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Exploring The Cognition and Attitude of Vocational High School Students Towards Autonomous Vehicles

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Abstract

With the growing emphasis on vocational education in China and the advent of the Internet of Things (IoT) and Connected and Autonomous Vehicles (CAVs), high school students, as future leaders of society, are poised to play an active role in advancing autonomous vehicle (AV) technology. To investigate the fundamental knowledge, intentions, and educational requirements of vocational high school students regarding AVs, we conducted a nationwide online questionnaire. Additionally, a Bayesian probit model was proposed to assess the final decisions of vocational high school students when deciding to participate in national college/university entrance exams and to determine whether education in AVs benefits them. The results indicate that background information, including gender, grade, speciality, and school location, is significantly correlated with participants' final choices. As for basic cognition, application areas, and cognitive sources of AVs are significant factors for vocational high school students. In terms of intention, students' attitudes towards AVs are closely tied to their final choice. Regarding educational needs, the content, value, methodology, and impact of AV education are crucial factors influencing vocational high school students' final choices and should be considered key areas of focus in education. Based on the analysis results, corresponding educational strategies are proposed to improve high school students' knowledge of AVs from the perspectives of educators, students and policymakers.

1. Introduction

Over the past decade, vocational education in China has undergone tremendous changes and garnered increased attention nationwide and within mainstream education. In 2022, the first World Conference of Vocational Technology Education Development was held in Tianjin, China, sharing vocational education experiences with the world and showcasing China's approach and insights. Furthermore, establishing effective mechanisms and platforms for global communication and cooperation is a significant means by which vocational education can support the new development paradigm and promote high-quality development worldwide.

On the other hand, with the emerging technologies in the fields of information technology, communication big data and artificial intelligence (AI), a large number of technological achievements have streamed into high school students' lives, making their lives more convenient and also changing their way of thinking. Therefore, as a crucial component of the national education system and human resource development, vocational education plays a pivotal role in fostering the future success of youth, particularly future college students who will become the leaders of society. It is imperative for them to acquire knowledge related to artificial intelligence.

Among the advanced technologies, autonomous vehicles (AVs) are considered a significant carrier as a critical part of the Internet of Things (IoTs) and Smart City, attracting numerous corporations and manufacturers around the globe. As future leaders, vocational high school students should be knowledgeable about AV technology, and their attitudes towards AVs can provide insights into how they perceive AVs in their future lives. Therefore, the objective of this study is to investigate high school students' knowledge of AV technology and its applications, as well as intentions and education needs regarding AVs. By understanding their cognition and attitudes, we aim to enable these students to become active participants in the era of intelligence and beneficiaries of intelligent life, while laying a solid foundation for their adaptation to future smart transportation and smart driving environments.

Therefore, some research questions are presented as follows:

(1) What is the level of basic cognition about AVs among vocational high school students?
- What is their understanding of AV technology, its applications, and potential impacts?
- How do they perceive the safety and ethical concerns associated with AVs?

(2) What factors influence students' intention towards AV-related learning and careers?
- What are their attitudes towards AVs and their potential role in society?
- How does their knowledge and exposure to AV technology affect their interest in related fields?
- What are their motivations and aspirations for pursuing AV-related education and careers?

(3) What are the educational needs of students regarding AV technology, and do these correlate with their academic choices?
- What are their preferences for learning methods and content related to AVs?
- What are their expectations for the value and impact of AV education?
- How does their interest in AV education relate to their choice between science and engineering or liberal arts?

2. Literature Review

In recent years, emerging technologies such as big data, AI, and intelligent algorithms have been applied in vocational education. Li et al. (2019) applied big data to higher vocational and technical education. Three steps were presented: determining the objectives, distinguishing between different types of problems, and incorporating them into actual classroom teaching practice. The results indicated that the smart system can be directly adopted to investigate the problems for higher vocational and technical education. Zeng et al. (2020) explored the application of teaching and practice methods involving big data and artificial intelligence in vocational education and demonstrated innovative applications of software technology. The results may facilitate the reform and development of vocational education. Chen et al. (2022) presented a data mining method to enhance student satisfaction with the teaching quality in high vocational education. A questionnaire was designed, and a survey was conducted to understand the current status of teaching quality in the basic entrepreneurship curriculum. The main factors were identified, and the results can be applied to enhance teaching quality in vocational education. Ma (2022) concentrated on English teaching with artificial intelligence for course selection in vocational education. The dataset was collected from students' course feedback, and a K-means neural network and a convolutional neural network were employed to cluster the data and improve accuracy via recursive elimination, respectively. The analysis demonstrated that the accuracy and precision exceeded 92%.

Among intelligent algorithms, deep learning plays an important role in artificial intelligence applications for vocational education.Tao (2025) improved the quality of vocational education in higher vocational colleges based on deep learning technology. GRU-Attention network was employed to analyse student behaviour and predict engagement levels, and the results highlighted the model's efficacy in improving educational management and student support. Lu et al. (2025) proposed a deep learning-based student performance prediction framework catered to vocational education environments with multi-source behavioural data. Principal component analysis (PCA) was used to extract dynamic behavioural features, and a gated recurrent unit (GRU) model was applied to predict student performance in vocational education. The framework offered a practical tool for educators and improved decision-making in vocational training environments.

In line with the requirements of the new times, opportunities coexist with challenges in vocational education. Di Valentin et al. (2015) presented the concept and a prototypical implementation of a recommender system for vocational education and training using adaptive social media, and suggested that social media skill level may benefit the teaching and learning process. From the perspective of teachers, Lei (2018) analysed the seven professional qualities in vocational education and proposed a cultivation path by integrating self-cultivation and institutional training. The suggestions for cultivating teachers' professional quality were enlightening. Ma (2019) and Zhang et al. (2020) summarised the opportunities and challenges of vocational education in the era of artificial intelligence. Vocational education should take advantage of reforming from the speciality setting, teaching content and teachers' aspects. Meng and Sumettikoon (2022) pointed out that emerging technologies and educational teaching had reached a new level in the context of "Internet+ education". Vocational education, teaching concepts, teachers, and the ability of information-based teaching should be emphasised in the education and teaching reform.

In summary, most current studies focus on applying advanced or emerging technologies (especially AI) to vocational education, whereas little work examines students' cognitive and acceptance levels of AI. Therefore, the purpose of this study is to investigate, from the perspective of vocational high school students, their knowledge and acceptance of AI — particularly AV technology — so that insights can be provided to align teaching and learning goals in a mutually beneficial way.

3. Methodology

Based on the literature review above, various methods and approaches have been employed to address vocational education. However, currently, few studies have utilized discrete models to accommodate future selections. Therefore, the selection of vocational education is modeled as binary (i.e., science and engineering, liberal arts), and the Bayesian binary probit model is considered to estimate cognition and attitudes towards AVs.

Whether high school students choose science and engineering or liberal arts in their future selections, the binary probit model can be expressed as:

$$U_i = \beta_i X_i + \varepsilon_i \tag{1}$$

where X_i is the vector of explanatory variables, β_i denotes the coefficients to be estimated, ε_i is the error term, which is assumed to be normally distributed (zero mean and unit variance). For the binary future selection, it can be specified that $Y_i = 1$ for $U_i > 0$ and $Y_i = 0$ for $U_i < 0$, then it can be obtained:

$$P(Y_i = 1|X_i) = P(U_i > 0) = 1 - P(U_i < 0) = 1 - P(U_i - \beta_i X_i \leq \beta_i X_i) = 1 - \emptyset(-\beta_i X_i) = \emptyset(\beta_i X_i) \tag{2}$$

where$P(Y_i)$ is the probability that subject *i* belongs to category 1. More details about the model estimation can be found in Yu and Abdel-Aty (2014).

In this study, a Bayesian estimation approach is employed for the binary probit model due to the following advantages over other methods (Yuan et al. 2020). In maximum likelihood estimation, the true value of the model parameters is considered as fixed but unknown. It maximises the likelihood of an unknown parameter $\theta$when given the observed data y through the relationship, whereas Bayesian estimation approximates the posterior density of y, $p(\theta|y) \propto p(\theta)L(\theta|y)$where$p(\theta)$is the prior distribution of $\theta$and $p(\theta|y)$is the posterior density of θ given y. Therefore, the posterior density of y given θ is the product of the prior distribution of $\theta$and the likelihood of the observed data as the following:

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{\int p(y|\theta)p(\theta)d\theta} \propto p(\theta)L(\theta|y) \tag{3}$$

In this study, a non-informative prior is utilized due to the absence of prior information. Additionally, a new class of simulation techniques, Markov Chain Monte Carlo (MCMC), is implemented to compute the joint posterior distribution. For model comparison, as verified by many other studies (Yuan et al. 2020; Xu et al., 2020) within the Bayesian framework, the Deviance Information Criterion (DIC) is adopted to compare the corresponding models above:

$$DIC = D(\bar{\theta}) + 2p_D = \bar{D} + p_D \tag{4}$$

where $D(\bar{\theta})$denotes the deviance evaluated at $\bar{\theta}$, the posterior mean of the parameter of interest, p_D represents the effective number of parameters in the model, and $\bar{D}$is the posterior mean of the deviance statistic$D(\bar{\theta})$. A lower DIC indicates a better model fit. Generally, a difference in DIC exceeding 10 definitive rules out the model with the higher DIC; differences between 5 and 10 are considered substantial, whereas differences less than 5 imply that the models are not statistically different.

4. Data Description

To objectively reflect the basic cognition, intention, and educational needs regarding "AVs" among high school students, a questionnaire (presented in the Supplementary Material) was designed and distributed online to high schools nationwide from June 28th to July 12th, 2022. Within 15 days, a total of 28,549 replies were received, of which 22,348 were from vocational high school students. The 597 cases were identified as “invalid” responses due to incomplete questionnaires, logical inconsistencies, or outliers. The regional distribution is shown in Figure 1. It can be seen that the responses cover all the provinces.

Among the 27,952 valid data samples, 5,604 are from ordinary high schools, and 22,348 are from vocational high schools. From questions 1 to 15 in section 2, the “basic cognition”, “intention” and “educational needs” of high school students are discussed from different perspectives as shown in Table 1. (For details of the questionnaire, please refer to Supplementary Material).

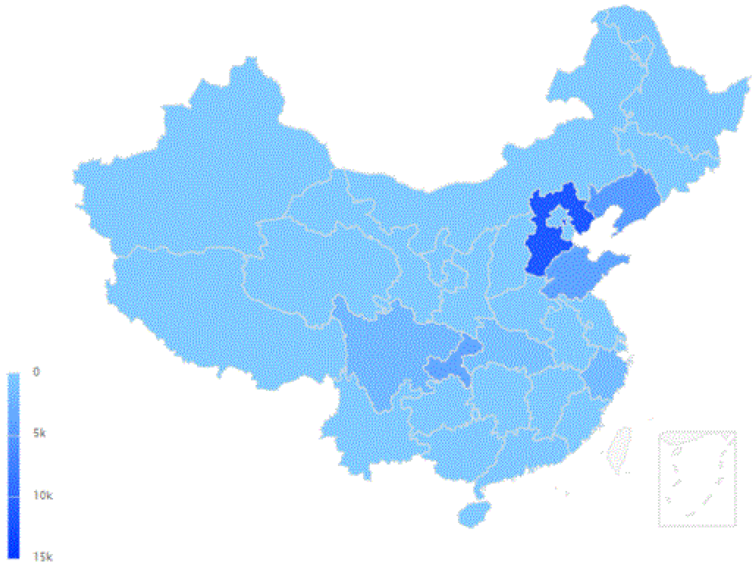

Fig. 1 *Response distribution*

Table 1 *Dimension division*

Basic Cognition	Automation division Q1	Application areas Q 2	Vehicle functions Q 3	Cognitive source Q 4	Safety and traffic Q 5
Intention	Interest level	Influencing factor	Concern level	Initiative level	
	Q 6	Q 7	Q 8	Q 9，Q 10	
Educational Needs	Education necessity	Education content	Education value	Education method	Education impact
	Q 11	Q 12	Q 13	Q 14	Q 15

In order to facilitate the analysis of various parameters, the study’s objectives are operationalized into three distinct dimensions: “basic cognition,” “intention,” and “educational needs” (as shown in Table 1), alongside background information. Specifically, the dependent variable for the Bayesian binary probit model is defined as “Question No.6 Final choice,” representing students’ binary decision between science/engineering and liberal arts for their future studies. The independent variables are derived from the remaining questionnaire items. For example, the geographical location is divided into 7 parts according to the administrative regions of China, namely North China (1), East China (2), Central China (3), South China (4), Northwest China (5), Northeast China (6), Southwest China (7), and overseas (0); similarly, the "interest level", "initiative", etc. are divided into 5 levels, that is, the range from “very compatible" to "very non-compliant" can be regarded as ordinal variables. There are 22 parameters involved in the entire dataset.

To extract the variables from the larger pool of questionnaire items (Q1-Q15), the selection process involves filtering the available data points to those most relevant for predicting the dependent variable. The criteria prioritise variables that are aligned with the three core research dimensions (cognition, intention, and needs) and background factors known to influence academic choices, such as gender, grade, specialty, and school location. These dimensions (e.g., Q1-Q5 for basic cognition, Q6-Q10 for intention, Q11-Q15 for educational needs) are aggregated or transformed into the final parameters used in the regression model.

5. Results

To estimate the proposed model, a correlation test is required to assess multicollinearity among the independent variables. The Pearson test reveals that the father's job is highly related to mother's, the AVs application fields (unclear) of No.2 is highly concerned with the corresponding contents of No.3 and No.4, while No.5 and No. 6, No.8, No.9 and No.10 are highly related to each other, so they are not adopted at the same time as the independent variables since the specific correlation thresholds (e.g., coefficients above 0.50) is defined "highly related" in this context.

As stated previously, a Bayesian probit model is used to evaluate the final choices of high school students. Normality tests are conducted on the residuals or error terms derived from the Bayesian estimation, and the use of MCMC simulation techniques, as mentioned in the methodology, helps meet the distributional requirements for valid inference. Table 2 presents the estimated results, along with 95% confidence intervals for the statistically significant variables obtained using STATA 16. Based on the DIC values, the Bayesian binary probit model outperforms the Bayesian multinomial probit model, even though categorical variables are more appropriately modelled using the multinomial probit model. Therefore, the explanation focuses on the binary probit model.

Table 2 *Estimation results of the proposed model*

	Bayesian binary probit			Bayesian multinomial probit		
	Mean	Std. Dev.	95% Cred. Interval	Mean	Std. Dev.	95% Cred. Interval
Gender	-1.196	0.007	(-1.210, -1.182)	1.717	0.020	(1.681,1.761)
Grade	-0.056	0.009	(-0.076, -0.038)	0.065	0.012	(0.041,0.088)
Specialty	0.019	0.001	(0.016, 0.022)	-0.027	0.002	(-0.031, -0.023)
School location	-0.017	0.003	(-0.022, 0.011)	0.023	0.004	(0.015, 0.032)
No.2						
Logistics delivery	-0.083	0.010	(-0.104, -0.061)	0.102	0.016	(0.069, 0.133)
Shared travelling	0.038	0.012	(0.014, 0.062)	-0.055	0.017	(-0.089, -0.021)
Military application	-0.079	0.008	(-0.096, -0.062)	0.127	0.019	(0.090, 0.166)
Regular travelling	-0.035	0.012	(-0.058, -0.012)	0.036	0.015	(0.004,0.067)
No.4						
Science museum	0.046	0.008	(0.030, 0.061)	-0.067	0.017	(-0.100, -0.033)
TV & Broadcasting	0.050	0.006	(0.037, 0.064)	-0.083	0.016	(-0.116, -0.052)
Books & Journals	-0.036	0.007	(-0.050, -0.022)	0.048	0.016	(0.017,0.083)
No.7						
Network & Media	-0.048	0.011	(-0.072, -0.027)	0.076	0.020	(0.035, 0.116)
Classmates	0.072	0.011	(0.050, 0.095)	-0.108	0.015	(-0.136, -0.074)
No.12						
Basic science principle of AVs	-0.187	0.013	(-0.214, -0.159)	0.268	0.022	(0.222, 0.309)
Developing history of AVs	-0.063	0.008	(-0.080, -0.045)	0.084	0.020	(0.045, 0.123)
Relevant laws and ethics of AVs	-0.108	0.014	(-0.135, -0.079)	0.190	0.016	(0.157, 0.221)
Related technologies of AVs	-0.174	0.008	(-0.190, -0.155)	0.258	0.014	(0.228, 0.286)
Future development of AVs	-0.115	0.011	(-0.138, -0.092)	0.154	0.013	(0.128, 0.181)
Pros and cons of AVs	-0.096	0.012	(-0.121, -0.007)	0.157	0.013	(0.130, 0.181)

	Bayesian binary probit			Bayesian multinomial probit		
	Mean	Std. Dev.	95% Cred. Interval	Mean	Std. Dev.	95% Cred. Interval
Impact on life of AVs	-0.100	0.012	(-0.125, -0.076)	0.161	0.009	(0.143, 0.180)
Competition of AV technology	-0.134	0.011	(-0.155, -0.111)	0.195	0.016	(0.164, 0.228)
No.13						
No value	0.060	0.009	(0.041, 0.079)	-0.058	0.022	(-1.027, -0.014)
Increase related knowledge of AVs	0.038	0.009	(0.019, 0.057)	-0.054	0.017	(-0.089, -0.019)
No.14						
Video teaching	0.042	0.008	(0.025, 0.059)	-0.056	0.013	(-0.081, -0.029)
Simulated game	-0.053	0.011	(-0.074, -0.031)	0.082	0.008	(0.067, 0.099)
Group communication	0.041	0.013	(0.015, 0.067)	-0.636	0.017	(-0.098, -0.030)
No.15						
Aided study of other courses	-0.055	0.015	(-0.084, -0.023)	0.059	0.144	(0.031, 0.088)
Mitigate study stress	0.035	0.011	(0.014, 0.057)	-0.055	0.013	(-0.081, -0.027)
Benefit future career selection	-0.060	0.013	(-0.086, -0.032)	0.065	0.017	(0.034, 0.100)
Constant	1.129	0.019	(1.090, 1.168)	-1.607	0.013	(-1.622, -1.580)
Goodness-of-fit						
No. of observation	22347					
DIC	25509.95				25512.79	

As indicated in Table 2, gender has a significant negative impact on the final choices of vocational high school students, suggesting that male students are more inclined to choose science and engineering compared to their female counterparts. This aligns with common sense, as males are more interested in science and engineering than females.

Grade exhibits a negative correlation with the final choices of vocational high school students, indicating that as grade level increases, students are more likely to opt for science and engineering, driven by information that encourages them to pursue this career path.

School location is significant for the final choices of vocational high school students, but it is met with negative concern. The pattern observed is that, compared to inland students, coastal students tend to opt for science and engineering. This tendency can be attributed to the greater availability of information and resources in the eastern region of China compared to the western region. Additionally, the specialties offered by vocational colleges are confined to specific fields, thereby limiting the options for vocational high school students. This aligns with the current situation in China, where colleges and universities prioritise employment rates, and science and engineering specialities constitute a significant proportion, thereby enhancing employment rates. For Policymakers, the finding that "school location" and regional resources significantly impact student choices highlights a systemic inequality in educational opportunities for AV technology. Policymakers are urged to "increase investment in this part of education resources, especially in remote and poor areas," as discussed. Addressing this regional disparity is essential to achieving the study's broader goal of equitable AI education nationwide.

In question No.2 of Section 2, logistics delivery, shared travelling, military application, and regular travelling significantly influence the final choices of vocational high school students, indicating that the application fields of AVs may guide students towards selecting science and engineering. Given that the application fields of autonomous vehicles (AVs) primarily depend on related AI and engineering technologies, especially in traffic and transportation, it is rational for students to choose science and engineering as their final decision. For Students, the results indicate that their educational choices (science vs liberal arts) are significantly influenced by their "basic cognition," including their awareness of AV application areas such as logistics and military use. This suggests that increasing students' exposure to real-world applications of technology can positively steer their academic and career trajectories towards science and engineering fields.

In question No. 4, science museums, TV and broadcasting, and books and journals are significantly correlated with the final choice. The positive correlation of the first two aspects suggests that high school students acquire AV knowledge from these sources, which may influence their selection. Conversely, the negative correlation indicates that books and journals are less influential compared to the first two aspects.

In question No. 7, the final choice is significantly influenced by the network & media and classmates, which makes sense. With the advent of the information age, the Internet and media play pivotal roles in the lives of high school students. Meanwhile, classmates have a significant impact on their decision-making process, as they may exchange information and follow their peers' choices. The positive correlation between "network & media" and choice suggests that students are already utilizing external resources to inform their decisions. Consequently, to achieve the study's goal of enhancing students' cognition and acceptance of AI, schools should encourage students to actively seek information through these channels and provide guidance on interpreting this information critically.

In question No. 12, all the AV-related content is significant, suggesting that it may help vocational students choose science and engineering. This may reflect that vocational students care more about AV technologies in science and engineering, since vocational high schools emphasise technology.

In question No. 13, both items are positively significant for the final choice, suggesting that they may help students choose science and engineering. This is consistent with the course design and layout, and knowledge of AVs may be extended across the AI field to benefit other courses, thereby improving students' determination in science and engineering.

In question No. 14, video teaching, group communication and a simulated game are all significantly related to the final choice, suggesting that traditional rote learning may be insufficient for engaging vocational students in complex topics like AVs, while the teaching pattern and content of AV courses may be useful for the final selection. Currently, the AV-related courses mainly focus on the contest or competition, and most of them choose science and engineering, whereas a few learn AV courses voluntarily. Therefore, if the aforementioned teaching pattern is widely applied, it may attract more students to choose science and engineering. Educators should therefore adopt active learning strategies and digital tools, such as simulations, to stimulate student interest. This aligns with the study's goal of finding effective educational methods to improve AV knowledge. Furthermore, the significance of "basic science principles" suggests that foundational STEM education is critical; teachers should focus on strengthening students' basic scientific literacy to facilitate their understanding of advanced technologies. The study supports the existing literature on the benefits of active and digital learning in vocational settings (e.g., Chen et al., 2022) [4], validating the need for pedagogical shifts.

In question No. 15, regarding the most helpful aspect of AV courses, all items are negatively significant in the final choice, indicating that these items are useful in helping students choose science and engineering. It is evident that AV courses not only contribute to personality development, social networking, and stress alleviation but also enhance knowledge and skills, particularly aiding in future speciality selection. This underscores the importance of AV courses and fully supports the objective of our study.

Additionally, the success of the "Bayesian binary probit model" in determining student choices provides policymakers with a data-driven tool for assessing the impact of educational policies. By understanding the factors that drive students towards science and engineering, policymakers can design targeted interventions and funding allocations to better prepare the vocational workforce for the era of intelligent transportation, thereby supporting the national strategic goals for vocational education and technological development.

The link between AV education and students' academic choices can be explicitly explained that exposure to autonomous vehicle technology acts as a crucial catalyst for stimulating vocational students' interest in science and engineering, as the application fields of AVs—such as logistics, military use, and transportation—primarily rely on AI and engineering technologies. The study shows that when students understand these practical applications and acquire knowledge through engaging methods such as video instruction and simulated games, their perception of science shifts from abstract theory to tangible, high-value career pathways, thereby making them more likely to choose science and engineering for their future studies. This connection supports the study's goal of using AV education to guide vocational students toward technical fields, rather than simply assuming its influence without evidence.

6. Discussion

Empirically, the following suggestions are presented: For educators, the empirical finding that video teaching and simulated games are significantly correlated with students' final choice of science and engineering implies that pedagogical shifts towards active, technology-enhanced learning are necessary to align with the study's goal of improving AV cognition. The current observation that AV-related courses primarily focus on contests suggests a need to reform curricula to include interactive elements such as simulations, which this study identifies as effective drivers of student interest in STEM fields.

For students, the result that cognitive sources like science museums and TV & broadcasting positively influence final choices, while books and journals show a negative correlation, suggests that students' academic decisions are heavily shaped by accessible, intuitive media rather than dense academic text. This supports the study's objective of investigating how vocational students consume AV information; it indicates that to effectively encourage students towards science and engineering education pathways, learning resources must be engaging and visually stimulating to resonate with their daily information consumption habits.

For policymakers, the finding that school location significantly affects choices, with coastal students more inclined toward science and engineering due to richer resources, underscores the urgent need for policy interventions to address regional educational inequality. To fulfil the study's broader goal of enhancing AV education nationwide, policymakers must prioritise resource allocation to remote and inland areas. This ensures equitable access to the digital teaching measures and empirical strategies identified in the results, thereby preventing future geographic disparities in the workforce trained in intelligent transportation technologies.

Finally, because the study is conducted in China, the education system, cultural background, and technological development may differ from those in other countries. We acknowledge these contextual factors which might influence the generalizability of our findings. For example, the emphasis on vocational education in China and the specific application areas of AVs in the country might not be directly applicable to other educational contexts; Attitudes towards technology and innovation might vary across different cultures. Various cultural factors may influence students' cognition and attitudes towards AVs. For instance, collectivist cultures might prioritise safety and ethical concerns more than individualistic cultures. The adoption and implementation of AV technology are at different stages in different regions. The level of technological development may affect students' awareness and understanding of AVs

7. Conclusions

Vocational education has been receiving increased attention in China in recent years, and with the advent of the AI era, the AVs are likely to become part of our lives in the near future. High school students, especially those in vocational programs, will play active roles in exploring AV technology. Accordingly, this study investigated the basic cognition, intention and educational needs of vocational high school students regarding AVs. In this study, a binary probit model within a Bayesian framework was applied to evaluate students' final choices regarding their field (science and engineering vs liberal arts) and to determine whether education on AVs benefits them. The results indicate that background factors— including gender, grade, speciality, and school location—are strongly correlated with vocational high school students' final choices. For basic cognition, knowledge of AV application areas and sources of AV information is a significant factor influencing students' decisions. In terms of intention, students' attitudes towards AVs significantly affect their final choice. Regarding educational needs, factors such as AV-related educational content, educational value, teaching method, and the perceived impact of AV education are crucial for students' final choices; these should be key areas in curriculum design and educational policy.

The contributions of this study are as follows: (1) To our knowledge, it's the first attempt to investigate high school students' cognition of AVs, covering three dimensions (basic cognition, intention and educational needs) and addressing the perspectives of vocational high school students on AV technology. This provides a new approach to understanding the educational impact of AVs on high school students; (2) By comparing the two models within Bayesian framework, the proposed Bayesian binary probit model reveals the determinants of vocational high school students' final choices, providing evidence-based insights and potential suggestions for educational interventions.

There are still some limitations in this study. Online questionnaire surveys are susceptible to biases, such as self-selection bias, in which students with a pre-existing interest in technology or AVs may be more likely to respond, thereby skewing the results compared to the general student population. Regarding regional differences in access, as stated above, the development of education philosophies, education technologies and education resources is uneven across China, which implies that students in remote or underdeveloped areas may have limited understanding of AVs, regardless of their actual aptitude. This lack of equitable access to information could distort the findings, making it appear that coastal students have a stronger preference for science and engineering simply because they have had greater exposure to AV technology, rather than a fundamental difference in academic preference. Additionally, the reliance on self-reported data introduces the risk of social desirability bias, as students may overstate their positive attitudes towards STEM fields or AVs to align with perceived social expectations rather than their true intentions. Finally, the influence of self-reported data limits the ability to objectively verify students' actual capabilities or behaviours, meaning the analysis relies on perceived knowledge and intentions rather than demonstrated competence or concrete actions. As stated above, spatial differences among school locations may lead to distinct student choice characteristics, warranting further exploration. A geographically weighted regression model that accounts for spatial factors could be applied in future research.

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Another issue is the transferability of our findings to different populations or datasets, which we plan to address in future work.

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Conflict of Interest

The authors declare that they have no conflicts of interest in this work.

Author Contribution

Conceptualization, investigation, project administration, supervision, writing-review & editing: *W. Li;* ***data collection, formal analysis, visualization:*** *Y. Liu and W. Shi;* ***conceptualization, formal analysis, funding acquisition, investigation, methodology, writing-original draft:*** *X. Xu.*

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