

2024 IEEE 4th International Conference on Human-Machine Systems (ICHMS 2024)

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Elderly Pedestrian-Crossing Strategy When Perceiving an Autonomous Vehicle in a Shared Space

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Abstract—This study clarified a pedestrian crossing strategy for elderly Japanese pedestrians when perceiving an autonomous vehicle in a shared space by eliminating road features. Crossing strategy is the basis of pedestrian crossing behavior, and this study distinguishes two types of crossing strategies: conservative and aggressive. We proposed a process for pedestrians who use a strategy to cross the road. Experimental data collected in a virtual reality facility were analyzed to investigate pedestrian-crossing strategies. The variables contributing to the pedestrian crossing behavior and crossing strategy selection were explored. The results indicated that the proposed crossing strategy predicted the observed behaviors of the participants. Pedestrian crossing behavior is influenced by gender, age, and vehicle speed. Higher vehicle speed and pedestrian age lead to pedestrians increasing their crossing time and selecting a conservative walking strategy. The study also showed that males selected an aggressive strategy more frequently than females and that males needed more time to cross the road than females.

Keywords—Autonomous vehicle, crossing behavior, elderly pedestrian, human-machine interaction, shared space

I. INTRODUCTION

Shared space traffic design has been utilized in several countries and areas to decrease traffic congestion and improve pedestrian safety and community issues, such as the zone in Graz, Austria, and the project of Bohmte, Germany. Monderman [1] pioneered the introduction of shared space, which has been considered the most suitable method for multiple modes of transport [2]. This is an urban design approach to decrease road utilization gaps between users by eliminating road features (e.g., traffic signs and road marks). However, the disappearance of these road features in shared spaces may confuse pedestrians and make their crossing behaviors different from regular road conditions. Moreover, this problem is aggravated when autonomous vehicles (AVs) enter shared spaces. Compared to human drivers, AVs have several limitations in predicting pedestrian intentions and behaviors [3]. For example, an AV may crash into a pedestrian by mismatching the image of one pedestrian with that of others [4]. Another limitation is that AVs lack the eye contact and social interaction that human drivers have with

pedestrians, which is a significant factor between vehicles and pedestrians for understanding each other's behavior [5]. Therefore, vehicle manufacturers should understand pedestrian crossing behavior in shared spaces to reduce potential crash risks between pedestrians and AVs. In particular, an investigation into elderly pedestrians is required. Due to older people's deteriorating perceptual and cognitive abilities [6], they have difficulty perceiving road situations and interacting with AVs.

To understand the interactions between elderly pedestrians and AVs in a shared space and investigate their crossing behaviors, this study proposed a pedestrian crossing strategy. In addition, variables influencing pedestrian crossing behavior were clarified. The structure of this study was described as follows. First, in section II, we explained the classification of pedestrian crossing behavior and proposed a pedestrian crossing strategy, which is the basis of pedestrian crossing behavior. In section III, we introduced the apparatus and collected data in the experiment. Next, in section IV, the crossing strategy selection variable was defined, and analysis results were illustrated. In section V, the influences of variables on crossing time and crossing strategy selection were discussed. Finally, we concluded our study contribution and limitation in section VI.

II. PEDESTRIAN CROSSING BEHAVIOR AND STRATEGY

A. Pedestrian Crossing Behavior

Pedestrian crossing behavior is defined as the performance of a pedestrian when crossing a road. Timmermans [7] highlighted two standards for pedestrian crossing behavior (choosing the next step and selecting the walking speed or type). In this study, we proposed two parameters for these two standards: pedestrians' waiting times (WT) for AVs to pass and pedestrians' crossing times (CT). The reason is that different waiting times illustrate pedestrians' planned steps for crossing (e.g., stopping to avoid the AV or ignoring the AV to continue to walk), and crossing time can calculate the walking speeds of the pedestrians.

The benefits of researching pedestrian crossing behavior are substantial. For instance, Papadimitriou, Lassaree, and Yannis [8] argued that understanding pedestrian crossing behavior enhances the design and planning of traffic environments and improves pedestrian safety when traveling.

Several studies have clarified the variables that influence pedestrian crossing behavior. Himanen and Kulmala [9] demonstrated that vehicle speed and size influence pedestrian crossing behavior. Tarawneh [10] integrated the effects of age and gender on pedestrian walking speeds. Considering the elderly participants' physical conditions, we fixed the vehicle size into a K-car. The reason is that an approaching big-size vehicle (e.g., truck and coach) may scare the participants, and multiple factors require them to execute repeat tests, which is difficult for older people to complete. Thus, due to the elderly participants' physical conditions, this study considered a fixed-size car and investigated the variables (i.e., gender, vehicle speed, and age) influencing pedestrian crossing behavior. Further, we hypothesized that the direction of AVs toward the pedestrian is another influencing variable.

In classifying pedestrian crossing behavior, Papadimitriou, Lassaree, and Yannis [11] summarized three components of pedestrian crossing behavior: 1. risk-taking and optimization, 2. conservative and public transport user, and 3. pedestrian for pleasure. However, their classification was based on questionnaire research. The intentional behavior of respondents may differ from the observed behavior of pedestrians. Moreover, recruiting elderly people to walk across entire street areas is challenging. Thus, it is necessary to consider the physical factors of older people when classifying their crossing behavior.

Andrijanto et al. [12] tested an experiment to observe elderly pedestrian behaviors in a shared space, and now this study utilized the experimental data. We used the pedestrian crossing behavior classification [11] to develop our classification. However, there were two differences between our study and [11]. Firstly, we aimed to investigate the elderly's behaviors when encountering an AV. Thus, before the experiment, we informed the participants that their behaviors would not influence the approaching vehicle's action (e.g., decrease the speed or change the direction to avoid crushing). Another difference was that pedestrians should walk following the marks set in the experiment for interacting with an AV rather than tending to walk for health purposes [11]. Thus, the classification of pleasure [11] was reduced in this study. Finally, our classification of pedestrian crossing behavior was explained as follows.

1. Aggressive behavior is related to optimizing the crossing process with a low safety perception, such as avoiding detours and saving time. In our experiment, aggressive behaviors were explained as disobeying the instructions to follow the route and not hesitating to cross in front of the AV.

2. Conservative behavior relates to increasing pedestrian safety, including following traffic marks, not avoiding detours, and crossing delays by yielding to vehicles. We treated that the participants obeyed our route for crossing and stopped to yield the AV as conservative behaviors.

B. Pedestrian Crossing Strategy

Our study hypothesized that a pedestrian should consider a crossing strategy before executing crossing behavior. Based

on Rumelt's definition [13], a strategy was developed using three elements: diagnosis, guiding policy, and action plans. We explained these three elements of the crossing strategy as follows.

Diagnosis: Pedestrians observe the road before crossing and perceive potential challenges. In this study, the challenge is assumed to be an approaching AV.

Guiding policy: After perceiving an AV, they should collect road situation information (i.e., vehicle speed and distance). Based on this information, they should select a crossing behavior from the proposed crossing behavior classification (i.e., aggressive and conservative behavior).

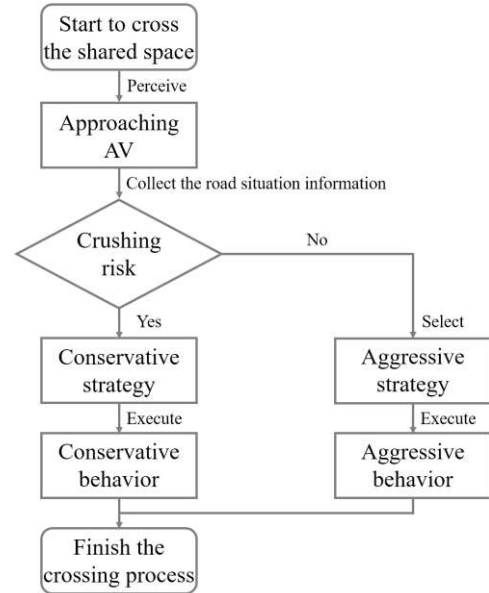


Fig. 1. The pedestrian-crossing process.

Action plans: Following the guiding policy, they execute crossing behaviors to end the crossing process.

We proposed that pedestrian crossing strategy is the basis of pedestrian crossing behavior. This study explains the categorization of pedestrian crossing strategies using the proposed crossing behavior classification. We named them Aggressive Strategy (AS) and Conservative Strategy (CS).

We designed a system process based on the previous discussion about the pedestrian crossing strategy. The system's purpose is to ensure the safety of the Japanese elderly when they cross a shared space facing an approaching AV. Pedestrians should collect the road situation information as the system input. Then, they should consider the information and decide on one crossing strategy (i.e., the system conversion process). Finally, they execute the crossing behaviors to finish the process by walking through the shared space as the system output.

Fig. 1 illustrates the pedestrian-crossing process. First, an elderly pedestrian walks into a shared space and perceives an AV approaching them. They then analyze the road situation information and select one of two strategies for crossing. Some elderly may consider the vehicle will not threaten their priority for walking. Thus, they prefer to choose AS. However, other pedestrians may fear being crashed by an AV and choose CS. Finally, they execute the crossing behaviors (i.e., aggressive or conservative behavior) according to the selected strategy and finish the crossing process.

III. EXPERIMENT

A. Apparatus and Task

The experiment of this study was based on the previous study [12], which was supported by a project of designing and utilizing "LargeSpace." The introduction of the project was as follows: Initially, an experimental virtual reality facility named "LargeSpace" was designed by Takatori et al. [14]. It is one of the largest immersive projection displays in the world and contains an encapsulated space for projecting visual images using several cameras around the area. "LargeSpace" provides the possibility to display a full-size virtual shared space. Fig. 2 illustrates this facility.



Fig. 2. Pedestrian and virtual vehicle in LargeSpace.

Further, Andrijanto et al. [12] conducted experimental scenarios for Japanese elderly pedestrians crossing the shared space based on "LargeSpace." They can observe the shared space from their viewpoints and walk independently. Finally, an experiment was developed based on the facility and scenario: an elderly pedestrian crossed the shared space while a virtual AV approached the pedestrian.

With the experiment's observed data (e.g., distance to collision point and deflection angle), Andrijanto et al. [12] analyzed pedestrian behaviors by trajectory. However, the influences of participants' demography and scenarios on pedestrian crossing behavior were not discussed in [12]. Thus, we collected the data for these variables for a more detailed analysis.

B. Data Collection

We collected data on vehicle speed, scenario, pedestrian crossing behavior, and demographics (i.e., gender and age) from the experiment. We observed the behaviors of the participants and obtained 984 available tests.

Vehicle speed: The experiment set the speed to 20, 25, and 30 km/h [12].

Scenario: We designed two scenarios by setting four points (i.e., A, B, C, and D) to clarify AV's travel direction's influence on the participants' crossing behavior. Fig. 3 shows the two scenarios. Scenario 1 ensures that the participants do not observe the AV before crossing. They should walk by the following points on the ground: A, B, C, and D. In Scenario 2, a pedestrian crosses points D, C, B, and A. The vehicle direction was the same in these two scenarios, which means the difference between the scenarios is whether pedestrians could perceive the vehicle before crossing.

Crossing time: The crossing time (CT) was measured when a pedestrian walked from the start to the final point, which was named traveling time by Andrijanto et al. [12]: — the range of the CT from 7.6 to 27.3s.

Waiting time: The waiting time (WT) was measured when a pedestrian stopped yielding to a vehicle [12]. The WT explains the three types of behaviors observed in this study.

Demographics: ten males and nine females aged 66 to 77 were recruited (mean age = 72.1; s.d. = 3.5).

To satisfy the standards of pedestrian crossing behavior (i.e., choosing the next step and selecting the walking speed or type) in [7], we proposed CT and WT to explain these two standards. CT was chosen as a dependent variable to illustrate pedestrians' walking speed. However, WT was transferred into the crossing strategy selection variable to present the pedestrian's next step standard.

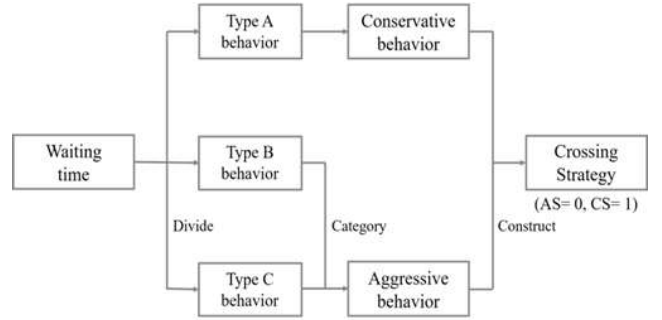


Fig. 3. Two scenarios.

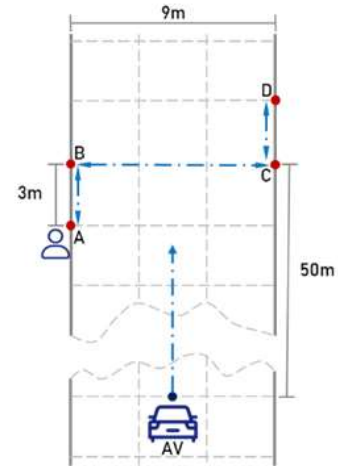


Fig. 4. Transfer process.

IV. DATA ANALYSIS

A. Variable Definition

The transfer process of the crossing strategy selection variable is illustrated in Fig. 4. First, we distinguished the three types of observed behaviors from the WT data and explained them as follows.

Type A: Pedestrians stop paces at point B or C and wait for the AV to pass through them. After the vehicle passes, they begin to cross the road.

Type B: Pedestrians initially attempted to cross the road. However, they give up and yield to the vehicle. After the car passes, they cross the street.

Type C: Pedestrians cross the road before AV arrives.

To explain the crossing strategy, the observed behaviors (i.e., Types A, B, and C) should be considered in the proposed crossing behavior classification (i.e., aggressive and conservative behaviors). Because pedestrians waited for the

vehicle in Type A, the WT data in Type A were considered conservative behavior. However, because the observed behaviors in Types B and C have a high risk of crashing with the vehicle, the WT data in these types were treated as aggressive behavior.

Finally, the observed behaviors in the WT explain the pedestrian's selection of the proposed crossing strategy and convert crossing strategy selection into a categorical variable. We defined this as AS = 0 and CS = 1.

After defining the crossing strategy, CT (Ya) and crossing strategy (Yb) were treated as dependent variables. Gender (x1), vehicle speed (x2), age (x3), and scenario (x4) were considered independent variables. Scenario and gender data were defined as a binary. Female = 0 and male = 1; scenario 1 = 0 and scenario 2 = 1.

B. Hypotheses

We proposed three hypotheses to prove the reasonability of the proposed pedestrian crossing strategy and the variables influencing the behavior. Fig. 5 presents the hypotheses.

H1: The proposed crossing strategy is reasonable for explaining pedestrian crossing behavior in the experiment;

H2: Gender, vehicle speed, age, and scenario have significant relationships with the CT;

H3: Gender, vehicle speed, age, and scenario have significant relationships with the selection of crossing strategy.

C. Results

A Hosmer-Lemeshow test proved the reasonability of the proposed crossing strategy [15]. This test evaluates the goodness-of-fit between the observed and predicted realities. For example, Sze and Wong [16] introduced the Hosmer-Lemeshow test to assess a pedestrian injury risk model.

The result of the Hosmer-Lemeshow test was $\chi^2 = 11.233$, $p = 0.189$. It revealed that the predicted pedestrian crossing behavior by the crossing strategy is similar to the observed behavior in the experiment ($p > 0.005$). Based on the results, H1 is supported. The proposed crossing strategy reasonably explains pedestrian crossing behavior.

Multiple regression analysis was used to estimate the correlation between the independent variables and the CT. Zheng et al. [17] showed that this method can explore the relationship between pedestrian behavior and personality traits.

Significant relationships exist between vehicle speed, pedestrian gender, age, and CT ($p < 0.01$ for each case) except for the scenario variable ($p = 0.301$). Therefore, the results in Table I partly support H2. Meanwhile, the variance inflation factor confirmed no multi-collinearity between the dependent variables [18]. From the results, it can be concluded that gender, vehicle speed, and age positively influence CT.

Synthesizing the analysis results from the above description, a linear model of the influencing variables on CT (Ya) was constructed.

$$Y_a = 0.377x_1 + 0.105x_2 + 0.289x_3$$

Logistic regression analysis was used to clarify the correlation between the selection of crossing strategy and variables. Kong and Yang [19] studied the pedestrian casualty

risk from the regression results. Ferencsak [20] studied the influence of pedestrian age and gender on pedestrian crossing behavior using regression analysis.

The logistic regression result illustrates that scenario variable does not significantly influence the dependent variable ($p = 0.121$). Thus, we reduced this variable and retained the other variables. Regression results are listed in Table II. The result indicates gender, vehicle speed, and age significantly correlate with Yb ($p < 0.01$ for each case). Thus, H3 is partially supported by these results. Significant relationships exist between vehicle speed, pedestrian gender, age, and the selection of crossing strategy. Males prefer to select AS compared with females. Higher vehicle speed and pedestrian age influence a pedestrian to choose CS.

The regression model for the influencing variables on crossing strategy selection (Yb) was developed as follows.

$$Y_b = -19.266 - 1.47x_1 + 0.326x_2 + 0.165x_3$$

V. DISCUSSIONS

A. Pedestrian Crossing Strategy

This study proposes a crossing strategy for the Japanese elderly to engage in crossing behavior when they perceive an AV in a shared space. We consider the crossing strategy as the basis for pedestrian crossing behavior. In this research, Hosmer-Lemeshow test proved the reasonability of the crossing strategy, and the strategy explained the pedestrian crossing behavior observed in the experiment. These results supported the appropriateness of adopting a crossing strategy to investigate the crossing behavior of elderly people in a shared space.

The proposed strategy comprised two parts: AS and CS. In 52% of the tests, we found that the participants selected AS. We explained that the participants were tested several times during the experiment. Hence, when the participants were familiarized with the test, they may attempt to choose aggressive crossing behavior, expecting to complete crossing faster. However, the gap between the AS and CS selection by the participants was not noticeable. We suggest that the AS and CS have no advantages over each other. Pedestrians should observe the situation information to select an appropriate strategy, as assumed in the conceptual model of the crossing process.

B. Scenario

In scenario 2, we hypothesized that the participants would adjust their behaviors before arriving at point C because they should perceive the coming AV. However, we rejected this hypothesis because of the insignificant relationships between the scenario and dependent variables.

There are two possible explanations for this. Zhuang and Wu [21] suggested that 57% of pedestrians do not look at vehicles when crossing the road because pedestrians believe they have priority to cross the road. If they check the road situation and notice the vehicle, they may hesitate to avoid the vehicle and give up the preceding priority. Thus, they prefer not to stare at the approaching vehicle to force the vehicle to avoid the crash by slowing down. This perception may cause the potential crashing risk. Therefore, AV manufacturers should consider these factors when designing vehicles.

TABLE I. HYPOTHESES 2 TESTING

Variable	Standardized Coefficients	t	Sig.	Collinearity Statistics	
	Beta			Tolerance	VIF
Gender	0.377	12.803	0.000	0.954	1.048
Vehicle speed	0.105	3.643	0.000	1.000	1.000
Age	0.289	9.797	0.000	0.954	1.048
Scenario	-0.030	-1.034	0.301	1.000	1.000

TABLE II. HYPOTHESES 3 TESTING

Variable	B	S.E.	Sig.	Exp(B)
Constant	-19.266	1.954	0.000	0.000
Gender(1)	-1.470	0.172	0.000	0.230
Vehicle speed	0.326	0.022	0.000	1.385
Age	0.165	0.025	0.000	1.179
Scenario(1)	-0.243	0.157	0.121	0.784

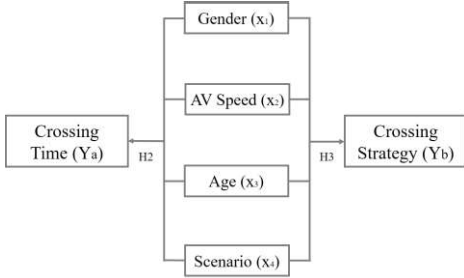


Fig. 5. Statistical hypotheses.

However, the participants monitored the shared space during the crossing process, expecting to check where the AV came from. Thus, they perceived the car as wherever they had started to cross. The participants' monitoring behaviors prove that limiting the participants' tracks to clarify the influence of the scenario on their crossing behaviors is unfeasible and does not reflect the features of the shared space. However, the points assisted our study in classifying the participants' crossing behaviors into the proposed classification. Thus, we should modify the experimental methods, such as limiting the participant's walking area rather than providing the walking tracks by points.

Another finding is that the participants' behaviors reflect pedestrians' low trust in high-level AV [22]. Because high-level AV systems may fail and cannot be adjusted by drivers, pedestrians prefer to pay attention to AVs on the road when they cross. Therefore, it is necessary to improve the pedestrian acceptance of AV for future adoption. One possible method is to introduce a technology acceptance model [23] to investigate perceptions of AVs.

C. Crossing Time

Here, we discuss some interesting findings regarding the variables that influence CT. First, the high speed of the virtual vehicle caused the participants to spend more time crossing the road. We observed that the participants hesitated to approach the AV because of the difficulty in recognizing its speed [6]. They may execute the same crossing behavior at different car speeds. We considered this to have been caused by the lack of an effective visual depth cue for judging the vehicle speed [24].

Second, age positively influenced CT. This finding supports Steffen et al.'s [25] finding that pedestrians of older ages spend more time walking.

Finally, male participants required more time to cross than female participants. This result differs from those reported by Bohannon and Andrews [26]. They measured the speed of elderly males walking faster than females. In addition, gender had the highest significance on the CT. Our post-investigation results explain these findings. Some female participants joined walking clubs. The participants walked swiftly during the experiment because of their daily exercise habits.

D. Crossing Strategy Selection

The logistic regression model clarified that a higher AV speed and pedestrian age forced them to choose CS in a shared space for crossing. Meanwhile, males participants behaved more aggressively toward the approaching AV than female participants.

We considered that vehicle speed influenced the crossing strategy similarly to that of the CT. Participants preferred CS because of their danger perceptions of the coming vehicle at high speed. We suggest decreasing AV speed in shared spaces to improve pedestrian safety and comfort.

Another finding is that gender influenced the selection of the crossing strategy of the participants the most. Our experiment proved that female participants prefer to yield vehicles despite their low speed. The results were supported by Ferencsik [20]: males exhibit more dangerous crossing behavior than females by waiting for shorter amounts of time and using the crosswalks less. Thus, we suggested AV manufacturers design different AV cruising modes by recognizing pedestrians' gender for encountering possible aggressive behaviors.

Finally, the correlation between age and strategy selection was minimal. The age gap between participants was limited because our experiment focused on investigating the crossing behavior of older people. Because the physiological factors of participants were similar, their crossing strategy selections might have been the same. Therefore, we believe that there is a significant difference between older and younger people in selecting a crossing strategy.

E. Limitations

One limitation of this study is that the fitness of the regression model was poor. The number of influencing variables was insufficient. Additional variables should be adopted to refine the analysis. We considered AV noise a significant variable, allowing pedestrians to perceive the vehicle before observation. Pedestrian gaze behavior [27] is

another variable worth researching. The second limitation is that we did not include the accelerating walking behavior in the crossing behavior classification. Thus, we can further expand pedestrian-crossing strategies.

VI. CONCLUSION

Considering the crossing behavior of Japanese pedestrians when perceiving an AV in a shared space, this study proposes a pedestrian crossing strategy. Strategies were divided into aggressive and conservative strategies. We offer a process for pedestrians to use the crossing strategy for finishing the crossing process: 1) a pedestrian will perceive an AV as challenging to cross the road, 2) they judge the road situation information and choose one crossing strategy, and 3) they execute crossing behaviors based on this strategy.

We clarified the influence of the variables (i.e., pedestrian age, gender, and vehicle speed) on the participant crossing time and strategy selection. Higher vehicle speed and older age caused the participants to spend more time crossing the road. Thus, pedestrians prefer CS under these conditions. The results also indicate that males behave aggressively toward approaching AVs more frequently than females. Nevertheless, their CTs were longer than those of the females.

We plan to address these limitations in the future. First, subsequent investigations will include vehicle noise and pedestrian gaze behavior as influencing variables to explore their potential influences on the crossing strategy. Moreover, we will extend the definition of the crossing strategy to include accelerating crossing behavior.

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REFERENCES

- [1] E. Clarke, H. Monderman, and B. H. Baillie, "Shared space: the alternative approach to calming traffic," *Traffic Eng. Control*, vol. 47, no. 8, pp. 290-292, Sep. 2006.
- [2] B. Hamilton-Baillie, "Towards shared space," *Urban Design International*, vol. 13, no. 2, pp. 130-138, Sep. 2008, DOI: 10.1057/udi.2008.13.
- [3] S. Ferguson, B. Lunders, R. C. Grande, and J. P. How, "Real-time predictive modeling and robust avoidance of pedestrians with uncertain, changing intentions," *Algorithmic Found. Robot.*, vol. XI, pp. 161-177, Apr. 2015, DOI: 10.1007/978-3-319-16595-0_10.
- [4] D. Parekh, N. Poddar, A. Rajpurkar, M. Chahal, N. Kumar, G. P. Joshi, and W. Cho, "A review on Autonomous Vehicles: Progress, methods and challenges," *Electronics*, vol. 11, no. 14, p. 2162, Jul. 2022, DOI: 10.3390/electronics11142162.
- [5] C. Frosch, D. Martinelli, A. Unnikrishnan, "Evaluation of Shared Space to Reduce Traffic Congestion," *Journal of Adv. Transp.*, vol. 2019, no. 2, pp. 1-10, Jun. 2019, DOI: 0.1155/2019/6510396.
- [6] D. Ridé, E. Rehder, M. Lauer, C. Stiller, and D. Wolf, "A literature review on the prediction of pedestrian behavior in urban scenarios" in, 2018 21st International Conference on Intelligent Transportation System (ITSC), Maui, Hawaii, USA: ITSC, 2018, pp. 3105-3112, DOI: 10.1109/ITSC.2018.8569415.
- [7] H. Timmermans, *Pedestrian Behavior: Models, Data Collection and Applications*. UK: Emerald, 2009, pp. 4-5., ch. 1.
- [8] E. Papadimitriou, S. Lassarre, and G. Yannis, "Human factors of pedestrian walking and crossing behaviour," *Transp. Res. Procedia*, vol. 25, pp. 2002-2015, Jun. 2017, DOI: 10.1016/j.trpro.2017.05.396.
- [9] V. Himanen and R. Kulmala, "An application of logit models in analysing the behaviour of pedestrians and car drivers on pedestrian crossings," *Accid. Anal. Prev.*, vol. 20, no. 3, pp. 187-197, Jun. 1988, DOI: 10.1016/0001-4575(88)90003-6.
- [10] M. S. Tarawneh, "Evaluation of pedestrian speed in Jordan with investigation of some contributing factors," *J. Saf. Res.*, vol. 32, no. 2, pp. 229-236, Aug. 2001, DOI: 10.1016/S0022-4375(01)00046-9.
- [11] E. Papadimitriou, S. Lassarre, and G. Yannis, "Introducing human factors in pedestrian crossing behaviour models," *Transp. Res. F*, vol. 36, pp. 69-82, Jan. 2016, DOI: 10.1016/j.trf.2015.11.003..
- [12] A. Andrijanto, Z. Chen, T. Kodama, H. Yano, and M. Itoh, "Application of LargeSpace for investigating pedestrians' behaviors when interacting with autonomous vehicles in shared spaces" in *IEEE VRW*, 2022, virtual event, pp. 97-100, DOI: 10.1109/VRW55335.2022.00032.
- [13] R. P. Rumelt, *Good Strategy, Bad Strategy: The Difference and Why It Matters*. Australia: Currency, 2017.
- [14] H. Takatori, Y. Enzaki, H. Yano, and H. Iwata, "Development of a large-immersive display LargeSpace," *Trans. of the Virtual Real. Soc. Jpn.*, vol. 21, no. 3, pp. 493-502, 2016, DOI: 10.18974/tvrsj.21.3_493.
- [15] D. W. Hosmer and S. Lemeshow, "Goodness of fit tests for the multiple logistic regression model," *Commun. Stat. - Theor. Methods*, vol. 9, no. 10, pp. 1043-1069, Sep. 1980, DOI: 10.1080/03610928008827941.
- [16] N. N. Sze and S. C. Wong, "Diagnostic Analysis of the logistic model for pedestrian injury severity in traffic crashes," *Accid. Anal. Prev.*, vol. 39, no. 6, pp. 1267-1278, Nov. 2007, DOI: 10.1016/j.aap.2007.03.017.
- [17] T. Zheng, W. Qu, Y. Ge, X. Sun, and K. Zhang, "The joint effect of personality traits and perceived stress on pedestrian behavior in a Chinese sample," *PLOS ONE*, vol. 12, no. 11, Nov., e0188153, 2017, DOI: 10.1371/journal.pone.0188153.
- [18] R. Goldstein, "Regression methods in biostatistics: linear, logistic, survival and repeated measures models," *Technometrics*, vol. 48, no. 1, pp. 149-150, 2006, DOI: 10.1198/tech.2006.s357.
- [19] C. Kong and J. Yang, "Logistic regression analysis of pedestrian casualty risk in passenger vehicle collisions in China," *Accid. Anal. Prev.*, vol. 42, no. 4, pp. 987-993, Jul. 2010, DOI: 10.1016/j.aap.2009.11.006.
- [20] N. N. Ferencsik, "Pedestrian age and gender in relation to crossing behavior at midblock crossings in India," *J. Traffic Transp. Eng. (English)*, vol. 3, no. 4, pp. 345-351, Aug. 2016, DOI: 10.1016/j.jtte.2015.12.001.
- [21] X. Zhuang and C. Wu, "Pedestrians' crossing behaviors and safety at unmarked roadway in China," *Accid. Anal. Prev.*, vol. 43, no. 6, pp. 1927-1936, Nov. 2011, DOI: 10.1016/j.aap.2011.05.005.
- [22] S. K. Jayaraman, C. Creech, D. M. Tilbury, X. J. Yang, A. K. Pradhan, K. M. Tsui, and L. P. R. Jr, "Pedestrian Trust in automated vehicles: Role of Traffic Signal and AV driving behavior," *Front. Robot. AI*, vol. 6, Nov. 2019, DOI: 10.3389/frobt.2019.00117.
- [23] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Q.*, vol. 13, no. 3, pp. 319-340, Sep. 1989, DOI: 10.2307/249008.
- [24] Y. C. Liu and Y. C. Tung, "Risk analysis of pedestrians' road-crossing decisions: Effects of age, time gap, time of day, and vehicle speed," *Saf. Science*, vol. 63, pp. 77-82, Mar. 2014, DOI: 10.1016/j.ssci.2013.11.002.
- [25] T. M. Steffen, T. A. Hacker, and L. Mollinger, "Age- and gender-related test performance in community-dwelling elderly people: Six-minute walk test, Berg Balance Scale, timed up & go test, and gait speeds," *Phys. Ther.*, vol. 82, no. 2, pp. 128-137, Feb. 2002, DOI: 10.1093/ptj/82.2.128.
- [26] R. W. Bohannon and A. W. Andrews, "Normal walking speed: A descriptive meta-analysis," *Physiotherapy*, vol. 97, no. 3, pp. 182-189, Sep. 2011, DOI: 10.1016/j.physio.2010.12.004.
- [27] M. Lanzer, M. Gieselmann, K. Mühl, and M. Baumann, "Assessing crossing and communication behavior of pedestrians at urban streets," *Transp. Res. F*, vol. 80, pp. 341-358, Jul. 2021, DOI: 10.1016/j.trf.2021.05.001.