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A novel causal inference method of exit choice behaviour analysis for passenger ships during emergency evacuation

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ABSTRACT

Due to the complex internal layout of passenger ships, the large number of passengers, and the presence of designated assembly points, route selection during evacuation onboard ships has increasingly become a crucial factor affecting the overall evacuation process. However, variations in passengers' risk perception and the heterogeneity of passenger groups often lead to marked differences in exit choice behaviour. To clarify the relationship between passengers' exit choice behaviour and influencing factors, the Double Machine Learning (DML) method is employed in this study with optimisation of the nuisance function applied to identify key factors affecting exit choice from a causal inference perspective. First, 1380 valid questionnaires are collected from passengers on ferry routes in the Bohai Bay area, covering essential dimensions such as individual attributes, behavioural preferences, and evacuation decision-making. Second, feature selection and model optimisation are conducted based on this dataset to construct a nuisance function with optimal average out-of-sample prediction performance. Finally, the DML approach is employed to conduct a causal effect analysis of exit choice behaviour, allowing for the systematic identification of key influencing factors. The findings indicate that alarm response and decision-making under congested conditions are identified by the DML as having significant causal impacts on exit choice. It is shown that relying solely on correlational analysis may lead to strategic misjudgements, whereas the application of causal inference enables more accurate identification of priority intervention targets.

1. Introduction

Although continuous improvements have been made in ship technology and management systems, passenger transport accidents still occur from time to time, with some incidents resulting in severe casualties [1–4]. For instance, in 1999, the "Dashun" ro-ro passenger ship capsized on a Bohai Bay passenger route, resulting in 290 fatalities [5]; the "Eastern Star" cruise ship sank on the Yangtze River in 2015, claiming 442 lives [6,7]. In most maritime accidents, passengers' effective evacuation in the initial moments of an emergency was considered crucial for reducing casualties [8]. Due to the relatively enclosed nature of ship interiors and the increased environmental complexity, passengers' behaviours during evacuation may have a significant impact on the evacuation process [9].

In the course of passenger evacuation behaviour and decision-making, the selection of an appropriate evacuation exit was considered particularly important [10]. If an incorrect exit was chosen during the evacuation, the time required for an individual passenger to reach a safe area was prolonged, which in turn posed a direct threat to that passenger's safety [11]. When multiple passengers make improper exit choices, counterflows may form as passengers headed toward different exits converge in certain areas, likely significantly slowing the overall evacuation process and creating congestion [12,13]. The resulting delays not only endanger individual safety but may also trigger cascading effects throughout the evacuation, thereby reducing overall efficiency. Therefore, it is essential to incorporate exit choice into the scope of evacuation studies. Research on evacuation exit choice has thus far encompassed multiple objective perspectives, including individual characteristics, past experience, and environmental factors [14,15,10]. However, existing studies have mainly focused on correlations or the

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relative importance among the perspectives, and the influence of subjective behavioural decision-making along with its causal relationships have not yet been thoroughly explored. In particular, the impacts of different behavioural decisions on various evacuation exit choice strategies remain underexamined, constraining the ability to provide further guidance in emergency situations [16].

Considering the critical role of exit selection in ensuring evacuation efficiency and passenger safety, it is necessary that analyses move beyond correlations and that the causal mechanisms underlying exit choice behaviour be further investigated [17]. To address the issue, the Double Machine Learning (DML) method is applied in this study to investigate the causal effects of multiple factors influencing exit choice during emergency evacuations. Specifically, both the joint and heterogeneous impacts of individual, behavioural, and situational factors on passengers' exit choice behaviour are examined, integrating traditional statistical analysis with causal inference. In addition, the effects of different types of behavioural decisions on evacuation exit choices are further analysed.

The remainder of this paper is structured as follows: Section 2 reviews the existing literature and outlines the research questions. Section 3 introduces the survey data, its characteristics, and the methodological framework. Section 4 presents the empirical analysis based on the questionnaire data. Section 5 discusses the key findings and offers relevant recommendations. And Section 6 concludes the study by summarising the main results.

2. Literature review

In emergency evacuation scenarios, passengers are frequently subjected to both temporal and spatial pressures, necessitating that rapid exit decisions be made. The effects of various factors on exit choice behaviour have been analysed by numerous scholars using a variety of methods. A comprehensive review of the relevant literature is presented from two perspectives: the factors influencing exit choice behaviour during emergency evacuations, and the analytical methods that have been employed to study exit choice behaviour.

2.1. Influencing factors of evacuation exit choice

In emergency evacuation events, the choices made by passengers in multi-exit environments constituted one of the key factors influencing both personal safety and overall evacuation efficiency [14,18]. Existing research suggested that exit choice behaviour is essentially a highly complex decision-making process that is driven by a combination of three main categories of factors, demographic characteristics [5], evacuation environment, and evacuation behaviours and decisions [19].

Demographic characteristics were shown to exert a significant influence on exit choice behaviour during individual evacuation processes. Variations in individual characteristics often result in distinct behavioural patterns in terms of risk perception, route assessment, and decision-making preferences. In particular, differences in physical capacity and mobility associated with gender and age could substantially affect walking speed during evacuation [20]. Yue et al. [19] found through simulation modelling that women and older adults faced greater challenges in exit choice, which was attributed to their reduced mobility compared with men and younger passengers. Ma et al. [21] further indicated that physical mobility affected passengers' evacuation route choices. Exits that appear safer or more familiar are often preferred by those with limited mobility such as the elderly or passengers with physical impairments. Assistance from others is also frequently relied upon, which can significantly affect overall evacuation efficiency. Beyond mobility, educational background is another significant demographic variable influencing individual evacuation behaviour. Studies by Salami et al. [22] and Halim and Brune [23] have shown that passengers with higher levels of education were generally more likely to follow evacuation instructions and adhere to established behavioural protocols. The tendency is associated with heightened risk awareness and a better understanding of evacuation procedures. Moreover, Wang et al. [13] demonstrated that passengers with greater maritime experience tend to be more familiar with ship layouts and evacuation procedures, enabling them to make decisions more quickly and select known or familiar exits. Additionally, Yang et al. [11] found that personnel who have received evacuation education or training generally exhibited higher evacuation efficiency, as they were more likely to follow evacuation instructions and choose appropriate exit routes.

Building on individual characteristics, the surrounding evacuation environment further shaped passengers' exit choice behaviour. The evacuation environment encompasses the external contextual conditions that influence individual behaviour under specific spatial and temporal circumstances. Its complexity and dynamic nature played a significant role in exit choice decisions. Research had shown that the internal spatial configuration and exit layout of ships or buildings directly affected passengers' path choices during evacuation [24]. Beyond spatial factors, the environmental conditions present during emergencies also significantly influence individual behavioural decisions. In the context of ship evacuations, weather and sea state variables such as wind speed and wave height could severely disrupt passengers' movement stability and speed, as well as affected their perception of exit locations [25]. Moreover, different types of hazards, such as fire, smoke spread, and ship tilting, can significantly alter local accessibility and the distribution of disaster risks, imposing practical constraints on passengers' exit choices [21,26]. It should be noted that the influence of the environment extends beyond the physical domain and also exerts effects at the psychological level. Lovreglio et al. [15] further demonstrated that under fire-induced high-pressure and panic conditions, passengers are often driven by a strong survival instinct, causing decision-making to deviate from rational paths and psychologically influencing exit choices during evacuation.

In addition to environmental factors, passengers' behavioural responses and interactions during different evacuation phases further influenced their exit choice decisions. During the response phase of evacuation, passengers adopting different strategies exhibit varying exit choice behaviours [27]. Wang et al. [5] reported that some passengers did not immediately evacuate upon hearing an alarm. Instead, they preferred to repeatedly confirm the situation through multiple channels. In the movement phase of evacuation, crowd congestion often occurs due to multiple factors. Fang et al. [9] found that some passengers exhibited competitive behaviours under congested conditions. The impact of the behaviour can be either positive or negative, depending on the intensity of competition. During emergency evacuations, passengers' decision-making is often disrupted by irrational factors such as emotional states, social relationships, and attachment to belongings, causing deviations from optimal or safe evacuation paths [28]. Kvamme [29] highlighted that even after receiving clear evacuation instructions, some passengers still refused to abandon their belongings. The behaviour significantly increases congestion and disorder in exit areas and intensifies the uncertainty of exit choice. In crisis situations, groups often spontaneously develop a series of coping strategies. Two prominent phenomena can be observed. The first is the social attachment effect, in which passengers tend to rely on and follow familiar groups to seek a sense of security [30,31]. The other is the leadership effect, where evacuees passively follow emergent leaders within the group [32]. Studies have shown that in passenger evacuation, team guidance can effectively optimise the use of exits and significantly alleviate congestion [2,33].

2.2. Methodologies for investigating evacuation exit choice

In the study of evacuation behaviour, exit choice has consistently been a central topic of research attention. Early research largely relied on traditional statistical analysis methods, such as hypothesis-based regression analysis, analysis of variance, and Monte Carlo simulation.

These approaches emphasised uncovering the links between influencing factors and outcome variables through linear or non-linear relationships [10,13]. Salem [34] utilized Monte Carlo simulation to estimate the entire process from alarm activation to successful passage through safety exits under different evacuation scenarios. Azizpour et al. [35] combined field experiments with statistical models to systematically evaluate the effects of life jacket usage on walking speed during evacuation at various ship inclinations. Kwee-Meier et al. [36] applied analysis of variance to explore the combined effects of physical load and psychological stress on passengers' escape decisions. In recent years, computing technologies have advanced rapidly. As a result, machine learning models have been increasingly incorporated into evacuation behaviour research [18,37]. Xiong et al. [38] employed back-propagation neural networks to identify fire risk levels in cruise ship cabins, supporting exit choice decisions. Wang et al. [39] used random forest models to analyse multiple factors influencing evacuation time and exit choice behaviours. Shi et al. [40] integrated field evacuation experiments with interpretable machine learning methods to systematically investigate the mechanisms affecting individual exit choice behaviours during emergency evacuation.

Although traditional statistical analysis and machine learning methods have been widely applied to the study of exit choice behaviour and have yielded certain results in identifying key influencing factors, they still exhibit clear limitations in explaining the true causal relationships among variables. Statistical analysis methods rely heavily on specific assumptions. They are susceptible to confounding factors and selection bias, which may lead to misinterpretation of variable relationships [41,42]. For machine learning models, their commonly cited "black-box" nature constrained the interpretation of the precise roles of various influencing factors during the evacuation process [43]. Although model interpretation techniques such as SHapley Additive exPlanations (SHAP) have improved model interpretability to some extent, they mainly quantify the contribution of features to prediction outcomes. They are less capable of revealing the underlying causal relationships between variables [44].

Therefore, causal inference methods are increasingly becoming a focus of researchers [45,46] and have been widely applied across various fields, including medicine [47], sociology [48], and psychology [49]. DML is a statistical method for causal inference. It was first proposed and theoretically validated by Chernozhukov et al. [50]. Huang et al. [44] applied the DML method to effectively analyse causal relationships within the data, providing strong support for addressing the limitations of traditional machine learning analysis. Similarly, Jiang and Sun [51] adopted the DML framework to address the limitations of traditional causal inference in highly complex settings, thereby mitigating the issue of the "curse of dimensionality". In causal inference, causal feature selection plays a critical role as well [52]. Wu et al. [53] applied an improved Markov boundary–based approach to causal feature identification, significantly enhancing the accuracy and robustness of feature selection in complex environments. Liang et al. [54] proposed a gradient-based local causal structure learning method that enabled effective causal feature selection without relying on conditional independence tests.

It is worth noting that the use of causal inference methods in evacuation research remains relatively limited compared with their development in other fields, and this gap is even more pronounced in studies of human evacuation behaviours in maritime context [18,55]. Existing literature mostly focuses on revealing statistical associations or building predictive models. However, these studies often provide insufficient treatment of potential confounding factors in complex behavioural systems and lack systematic methodological approaches for identifying causal mechanisms. In this research context, this study develops a DML framework to more effectively identify the key factors underlying exit choice. Relying on its ability to perform robust modelling and control confounding in highly complex feature environments, the DML framework has the potential to compensate for the limitations of traditional analytical methods that emphasise correlation rather than causal identification.

2.3. Research gaps and contributions

Although research on exit choice has increased in recent years, certain limitations remain. Existing studies struggle to accurately identify the underlying causal structure and often remain at the level of correlation between variables. Therefore, these studies cannot answer the critical question of which factors truly drive individual decision-making. To address this gap, an analytical framework based on a questionnaire survey is established in this study, which combines four commonly used machine learning models with information theory to improve the DML model, thereby enabling causal inference of exit choice. The approach helps enhance the accuracy of factor analysis and demonstrates promising practical applicability.

To clearly present the contributions of this study, the following summarizes three main gaps (G1–G3) identified in previous research, correspondingly, three Contributions (C1–C3) of the present study are proposed.

C1. This study introduces the concept of causal inference and establishes an analytical framework based on DML.

G1. Most existing studies rely on traditional statistical methods or machine learning approaches. While these methods can reveal correlations between variables, they are inherently limited in uncovering decision-making mechanisms. Influenced by confounding factors and selection bias, they fail to accurately identify the true causal effects of various factors on exit choice. As a result, the analytical outcomes may be biased.

Solution: This study innovatively applies causal inference to the analysis of evacuation exit choice behaviour. By adopting the DML approach, it constructs a causal inference framework that overcomes the limitation of conventional methods in distinguishing causality from correlation. The framework enables robust estimation of treatment effects in highly complex covariate settings and provides a solid theoretical foundation for exploring the causal mechanisms underlying evacuation behaviour.

C2. Intelligent variable selection is introduced to enhance the interpretability and precision of causal inference.

G2. Research on exit choice during maritime evacuation involves complex passenger behaviours and the influence of external maritime environments. Compared with other fields, it may involve a greater number of potential influencing factors. In such highly complex settings, it is often difficult to accurately identify the key determinants. Current causal inference studies still face limitations in the selection of treatment variables, which are the key influencing factors. Excessive reliance on prior experience and the lack of systematic screening methods are often observed, preventing models from focusing on the core variables that truly drive exit choice. Although causal feature selection methods have emerged in recent years, their practical applications remain constrained by factors such as data quality, model assumptions, and stability. These limitations make it challenging to directly apply such methods to complex behavioural datasets in maritime context.

Solution: This study develops an automated treatment variable selection mechanism based on feature importance, informed by influencing factors extracted from the literature review. The mechanism is designed to precisely identify variables with substantive causal effects on exit choice. In doing so, it ensures that the DML model remains focused on core treatment factors, thereby enhancing both the interpretability of the model and its practical value.

C3. Optimising perturbation function estimation to enhance the

robustness of causal effect estimation.

G3. In previous applications of the DML method, estimation of perturbation functions has typically been performed using a single machine learning model. Reliance on a single model may result in biased estimates and instability across different samples or in highly complex covariate settings. Since the perturbation function directly affects the calculation of treatment effects, inaccurate or unstable estimation weakened the reliability of causal inference and limits the practical value of DML in complex evacuation behaviour research.

Solution: This study introduces an innovative multi-model comparison and dynamic selection mechanism. By combining cross-fitting with model evaluation metrics, the approach identifies the optimal model for perturbation function estimation. The optimisation strategy strengthens the fitting performance of the perturbation function and the robustness of residual estimation, thereby improving the accuracy and stability of causal effect inference.

3. Materials and methodologies

A three-stage analytical framework is adopted in this study, as illustrated in Fig. 1. The first stage involves data acquisition, in which a questionnaire is employed for data collection. The collected data are standardised and cleaned to construct the analytical dataset. The second stage focuses on model refinement, during which feature selection and model optimisation are performed to identify the optimal nuisance function. The third stage addresses causal inference, where residual orthogonalization is applied to eliminate confounding, producing a robust estimate of the Average Treatment Effect (ATE). The framework encompasses the entire modelling flow, thereby ensuring both predictive accuracy and the reliability of causal inference.

3.1. Research data

3.1.1. Questionnaire data acquisition

The Bohai Bay passenger ferry route is regarded as a crucial maritime corridor connecting the major economic regions of Shandong and Liaoning provinces in China and is recognized as the longest cross-bay passenger ferry route in the country. According to data released by the Liaoning Maritime Safety Administration (Liaoning MSA) of the People's Republic of China, Bohai Ferry transported nearly 4 million passengers and 1.2 million vehicles across the Bohai Bay in 2024 [56]. COSCO Shipping Passenger Transport Co., Ltd., a state-owned enterprise directly managed by COSCO Shipping Group, primarily operates passenger and vehicle transport services along China's coast, especially within the Bohai Bay region, and maintains modern ro-ro passenger ships. For instance, the ferry "Yongxing Island" is 167.5 m long and 25.2 m wide, with a gross tonnage of 24,572 tons. It is staffed by 23 crew members and 27 service personnel, accommodate up to 1400 passengers and features a car deck area of 2000 square meters [5]. The ship regularly sails between Yantai Port and Dalian Port, completing the journey in approximately six hours per trip.

Based on existing research findings, a questionnaire was designed by the research team to investigate the characteristics of passengers on the Bohai Bay ferry route and their potential behaviours during emergency evacuations. The questionnaire was approved by the shipping companies and was granted ethical clearance by the Human Research Ethics Committee of Dalian Maritime University. A random sampling method was employed, targeting passengers on the Bohai Bay ferry route. All participants provided informed consent and completed the questionnaire anonymously and voluntarily. Prior to distribution, training sessions were conducted for service staff to ensure timely responses to passengers' inquiries during data collection and to guarantee the accuracy and reliability of the data. It is worth noting that on the routes where the survey was conducted, the ships carrying passengers and vehicles were all roll-on/roll-off passenger ships, which guaranteed the consistency of the research carrier. Among the passengers on the ships of

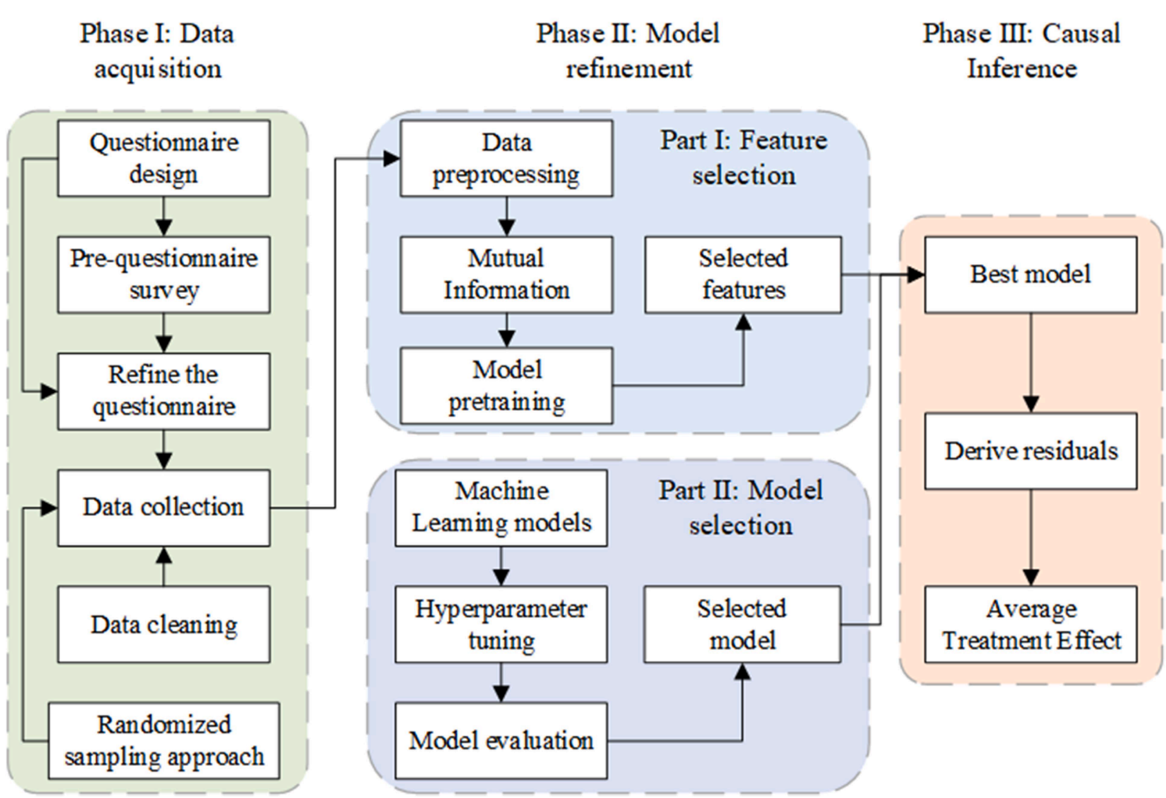

Fig. 1. The Research Framework in This Study.

this route, they were all travellers traveling between Dalian and Yantai, and not people traveling for tourism purposes.

3.1.2. Questionnaire data overview

The questionnaire data collection process spans 45 days, during which 1800 questionnaires are distributed. Missing values and outliers were examined during data pre-processing, and a small number of problematic cases were removed due to their very low proportion. A total of 1550 were returned. After excluding invalid or damaged questionnaires, 1380 valid responses are obtained, yielding an effective response rate of 89 %.

The questionnaire was structured into three main modules: passenger basic information, evacuation behaviours and decision-making, and exit choice preferences. The basic information section consisted of participants' demographic characteristics and travel-related information, with detailed data presented in Table 1 and Table 2, respectively. By collecting and analysing these data, the research team was able to gain an in-depth understanding of the fundamental attributes of the passengers, thereby providing a solid foundation for subsequent analyses of evacuation behaviours, decision-making processes, and exit choice tendencies.

The 16 specific items of evacuation behaviours and decision-making are encompassed in Fig. 2. The items are classified into four major categories: response-phase behaviours, behaviours during congestion, emergency evacuation decision-making, and group behaviours. Response-phase behaviours describe the reactions and subsequent actions of evacuees from the moment they hear the evacuation alarm until they decide to initiate movement. This category facilitates assessment of behavioural choices and decision patterns during the initial phase of emergency evacuation, providing a deep insight into passengers' psychological states and coping strategies under sudden alarm conditions. Key behaviours include waiting for staff confirmation, escape immediately, observing others' movements, and proactive confirmation. Behaviours during congestion cover decisions and behavioural patterns exhibited when evacuees encounter congestion during the evacuation process. Focus is placed on individual coping strategies, route choices, and interactions with others under congested conditions, involving behaviours such as patient queuing, independently seeking alternative exits, pushing forward, and following crew instructions. Emergency evacuation decision-making is concerned with strategies and decision processes adopted when rapid choices are required during evacuation, reflecting individual judgment, risk assessment, and action tendencies under crisis conditions. Specific behaviours include returning to retrieve valuables or family, help others, overtaking others, and carrying luggage. Lastly, group behaviours refer to social interaction patterns manifested during emergencies, encompassing spontaneously formed temporary cooperation and mutual aid networks as well as irrational behaviours and collective panic responses triggered by emotional contagion. Specific manifestations include moving with companions, panic during fire incidents, and following temporary leaders. The indicators enable an in-depth analysis of passengers' choice tendencies under emergency conditions, critical evidence for studying behavioural selection patterns during emergency evacuations.

Table 1
Demographic Characteristics of Survey Participants.

Demographic Characteristics	Classification	Frequency	Percentage
Gender	Female	808	58.8 %
	Male	565	41.2 %
Age	16 and below	83	6.0 %
	17-25	376	27.4 %
	26-30	232	16.9 %
	31-40	136	9.9 %
	41-50	262	19.1 %
	51-60	246	17.9 %
	61 and above	38	2.8 %
Educational Attainment	Primary and below	246	18 %
	Secondary school	650	47.3 %
	College	309	22.5 %
	Graduate students and above	168	12.2 %
Mobility level	Very poor	60	4.4 %
	Poor	131	9.5 %
	Neutral	451	32.8 %
	Good	384	28 %
	Very good	347	25.3 %

Table 2
Travel Situation of Survey Participants.

Experience of Traveling by Ship	Classification	Frequency	Percentage
Number of Companions	Alone	121	8.8 %
	1	208	15.1 %
	2–5	549	40.0 %
	6–10	401	29.2 %
	11 or more	94	6.9 %
Experience of Traveling by Ship	0	118	8.6 %
	1	272	19.8 %
	2–4	773	56.3 %
	5 or more	210	15.3 %
Experience in evacuation education/training	Never	382	27.8 %
	Have, but do not remember	533	38.8 %
	Once a year	213	15.5 %
	More than once a year	245	17.9 %

Based on the aforementioned behavioural categories, exit choice behaviour is further examined in this study and is regarded as a critical dimension in emergency evacuation contexts. The selected core indicators include "choose the nearest exit", "choose the most familiar exit", "follow the majority", and "follow the evacuation guide". The indicators are chosen because they represent fundamental aspects of evacuees' decision-making processes. "Choose the nearest exit" is regarded as reflecting the instinctive drive to seek the fastest escape route. "Choose the most familiar exit" is considered to signify psychological reliance on familiar environments and the pursuit of perceived safety. "Follow the majority" is seen as highlighting the influence of social dynamics and conformity under pressure. "Follow the evacuation guide" is emphasised as underscoring the importance of orderly instruction in facilitating safe evacuation. By analysing these behaviours, a more comprehensive understanding is gained of the diverse motivations and strategies adopted by evacuees in emergency situations, thereby providing valuable insight into the mechanisms that influence exit choice behaviour. Given the highly subjective nature of evacuation behaviours and the difficulty of directly quantifying decision-making processes, a five-point Likert scale is employed for measurement. Each item is rated on a scale from 1 to 5, where 1 corresponds to "strongly disagree", 2 to "disagree", 3 to "neutral", 4 to "agree", and 5 to "strongly agree". Passengers' evacuation behaviours and decision-making tendencies in emergency situations are systematically converted into quantifiable data using the method, providing a solid empirical foundation for subsequent analyses.

Next, a preliminary analysis of the questionnaire results was conducted, and the normality of the data was first assessed using the Anderson-Darling test [57]. An Anderson-Darling statistic of 1236.39 is obtained by the test, and the normality hypothesis is rejected at the 1.0 % significance level. Consequently, the data are determined to be non-normally distributed. Subsequently, a one-sample Wilcoxon signed-rank test is performed for each item to examine whether the mean significantly deviated from the neutral score of 3. The results indicate that the null hypothesis is rejected at the 99 % significance level. Thus, the results demonstrate that the means differed significantly from the neutral value of 3. The reliability and validity of the

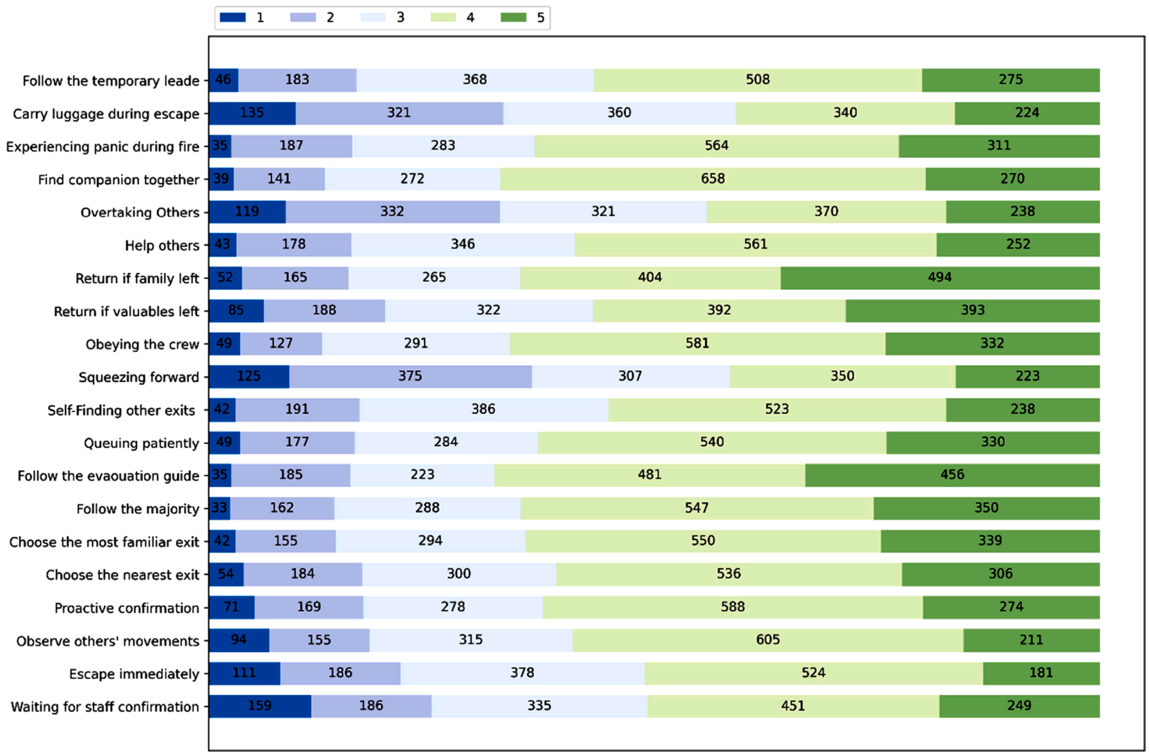

Fig. 2. Evacuation Behaviours and Decision-Making of Survey Participants.

questionnaire were assessed using Cronbach's Alpha test [58]. The Cronbach's Alpha coefficient of 0.8533 is obtained, indicating a good degree of internal consistency and high reliability, and confirming the questionnaire's suitability for further analysis. Validity was subsequently evaluated using the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity [59]. The KMO value of 0.8528 demonstrated that the data are adequate for factor analysis. Bartlett's test produced a chi-square value of 2443.00 with a p-value approaching zero, leading to rejection of the null hypothesis and confirming the appropriateness of the data for factor analysis. Overall, the results indicate satisfactory reliability and validity, supporting the use of the data for subsequent factor analysis and in-depth investigation.

3.2. Optimisation of the nuisance function estimation

In emergency evacuation scenarios, exit choice behaviour is shaped by complex, nonlinear interactions among individual characteristics, personal experiences, and environmental conditions [16,60]. By incorporating machine learning algorithms, these nonlinear patterns can be effectively captured and processed, thereby enhancing the precision of the analysis [50]. However, in the field of causal inference existing studies largely rely on a single model for the estimation of treatment and nuisance functions, and model selection and adaptability have not been sufficiently explored. Therefore, in this study, an optimised analytical framework was developed to enhance the reliability and interpretability of causal inference in complex evacuation behaviour.

3.2.1. Feature selection

To identify suitable treatment variables, a comprehensive analysis was conducted using questionnaire data, with deliberate care taken to avoid indiscriminate inclusion of all available features. Incorporating variables that exhibit weak associations with the outcome may introduce unnecessary noise, thereby distorting the causal estimates. To ensure the effectiveness and robustness of causal inference, scientifically sound feature selection methods must be adopted, prioritising features with strong explanatory power and relevance to the target variable [61]. However, defining the threshold of association strength that justifies inclusion remains a methodological challenge.

Inspiration from recent developments in neural network modelling, particularly the Mutual Information Dropout method proposed by Song and Ma [62] to prevent overfitting. Building on the rationale, a mutual information–based approach is developed for the selection of treatment variables. The mutual information between each feature and the target variable is quantified, and only features exhibiting high information gain are retained, thereby avoiding redundancy and improving model efficiency. Moreover, as the nuisance function in the DML framework is estimated using machine learning algorithms, its average out-of-sample predictive performance can be independently evaluated. To this end, the Root Mean Squared Error (RMSE) is employed as the evaluation metric [37]. RMSE measures the deviation between predicted and observed values, providing a scale-consistent and interpretable assessment of model accuracy. A robust foundation for evaluating the predictive capacity of the nuisance function is provided by the metric, thereby supporting the validity of subsequent causal inference. The formula for RMSE is shown in Eq. (1), where y_i denotes the observed value, $\hat{y}_i$ the predicted value, and n the sample size.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (1)$$

During the data pre-processing stage, a mutual information-based filtering method was first employed to identify features significantly associated with the outcome variable under multiple threshold settings. Machine learning models were subsequently constructed to evaluate the predictive performance of each candidate feature set, allowing the optimal threshold to be determined. It is ensured through the two-step process that the selected features were statistically significant and exhibited strong predictive capacity and stability. Through the procedure, the original questionnaire data are systematically pre-processed, enhancing the representativeness and interpretability of the input variables. Meanwhile, model complexity and the risk of overfitting were reduced, thereby improving overall model performance and generalizability.

3.2.2. Model selection

Different types of data features and research objectives are often optimally addressed by specific categories of machine learning models. Consequently, the principle of "targeted modelling" should be adhered to during the modelling process. Within the DML framework, the choice of machine learning models may influence the accuracy and robustness of causal effect estimation. Based on existing maritime research [18], this study selects four benchmark machine learning models that have demonstrated strong practical applicability in evacuation studies, namely Random Forest (RF), Support Vector Regression (SVR), Linear Regression (LR), and K-Nearest Neighbours (KNN). Model selection was guided by two criteria. The first criterion is strong predictive performance in prior maritime or traffic accident research; the other criterion is implementation via standardised interfaces supported by mainstream frameworks such as Scikit-learn, whose modular architectures facilitate model selection during the DML training process. The algorithmic principles, advantages, and applicable scenarios of each candidate model are summarised in Table 3, serving as a solid theoretical foundation and practical reference for the scientific evaluation and rational selection of machine learning models.

The selection of hyperparameters plays a crucial role in determining the performance of machine learning models. To address the issue, K-fold cross-validation was employed for hyperparameter optimisation [66]. The dataset is partitioned into K subsets in K-fold cross-validation, as shown in Fig. 3. In each iteration, one subset is used as the validation set while the remaining K–1 subset serves as the training set. The process is repeated K times to ensure robust training and evaluation of the model.

Existing studies have demonstrated that setting K = 5 provided an optimal balance between computational cost and the accuracy of model performance evaluation [67]. Therefore, a five-fold cross-validation approach is ultimately adopted in this study. The comprehensiveness of model evaluation is enhanced, and the training data are efficiently utilised, thereby improving the robustness and accuracy of the model selection process.

Table 3
Machine Learning Models Used in the Study.

Name	Core	Advantage	Application	References
RF	An ensemble of decision trees aggregates outputs by voting or averaging, improving generalization and reducing overfitting.	The model demonstrates strong anti-overfitting ability, handles high-dimensional data well, and is robust to missing or anomalous values.	Classification and regression problems, particularly in scenarios characterized by high feature dimensionality or substantial data noise.	[39,63]
SVR	SVR finds a function that fits most data points within a specified error margin while emphasizing smoothness.	Effectively handles nonlinear problems, performs well on high-dimensional, small-sample data, and achieves robust generalization.	Nonlinear regression problems with small sample sizes but high feature dimensions.	[37]
LR	Fits a linear model by minimizing the sum of squared residuals using least squares.	A simple model with high interpretability is employed, and its implementation is straightforward.	Suitable for datasets exhibiting linear relationships between variables.	[64]
KNN	Generates predictions by averaging the outcomes of the K nearest training samples without explicit model fitting.	Easy to understand and implement, requires no training phase, and is robust to outliers.	Small datasets with low-dimensional feature space and relatively uniform distribution for classification or regression tasks.	[65]

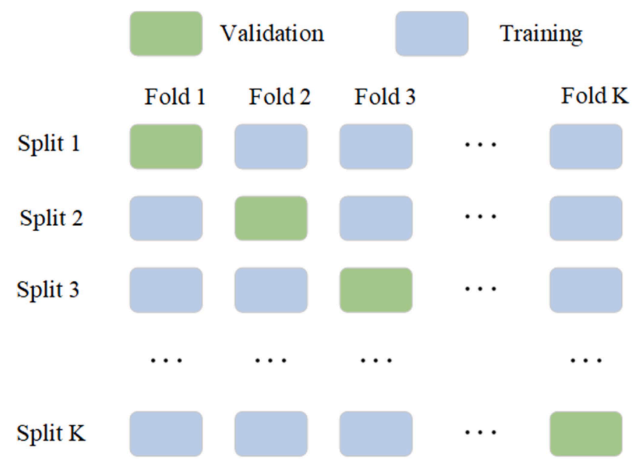

Fig. 3. The process of K-fold cross-validation.

3.3. Causal inference analysis procedure

In complex systems, variables are often intertwined through intricate associations. Statistical relationships between variables can be revealed by traditional correlation analysis, but the fundamental question of causality is not addressed. The limitation becomes particularly critical in high-risk scenarios such as emergency evacuations, where reliance on correlational information to determine whether a certain behaviour or characteristic causes a change in exit choice may lead to misleading conclusions. Therefore, accurately identifying causal effects had become a central objective in the study of human behaviour [68].

3.3.1. Double machine learning modelling

Causal inference is an analytical framework designed to identify causal relationships between variables, with a particular focus on distinguishing correlation from causation. Compared with traditional statistical methods, causal inference places greater emphasis on controlling for confounding factors, thereby enabling analyses that more closely approximate counterfactual scenarios. In general, this process is achieved by jointly characterizing the dependency structure among the treatment variable, the outcome variable, and the covariates. During model construction, potential confounding factors such as demographic characteristics, experiential background, psychological traits, and situational conditions are incorporated into the analytical framework. In the estimation stage, the systematic variation explained by these covariates is explicitly controlled for or removed. As a result, the association between the treatment and outcome variables is no longer influenced by shared driving factors. Through this approach, causal inference enables the construction of an approximate counterfactual comparison using observational data. It thus identifies changes in the outcome attributable to variations in the treatment variable while holding other conditions constant, rather than merely capturing co-movement among variables [69].

In evacuation behaviour research, this distinction is particularly important because observed behavioural–decision associations are often intertwined with background characteristics. For example, in emergency evacuation scenarios, it may be observed that passengers who "follow crew instructions" tend to select main exit routes. Traditional statistical approaches might interpret the behaviour as the cause of that particular choice. However, the behaviour could instead be a manifestation of underlying characteristics, such as higher safety awareness or prior evacuation training. Only by controlling for confounding variables such as gender, age, background, and experience, can the true causal effect of the behaviour be accurately identified. In practical evacuation studies, causal inference is often conducted in highly complex behavioural settings, where flexible machine learning models are increasingly adopted to control for complex confounding structures. A critical challenge in applying machine learning models to causal analysis lies in the presence of regularization bias. When machine learning algorithms are directly used to estimate the effect of a behavioural variable on an outcome, their inherent shrinkage or feature selection mechanisms may distort the estimated effect, particularly in highly complex settings with strongly correlated covariates. As a result, even machine learning models with high predictive accuracy may yield effect estimates that remain fundamentally correlational rather than causal. To address this issue, Chernozhukov et al. [50] introduced the concept of orthogonalization, which constitutes the core mechanism of the DML framework. The key idea is to explicitly separate the estimation of nuisance components from the estimation of the causal parameter of interest. Within DML, machine learning models are not used to directly estimate causal effects. Instead, they are deliberately restricted to capturing the systematic variation in the treatment and outcome variables that is explained by observed covariates. These components are subsequently removed through residualization, ensuring that the remaining variation is orthogonal to the space spanned by the confounders.

DML is widely recognized as a powerful framework for causal inference. The method operates through a two-stage process: first, it leverages flexible machine learning algorithms to estimate nuisance functions in highly complex covariate spaces; then, it applies orthogonalized residual regression to robustly identify treatment effects. This approach effectively controls for confounding variables while enhancing the accuracy of causal effect estimation [70]. By integrating the flexible modelling capabilities of machine learning with the statistical rigor of causal inference [49], DML is particularly suited for analysing complex behavioural dynamics. In evacuation studies, where passenger decision-making often exhibits nonlinear patterns and is influenced by multiple confounders, DML enables more robust identification of causal relationships.

The DML approach is grounded in the Frisch–Waugh–Lovell (FWL) theorem from econometrics. The central premise of the FWL theorem can be stated as follows. Within a multivariate regression framework, the marginal effect of a specific explanatory variable on the dependent variable can be consistently estimated. The estimation is performed by regressing the residuals of the outcome and treatment variables after the influence of control variables has been removed. For a multivariate regression model as specified in Eq. (2), the same principle is applied.

$$Y = \alpha_0 + \alpha_1 X + \alpha_2 D_1 + \ldots + \alpha_{n+1} D_n + \varepsilon \tag{2}$$

where, Y denotes the outcome variable, X the treatment variable, D the set of control variables, α_0 the intercept, α_1 the causal effect of the treatment variable, $\alpha_2, \ldots, \alpha_{n+1}$ the coefficients of the control variables, and ε the error term. Eqs. (3) and (4) respectively apply orthogonalization to the treatment and outcome variables in order to remove the influence of the control variables D.

$$X = \mu_0 + \mu_1 D_1 + \ldots + \mu_n D_n + \varepsilon_1 \Rightarrow \widetilde{X} = X - \widehat{X} \tag{3}$$

$$Y = \lambda_0 + \lambda_1 D_1 + \ldots + \lambda_n D_n + \varepsilon_2 \Rightarrow \widetilde{Y} = Y - \widehat{Y} \tag{4}$$

where, $\widehat{Y}$ and $\widehat{X}$ represent the fitted values from the regression equations. $\widetilde{Y}$ and $\widetilde{X}$ denote the residuals, μ_0 and λ_0 the intercepts, μ_1 and λ_1 the causal effects of the treatment variables, and $\mu_2, \ldots, \mu_{n+1}$ and $\lambda_2, \ldots, \lambda_{n+1}$ the coefficients of the control variables. As shown in Eq. (5), the final step involves regressing the residuals. This effectively isolates the net relationship between the treatment variable and the outcome variable within a highly complex model.

$$\widetilde{Y} = \beta_0 + \beta_1 \widetilde{X} + \varepsilon_3 \tag{5}$$

where, β_0 denotes the intercept, and β_1 the net effect of the treatment variable X on the outcome variable Y.

In the context of this study, the FWL theorem functions as the key mechanism that enables DML to separate confounding effects from true causal effects. By residualizing both the treatment and outcome variables, DML ensures that the final estimator captures only the net causal effect of the treatment, rather than spurious relationships driven by strong correlations. To avoid confusion with purely correlational machine learning estimates, it is important to note that causal identification under the DML framework relies on standard assumptions commonly adopted in causal inference. Specifically, the analysis assumes conditional ignorability given the observed covariates, sufficient overlap between treatment conditions, and the absence of interference between units. Under these assumptions, the orthogonalization procedure based on the Frisch–Waugh–Lovell theorem ensures that the estimated treatment effects reflect causal relationships rather than residual correlations.

Within this identification structure, machine learning plays a supportive rather than a substitutive role. In DML, machine learning models are employed exclusively to estimate nuisance functions in Eqs. (3) and (4). The causal parameter itself is then identified through the orthogonalized estimating equation. This design avoids imposing restrictive parametric assumptions on nuisance components, allows complex and nonlinear structures to be flexibly captured, and at the same time preserves the causal interpretability of the estimated effects. Ultimately, the causal effect coefficient β_1 estimated by Eq. (5) represents the ATE, which quantifies the overall average impact of a specific intervention on the target population.

3.3.2. *Placebo experiment*

Although DML exhibits considerable flexibility and accuracy in estimating causal effects, relying solely on model outputs remains insufficient to guarantee robustness and interpretability. After estimating causal effects and conducting variable analyses, additional validation techniques are necessary.

Placebo tests are employed to exclude potential systematic biases or overfitting risks and serve as a robustness assessment tool. The tests verify whether the model is sensitive to irrelevant random noise and further confirm the validity of the identified causal effects [71]. The experiment effectively detects the presence of "spurious causality", in which significant estimates may arise despite the absence of a true causal relationship and evaluates the model's applicability and stability in practical data settings. Specifically, the placebo experiment comprises the treatment and outcome placebo. In the treatment placebo stage, a random sequence statistically independent of the original covariates is generated for each actual treatment variable, serving as a pseudo-treatment. The DML estimation procedure is then repeated. If significant causal effects are still observed, potential overfitting or biased variable selection may be indicated. Subsequently, the outcome placebo stage is conducted, where the dependent variable is randomly permuted and reassigned. The model is re-estimated to determine whether structural biases emerge. If the estimated effects tend to become insignificant under random perturbation, the robustness and credibility of the original findings are further supported.

Overall, the placebo experiment serves as a critical supplementary step within the methodological framework, providing a reverse validation of the causal relationships identified by the DML approach. The procedure enhances the credibility of causal inference results and mitigates estimation biases arising from model specification, sample structure, or variable handling.

4. Results and analysis

4.1. Analysis of findings based on statistical results

4.1.1. Descriptive analysis

A descriptive analysis is conducted on the factors influencing exit choice, with passengers' responses across different scenarios examined. Survey data indicate that the distribution of behavioural options is measured using a five-point Likert scale as follows.

The basic demographic profile of the respondents indicates that 58 % are female and 42 % male. Regarding age distribution, the largest groups are those aged 17–25 and 41–50, accounting for 27 % and 19 %, respectively. In terms of educational attainment, most respondents had completed high school or technical secondary education (47 %) and junior college (23 %), 18 % had attained primary school education or below. Regarding mobility, 86 % of respondents reported medium or higher levels of evacuation mobility, with only 14 % experiencing some degree of mobility impairment. Concerning travel mode, the majority travelled accompanied by others: over half (55 %) of respondents reported travelling in groups of 1 to 5 people, whereas solo travellers constituted only 8.8 %. Regarding maritime experience, 91 % of respondents had boarded a ship at least once, indicating a relatively high familiarity with the ship environment. Concerning emergency evacuation training, it is noteworthy that coverage was relatively extensive, with 72 % of respondents reporting prior safety education or practical drills. However, among these, 39 % were unable to recall specific training details.

In emergency evacuation scenarios, a coexistence of proactive responses alongside a degree of reliance and hesitation is revealed by respondents' ratings on multiple key behaviours. For instance, a general willingness for prompt evacuation is indicated by the mean score for "Escape immediately," which is 3.35, slightly above the neutral midpoint. Concurrently, an average score of 3.32 is received by "Waiting for staff confirmation," suggesting that a proportion of respondents are reliant on official instructions, reflecting a relatively conservative evacuation response. Regarding behavioural compliance during evacuation, an overall orderly conduct is denoted by "Queuing patiently," which attains a mean score of 3.67. However, a score of 3.52 is received by "Self-finding other exits," demonstrating that some respondents are aware of route adjustment and tend to avoid congestion flexibly. Similarly, a mean of 3.58 is achieved by "Help others," implying a basic willingness to assist others. Meanwhile, a score of 3.71 is attained by "Find companion together," further highlighting a preference for relying on familiar passengers to enhance safety during emergency decision-making. Additionally, a score of 3.67 is obtained by "Experiencing panic during fire," indicating that significant emotional fluctuations may be experienced by some respondents under high-pressure conditions, potentially resulting in irrational behaviour. Overall, evacuation behaviour characterized by a coexistence of initiative and dependency, order and flexibility, as well as emotional drive intertwined with social bonding is exhibited by respondents. In terms of initial alarm responses, a slightly higher inclination to "Observe others' movements before acting" is shown by females, with a mean score of 3.49 compared to 3.46 for males. Reliance on social cues for decision-making in emergency situations is demonstrated by women. Further analysis reveals that greater behavioural compliance is correlated with higher educational attainment (coded 3–4). For example, a score of 3.66 is attained by passengers with higher education on "Queuing patiently." Meanwhile, their mean score for the less orderly behaviour "Squeezing forward" is only 3.20, indicating a lower propensity towards non-compliance. Evacuation behaviour is significantly influenced by education level, with higher education linked to more orderly and rational responses.

In summary, evacuation behaviours reflected by respondents are characterized by a complex interplay between proactive actions and reliance on instructions, combining orderly evacuation with adaptive flexibility. Gender and education were found to exert notable influences on behavioural choices. Although emergency training is widespread, its efficacy appears to be limited.

4.1.2. Correlation analysis

Based on the distribution of the data, Cramér's V was employed in this study to assess the strength of association between variables, alongside Chi-square tests [72]. To address the issue of inflated false positives resulting from multiple hypothesis testing, the Benjamini–Hochberg procedure was applied to adjust the p-values across all variable combinations. Associations with p-values less than 0.05 were considered statistically significant [73]. The strength of association between various explanatory variables and the outcome variable of exit choice behaviour is illustrated in Fig. 4. The values of Cramér's V are represented through a colour gradient, while statistical significance is indicated using asterisks. Associations with p-values significantly below the 0.05 threshold were marked as highly significant [72]. The Benjamini–Hochberg procedure was applied to control for false positives arising from multiple hypothesis testing, with p-values below 0.05 considered statistically significant [73].

A multidimensional correlation analysis is conducted to examine the statistical associations between 23 antecedent characteristics and passengers' exit choice behaviour. The analysis encompasses key dimensions including demographic attributes, response-phase behaviours, behaviours during congestion, emergency decision-making behaviours, and group behaviours. It is revealed that 84.8 % of the variables are significantly associated with exit choice behaviour, as indicated by Benjamini–Hochberg adjusted p-values below 0.05. Notably, behaviour-related variables demonstrate stronger explanatory power than demographic or situational characteristics. Specifically, features such as "Follow the temporary leader," "Proactive confirmation," and "Having received evacuation training" emerged as core predictive factors, each with effect sizes exceeding the threshold for a moderate association (Cramér's V $\geq$ 0.3). The results indicate a systematic statistical relationship between behavioural regularity, emergency preparedness, and exit choice in evacuation contexts.

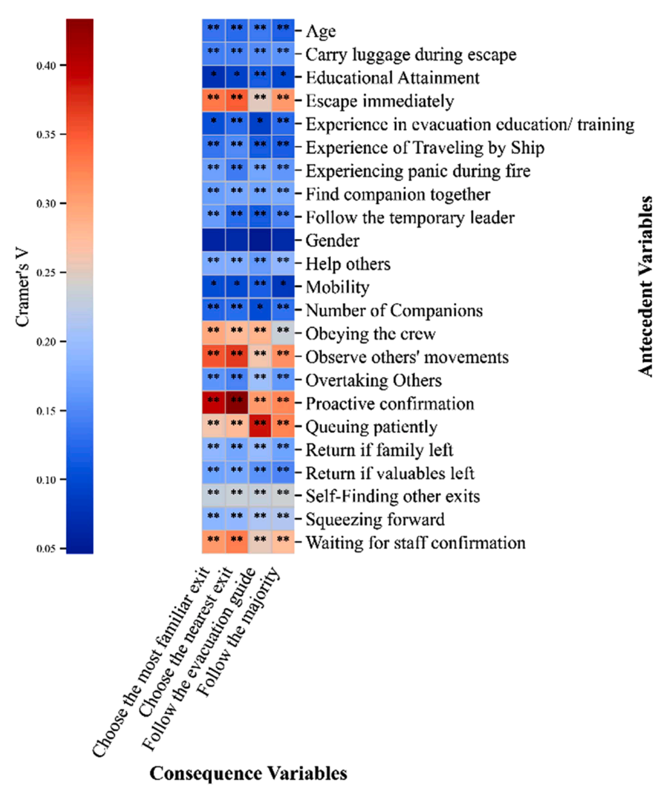

Fig. 4. Results of the Chi-Square Test with Multiple Testing Correction.

From the perspective of statistical association, a considerable analytical value is held by the selected features. The high proportion of statistically significant results, particularly among behavioural variables, provides a solid empirical basis for the development of evacuation behaviour prediction models and the refinement of response strategies. By contrast, while variables such as “Gender” and “Carry luggage during escape” reached statistical significance, their weak effect sizes indicate only limited association with exit choice behaviour, suggesting that their influence may be highly context-dependent. The results highlight the need for further analysis of variable interactions. Collectively, the questionnaire-based features demonstrate substantial relevance in identifying the key behavioural drivers of exit choice, affirming the necessity and significance of this study. To further investigate the dynamic relationships among variables, Spearman’s rank correlation coefficient was employed, with particular attention to the strength and direction of these associations. By using Spearman’s ρ, structural links between various features and exit choice behaviour could be revealed. The insights provide a deeper understanding to support the optimisation of evacuation strategies. The Spearman correlation coefficients between antecedent characteristics and passengers’ exit choice behaviour are presented in Fig. 5. The thickness of each connecting line reflects the magnitude of the corresponding coefficient.

As illustrated in Fig. 5, behaviour-related variables exhibit the strongest correlations with exit choice behaviour among all factor categories, followed by emergency decision-making behaviours and group behaviours. In contrast, demographic characteristics show comparatively weak correlations. Specifically, among behaviour-related factors, variables such as “Follow the temporary leader”, “Proactive confirmation”, and “Having received evacuation training” demonstrate relatively strong associations with exit choice behaviour. Within the domain of emergency decision-making, the strongest correlation was observed for "Help others", followed by “Return if valuables left”, while the correlation for "Carry luggage during escape" was relatively weak. In terms of group behaviours, “Find companion together” showed a moderate correlation with exit choice behaviour, which was clearly weaker than those of behaviour-related or emergency decision-making variables. The results indicate that while collective tendencies during crises do contribute to exit selection decisions, their influence appears to be less substantial than that of individual behavioural factors. It should be emphasised that correlation coefficients merely reflect statistical associations if confounders are not controlled. Correlations do not imply causality. Only under conditions of randomisation or sufficient adjustment for confounding can correlations approximate causal effects. Otherwise, strong correlations may result from shared underlying influences. Accordingly, the findings represent conventional statistical associations. Although valuable are used for exploratory purposes, they are insufficient to reveal deeper causal mechanisms [44].

4.2. Analysis of results based on nuisance function optimisation

Based on mutual information theory, the interaction strengths between four representative evacuation behaviours are presented. The evacuation behaviours “choose the nearest exit”, “follow the evacuation guide”, “follow the majority”, and “choose the most familiar exit” are

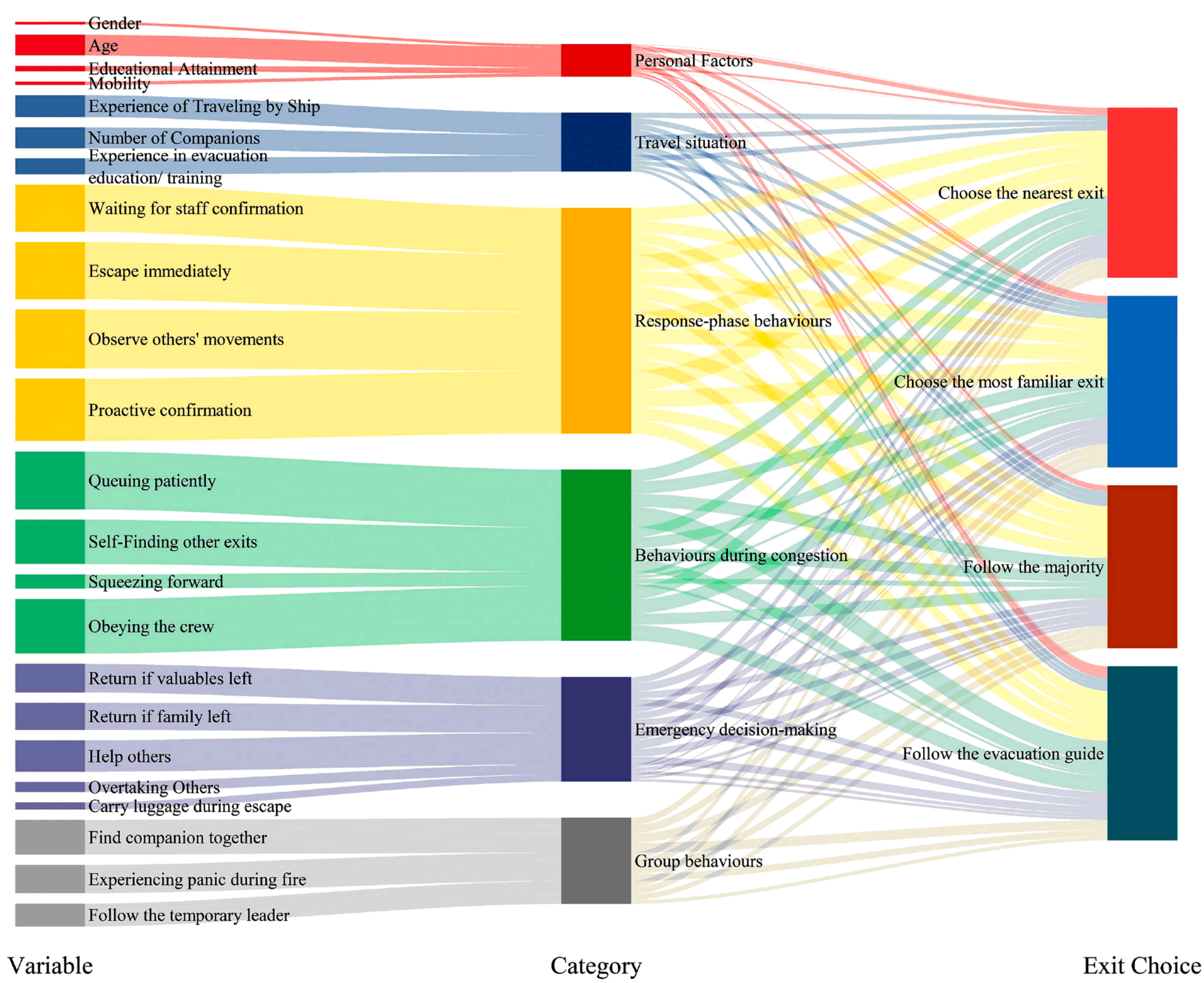

Fig. 5. Spearman Correlation Coefficients between Influencing Factors and Exit Choice Behaviour.

associated with a set of multidimensional influencing factors shown in Fig. 6. Mutual information values were calculated between each behavioural decision variable and 23 potential influencing factors. Based on these values, an interaction map was constructed to capture the associations between dynamic behavioural features and static individual attributes. The map serves as a basis for subsequent feature selection.

Based on mutual information strength, multiple feature sets were constructed using different threshold values and served as the foundation for subsequent analyses. The sets were then input into the selected machine learning models for training, and their out-of-sample predictive performance was evaluated. To further validate the effectiveness of the mutual information–based feature selection strategy, this study also employed two representative causal feature selection methods. These methods include the Common and Target-specific MB-driven Multi-Label Feature Selection (CLFS) [74] and the Incremental Association Markov Blanket (IAMB) algorithm [75,76]. The feature sets obtained from these methods were likewise fed into the machine learning models for training and evaluation. The experimental results were shown in Fig. 7, with the horizontal axis representing the number of features selected according to the mutual information criterion and the vertical axis indicating RMSE values across different models and feature sets. All RMSE values were obtained from the best-performing models following hyperparameter tuning. As shown in Fig. 7, under the behavioural data setting of this study, the feature sets selected by CLFS and IAMB did not achieve the best out-of-sample predictive performance. In comparison, the mutual information–based approach yielded consistently better predictive results across the evaluated models. Because maritime evacuation behaviour variables typically involve weak dependency structures, high levels of noise, and pronounced individual heterogeneity, CLFS and IAMB tend to be sensitive to these characteristics during feature selection. As a result, the selected features may show insufficient mutual relevance or include excessive redundancy, leading to notable fluctuations in out-of-sample predictive performance. In comparison, the mutual information approach does not rely on strong structural assumptions and instead ranks variables based on their information contribution, enabling a more robust selection of feature combinations

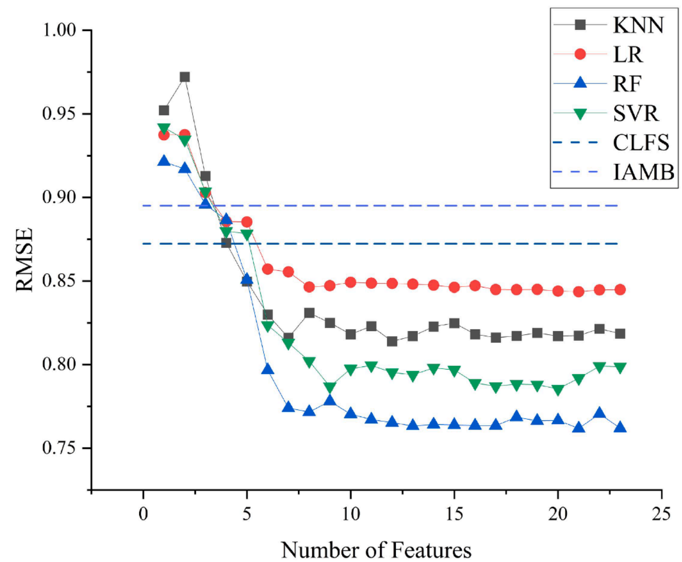

Fig. 7. Model Performance Across Feature Sets Selected by Mutual Information Thresholds.

with higher information value and lower redundancy. In contrast, when the number of selected features reaches nine, the RMSE values across mutual information–based approaches begin to stabilise and gradually converge. The detailed results are reported in Table A1 and Table A2 of Appendix A. The results indicate that increasing the number of features initially helps reduce prediction error. However, once the feature count exceeds nine, further improvements become marginal, suggesting diminishing returns in model performance. Adding additional features beyond the point does not substantially enhance predictive accuracy and may introduce redundant variables with low mutual information, increasing computational burden and the risk of overfitting. Ultimately, the inclusion of redundant or low-information features can undermine

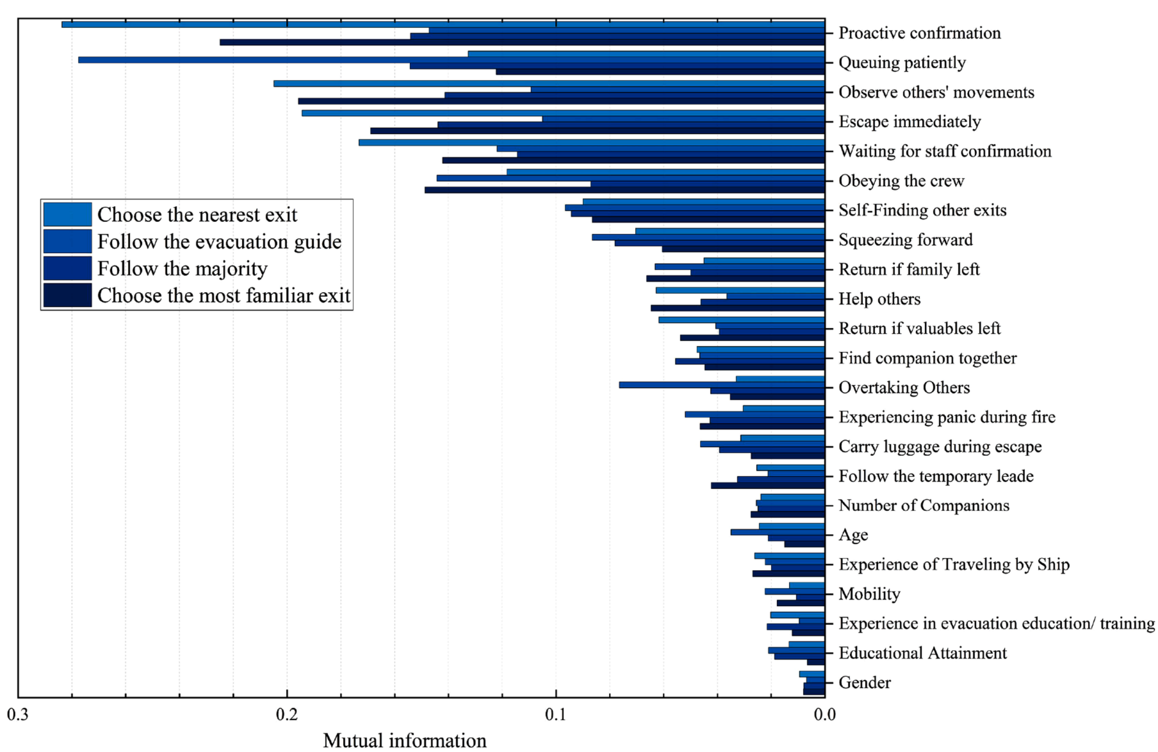

Fig. 6. Mutual Information Results between Influencing Factors and Exit Choice Behaviour.

the reliability and stability of causal inference.

Building on this trend and given that model parsimony and computational efficiency are the core objectives of this step, selecting an excessive number of features as treatment variables deviates from the intended research goal and reduces model stability. To balance model efficiency and predictive performance, the final set of treatment variables is constructed from the top nine features ranked by mutual information. The nine selected variables include “Return if family left”, “Squeezing forward”, “Self-finding other exits”, “Obeying the crew”, “Waiting for staff confirmation”, “Escape immediately”, “Observe others' movements”, “Queuing patiently”, and “Proactive confirmation”. The subset effectively balanced performance by avoiding redundant features with limited explanatory power and enhances model accuracy and robustness. It is observed that the features with the highest mutual information mainly belong to two behavioural categories in Fig. 6. The first category is response-phase behaviours, such as “Proactive confirmation” and “Escape immediately”. The second category is behaviours during congestion, such as “Queuing patiently” and “Observe others' movements”. In other words, passengers’ reactions immediately following the initial alarm contribute the greatest informational value to exit choice behaviour. Their strategic adjustments in response to congestion also play an important role. After the pre-processing phase and the selection of treatment variables with sufficient mutual information, the data were formally input into the selected machine learning models to allow identification of the most suitable algorithms under different conditions. The results, derived from the best-performing models following hyperparameter tuning, are presented in Fig. 8.

The performance of four different models across various target variables is presented in Fig. 8. In most cases, the RF model outperforms the others, demonstrating strong adaptability to diverse data characteristics and delivering accurate predictions. In a few specific scenarios, the KNN algorithm achieves superior performance, indicating its potential to capture local patterns or structures more effectively under certain conditions. Based on such findings, in this study, further analysis was conducted by using the best-performing model for each specific scenario.

4.3. Analysis of results based on causal inference

Based on the previously selected optimal feature set and the best-performing models identified for different scenarios, the DML procedure is implemented in the section. The analysis was conducted using Python 3.12.7, with predictive models developed through the scikit-learn machine learning library. The complete DML workflow was executed using the dedicated DML causal inference framework. The estimated ATEs of the treatment variables on the target variable are presented in Table 4. In this study, the ATE values have direct behavioural meaning. Since exit choice is measured on a 1–5 scale, each ATE represents the expected change in a passenger’s preference for a given exit option when a behaviour shifts from “strongly disagree” to “strongly

Table 4
Estimated ATEs of Influencing Factors on Target Variables.

	Choose the most familiar exit	Choose the nearest exit	Follow the evacuation guide	Follow the majority
Proactive confirmation	0.341	0.459	0.205	0.233
Queuing patiently	0.192	0.187	0.455	0.230
Observe others' movements	0.286	0.336	0.177	0.302
Escape immediately	0.290	0.341	0.237	0.277
Waiting for staff confirmation	0.204	0.223	0.193	0.198
Obeying the crew	0.168	0.203	0.295	0.183
Self-finding other exits	0.129	0.150	0.202	0.140
Squeezing forward	0.053	0.072	0.032	0.080
Return if family left	0.054	0.065	0.028	0.050

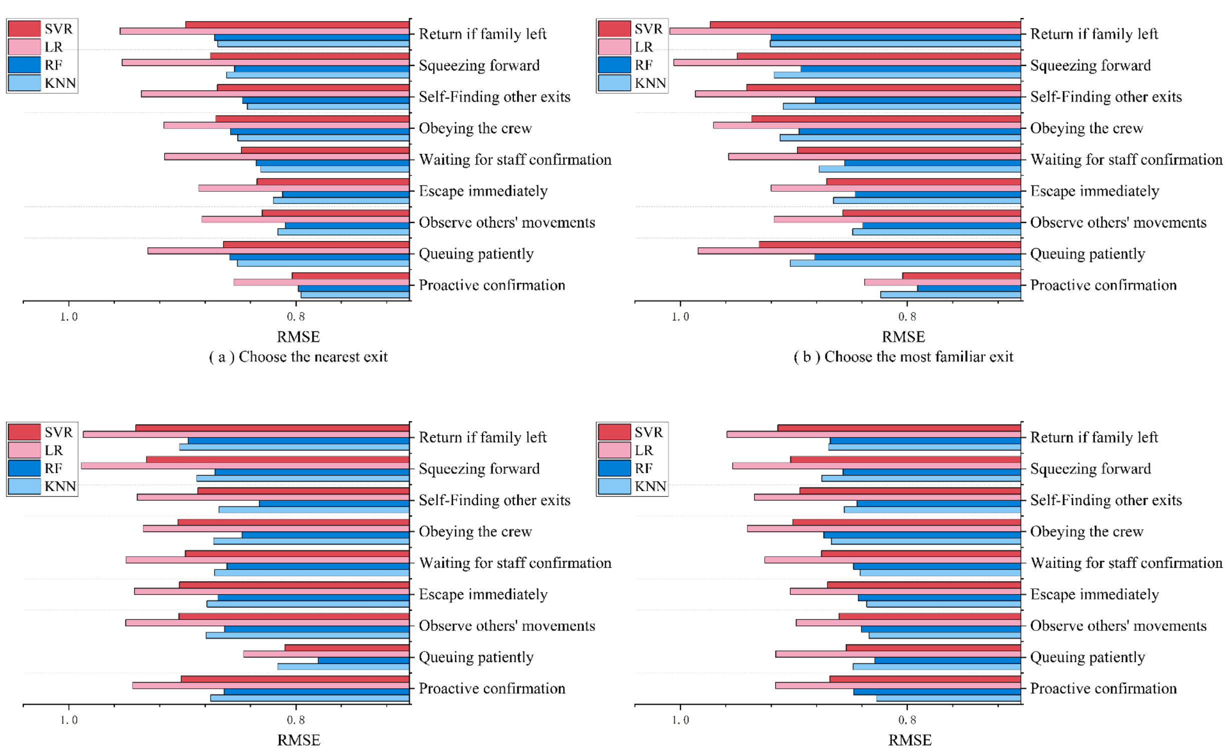

Fig. 8. Model Performance on Exit choice Behaviour Across Various Target Variables.

agree", controlling for all confounders. For instance, an ATE of 0.45 indicates an average increase of 0.45 points in the likelihood of choosing that exit strategy. Thus, larger ATEs identify behaviours with greater potential to improve decision accuracy and overall evacuation efficiency.

During the model training process, it was initially assumed that there was no significant causal relationship between the treatment variables and the target outcomes. A p-value lower than 0.05 indicates a rejection of the null hypothesis, suggesting that a statistically significant causal relationship does exist between the treatment and the outcome variables.

Following the DML analysis, a placebo test was conducted to further assess the robustness of the model. Specifically, pseudo-variables that preserved the marginal distribution but completely disrupted the structural relationships among variables were constructed, and 1000 iterations of both treatment placebo and outcome placebo experiments were performed. The resulting placebo ATE distributions are presented in Fig. 9, where panel (a) corresponds to the treatment placebo results and panel (b) corresponds to the outcome placebo results. As shown in Fig. 9, the ATE distributions of both types of placebo variables are tightly concentrated around zero, indicating the absence of any systematic association between the pseudo-variables and the exit-choice outcomes. In contrast, the ATE values derived from the real treatment variables clearly deviate from this noise band, demonstrating that their causal effects are not driven by random fluctuations or spurious correlations. These findings collectively validate the causal identification capability of the model and further support the robustness of the conclusions drawn in this study. Due to space limitations, Fig. 9 presents only the results related to the "Choose the nearest exit" option, while the complete placebo ATE distribution plots are provided in Appendix B. Specifically, Figs. B1-B4 present the results of the treatment placebo experiment, and Figs. B5-B8 present the results of the outcome placebo experiment.

Subsequently, to further verify the reliability of the causal inference framework from the perspective of statistical significance, the corresponding results were plotted. As shown in Fig. 10, each group of panels presents the p-values obtained from the treatment placebo, outcome placebo, and real experimental settings, thereby providing an intuitive basis for comparative analysis.

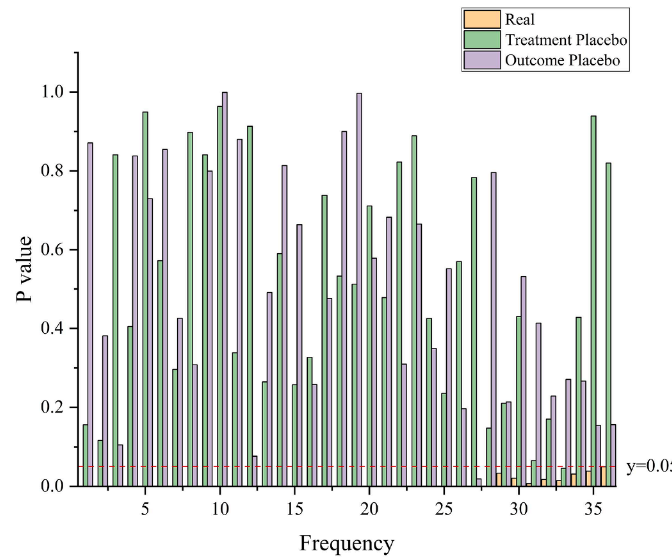

Fig. 10. Results of the Placebo Experiment.

It is observed that all p-values corresponding to the real experiments are below 0.05 in Fig. 10, indicating that statistically significant causal relationships exist between the treatment variables and the target outcomes. Meanwhile, the p-values associated with the treatment placebo variables all exceed 0.05, indicating that the randomly generated pseudo-treatments do not introduce systematic bias and support the robustness and validity of the model under random perturbations. Furthermore, even after randomly reassigning the outcome labels related to exit choice, the estimated effects of the original treatment variables remain statistically insignificant, indicating that the model's estimates are not affected by structural biases in the outcome variable. In summary, the validation results confirm the suitability of the DML approach for the present analysis. They effectively rule out major sources of estimation bias and ensure the stability and reliability of the causal effect estimates.

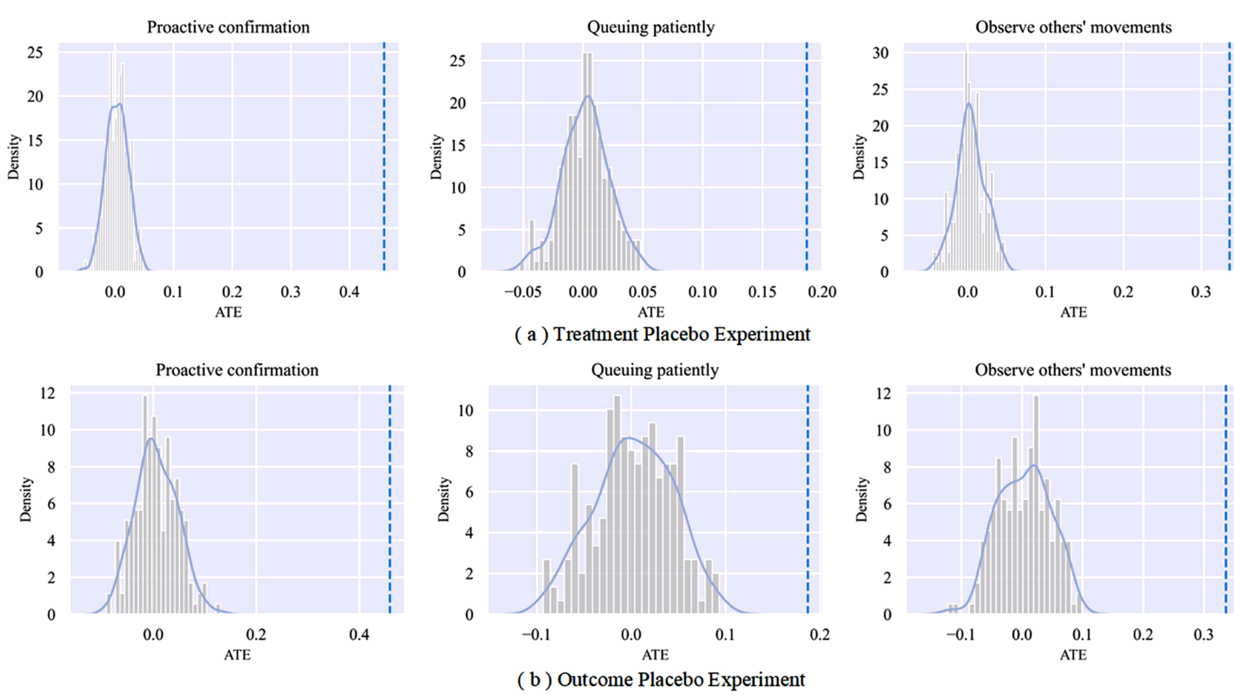

Fig. 9. Placebo Experiment ATE Distributions.

Fig. 9 and Fig. 10 together provide a two-layer validation of the DML framework. Fig. 9 evaluates identification validity by demonstrating that placebo variables are constructed to break all structural relationships. These variables produce ATE estimates that are tightly centred around zero, which matches the theoretical expectation under the null hypothesis. Fig. 10 complements this by confirming statistical reliability. Only the real treatment variables yield p-values below 0.05, whereas both treatment and outcome placebo variables remain non-significant. These diagnostics are particularly essential for DML, which relies on orthogonalization to eliminate confounding. Showing that randomised pseudo-variables generate no artificial causal signals provides direct methodological evidence that the orthogonalization step works as intended. Overall, the placebo analyses confirm both the correctness and the robustness of the estimated causal effects, reinforcing the suitability of DML for the present behavioural analysis.

Building on these results, further analysis was conducted based on the data presented in Table 4. For the strategy of "choose the nearest exit," the three most influential response-phase behaviours are "Proactive confirmation" with an ATE of 0.459, "Escape immediately" with an ATE of 0.341, and "Observe others' movements" with an ATE of 0.336. These behaviours exhibit significant causal influence on passengers' decisions, indicating their practical impact during the response phase. In contrast, under the strategy of "choose the most familiar exit," the same response-phase behaviours still demonstrate relatively strong causal effects, but their ATE values are generally lower than those observed in the "choose the nearest exit" scenario, suggesting a slightly reduced influence of behaviours on passenger decisions under this strategy. Meanwhile, "Self-finding other exits" during the congestion phase yields an ATE of 0.129, indicating a limited causal effect, though it may still influence individual decisions in specific circumstances. For the strategy of "follow the majority," the response-phase behaviours "Escape immediately" and "Observe others' movements" continue to exhibit relatively high causal effects, showing that these behaviours can drive group decision-making to some extent. Other congestion-phase behaviours show low ATE values, suggesting that their influence is relatively limited during collective following. For the strategy of "follow the evacuation guide," the behaviour "Queuing patiently" demonstrates the most prominent causal effect during congestion, with an ATE of 0.455, markedly higher than other features, highlighting its key role in the evacuation process. Meanwhile, "Obeying the crew" has an ATE of 0.29, reflecting a moderate but significant causal effect, whereas "Squeezing forward" shows low correlation and ATE, indicating a limited influence on decision-making. The behaviour "Return if family left" does not show significant causal effects across any exit choice strategy, with consistently low ATE values. This suggests that while some passengers may temporarily adjust evacuation paths due to family considerations, the overall influence of this behaviour on exit choice remains limited. Additionally, analysis of other less emphasized behaviours (such as observing others' movements) generally shows low causal effects and ATE values, indicating that their contribution to overall exit choice is limited, though they may still play a role in individual differences or specific scenarios.

After emphasizing causal effect analysis, correlation-based findings were explicitly compared with causal inference results for specific behaviour–exit choice pairs. Under conventional correlational analysis, behaviours such as "escape immediately" and "obey evacuation guidance" exhibit relatively low correlation coefficients with exit choice outcomes and would therefore typically be regarded as secondary factors. However, when these behaviours are analysed within the DML framework, while controlling for demographic attributes, travel experience, situational conditions, and other behavioural factors, their estimated Average Treatment Effects reach 0.277. This magnitude ranks at a moderate-to-high level among all influencing factors, indicating a stable and non-negligible causal impact on exit choice tendencies. A similar contrast is observed for the behaviour "self-finding other exits" with respect to the exit choice strategy "following the majority". Although the raw correlation between this behaviour and the corresponding exit choice appears weak, the causal analysis yields an ATE of 0.202 after confounding effects are removed. This result indicates that the behaviour can still substantially shift passengers' exit choice preferences, even if the two do not frequently co-occur in the observed data. These discrepancies highlight a fundamental limitation of correlational analysis, which primarily captures co-occurrence patterns or synchronous variation rather than identifying behaviours that truly drive decision changes. In complex evacuation contexts, certain behaviours may appear weakly correlated due to situational constraints, group dynamics, or individual heterogeneity. However, this does not imply that they are unimportant in shaping decision-making. By systematically removing the influence of confounding factors, causal analysis reveals the decisive role of these "low-correlation but high-causal-impact" behaviours. Therefore, exclusive reliance on correlational analysis may obscure key behavioural drivers and underestimate their contribution to evacuation efficiency and safety. In contrast, the ATE captures outcome changes attributable to behavioural variation while holding other conditions constant, providing a more faithful representation of the underlying decision mechanism. These findings underscore the necessity and value of incorporating causal inference into studies of passengers' exit choice behaviour and offer a more rigorous foundation for targeted evacuation management and safety interventions.

5. Discussions and implications

5.1. Discussions

The findings of this study provide insights into the mechanisms governing passengers' evacuation behaviours. The DML framework established here enables more accurate identification of the true causal relationships underlying these behaviours, thereby reducing the risk of misinterpretations caused by confounding factors or reverse causality. The results show that the key factors affecting evacuation exit choice mainly lie in response-phase behaviours and behaviours during congestion. Response-phase behaviours reflect passengers' instantaneous decision-making and reaction capabilities upon receiving an emergency alert, directly affecting their directional choices, initiation timing, and response speed [13]. In contrast, behaviours during congestion capture passengers' strategic adjustments and adaptive mechanisms when encountering restricted passages or crowd density [10]. The two behaviour types correspond to the initial and movement phases of evacuation respectively, forming the critical decision-making mechanisms governing passengers' exit selection.

During the response phase of evacuation behaviour, passengers' actions such as "proactive confirmation", "escape immediately", "observe others' movements", and "waiting for staff confirmation" exert a critical influence on exit choice. The behaviours reflect passengers' immediate reaction capabilities, environmental awareness, and willingness to respond to risk upon sudden alarms. From a psychological perspective, "proactive confirmation" helps alleviate cognitive uncertainty regarding the situation, enhancing passengers' sense of control and safety, thereby facilitating rapid action [32]. "Escape immediately" indicates that some passengers possess heightened risk sensitivity, enabling them to promptly trigger escape motivation and reduce unnecessary hesitation and delay [77]. Meanwhile, "observe others' movements", as a typical social information strategy, allows passengers to make more rational judgments under conditions of insufficient information by leveraging group cues [78]. In contrast, "waiting for staff confirmation" reflects an information-dependent decision-making mechanism, whereby passengers partly delegate decision authority to an authoritative information source to reduce their own risk burden. Although passengers exhibiting the behaviour tend to act more cautiously and at a slower pace, their decision directions are generally clearer, favouring evacuation via exits that are both familiar and close [40]. The behaviours not only accelerate decision initiation but also strengthen the certainty of path selection, constituting key mechanisms enabling passengers to achieve rapid escape under high-pressure conditions [79,80].

During the congestion phase of evacuation, the behaviours adopted by passengers also exert a profound impact on exit choice. Among these, "queuing patiently", "obeying the crew", "self-finding other exits", and "squeezing forward" represent distinct attitudes toward order and adaptive strategies to the environment. From psychological and behavioural perspectives, "queuing patiently" reflects passengers' ability to maintain order recognition amid chaotic conditions. By mitigating crowd conflicts and suppressing local disorder, the behaviour complements "Obeying the crew" in forming the behavioural foundation for maintaining on-site evacuation order [13]. "Obeying the crew" is an external authority-dependent coping mechanism, particularly prominent when spatial familiarity is low or when exit route choices are difficult. The behaviour is largely influenced by passengers' trust in professionals and can significantly improve decision-making efficiency, preventing blind actions under pressure [81]. Similar to "waiting for staff confirmation" in the response phase, the behaviour represents an authority-reliant path decision mode, but its role is more focused on continuous guidance and order maintenance, showing greater contextual adaptability and directional clarity. In contrast, "self-finding other exits" demonstrates higher initiative and adaptability. Passengers exhibiting the behaviour tend to explore alternative routes to avoid risks when primary passages are blocked or congested, reflecting independent situational judgment. The behaviour alleviates crowd pressure in core passages and contributes spatial diversity to the overall evacuation. However, its effectiveness depends on passengers' knowledge of the ship layout and real-time information availability. Inadequate guidance systems or unclear spatial configurations may lead to route confusion, detours, or even entry into restricted areas [10]. "Squeezing forward", as a highly competitive behaviour, reflects passengers' anxiety-driven attempts to access limited resources during evacuation bottlenecks. Often triggered by panic, time pressure, or social conformity, the behaviour involves breaching orderly movement in pursuit of priority access. However, it frequently leads to pushing, tripping, and other localised safety hazards, which undermine both individual efficiency and overall evacuation order [9]. Its low causal effect further indicates that "squeezing forward" has limited practical influence on exit choice and is more likely an immediate response under stress, providing minimal support for passengers' decision-making.

In addition to the average effects reported above, it is important to recognize that passengers may not respond to evacuation cues in a uniform manner. The ATE findings reveal the overall causal influence of behavioural factors. However, different demographic or situational subgroups may exhibit distinct behavioural response patterns during emergencies. These include older adults, passengers with limited mobility, and individuals unfamiliar with marine environments. Such heterogeneity is especially relevant in evacuation settings, where risk perception, decision latency, and adaptive capacity differ substantially across individuals. To further enrich the interpretation of the present results, future research could extend the current framework by estimating Heterogeneous Treatment Effects (HTE). Methods such as causal forests or subgroup-specific residualization within the DML framework would allow for the identification of group-dependent causal mechanisms. These approaches could further reveal heterogeneous behavioural responses among different demographic or situational groups. Incorporating HTE analysis would thus deepen the behavioural insights of the model and strengthen its practical relevance for designing targeted, group-sensitive evacuation management strategies.

5.2. Implications

This study contributes to the research on exit choice in maritime evacuations by addressing key challenges in contributing factor analysis. It focuses particularly on causal inference modelling and the identification of critical influencing factors. This study systematically advances knowledge in data analysis, model selection, and causal inference. The findings hold significant value for both theoretical understanding and practical safety management.

5.2.1. Theoretical implications

(1). Construction of the Causal Inference Framework.

The concept of causal inference is applied to construct a DML-based framework for analysing exit choice in evacuation domain. The framework addresses the limitations of traditional statistical methods and conventional machine learning in distinguishing causality from correlation, effectively mitigating the influence of confounding factors and selection bias. By systematically integrating passenger behavioural characteristics, ship layout, and external environmental factors, the causal mechanisms underlying exit choice are characterised with precision. This study thus enriches the methodology for analysing passenger evacuation behaviour and provides a robust theoretical foundation for future investigations into complex human behavioural causal mechanisms.

(2). Intelligent Selection of Key Contributing Factors.

An automated treatment factor selection mechanism is developed to account for the complex passenger behaviours and multiple external environmental factors influencing evacuation exit choice on passenger ships. The mechanism, based on feature importance, prevents over-reliance on empirical judgment and the inclusion of low-relevance factors, thereby enhancing the interpretability and practical value of the model. By concentrating on key treatment variables, the causal inference process is optimised in highly complex data settings, providing a generalisable variable selection method for related fields.

(3). Optimisation of the Nuisance Function.

The estimation of the nuisance function in the DML method is optimised through multi-model comparison and dynamic selection strategies. When combined with cross-fitting and model evaluation metrics, the approach strengthens the robustness of residual estimation and the reliability of causal effect inference. In contexts characterised by complex passenger behaviours and multi-scenario interactions, the optimisation method markedly improves the accuracy and adaptability of causal inference. It provides robust technical support for the analysis of highly complex behavioural data and offers a framework for integrating artificial intelligence techniques with existing emergency evacuation prediction models.

5.2.2. Practical implications

Previous studies indicate that passengers' behavioural characteristics during evacuation directly influence overall efficiency and safety. This study highlights that emergency evacuation training and drills should target the behavioural traits identified as having significant causal effects. Systematic training enhances passengers' emergency response capabilities and their ability to select evacuation routes effectively. Training content should be practical, emphasising simplicity and ease of execution, while accounting for differences in age, physical condition, educational level, and prior experience. Overly complex or difficult procedures should be avoided. Passenger ship operators can implement tiered training programmes combining concise theoretical explanations with practical drills, enabling passengers to acquire essential skills such as rapidly recognising alarm signals, locating the nearest safe exits, and coordinating with others [82]. Methods should be diversified, including scenario simulations, video guidance, and interactive exercises to enhance engagement and effectiveness. Regular refresher courses and drills consolidate emergency skills and psychological readiness, allowing passengers to respond confidently and effectively in unforeseen situations.

During the congestion phase, the understanding of common passenger behaviours should be enhanced through public education and practical simulation drills to reinforce awareness of orderly queuing. Passengers benefit from understanding that maintaining order not only reduces passage conflicts but also enhances overall evacuation efficiency while promoting self-control and a sense of responsibility under high-pressure conditions. Crew members form the core of on-site order maintenance and should undergo professional emergency training to improve command, communication, and emotional guidance skills. In addition to conventional training, interactive passenger evacuation drills may be introduced to simulate realistic congestion scenarios. These drills can help passengers internalise correct response strategies and reduce hesitation during real emergencies. Guidance should employ diverse methods, including announcements, hand signals, and visual cues, complemented by technological measures such as high-contrast dynamic lighting and multilingual prompts to increase the visibility and recognisability of evacuation signs. Furthermore, the optimised placement of evacuation signs can further support passengers in rapidly identifying safe and efficient routes. This is particularly important at decision points and in areas prone to crowding. Real-time transmission of evacuation information via broadcasts, videos, and wearable devices supports passengers in making timely and appropriate route choices, thereby reducing decision delays and path conflicts. Auxiliary evacuation signs should be enhanced to relieve corridor congestion, while backup exits and alternative routes must remain clearly visible. Safety education should encourage passengers to familiarise themselves with these alternative routes, enhancing adaptability to the environment. A comprehensive risk education system can prevent rushed behaviours arising from nervousness or impatience. Coupled with on-site monitoring and the strategic diversion of personnel, order violations can be promptly addressed, fostering a calm and orderly evacuation environment. By integrating clear information delivery with dynamic on-site response, the organisation and overall safety of evacuation are effectively improved, while individual capacity to respond to emergencies is strengthened [83].

6. Conclusions

Passenger safety is the paramount concern during emergency evacuations on passenger ships, making it critical to understand the causal mechanisms driving exit choices. To this end, this study developed a comprehensive analytical framework incorporating the DML approach, leveraging the combined strengths of machine learning and statistical inference to robustly identify causal effects.

The research results indicate that the key determinants of passengers' exit choice are primarily concentrated in response-phase behaviours and behaviours during congestion. Significant causal effects are exhibited by these behaviours, which are regarded as core determinants of exit choice. However, high correlation does not necessarily imply strong causality; some behaviours that appear prominent in correlation analysis do not exert significant influence in causal analysis. Based on the findings, evacuation training should be designed to enhance passengers' ability to recognise and respond to alarms and to reinforce orderly coping strategies during congestion. Simulation drills targeting these key behaviours can enable passengers to respond more promptly to alarms, select evacuation routes effectively, and manage congestion, thereby improving overall evacuation efficiency and safety.

This study provides data support and new insights for further exploring the mechanisms underlying evacuation exit choice. However, certain limitations remain. The questionnaire survey relies on cross-sectional data, which makes it difficult to dynamically capture the process of passengers' evacuation decision-making over time or across different scenarios. Therefore, it has certain shortcomings in revealing complex psychological and behavioural mechanisms. Moreover, the sample is drawn from a specific regional route which may limit the generalisability of the findings. Future research will further address the issues by expanding data collection to additional ship types and more diverse passenger groups to overcome the limitations.

Data availability

The data and source code are publicly available at: https://github.com/AdvMarTech/Eva_Exit-Choice.

CRediT authorship contribution statement

Xinjian Wang: Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Yiquan Yuan:** Writing – original draft, Validation, Methodology, Conceptualization. **Siming Fang:** Writing – original draft, Validation, Resources, Investigation. **Zhiwei Zhang:** Writing – review & editing, Validation, Investigation, Formal analysis. **Jin Wang:** Writing – review & editing, Supervision, Resources, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. RMSE values across mutual information–based approaches

Table A1
The RMSE Value of Different Machine Learning Models Based on Mutual Information.

Number of features	KNN	LR	RF	SVR
1	0.95221	0.93747	0.9213	0.94193
2	0.97225	0.93758	0.91708	0.93462
3	0.91287	0.9029	0.89591	0.90361
4	0.87282	0.88563	0.88645	0.87983
5	0.84973	0.88534	0.85066	0.87838
6	0.82997	0.85713	0.79664	0.82358

(*continued on next page*)

Table A1 (*continued*)

Number of features	KNN	LR	RF	SVR
7	0.81601	0.85553	0.77406	0.8131
8	0.83099	0.8464	0.77171	0.80211
9	0.82497	0.84723	0.7781	0.78684
10	0.81814	0.8493	0.77033	0.79754
11	0.82295	0.84873	0.7672	0.79957
12	0.81395	0.84861	0.76527	0.79538
13	0.81706	0.84817	0.76326	0.7939
14	0.82277	0.84758	0.76421	0.79808
15	0.82485	0.84621	0.76393	0.79682
16	0.81826	0.84722	0.76351	0.78898
17	0.81613	0.84495	0.7635	0.78711
18	0.81714	0.84485	0.76861	0.78836
19	0.81899	0.84497	0.76639	0.78796
20	0.81708	0.84396	0.76664	0.78543
21	0.81741	0.84358	0.76183	0.79183
22	0.82149	0.84467	0.77058	0.79909
23	0.81856	0.84484	0.76193	0.79878

Table A2
The RMSE Value of Causal Feature Selection Methods.

Model	CLFS	IAMB
RMSE	0.87241	0.89513

Appendix B. Placebo ATE distribution plots

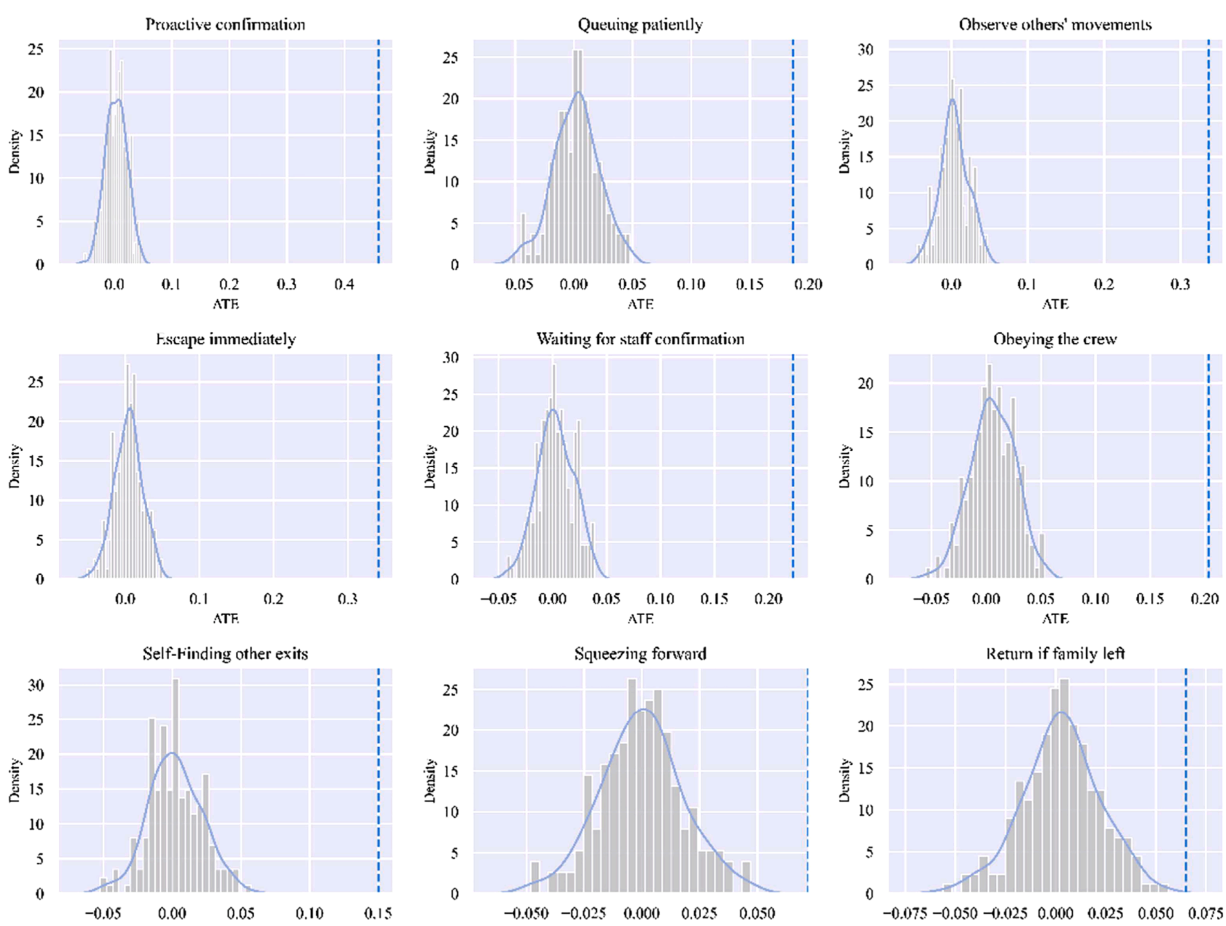

Fig. B1. Results of the Treatment Placebo Experiment (Choose the Nearest Exit).

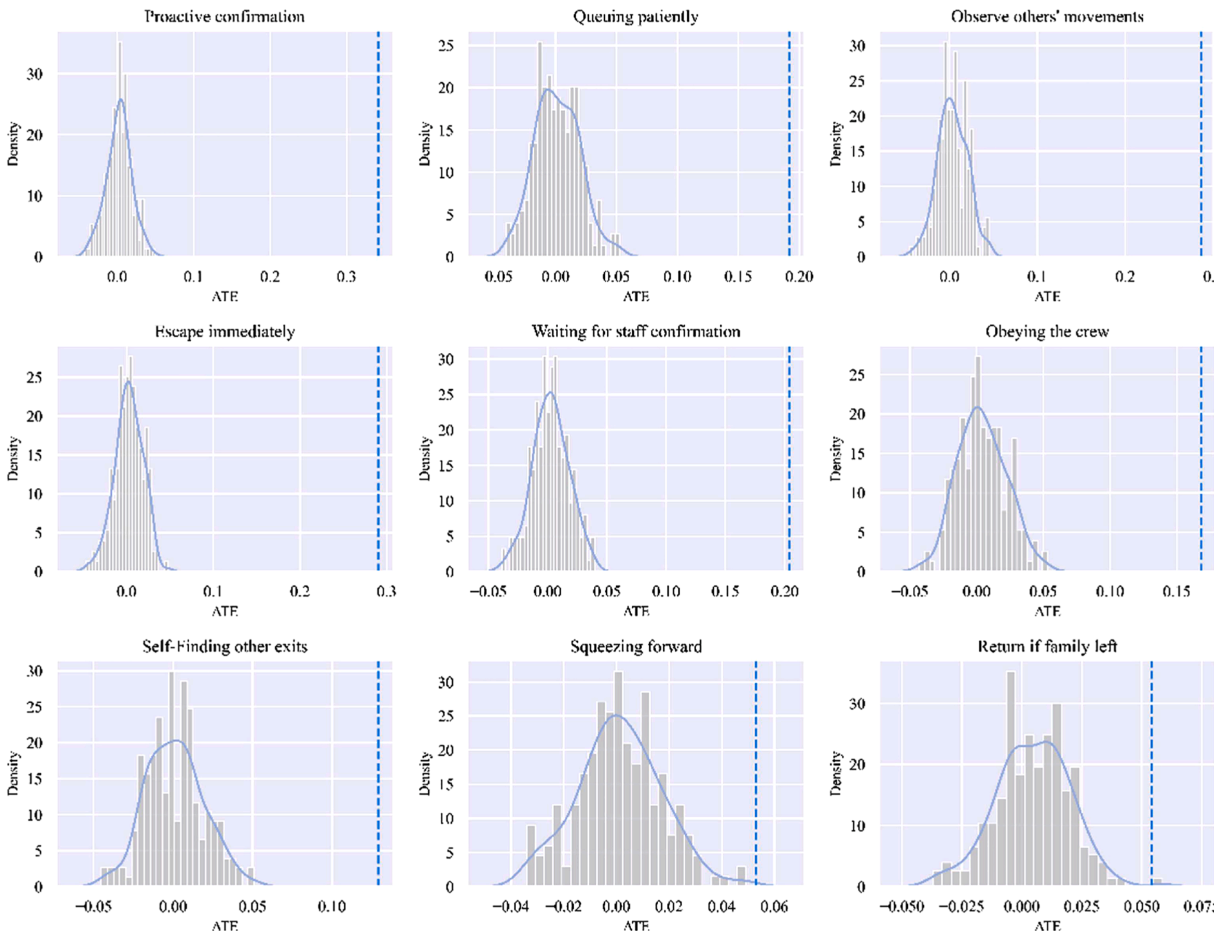

Fig. B2. Results of the Treatment Placebo Experiment (Choose the most familiar exit).

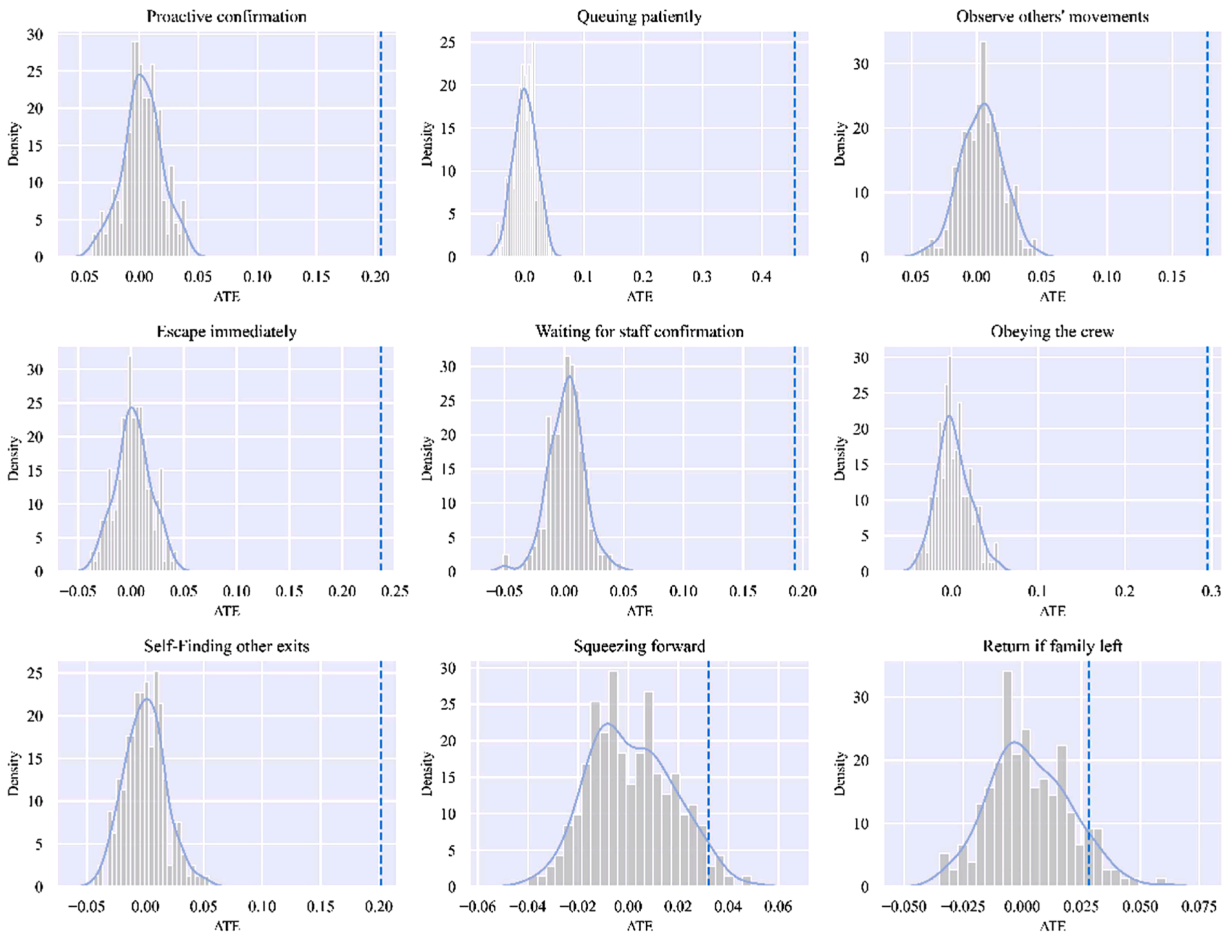

Fig. B3. Results of the Treatment Placebo Experiment (Follow the evacuation guide).

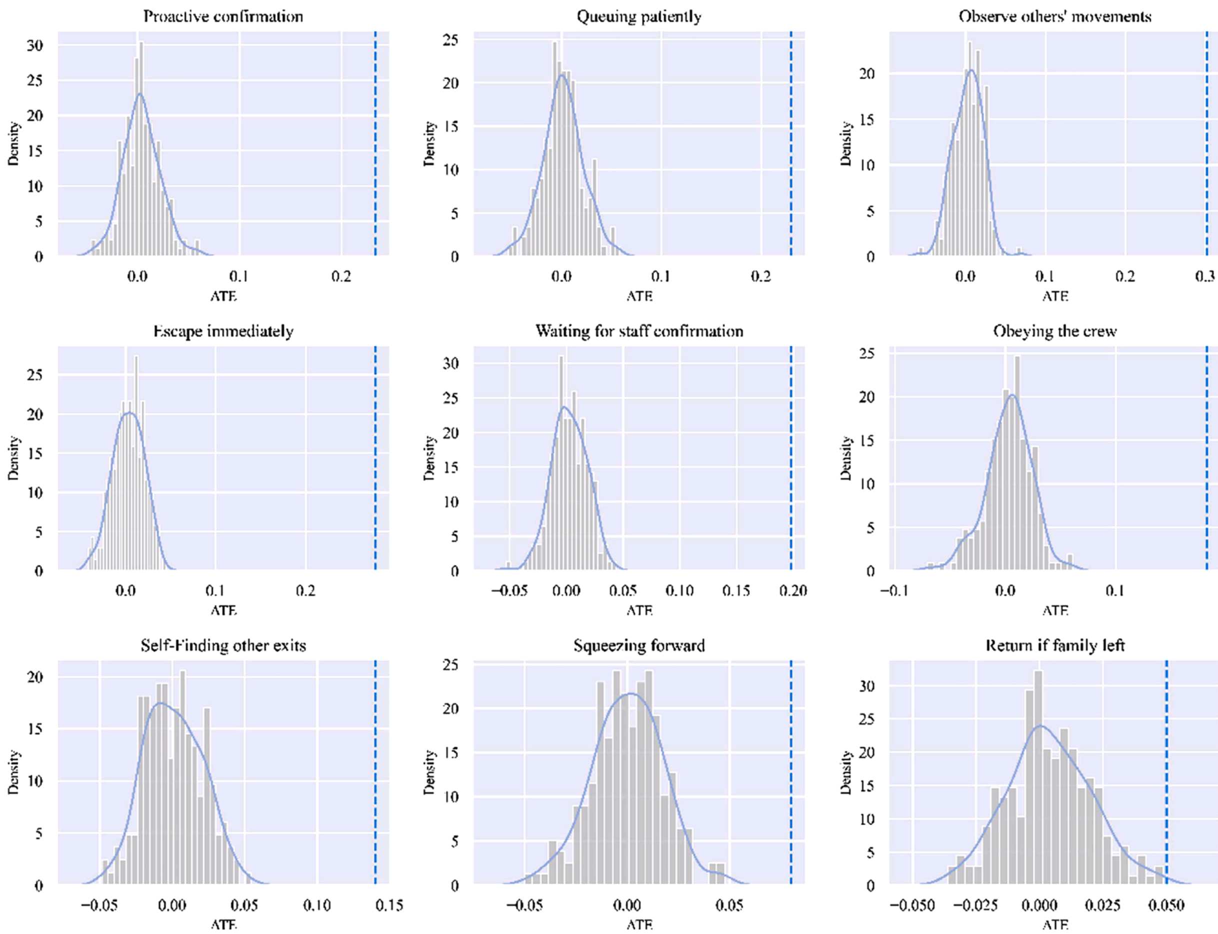

Fig. B4. Results of the Treatment Placebo Experiment (Follow the majority).

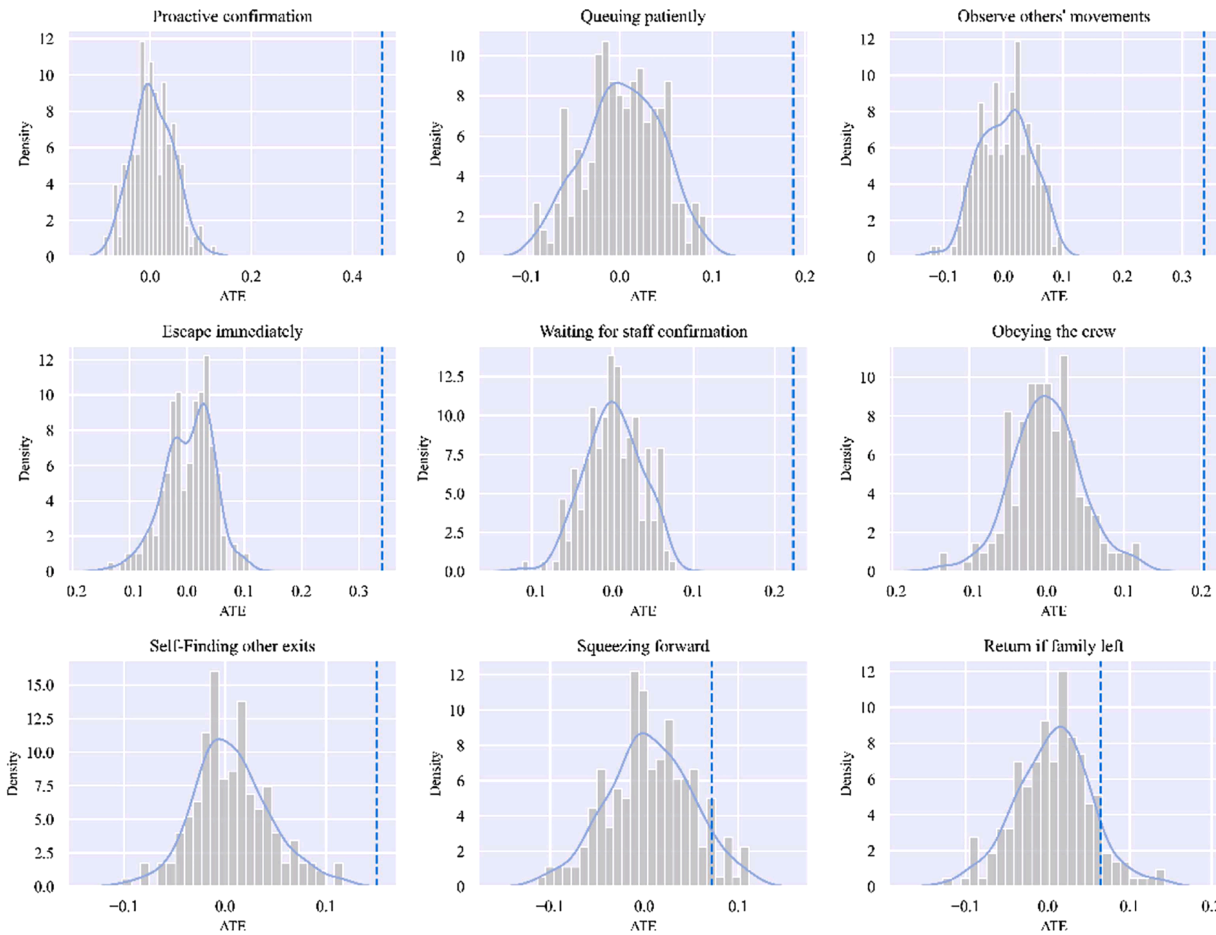

Fig. B5. Results of the Outcome Placebo Experiment (Choose the Nearest Exit).

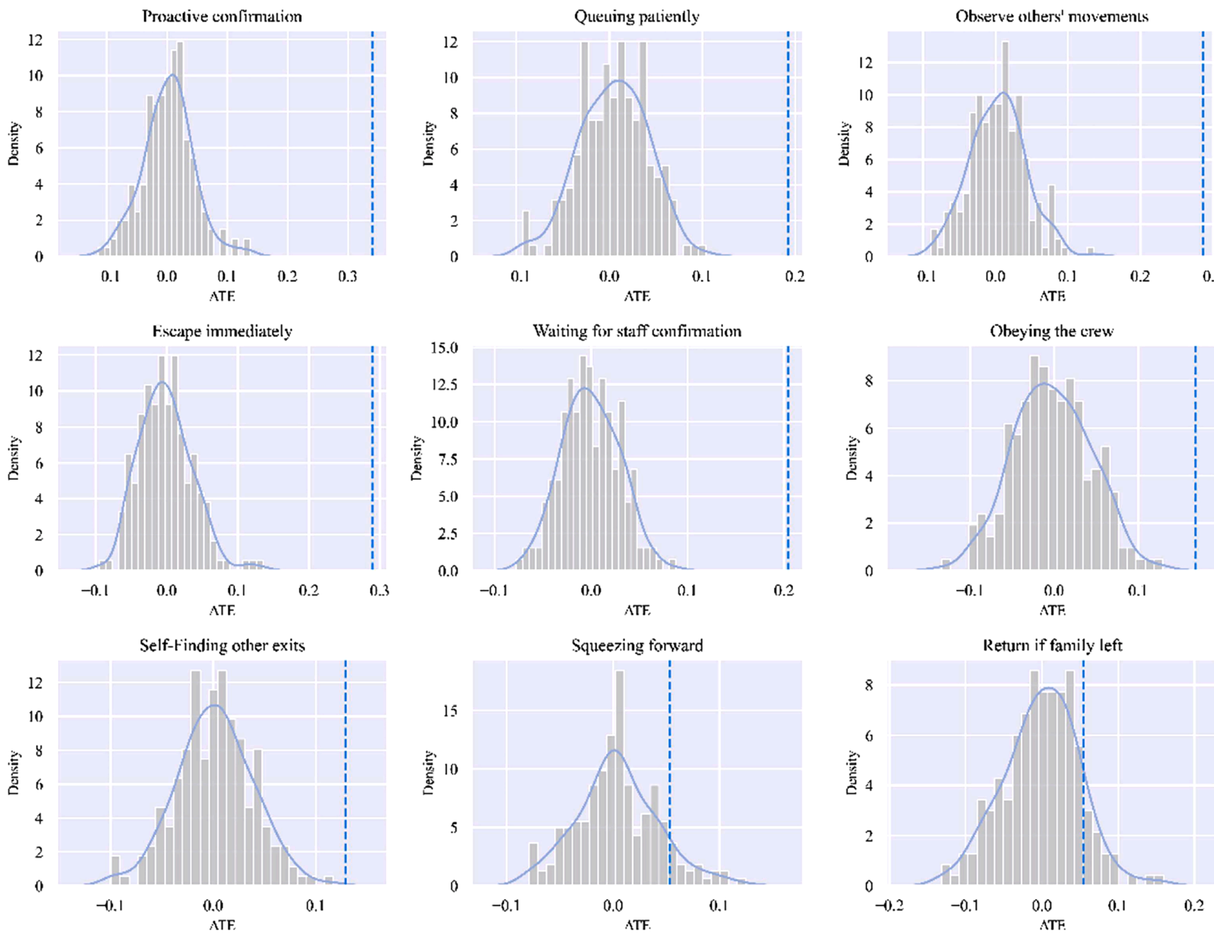

Fig. B6. Results of the Outcome Placebo Experiment (Choose the most familiar exit).

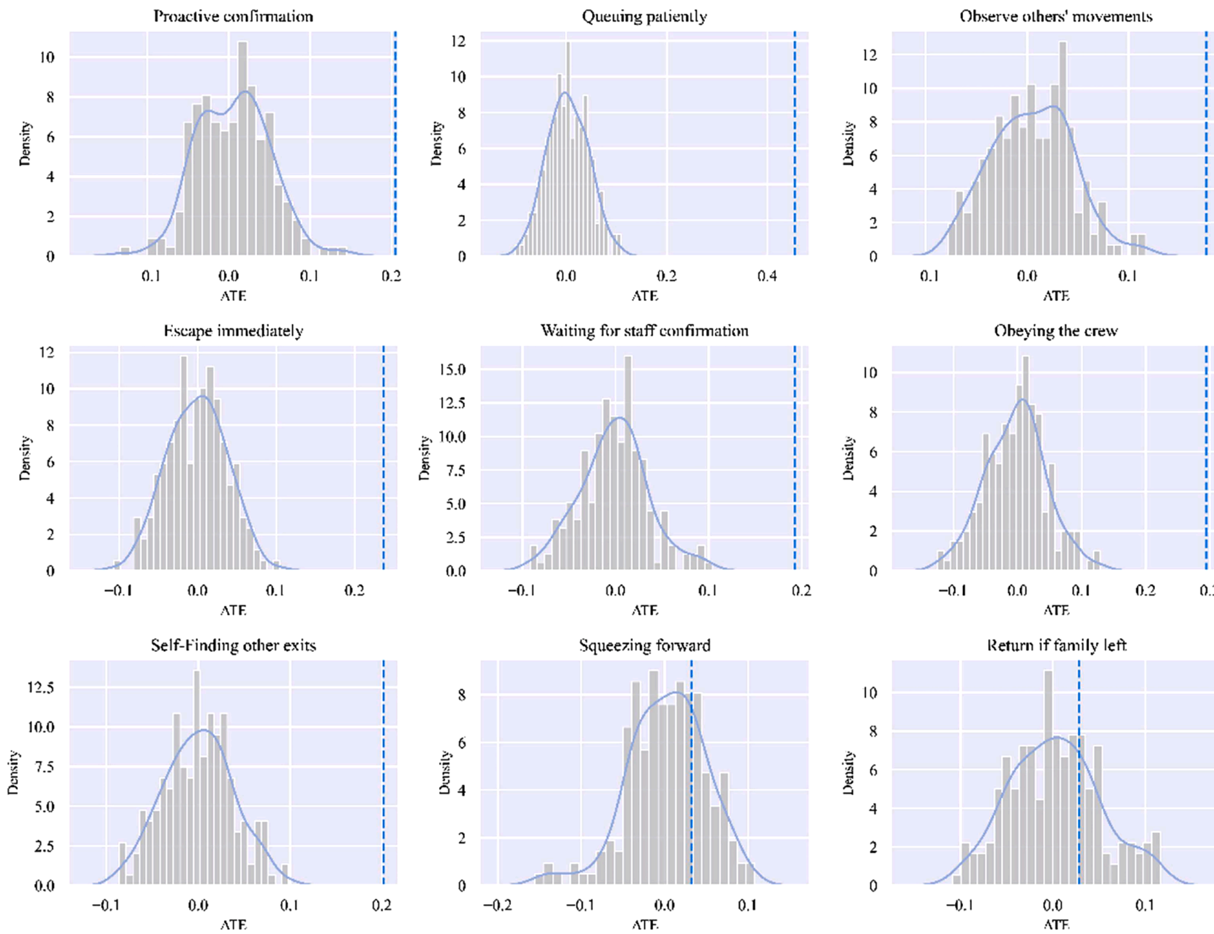

Fig. B7. Results of the Outcome Placebo Experiment (Follow the evacuation guide).

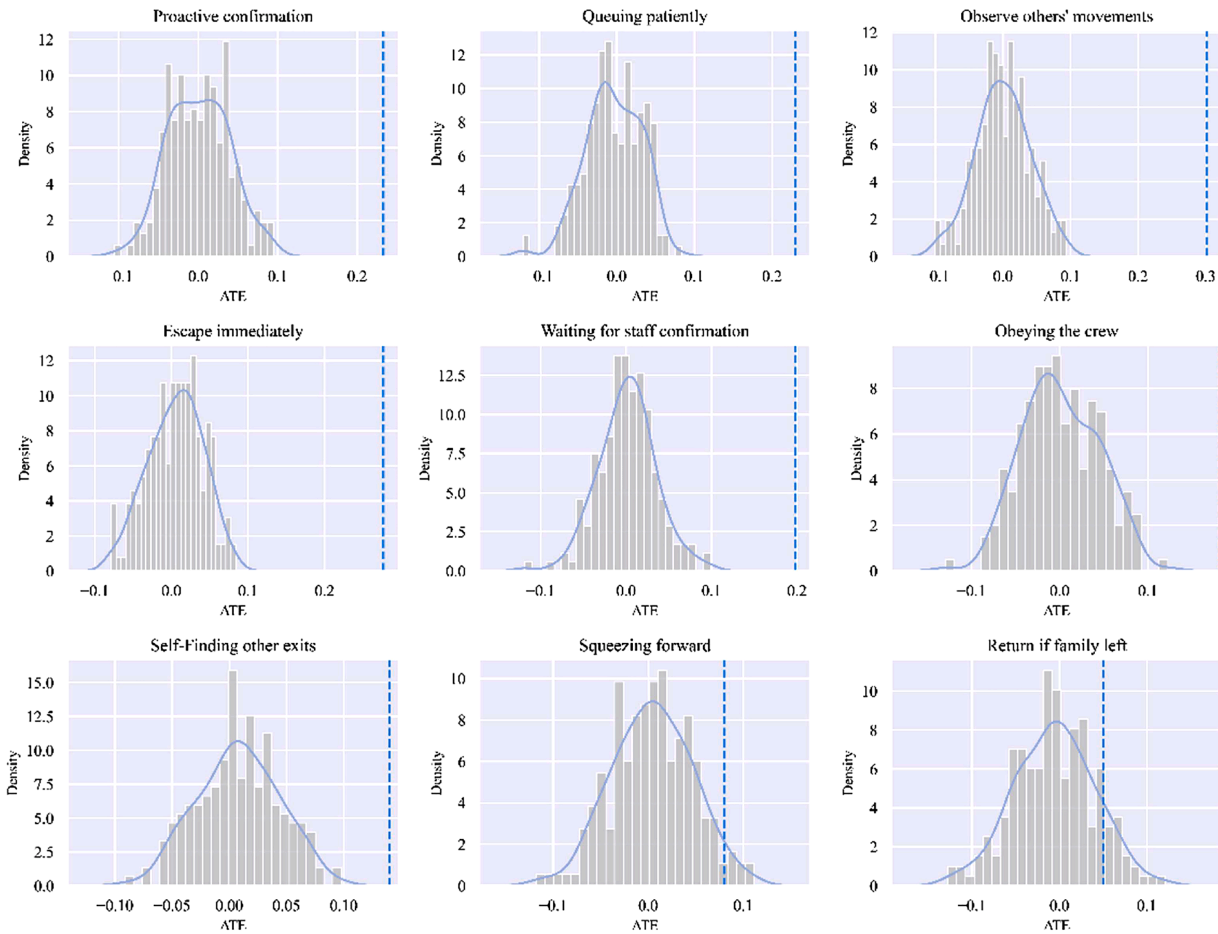

Fig. B8. Results of the Outcome Placebo Experiment (Follow the majority).

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