−37.92)	(−37.75)	(−5.93)	(27.97)	(−0.14)	(10.97)	(−3.89)
Observations	3137	3137	3137	3137	3137	3137	3137	3137	3137	3137	3137	3137	3137
Model	MRM	MRM	MRM	MRM	MRM	MRM	MRM	MRM	Tobit	MRM	Logit	Tobit	MRM
Adjusted R2	0.407	0.495	0.496	0.373	0.486	0.299	0.490	0.510	/	0.365	/	/	0.244

Note: *** $p < 0.01$, ** $p < 0.05$. Each column represents a separate regression model. Robust t-statistics in parentheses. Each column signifies an individual regression model. In equations where the dependent variables were "ln*ANIOH*" and "*TNC*", "ln*TOR*" was additionally incorporated as a control. Similarly, in equations involving "ln*ANOOH*" as the dependent variable, "ln*TOR*" and "ln*TOOV*" were also included as a supplementary control. The robustness testing regressions adhere to an analogous methodology.

Table 4. Robust check of age impacts on performance indicators.

Variables	(1) lnTOR	(2) lnANIOH	(3) lnANOOH	(4) lnTOTD	(5) lnTOOV	(6) lnTOC	(7) ROTT	(8) ROTD	(9) TNC	(10) lnTCO2	(11) NE	(12) TRV	(13) lnAOTS
old	0.038 *	−0.065 ***	−0.039 ***	0.068 ***	0.065 ***	0.040 **	0.007 ***	0.004 **	−0.181 *	0.092 ***	−0.465 ***	0.453 ***	−0.017 ***
	(1.76)	(−2.99)	(−6.02)	(2.99)	(2.96)	(2.18)	(3.20)	(2.52)	(−1.74)	(3.77)	(−4.76)	(3.79)	(−4.97)
offdi	3.015 ***	−0.512 ***	0.096	2.956 ***	3.739 ***	2.361 ***	0.116 ***	0.093 ***	−2.654 ***	2.670 ***	2.174 ***	−0.255	−0.488 ***
	(24.18)	(−3.64)	(1.56)	(23.35)	(35.14)	(24.55)	(10.27)	(9.27)	(−4.14)	(20.80)	(4.69)	(−0.41)	(−23.23)
ondi	−0.978 ***	−0.049	0.009	−0.981 ***	−1.369 ***	−0.633 ***	−0.045 ***	−0.030 ***	3.597 ***	−0.883 ***	−0.755 ***	0.370	0.217 ***
	(−13.03)	(−0.65)	(0.30)	(−12.64)	(−20.26)	(−10.52)	(−7.03)	(−5.32)	(10.07)	(−10.92)	(−2.68)	(0.95)	(18.86)
ln*dt*	1.068 ***	0.705 ***	−0.067 ***	1.057 ***	1.322 ***	0.457 ***	−0.155 ***	−0.136 ***	−1.143 ***	1.242 ***	−0.020	1.852 ***	−0.024 ***
	(25.32)	(13.83)	(−3.27)	(24.41)	(35.78)	(14.87)	(−37.93)	(−37.78)	(−5.87)	(27.76)	(−0.12)	(11.05)	(−3.90)
Observations	3137	3137	3137	3137	3137	3137	3137	3137	3137	3137	3137	3137	3137
Model	MRM	MRM	MRM	MRM	MRM	MRM	MRM	MRM	Tobit	MRM	Logit	Tobit	MRM
Adjusted R2	0.404	0.496	0.497	0.368	0.483	0.296	0.489	0.509	.	0.359	.	.	0.234

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust t-statistics in parentheses.

However, older drivers underperform in two environmental metrics (*TCO2* and *NE*). Factors like conventional vehicle models, older vehicle age, and a higher cumulative workload may contribute to these observed differences. As the age of drivers grows, their cumulative workload increases, and they may become overconfident in their driving skills due to abundant experience. Excessive workload and overconfidence could lead to negligence, which may partially explain their lower compliance to traffic rules (*TRV*) compared to younger counterparts. In addition, older drivers exhibit a lower average occupied travel speed (*AOTS*) while driving taxis with passengers. This occurrence may be attributed to the aging process, leading to a decline in their physical capabilities and cognitive functions, prompting a more cautious approach in their passenger-carrying journeys. Considering the two safety performance indicators in combination, we believe that the performance of older drivers is slightly inferior to that of younger drivers. These

conclusions align with the results from the two-sample *t*-tests and gain further support from the robustness checks.

4.1.2. Results of SEM Analysis

Subsequently, we delve deeper into the direct and indirect pathways through which aging affects the performance of taxi services using the SEM model. This exploration surpasses the capabilities of the MRM, given the latter's inability to extract indirect effects through the comparison of outcomes derived from distinct MRMs. For example, based on the coefficient of age (ln*age*) in Table 3, a 1% increase in a driver's age leads to a 0.275% increase in their total revenue. In a similar vein, a 1% increase in age is associated with a 0.368% decrease in total occupied travel distance. However, this does not imply that age has a greater impact on the total occupied travel distance. The units and magnitudes of explanatory variables, such as the total revenue and total occupied travel distance, vary across different MRMs, which significantly affects the size of the aging coefficient.

Directly comparing the results from the MRM and SEM is challenging, as the coefficients from different MRMs are not directly comparable. Nonetheless, in both models, the influence of each explanatory variable on the response variable is consistently assessed. This further underscores that all the identified correlations between aging and taxi operational performance metrics can be interpreted as robust. It should be noted that no latent variables were specified in the SEM; instead, the standardized path coefficients were estimated based on a path analysis. For the SEM analysis, only four direct performance metrics were selected. In addition, the model includes one extra control variable—the average demand intensity at passenger drop-off points (*offdi*). The relevant paths of *offdi* were not depicted in Figure 4 due to the insignificance of the path from ln*age* to *offdi*. Finally, the goodness-of-fit statistics fell within expected ranges for this model based on the 2022 operational data of taxi drivers in urban Ningbo: comparative fit index (CFI) = 0.999 > 0.90, root mean square error (RMSE) = 0.041 < 0.05, standardized root mean square residual (SRMR) = 0.005 < 0.05.
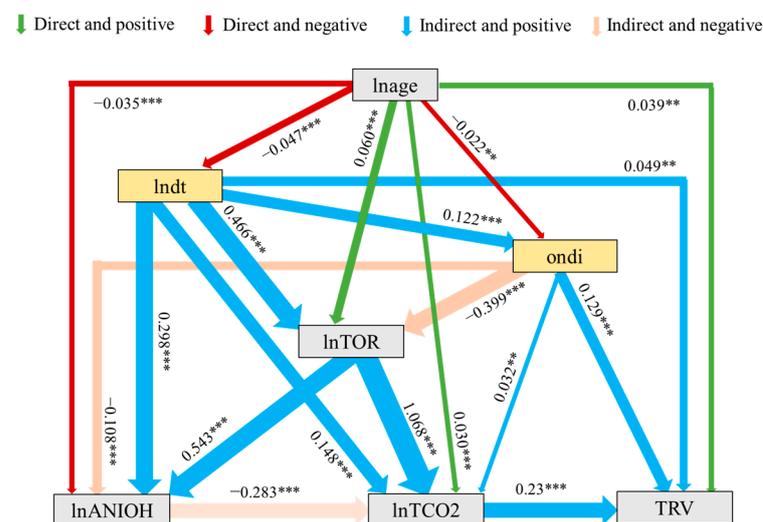
Figure 4. SEM determining the effect of age on performance indicators. (Note: the asterisks indicate the statistical significance level based on *p*-values: ** $p < 0.05$, *** $p < 0.01$. The numbers adjacent to the arrows represent standardized path coefficients, indicating the extent to which the standard deviation of the dependent variable changes when each independent variable changes by one standard deviation. The thickness of the arrows is proportional to the strength of the standardized path coefficients.)

Using the results from the SEM, the direct and indirect effects of aging on standardized path coefficients are illustrated in Figure 4 and Table 5. In the results presented in Table 5, it can be observed that a significant portion of the impact is indirectly mediated through

daily working hours (ln*dt*) and the average demand intensity at pick-up points (*ondi*). For instance, the standardized path coefficient of aging's direct impact on net income per operating hour is −0.035, but its indirect effects through the average demand intensity at pick-up points and daily working hours are 0.002 and −0.014, respectively. This results in a net effect of −0.047 for aging on net income per operating hour, indicating that the indirect effects exacerbate the negative impact of aging. This suggests that measures aimed at mitigating the negative effects of aging on taxi operations could potentially be taken by altering daily working hours and the choice of pick-up locations.

Table 5. Pathways of effect influence.

	ln*TOR*		ln*ANIOH*		ln*TCO2*		*TRV*	
	Effect	Ratio	Effect	Ratio	Effect	Ratio	Effect	Ratio
Direct effect	0.060	66.17%	−0.035	68.12%	0.030	79.66%	0.039	88.35%
Indirect effect from *ondi*	0.009	9.68%	0.002	4.62%	−0.001	1.87%	−0.003	6.43%
Indirect effect from ln*dt*	−0.022	24.15%	−0.014	27.26%	−0.007	18.47%	−0.002	5.22%
Net effect	0.047		−0.047		0.022		0.034	

Note: according to Figure 4, we can directly infer the standardized path coefficients from age to the dependent variables. Indirect effects are calculated as the product of all effects in a single path. The net effect is the sum of all direct and indirect effects. The ratios are the absolute values of direct or indirect effects divided by the sum of the absolute values of all effects. From this, we derived the effects of direct and indirect influences, as shown in Table 5.

4.2. Discussion

4.2.1. Effects of Aging on Economic Performance of Taxi Service

This study quantifies the service economic performance of taxis from multiple aspects, including cumulative workload (total operating order volume, total occupied travel distance, total operating cost, and total operating revenue), operational efficiency (ratio of occupied travel time and ratio of occupied travel distance), service quality (total number of complaints), and time efficiency (average net income per operating hour, average number of orders per operating hour). Our results indicate that older drivers demonstrate better performance in the metrics of operational efficiency, service quality, and cumulative workload. This suggests their pursuit of more stable working patterns, coupled with their extensive road experience and a keen understanding of passenger needs, which enable them to execute tasks with greater efficacy. However, the more conservative personality of older drivers makes them prefer maintaining a more comfortable pace of work rather than profit maximization, thus attenuating their time efficiency.

There is a paucity of research investigating the correlation between the age of taxi drivers and the economic performance of taxi services. In a seminal study, Koh et al. [47] divided 256 drivers from Singapore into a young group (28–44 years old) and an old group (45–63 years old). They compared parameters such as physical health, working hours, driving distances, and accident rates between the two age groups, finding no significant differences across these variables, which stands in contrast to our findings. More recently, Meng et al. [15] examined the temporal patterns of driving fatigue and performance among 50 male taxi drivers in Hong Kong, leveraging self-reported surveys and driving simulator experiments. They discovered that younger drivers (under 35 years old) had higher daily net incomes, a greater frequency of serving passengers, and higher work intensity compared to their older counterparts. These findings align more closely with our results. However, the robustness and depth of our study findings are enhanced by the employment of two-sample *t*-tests, multivariate regression models, and robustness checks, as well as structural equation modeling. This lends a higher degree of confidence and validity to our results.

4.2.2. Effects of Aging on Safety Performance of Taxi Services

Our study used the cumulative number of times that traffic rules were violated and the average occupied travel speed in 2022 as two metrics to quantify safety performance. Our research finds that driver age exhibits a significant positive correlation with the direct

metric related to traffic rule violations, suggesting that older drivers may have a lower compliance with traffic regulations as their age increases. This could be attributed to their overconfidence in driving skills due to abundant experience or a greater cumulative workload [71]. Additionally, with the increasing age of drivers, older drivers tend to exhibit a lower average occupied travel speed while driving taxis with passengers. Possible explanations may lie in the decline in their physical and cognitive abilities as they age, forcing them to exercise greater caution in passenger-carrying journeys. In general, the safety performance of older drivers falls slightly behind that of younger drivers, especially in terms of the direct indicator of traffic rule violations. This contrasts with research suggesting that younger drivers' lack of experience makes them more prone to risky driving behaviors [40,41], but is consistent with studies recognizing older drivers' greater safety concerns [12,42,72,73].

4.2.3. Effects of Aging on Environmental Performance of Taxi Services

Taxis significantly contribute to urban transport emissions [74] and have received much research attention [56,57]. Despite this, there appears to be a dearth of research exploring how the aging of taxi drivers impacts the environmental performance of taxi services. In this study, two metrics for environmental performance are established: the utilization of new-energy taxis (0 = No, 1 = Yes) and the total CO_2 emissions. The results from multivariate regression analysis indicated that older drivers demonstrated a decreased propensity towards using new-energy taxis and produced higher levels of CO_2 emissions during their operational activities. This suggests that older drivers may negatively impact environmental performance, possibly because they are more accustomed to familiar taxis that have accompanied them for years. Given the considerations of cost and preference, older drivers tend to favor non-new-energy vehicles. The energy types of the taxis they operate and their increased workload contribute to higher CO_2 emissions.

4.2.4. Implications of Findings

Collectively, across all regression models implemented in our study, drivers' driving strategies were employed as the primary control variable. The outcomes derived from a multivariate regression analysis revealed that, with the exception of the average net income per operating hour and the average number of orders per operating hour, aging had a positive effect on the majority of metrics related to taxi service economic performance. Conversely, it exhibited a markedly negative impact on both safety performance and environmental performance. Subsequently, we incorporated the direct metrics in the taxi service performance index system and employed structural equation modeling to explore the direct and indirect influence paths of aging on them. The results found the net effects of aging on these metrics were consistent with the multivariate regression analysis results. Furthermore, it was discerned that a significant portion of the influence was indirectly accounted for through variables such as the average daily working hours and the average demand intensity of pick-up points. In the influence path of the average net income, the indirect effect accounted for about one third, and age exacerbated the negative impact on this metric through the indirect effect, making the absolute value of the net effect larger than the direct effect's value.

Therefore, drivers can effectively mitigate the negative effects of age on taxi service performance by adjusting their daily working hours and boarding locations. Longer working hours can generate more output, but also intensify driver fatigue [68], posing safety hazards. Drivers should coordinate the ratio of operating time to rest time based on their own conditions. The government should implement stricter laws to restrict drivers' working hours so that they can schedule rest more effectively [12]. The demand intensity around boarding locations is seen as an important factor affecting taxi drivers' income [75], but denser boarding demand areas also mean traffic congestion and complex traffic conditions, which may pose safety hazards for drivers and more CO_2 emission concerns [76]. Overall, the results of the MRM indicate that the average daily working

hours and the average intensity of demand at pick-up points partially mediate the effect of aging on the performance metrics. This implies that controlling for drivers' working hours and passenger pick-up preferences can mitigate the pressures of aging on taxi service performance to some extent.

5. Conclusions

This research provides an in-depth investigation of how taxi driver age affects various dimensions of taxi service performance, including economic, safety, and environmental metrics. The empirical analysis using robust statistical models reveals that aging has mixed effects. Older drivers demonstrate strengths in service efficiency, service quality, workload output, and other economic performance areas, owing to their extensive experience, familiarity with passenger needs, and preference for more stable work patterns. However, they underperform in time efficiency metrics like income per hour worked due to a more conservative working style. More notably, aging exhibits negative effects on safety and environmental performance. The violation of traffic regulations was significantly higher among older drivers, indicating lower compliance, possibly due to overconfidence-induced negligence. Additionally, the decreased cognitive and physical capabilities in older drivers may contribute to the lower average occupied travel speed. Moreover, older drivers show less inclination to use new-energy vehicles and generate higher CO_2 emissions during operations.

By exploring the mediating role of daily working hours and pick-up location demand intensity, this study provides valuable practical insights. Regulating drivers' working hours and passenger searching preferences can partially mitigate the pressures of aging on the taxi industry. Governments should consider stricter regulations on driving hours, while drivers must balance their operating time and rest time based on individual circumstances. Additionally, avoiding overcrowded pick-up areas with congestion and complex traffic could improve safety and emissions. Overall, this research fills a gap in the knowledge on aging's effects within the taxi industry. The empirical findings based on robust analyses provide strong evidence that aging has a nuanced, multi-faceted impact. Balanced policies should consider economic, safety, and environmental aspects to enable aging drivers to leverage their strengths while minimizing downsides.

Most traditional taxi drivers have started to offer taxi-hailing services since 2019 in Ningbo, an indication that Ningbo's traditional cruising taxi service and ride-hailing services have gradually merged. As a result of this convergence, it is not possible to clearly distinguish the orders received by taxi drivers from traditional cruise taxi services and ride-hailing services. Therefore, in our analysis, we did not distinguish the potential dual role of taxi drivers as online ride-hailing drivers. Future research focusing on the intersection of traditional taxi services and online ride-hailing may be worth further investigation.

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