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Quantifying variable contributions to bus operation delays considering causal relationships

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ABSTRACT

Bus services often face operational delays due to dynamic conditions such as traffic congestion, which can propagate through bus routes, affecting overall system performance. Understanding the causes of bus arrival delays is crucial for effective public transport management and control. Moreover, understanding the contribution of each factor to bus delays not only aids in developing targeted strategies to mitigate delays but is also crucial for effective decision-making and planning. Traditional research primarily focuses on correlation-based analysis, lacking the ability to reveal the underlying causal mechanisms. Additionally, no studies have considered the complex causal relationships between factors when quantifying their contributions to outcomes in public transport. This study aims to analyze the factors causing bus arrival delays from a causal perspective, focusing on quantifying the causal contribution of each factor while considering their causal relationships. Quantifying a factor's causal contribution poses challenges due to computational complexity and statistical bias from the limited sample size. Using a causal discovery method, this study generates a causal graph for bus arrival delays and employs the causality-based Shapley value to quantify the contribution of each variable. The study further uses the Double Machine Learning (DML) approach to estimate the causal contributions, which provides a consistent and computationally feasible method. A case study was conducted using Google Transit Feed Specification (GTFS) data, focusing on high-frequency bus routes in Stockholm, Sweden. To validate the model, cross-validation was performed by comparing variable importance rankings with traditional models, including Linear Regression (LR) and Structural Equation Modeling (SEM). The comparison shows that results from the causality-based Shapley value significantly differ from those obtained by traditional methods in terms of importance rankings and influence magnitudes. The findings underscore the significant impact of origin delays on bus punctuality, a factor often underestimated in previous studies. Additionally, it demonstrates that employing a causal discovery model can not only infer causal relationships but also reveal direct and indirect effects, which can provide more intuitive explanations. Finally, although the causal results are mathematically and intuitively sound, it is important to further investigate the real causality impact in practice using lab experiments or A/B tests in real-world settings.

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1. Introduction

Public transport systems, represented by bus networks, form the backbone of urban mobility, facilitating the daily commute for millions worldwide. These systems operate within complex, shared transportation networks that are constantly influenced by both internal and external factors. Specifically, bus operations within urban transit networks, which are shared with various types of vehicles, often encounter disturbances that are either recurrent (systemic) or non-recurrent (stochastic). These disturbances include traffic congestion, infrastructure breakdowns, and extreme weather (Walker, 2024; Rodriguez-Deniz and Villani, 2022; He et al., 2020; Yu et al., 2017; Kathuria et al., 2020). Service delays in public transport systems do not necessarily imply failures, as they may be affected by operational considerations, such as maintaining proper headway during peak hours (Wessel et al., 2017). These delays can disrupt the schedule and propagate through the network, leading to a reduction in the operational efficiency of the transport system. Therefore, understanding the causes of bus delays is essential and paramount for improving the reliability and efficiency of public transport. Furthermore, understanding the contribution and impact of each factor on bus delays is essential for developing targeted strategies to mitigate delays and making informed decisions in transport planning.

Existing research in bus delay analysis has primarily relied on regression models to analyze the correlation between factors and bus arrival delays (Ma et al., 2015, 2017; Kathuria et al., 2020; Chen et al., 2009). These studies ignore the interrelationships between factors and fail to reveal underlying causal relationships. Although more advanced models (e.g., machine learning-based methods (Huang et al., 2021; Zhou et al., 2022; Singh and Kumar, 2022)) have provided a deeper understanding of these dynamics, they still do not go beyond correlation-based analysis and remain insufficient in explaining underlying delay mechanisms. Moreover, no literature quantifies the contribution of variables that affect bus arrival delays, which is a prerequisite for understanding the mechanisms of bus delays and developing targeted prevention strategies. Although some studies in public transportation have used attribution methods based on Shapley values to analyze the contribution of factors to outcomes (Gnecco et al., 2021; Li et al., 2024; Ji et al., 2022), they did not consider the causal relationship between factors. The variables that affect bus delays are interrelated and may have causal relationships, which is crucial to accurately quantify their real contribution. Therefore, a significant gap lies in quantifying the contribution of each variable to bus delays by considering the causal relationships among these variables.

Causality describes the concept of a cause leading to an effect, where one event/variable (the cause) initiates or impacts another (the effect) (Holland, 1986). This concept asserts that one variable causes changes in another. Unlike correlations, which merely indicate a statistical relationship, causality denotes a directional connection where changes in the cause precede and result in changes in the effect. Inferring causal effects is a critical challenge across data science disciplines, addressing questions such as '*what would the outcome be if inputs were set to specific values ?*'. Causal discovery involves using algorithms and statistical methods to infer causal relationships and uncover the underlying causal structure from observational dataset (Hasan et al., 2023). The primary output of these methods is a causal graph, where nodes represent variables, and edges indicate causal relationships. These relationships suggest that a change in the source variable (parent) can lead to a change in the target variable (child). A large number of causal discovery methods have been developed to infer causal links, such as the Peter-Clark (PC) algorithm (Spirtes et al., 2000), Greedy Equivalence Search (GES) (Chickering, 2002), and Linear Non-Gaussian Acyclic Model (LiNGAM) (Shimizu et al., 2006), etc.

Beyond causal inference, interpreting results is crucial. In the context of bus delay analysis, this involves quantifying the contribution of variables that cause delays, which enables the implementation of targeted strategies to reduce delays and enhance service timeliness. This process is called quantifying/measuring causal contributions, assessing the impact of each variable on an outcome. It is the domain of Explainable Artificial Intelligence (XAI), which aims to make the decisions and operations of AI systems both transparent and understandable to humans (Arrieta et al., 2020). The typical attribution method is the Shapley value (Shapley et al., 1953), which is derived from cooperative game theory and is one of the most prominent model-agnostic methods in XAI. It ensures fair distribution of payoffs among players by quantifying their contribution to the overall outcome. However, the classical Shapley value and some attribution methods (Štrumbelj and Kononenko, 2014; Datta et al., 2016) assume variable independence and overlook interrelationships between variables, leading to potentially misleading explanations when variables are highly correlated. To address this, Aas et al. (2021) considered the correlation (rather than causation) between variables to explain individual predictions, which provides more accurate approximations of the Shapley value. More recently, research has focused on measuring contributions based on causation (Heskes et al., 2020), computing causal Shapley value based on causal chain graphs when only partial information is available. This method provides a theoretical foundation for our study.

To bridge existing research gaps, this study aims to estimate each variable's causal contribution to bus arrival delays, considering the causal relationships between variables to gain a comprehensive understanding of the mechanisms underlying bus delays. Unlike traditional correlation-based analysis, this study first focuses on inferring causal relationships between variables and then incorporates these relationships into the process of quantifying individual causal contributions. Specifically, the paper employs a causal discovery model to generate a causal graph for bus delays, which captures the causal relationships between variables. This method considers scenarios involving confounding variables (the main source of spurious correlations), which may lead to biased results in traditional correlation-based analyses. Subsequently, based on these causal relationships, the causality-based Shapley value method is utilized to quantify the causal contribution of each variable to bus arrival delays. The main contributions of this paper are:

- Propose a data-driven causal discovery method that systematically analyzes the underlying causal relationships influencing bus operation delays, considering confounding variables.
- Develop a framework that leverages the causal graph and causality-based Shapley value approach to quantify the causal contributions of each factor considering complex causal relationships, overcoming computational and statistical challenges.

- Conduct cross-validation by comparing the variable importance ranking to discuss the difference between traditional methods and the causality-based Shapley value method.

The paper is organized as follows: Section 2 presents the most relevant literature related to bus delay analysis, causal discovery methods, and attribution approaches. Section 3 outlines the research problem and the framework for quantifying each variable's contribution to bus arrival delays. Section 4 describes the data, generates the causal graph, estimates causal contributions, and conducts cross-validation. Section 5 discusses the findings and their practical implications for public transport systems. The final section summarizes the key findings, limitations, and future research directions.

2. Literature review

This section presents the most relevant literature in three areas: (1) Bus delay analysis, (2) Causal discovery methods, and (3) Shapley values-based models.

2.1. Bus delay analysis

Fewer studies have explicitly focused on factors that affect bus arrival delays. Zhang et al. (2024) analyzed the heterogeneous impact of these factors along the bus route. Their findings show that the significant factors impacting bus arrival delays are primarily associated with bus operations, such as delays at consecutive upstream stops, dwell time, scheduled travel time, recurrent congestion, and current traffic conditions. Wessel et al. (2017) pointed out that maintaining adequate headways between vehicles during peak hours is important for the efficient operation of the public transport service system. When operating on a road network shared with other vehicles, bus services often encounter various types of disruptions, which can be divided into regular (systematic) and non-regular (random). Systematic disruptions include daily problems such as traffic congestion (Nguyen-Phuoc et al., 2018; Kodupuganti and Pulugurtha, 2023) and infrastructure failures (Mishra et al., 2023), while random disruptions cover unpredictable factors such as disruptive events (Cebecauer et al., 2021) and weather conditions (Lian et al., 2023; Zhou et al., 2017). These disruptions not only affect the punctuality of buses, but may also have a negative impact on the overall operational efficiency. Research conducted by Park et al. (2020) shows that service delays can cause a cascade of downstream delays along a route when delayed buses are unable to stop at the remaining scheduled stops. Therefore, the delay at preceding stops is also a main factor. These delays can be exacerbated by other delay factors and can be mitigated if bus drivers are able to take advantage of these conditions to compensate for the delay.

To enhance the accuracy of bus arrival time predictions at various stops, researchers have considered numerous factors, including geographical location, the number of intersections, and levels of congestion (Achar et al., 2019; Čelan and Lep, 2020). Additional variables include the travel time that buses spend at each section (Dai et al., 2019; Büchel and Corman, 2022), the scheduled travel times (He et al., 2018), and the actual times taken to travel between preceding stops (Yu et al., 2018; Pang et al., 2018). As more types of data become available and research questions become more complex, researchers are turning to more complex models in the hope of achieving better predictions. These include advanced nonlinear models rooted in traditional machine learning (Huang et al., 2021; Liu et al., 2023a; Chen, 2018), deep learning techniques (Jin et al., 2022; Liu et al., 2023b), and hybrid approaches (Xie et al., 2021). While these models tend to surpass probabilistic and statistical ones in accuracy (Wepulanon et al., 2018), they also require more complex architectural frameworks and involve higher computational demands.

2.2. Causal discovery methods

A range of causal discovery methods have been designed to infer causal relationships from observational data. Generally, these algorithms fall into four categories based on their operational principles: constraint-based, score-based, functional causal model (FCM)-based, and hybrid models.

Constraint-based models perform Conditional Independence (CI) testing among variables to determine the presence of causal links. These models identify CI tests and seek a Directed Acyclic Graph (DAG) that encompasses these independencies, adhering to the d-separation criterion (Triantafillou and Tsamardinos, 2016). They utilize various CI tests, including the Conditional Distance Correlation (CDC) test (Wang et al., 2015), Momentary Conditional Independence (MCI) (Runge et al., 2019b), and others. Representative algorithms include the Peter-Clark (PC) (Spirtes et al., 2000) and Conservative PC (CPC) (Ramsey et al., 2012) algorithms.

Score-based models aim to identify the most suitable causal graph by exploring all possible DAGs and evaluating them using a scoring function. These functions, such as the Bayesian Information Criterion (BIC) (Neath and Cavanaugh, 2012), Akaike Information Criterion (AIC) (Akaike, 1998), balance model fit and complexity to avoid over-fitting and favor simpler causal graphs. After assessing the quality of potential causal graphs with the score function, score-based methods produce one or more causal graphs that attain the highest scores. A classic example is the Fast Greedy Equivalence Search (FGES) (Ramsey et al., 2017).

The FCM-based models define causal relationships in a functional form, expressing a variable as a function of its direct causes and some unmeasured noise (Zhang et al., 2015). FCM-based approaches can differentiate between various DAGs within the same equivalence class by applying additional assumptions about the data distributions and/or the types of functions used. An illustrative instance is the Linear Non-Gaussian Acyclic Model (LiNGAM) as described by Shimizu et al. (2006).

Hybrid models combine different types of causal discovery methods. For instance, they can integrate CI tests from constraint-based models with scoring functions from score-based models, creating a comprehensive strategy for inferring causal relationships. Example models include Greedy Fast Causal Inference (GFCI) (Ogarrio et al., 2016), Greedy Relations of Sparsest Permutation (GRaSP) (Lam et al., 2022), and Fast Adjacency Skewness (FASK) (Sanchez-Romero et al., 2018).

2.3. Shapley value-based models

The Shapley value (Shapley et al., 1953) is a concept from cooperative game theory. It offers a 'fair' distribution of total gains or payoffs produced by a coalition of players based on their respective contributions. However, the Shapley value assumes that the factors are independent and quantifies the marginal contribution of the factors. Aas et al. (2021) argue that marginal Shapley value may lead to misleading explanations and propose conditional Shapley value, an improved version of the Kernel SHAP method that efficiently approximates Shapley value in higher dimensions. It is particularly designed to address dependencies among variables. Additionally, Janzing et al. (2020) explored a causal interpretation of the Shapley value, where they shift from traditional conditioning by observations to conditioning by intervention, similar to Pearl's do-calculus (Pearl, 2012). Frye et al. (2020) introduced a less restrictive framework, Asymmetric Shapley values (ASVs), which are rigorously based on a set of axioms, applicable to any AI system, and flexible enough to incorporate any known causal structure within the data. Furthermore, Heskes et al. (2020) presents a causal Shapley approach that utilizes Pearl's do-calculus. This method, applicable to general causal graphs, maintains all desirable properties and allows for the separation of direct and indirect effects. This approach is particularly relevant to our research as it necessitates consideration of causal links within causal graphs.

Currently, in the transportation field, several explanation methods based on the Shapley value have been explored for practical implementation. For example, Gnecco et al. (2021) focuses on estimating the importance of transfer points in public transport networks using the Shapley value method, which incorporates network topology and user demands, and addresses the computational challenges through a Monte Carlo approximation. Li et al. (2024) developed a two-layer road data asset revenue allocation model using a modified Shapley value approach to fairly distribute revenue among data collectors, processors, and producers. This model considers both qualitative and quantitative contributions, using methods like entropy weighting and rough set theory to ensure equitable revenue distribution. Ji et al. (2022) employed XGBoost and SHAP to analyze the complex non-linear relationships and interaction effects among road network patterns, demographic, trip, and built environment characteristics on cycling distance. In autonomous vehicle areas, Li et al. (2023) proposed a maximum entropy base value to explain lane change decisions, aiming to explain AI decision-making processes and enhance public trust by providing intuitive and statistically analyzed explanations.

2.4. Summary and research gaps

The key research findings and gaps are summarized below.

(1) The factors affecting bus arrival delays can be broadly classified into three main categories: (1) Operational factors: scheduled travel time, dwell time, initial delays, preceding stop delays, preceding stop delays, etc. (2) Planning variables: number of signals, signal intersections, and bus reserved lanes, bus speed, route distance, number of stops, etc. (3) External variables: calendar, weather, mechanical issues, and disruptions events, etc. However, existing literature on bus arrival delays primarily uses correlation-based methods, with few studies employing causal analysis to explore the causal relationships between influencing factors and delays.

(2) Various causal discovery and inference models have developed to infer causal relationships and widen their applicability across disciplines. These models include constraint-based, score-based, FCM-based, and hybrid models, each employing distinct principles to infer causal relationships. Although they have succeeded in many fields (e.g., biology, medicine, meteorology, etc.), the exploration of cause graph discovery and its applications within public transport remains a relatively uncharted area.

(3) The Shapley value assumes independence among factors and quantifies the marginal contribution of each factor. Advanced Shapley value methods have been developed to consider the conditional contribution and causal links, which can better model complex factor interdependencies. Aligned with Pearl's do-calculus, these methods differentiate direct and indirect effects, enhancing the accuracy and applicability of quantifying the contribution of influence factors. Although some explanatory models have been used in transportation, existing research overlooks the intricate causal relationships among factors in public transport systems.

Therefore, this study aims to explore the factors that cause bus delays from a causal perspective, with a particular focus on quantifying and analyzing the causal contributions of each variable while considering the causal relationships among these variables.

3. Methodology

This section introduces the research problem and framework, the causality-based Shapley value model and estimation approach, as well as the data and variables used to quantify the factors' contribution to bus arrival delays. The notation used throughout the paper is shown in Table 1.

3.1. Research problem and framework

Understanding the difference between correlation and causation is essential for addressing our research question. These concepts address distinct aspects of physical phenomena. Correlation analysis, a data-driven statistical method, evaluates the strength and direction of a linear relationship between two variables. It is useful for initial analyses and detecting patterns in data, but it fails to uncover the underlying causes of observed phenomena. In contrast, causation delves deeper into the underlying mechanisms, aiding in distinguishing between direct and indirect causal effects. It can identify confounding factors and more precisely determine how various factors contribute to changes in complex systems. Causal discovery methods rely on mathematical principles and specific assumptions (e.g., causal faithfulness and sufficiency) to provide robust, practical causal insights. This is vital for implementing interventions and understanding the dependencies and mechanisms within complex real-world systems.

Table 1
Notation.

Notations	Explanation
$\mathbf{v}$	A set of variables $\mathbf{v} = \{v_1, \dots, v_n\}$
N	Number of variables (players in a cooperative game), $N = \{1, \dots, n\}$
S	A variable subset/coalition of N, $S \in N$
$\lvert N\rvert, \lvert S\rvert$	Number of the variables and numbers of the subset variables
y	Prediction output of a machine learning model
G	Causal graph
D	Dataset
ϕ_{v_i}	The causal contribution of variable v_i
ϕ_0	The baseline of the output
$do(x)$	The mathematically presentation of do–operator, shortly of $do(v_i = x)$
P	The distribution probability
$\mathbf{u}$	A set of unobserved (latent) variables $\mathbf{u} = \{u_1, \dots, u_k\}$
$pa(v_i)$	The parents (ancestors) of variable v_i (including unobserved parents)
$\mathbf{v}_S$	A subset variables, $\mathbf{v}_S \subseteq \mathbf{v}$
$\mathbf{v}_{\overline{S}}$	The complement set of $\mathbf{v}_S$, $\mathbf{v}_{\overline{S}} = \mathbf{v} \setminus \mathbf{v}_S$
$\mathbf{V}_S$	A subset variables indexed by $S = \{d_1, d_2, \dots, d_s\} \subseteq N$
ω	The inverse probability weight
$\mathbf{1}_A(x)$	The indicator function, if $x \in A$ $\mathbf{1}_A(x) = 1$, otherwise $\mathbf{1}_A(x) = 0$
θ	The outcome regression parameter
δ	The double machine learning estimation parameter
E^{dml}	The double machine learning estimator
M	The number of permutations
π_j	The j-th permutation of variables
$pre_{\pi_j}(i)$	The set of variables that precede the i-th variable in permutation π_j

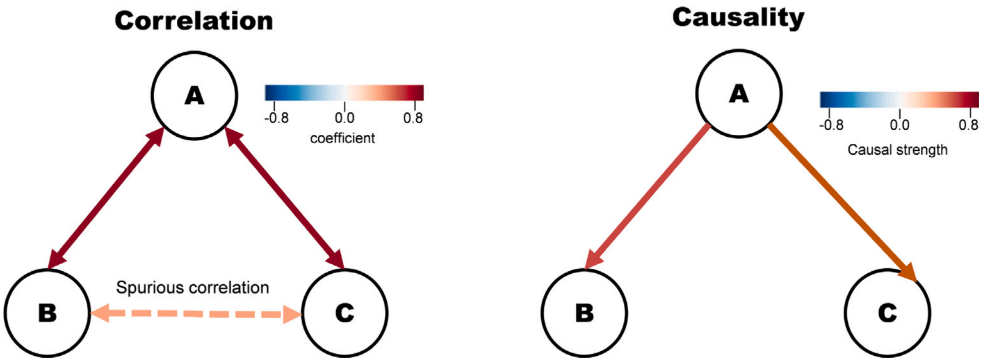

Fig. 1. Example applications of correlation-based and causality-based models for bus delay analysis (B- ->C means a spurious correlation between variables B and C).

Fig. 1 shows an example application of correlation-based and causality-based models in analyzing bus delays, using three variables A, B, and C. From a data-driven perspective, strong correlations among these variables are observed. However, causality-based models reveal only two causal links: $A \rightarrow B$ and $A \rightarrow C$, which explains the observed correlations between A and B, and between B and C. The correlation between B and C arises due to A acting as a confounding variable that influences both B and C, leading to a spurious correlation.

For example, traffic congestion might cause prolonged section travel times for both preceding and current bus trips. While data alone may show a positive correlation between these section travel times, it is misleading and does not imply a direct causal relationship. Thus, correlation does not imply causation, and relying solely on correlation-based analysis may lead to biased results. Therefore, a causality-based method capturing the confounding effect is a necessity for accurately analyzing and quantifying the real impact of operational factors on bus delays.

The research problem is defined as follows: Consider a set of variables $\mathbf{v} = \{v_1, v_2, \dots, v_n\}$ and a target variable, the bus arrival delay, denoted as y, along with a dataset D. Our research problem comprises two phases. The initial phase involves using a causal discovery model to infer causal relationships $\mathbf{R} = \{r_1, \dots, r_n\}$ between the variables. The subsequent phase quantifies the causal contribution of each variable v_i on bus arrival delays, based on the established causal relationships $\mathbf{R}$.

Specifically, utilizing a machine learning model, the bus arrival delays can be expressed as $y = f(\mathbf{v})$. To quantify each variable's causal contribution, we use an attribution method. It allocates a proportionate impact to each variable v_i, thereby elucidating the contribution of each variable to the overall output:

$$f(\mathbf{v}) = \phi_0 + \sum_{i=1}^{n} \phi_{v_i} \tag{1}$$

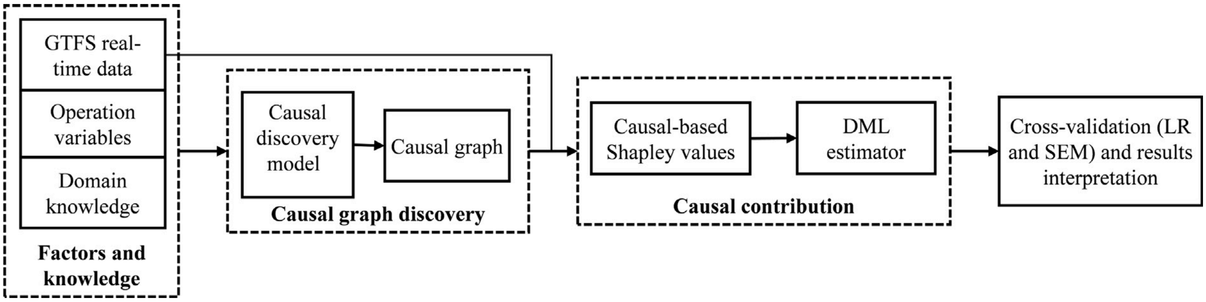

Fig. 2. The framework for quantifying each variable's causal contribution.

Fig. 3. Working process of the FGES.

where n is the number of variables, ϕ_{v_i} the contribution of variable v_i for the output on $\mathbf{v}$. ϕ_0 is the baseline (no variable) and presented by the average prediction $\phi_0 = \mathbb{E}[f(\mathbf{v})]$. However, the traditional Shapley value method does not consider the dependence between variables. Therefore, our task is to quantify the contribution of each variable v_i on the prediction/output $f(\mathbf{v})$, taking into account the causal links in $\mathbf{R}$.

Fig. 2 shows the framework for quantifying the causal contribution of each variable, comprising two main components: causal graph discovery and causal contribution. The procedure initiates with the preparation of input data, encompassing GTFS real-time data, operation variables, and domain knowledge (the general knowledge prevalent in public transport). Subsequently, this input data is processed through a causal discovery model to construct a causal graph. The causal relationships in the causal graph then serve as the input for estimating causal contributions using the causality-based Shapley value approach and Double Machine Learning (DML) estimator. The final step involves interpreting the results and performing cross-validation by comparing the variable's importance ranking with Linear Regression (LR) and Structural Equation Modeling (SEM).

3.2. Causal graph discovery

Various causal discovery methods are available, but selecting an appropriate model for our research problem (i.e., cause analysis of bus delays) poses a challenge. Zhang and Ma (2024) investigated various causal discovery methods to determine the most effective method for analyzing bus arrival delays. The findings indicate that incorporating domain knowledge significantly improves the accuracy of causal graphs, and the FGES model outperforms other models.

The FGES (Ramsey et al., 2017), a score-based model, is designed to discover the optimal causal graph by exploring all possible DAGs space. It uses a search algorithm to search through these spaces, evaluating potential graphs using a scoring function (e.g., BIC). Fig. 3 illustrates the working process of the FGES model. It starts with an empty graph. The process then unfolds in two stages: first, Forward Equivalence Search (FES) adds edges to improve the score until reaching a local maximum. Next, Backward Equivalence Search (BES) removes edges to further improve the score until the global maximum is reached.

This section aims to infer causal relationships $\mathbf{R}$, serving as input for subsequent analytical steps. FGES is selected for its accuracy, robustness, and computational efficiency (Ramsey et al., 2017). It rapidly updates potential edge scores using pre-computed values and leverages parallelization to significantly reduce processing time, making it highly suitable for large and complex datasets. Moreover, the scoring function balances model fit and complexity, preventing overfitting and ensuring that the identified causal relationships accurately reflect the underlying processes (Hasan et al., 2023).

3.3. Causality-based shapley value

This section introduces the concept of causality-based Shapley value, a method rooted in the Shapley value (Shapley et al., 1953), specifically designed for quantifying causal contributions. This approach leverages do-interventions (Pearl, 2009) to assess the impact of various factors within a causal framework. To address dependencies among these variables, it is more accurate to employ the conditional distribution of variables rather than the marginal distribution. Following the method described by Aas et al. (2021), the contribution function $g(S)$ for a certain subset $\mathbf{v}_S$ ($S \subseteq N$) can be measured by using the expected output of the predictive model $f(\mathbf{v})$, conditional on the variable of the subset $\mathbf{v} = \mathbf{v}_S$:

$$g(\mathbf{v}_S) = \mathbb{E}[f(\mathbf{v})|\mathbf{v} = \mathbf{v}_S] \tag{2}$$

The basic principle of our method is to simulate a randomized controlled trial (RCT). Based on the causal relationships between variables, we adjust the values of existing variables through 'interventions' and observe the changes before and after the intervention. Mathematical representations of such interventions on random variables are frequently represented using the do–operator (Pearl, 1995), that is, by applying $do(v_i = x)$ (shortly $do(x)$). Specifically, we adjust the value of variable v_i to a specific value x and assess its impact on the model's predictions, thereby isolating the causal contribution of v_i to the outcome. This operation facilitates the examination of the system's dynamics post-intervention, thereby obtaining the intervention distribution $P(\mathbf{v} = v \mid do(v))$, which is the probabilistic impact of the intervention on the system variables. Therefore, the conditional probabilities can be replaced by the intervention probabilities. Then the Eq. (2) can be became:

$$g(\mathbf{v}_S) = \mathbb{E}[f(\mathbf{v})|do(\mathbf{v}_S)] \tag{3}$$

Now, based on the function of Shapley values (Shapley et al., 1953), the causality-based Shapley values ϕ_{v_i} that quantify the causal contribution of variable v_i considering the causal relationships can be expressed as:

$$\phi_{v_i} = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\ (|N| - |S| - 1)!}{|N|!} (\mathbb{E}y|do(\mathbf{v}_{S,i}) - \mathbb{E}[y|do(\mathbf{v}_S)]) \tag{4}$$

To calculate the $\mathbb{E}[y|do(\mathbf{v}_S)]$, we should know the conditional probability of the variable set $\mathbf{v}_S$. In any causal model, there exists a relationship between its causal graph and the probability distribution P, which can be expressed as (Shpitser and Pearl, 2006):

$$P(v_1, \dots, v_n, u_1, \dots, u_k) = \prod_i P(v_i \mid pa(v_i)) \prod_j P(u_j) \tag{5}$$

where $v_1, \dots, v_n$ represent the observable variables in the set $\mathbf{v}$; $u_1, \dots, u_k$ are the unobserved (latent) variables in the set $\mathbf{u}$, and these latent variables are independent of each other; $pa(v_i)$ is the parent (ancestor) of variable v_i (including unobserved parents). Therefore, the $\mathbb{E}[y|do(\mathbf{v}_S)]$ can be present as:

$$\mathbb{E}[y|do(\mathbf{v}_S)] = \begin{cases} \sum_{\mathbf{v}_{\overline{S}}} \mathbb{E}[y|\mathbf{v}] \prod_{i \in \overline{S}} P(v_i \mid pa(v_i)) \prod_j P(u_j), & \text{if } u_j \in pa(v_i), \\ \sum_{\mathbf{v}_{\overline{S}}} \mathbb{E}[y|\mathbf{v}] \prod_{i \in \overline{S}} P(v_i \mid pa(v_i)), & \text{if } \mathbf{u} \cap pa(v_i) = \emptyset, \\ \sum_{\mathbf{v}_{\overline{S}}} \mathbb{E}[y|\mathbf{v}] \prod_{i \in \overline{S}} P(v_i), & \text{if } pa(v_i) = \emptyset. \end{cases} \tag{6}$$

where $\mathbf{v}_{\overline{S}} = \mathbf{v} \setminus \mathbf{v}_S$ is the complement set of $\mathbf{v}_S$. For the case $pa(v_i) = \emptyset$, it implies that the variable v_i has no parents in the causal graph, which typically means that v_i is independent of the other variables.

3.4. Estimation algorithm

To estimate the Eq. (6), we introduce the estimation algorithm in this section. Computing Shapley value, including the causality-based Shapley value, faces well-recognized computational challenges. Specifically, the time necessary to calculate every subset $S \subseteq N$ grows exponentially with the increase in the number of variables n (requiring $O(2^n)$ computations). In this study, the Double Machine Learning (DML) approach (Jung et al., 2022) is applied to estimate the causality-based Shapley value, which performs well in terms of consistency, computational efficiency, and statistical robustness. It combines two machine learning models, namely Inverse Probability Weighting (IPW) and Outcome Regression (REG), to reduce biases and improve the estimation accuracy. In this method, all variables are assumed to be discrete, which can be applied to observational datasets and enables the calculation of conditional probabilities. Algorithm 1 shows the systematic procedure for calculating the causality-based Shapley value using DML estimators.

The input of the algorithm is the number of permutations M, dataset D, and the causal graph G generated from FGES. It first initializes the causal contribution for all variables to 0, that is, $\hat{\phi}_{v_i} = 0$. The dataset D is divided into two parts, D_0 and D_1. The dataset splitting is used to guarantee statistical consistency. Then it use the DML estimator E^{dml} to estimate the value of Eq. (6) (lines 6–15 in Algorithm 1). The construction of the DML estimator contains three steps:

- **IPW estimation**. The IPW aims to simulate simple random sampling, thereby reducing the impact of sample selection bias on the results. The weight ω is the inverse probability of the variable being observed. It is used to adjust for the distribution of the observational data, making it closer to the expected distribution under a random intervention scenario $do(\mathbf{v}_S)$. Given an index set $\mathbf{V}_S$ indexed by $S = \{d_1, d_2, \dots, d_s\} \subseteq N$, the weight ω can be expressed as:

$$\omega = \begin{cases} \prod_{j=1}^{k} \frac{1_{v_{d_j}}(V_{d_j})}{P(V_{d_j}|pa(V_{d_j}))}, & \text{for } k = s, \dots, 1, \text{ if } \mathbf{u} \cap \mathbf{V}_S = \emptyset, \\ \frac{1_{\mathbf{v}_S}(\mathbf{V}_S)}{P(\mathbf{V}_S|\mathbf{V}_{\overline{S}})}, & \text{if } pa(v_i) = \emptyset \ \&\ i \in \overline{S}. \end{cases} \tag{7}$$

where $1_{v_{d_j}}(V_{d_j})$ is an indicator function that is equal to 1 when the variable $v_{d_j} = V_{d_j}$. Then, we can get $\mathbb{E}[y|do(\mathbf{v}_S)] = \mathbb{E}[y\omega]$.

- **REG estimation**. Given an index set $\mathbf{V}_S$ indexed by $S = \{d_1, d_2, \ldots, d_s\} \subseteq N$, the recursive process is initiated with $\theta_1^s = y$. For $k = s$ down to 1, the recursive calculation for the case $\mathbf{u} \cap \mathbf{V}_S = \emptyset$ and case $pa(v_i) = \emptyset$ & $i \in \overline{S}$ are :

$$\begin{cases} \theta_2^k = \mathbb{E}\left[\theta_1^k \mid V_{d_k}, pa(V_{d_k})\right] \\ \theta_1^{k-1} = \mathbb{E}\left[\theta_1^k \mid v_{d_k}, pa(V_{d_k})\right] \end{cases} \tag{8}$$

$$\begin{cases} \theta_b = \mathbb{E}[y \mid \mathbf{V}_S, \mathbf{V}_{\overline{S}}] \\ \theta_a = \mathbb{E}[y \mid \mathbf{v}_S, \mathbf{V}_{\overline{S}}] \end{cases} \tag{9}$$

Then, we can get $\mathbb{E}[y|do(\mathbf{v}_S)] = \mathbb{E}[\theta]$ where $\theta = \theta_1^0$ for the case $\mathbf{u} \cap \mathbf{V}_S = \emptyset$ and $\theta = \theta_a$ for the case $pa(v_i) = \emptyset$ & $i \in \overline{S}$.

- **DML estimation**. The DML estimation δ includes the estimation of IPW and REG, which is defined as:

$$\delta = \begin{cases} \theta_1^0 + \sum_{k=1}^{s} \omega\left(\theta_1^k - \theta_2^k\right), & \text{if } \mathbf{u} \cap \mathbf{V}_S = \emptyset, \\ \theta_a + \omega(\theta_a - \theta_b), & \text{if } pa(v_i) = \emptyset \ \& \ i \in \overline{S}. \end{cases} \tag{10}$$

Then, we can get $\mathbb{E}[y|do(\mathbf{v}_S)] = \mathbb{E}[\delta]$.

The DML estimator E^{dml} is the average of the estimated outcomes from both splits datasets:

$$E^{dml} = \frac{\mathbb{E}_{D_0}[\delta_1] + \mathbb{E}_{D_1}[\delta_0]}{2} \tag{11}$$

Finally, the causality-based Shapley value estimated by the DML estimator can be mathematically represented as:

$$\phi_{v_i} = \frac{1}{M} \sum_{j=1}^{M} \left(E^{dml}\left(\{v_i, pre_{\pi_j}(v_i)\}\right) - E^{dml}\left(pre_{\pi_j}(v_i)\right) \right), \tag{12}$$

where M is the number of permutations, E^{dml} denotes the estimated outcome from the DML estimator, π_j is the j-th permutation of variables, and $pre_{\pi_j}(i)$ is the set of variables that precede the i-th variable in permutation π_j.

Algorithm 1 Causality-based Shapley value estimation.

Input Number of permutations M, Dataset D, Causal graph G.
Output: Causal contribution $\{\hat{\phi}_{v_i}\}_{i=1}^{n}$.
Initialize $\hat{\phi}_{v_i} = 0$ for all $v_i \in \mathbf{v}$.
Split dataset D into D_0 and D_1.
Get the parent variable set $pa(v_i)$ based on causal graph G.
for $j = 1$ to M **do**
  Generate the random permutation π_j.
  for $i = 1$ to n **do**
    for $i == 1$ **do**
      $E^{dml}(pre_{\pi_j}(v_i)) = \bar{y}$
    end for
    Calculate $E^{dml}(\{v_i, pre_{\pi_j}(v_i)\})$
    $\hat{\phi}_{v_i} \leftarrow \hat{\phi}_{v_i} + E^{dml}(\{v_i, pre_{\pi_j}(v_i)\}) - E^{dml}(pre_{\pi_j}(v_i))$.
  end for
end for
$\hat{\phi}_{v_i} = \hat{\phi}_{v_i}/M$
return $\{\hat{\phi}_{v_i}\}_{i=1}^{n}$.

3.5. Data and variable

This study focuses on operational variables and measures their causal contributions to bus arrival delays. Operational variables are selected by reviewing existing literature, including preceding stop delays, dwell time, scheduled travel time, and knock-on delays, which significantly influence bus arrival delays (Zhang et al., 2024; Rodriguez-Deniz and Villani, 2022; Yu et al., 2017; He et al., 2020). The bus operational data was collected from Trafiklab (https://www.trafiklab.se/), which offers open access to transit data. This data includes real-time vehicle location updates to inform arrival times. Our analysis specifically leveraged these real-time GTFS updates, focusing on trip information that describes the actual arrival and departure times at each stop. These real-time insights provide a historical record of bus timeliness, pinpointing variations from the planned schedule down to the second. This data is refreshed periodically at predetermined intervals, producing the most current snapshot of bus timing, reflecting any service delays during its operation.

Table 2 shows the list of operational variables studied, with detailed descriptions. The response variable is the current bus arrival delays, while the explanatory variables are various operational variables. Origin delay quantifies the effect of initial delays at the start of the route and explores its potential to affect subsequent stops. Moreover, previous bus delay (knock-on delay) examines the subsequent impact that delays of the preceding bus might have on the arrival time of the next bus, thereby exploring the cascading effects of delays through the bus network.

Table 2
Description of variables.

Variables	Notation	Description
Response variable		
Arrival delays	$d_{i,j}$	The arrival delay of bus j at stop i is the difference between the actual arrival time $t^a_{i,j}$ and the scheduled arrival time $t^s_{i,j}$.
Exploratory Variables		
Dwell time	$dw^a_{i-1,j}$	The actual dwell time at the preceding stop $i-1$ is the difference between the actual departure time $t^d_{i-1,j}$ and the actual arrival time $t^a_{i-1,j}$ of bus j.
Preceding section travel time	$r^a_{i-1,j}$	The actual running time between stop $i-2$ and $i-1$ is calculated as the difference between the actual arrival time $t^a_{i-1,j}$ at stop $i-1$ and the actual departure time $t^d_{i-2,j}$ at stop $i-2$. This measurement seeks to identify subtle variations from earlier segments, capturing changes driven by underlying factors such as driver behavior, which affect both the previous and current sections.
Scheduled travel time	$r^s_{i-1,j}$	The scheduled running time between stop $i-1$ and stop i is the difference between the scheduled arrival time $\hat{t}^a_{i,j}$ at stop i and the scheduled departure time $\hat{t}^d_{i-1,j}$ at stop $i-1$.
Preceding stop delay	$d_{i-1,j}$	The actual arrival delay of bus j at stop $i-1$ is the difference between the actual arrival time $t^a_{i-1,j}$ and the scheduled arrival time $t^s_{i-1,j}$ at stop $i-1$.
Previous bus delay (Knock-on delay)	$d_{i,j-1}$	The previous bus delay is the actual arrival delay of the preceding bus $j-1$ before bus j at stop i. It is the difference between the actual arrival time $t^a_{i,j-1}$ and the scheduled arrival time $t^s_{i,j-1}$ of bus $j-1$ at stop i.
Previous bus travel time	$r^a_{i,j-1}$	The previous bus travel time is the actual running time of the preceding bus $j-1$ between stops $i-1$ and i. This serves as an indicator of the current traffic conditions.
Recurrent delays	$d^r_{i,j}$	Recurrent delays are trip-based, representing the mean historical travel time of previous buses between stops $i-1$ and i on the same trip and the same day of the week. This measure captures the recurring bus delays observed at the current stop for the same trip, providing an indicator of regular congestion during rush hours.
Origin delay (Initial delay)	$d_{1,j}$	Origin delay refers to the actual arrival delay of bus j at the first stop.
Scheduled headway	$\hat{h}^s_{i,j}$	The scheduled headway is the planned time interval between the arrival times of two consecutive buses $j-1$ and j at stop i.
Section length	l_i	The distance between stop $i-1$ and i.

Note: The unit of section length is meters, while the units for other variables are in seconds.

4. Case study

4.1. Data preparation

We select the trunk line network in Stockholm as our case study. Fig. 4 shows the four main bus lines integral to Stockholm's inner-city public transport system. These four routes, encompassing over 200 stops and spanning 80 kilometers, form the backbone of Stockholm's inner-city bus network. These routes have high-frequency services (within 15 min), designated lanes on main streets, traffic signal priority, and real-time information displays at all stops. Each route includes two to four public transport transfer stops. The bus typology on these lines includes both standard and articulated buses, which are common on routes navigating congested urban segments during rush hours. Collectively, these lines account for 60% of the area's total ridership, serving approximately 120,000 boarding passengers daily from 7:00 AM to 7:00 PM (Cats and Loutos, 2016). These routes exemplify typical busy urban public transport patterns and provide a substantial data sample for analyzing the causal effects of operational factors on bus delays. For this analysis, data related to bus arrival delays were collected for May 2022, specifically during the service operational hours from 6:00 to 22:00.

However, to quantify the causal contribution of each variable, the model assumes that all variables are discrete. Therefore, we need to discretize the continuous data. This study applied the equal-width discretization method to discretize continuous data, and the width of each bin is 10. This approach balances preserving insights with ensuring estimation quality. Theoretically, smaller intervals could provide more precise data. However, excessively small intervals can lead to conditional probabilities of 0 for many variables, resulting in numerous zero estimation results, which is inconsistent with reality. Based on the data characteristics, the interval of 10 offered the best balance.

4.2. Causal graph on bus delays

Incorporating domain knowledge enhances causal discovery models and corrects the inaccuracies in causal inferences derived from purely data-driven approaches (Teshima and Sugiyama, 2021). It can generate more accurate and logical causal graphs, thereby improving the model's reliability and interpretability. Therefore, we incorporate domain knowledge by organizing the variables into different tiers. In this hierarchy, causal relationships can only be directed from higher to lower tiers, and higher tier variables are not affected by lower tier variables. The tiers are structured as follows:

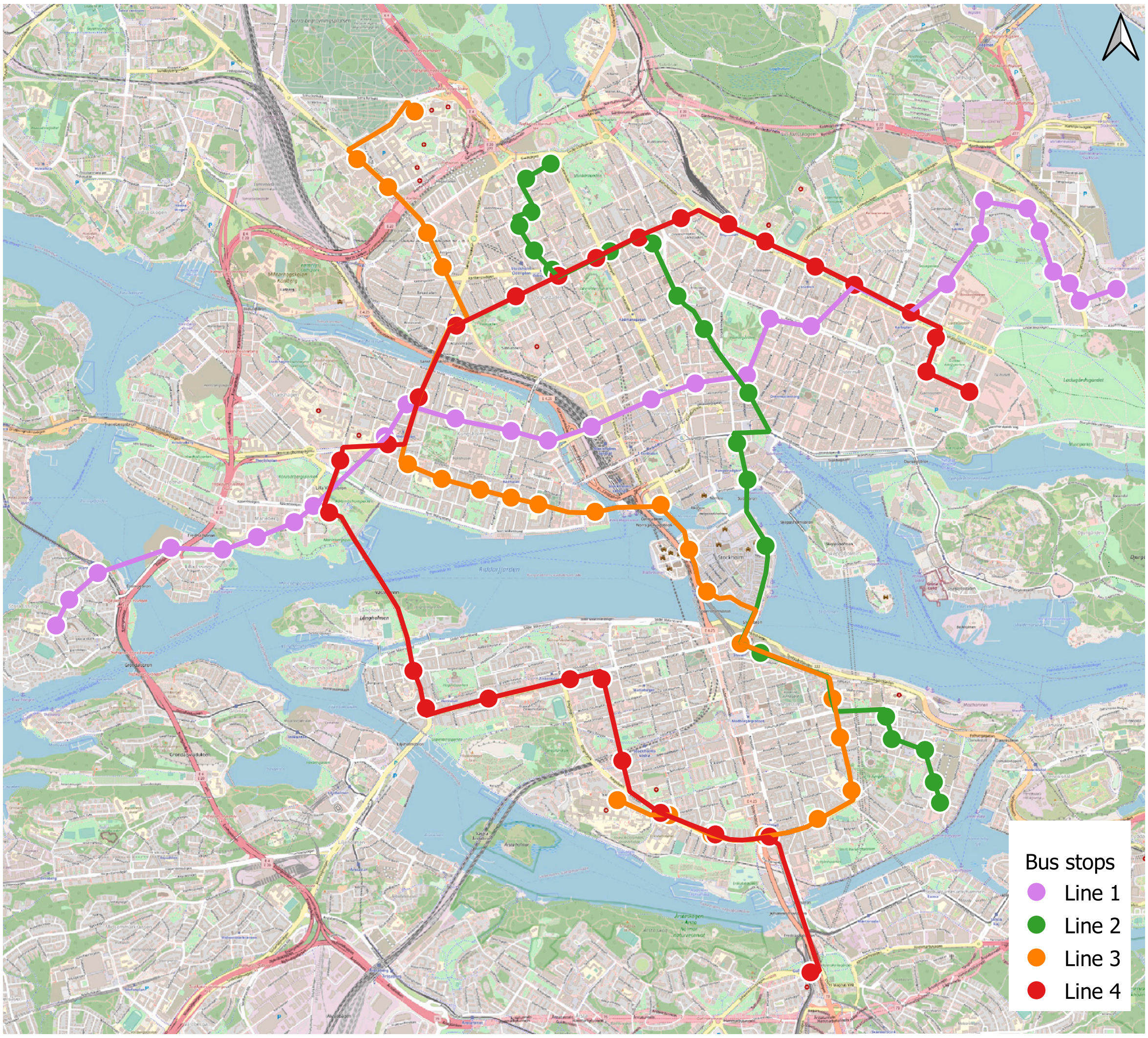

Fig. 4. The inner-city bus line routes, Stockholm.
Source: OpenStreetMap

- *Tier 1:* Section length;
- *Tier 2:* Scheduled travel time, Scheduled headway, Recurrent delay;
- *Tier 3:* Previous bus travel time, Previous bus delay;
- *Tier 4:* Origin delay, Preceding section travel time;
- *Tier 5:* Dwell time, Preceding stop delay;
- *Tier 6:* Arrival delay;

In this study, we structured the tiers of variables based on the inherent spatiotemporal sequence of events in the public transport system and common sense. For instance, tier 1 variables (Section Length) are fixed and unaffected by other factors. This structure requires minimal effort to define the above tiers, avoiding the imposition of excessive prior knowledge on the model and saving modeling efforts (even for non-professionals). For example, tier 2 variables (Scheduled Travel Time, Scheduled Headway, and Recurrent Delay) are determined by route demand or historical bus service performance; thus, they are not influenced by variables in tiers 3 to 6. Variables in tier 3 (Previous Bus Travel Time and Previous Bus Delay) occur earlier than those in tiers 4, 5, and 6. It should be noted that this tiered structuring reflects general domain knowledge prevalent in the public transport field.

The causal graph was generated using the py-tetrad library (Ramsey and Andrews, 2023), which is known for its robust causal discovery algorithms. To quantify the causal effects, SEM was employed, facilitated by the 'semopy' Python library (Igolkina and Meshcheryakov, 2020). Fig. 5 illustrates the causal graph produced by the FGES algorithm after incorporating domain knowledge. The edges represent causal relationships, with the arrowhead pointing to the effect and the tail indicating the cause. The red arrows

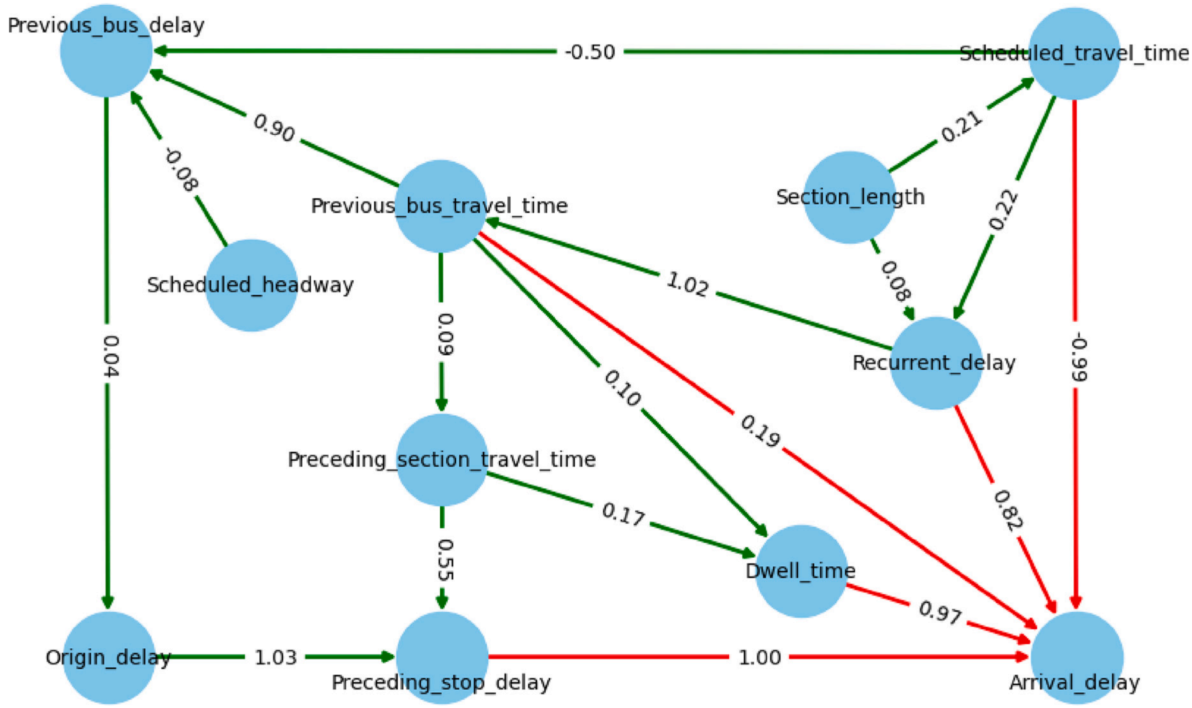

Fig. 5. Causal graph generated from FGES model with domain knowledge.

represent the direct causal effects on bus arrival delays, while the green ones indicate the indirect causal relationships. The values on the edges represent the causal coefficients, which measure the influence between interconnected variables. Specifically, an edge $v_i \rightarrow v_j$ with a coefficient α indicates that a one-unit increase in v_i is associated with an α-unit change in v_j.

The causal graph reveals significant direct causal effects on bus arrival delays from preceding stop delay (1.00), dwell time (0.97), and recurrent delay (0.82). A significant negative direct causal effect is observed from scheduled travel time on both current and previous bus arrival delays, with coefficients of −0.99 and −0.5, respectively. Additionally, origin delay, knock-on delay, and preceding section travel time do not directly influence bus arrival delays; instead, they affect preceding stop delays, which indirectly impact arrival delays. The causal pathway '$Origin\ delay \rightarrow Preceding\ stop\ delay \rightarrow Arrival\ delay$' suggests that early stop delays can propagate downstream, a phenomenon supported by previous research (Park et al., 2020).

Moreover, the causal graph illustrates the complex interrelationships between the variables, providing insight into the dynamics of the system. For example, the previous bus travel time has a notable positive direct causal effect on both the previous bus delay and current bus delays, implying that traffic conditions affecting previous buses can impact subsequent bus service. It is also observed that there is a significant positive causal coefficient of 1.02 between recurrent delays and previous bus travel time. Meanwhile, the graph reveals minor direct causal effects between some variables, with path coefficients ranging from 0.1 to −0.1; for example, scheduled headway slightly influences previous bus delays. This suggests that more significant impacts might arise from factors not included in this study, and further in-depth research is needed to fully understand these causal relationships.

4.3. Causal contribution on bus arrival delay

Based on the causal structure obtained from the FGES model, we quantified each variable's causal contribution to bus arrival delays. Fig. 6 shows a boxplot of the causality-based Shapley value, which offers the causal contribution of each variable to bus arrival delays. In our experiments, we randomly selected 100 samples with the number of permutations set to $M = 30$. The dataset was randomly split into 50% and 50% sub-datasets for estimation. We utilized the XGBoost model (Chen and Guestrin, 2016), which was trained over 20 rounds. To enhance comprehension and analysis, we normalized the original results of each sample, ensuring the sum of all variable contributions equals 1. For each sample, the normalization of each variable v_i is calculated as follows:

$$\phi'_{v_i} = \frac{\phi_{v_i}}{\sum_{i=1}^{n} \phi_{v_i}} \tag{13}$$

This normalization clearly illustrates the magnitude of each variable's contribution to a one-unit increase or decrease in bus delay.

In Fig. 6, each color represents a variable and the values represent the magnitude of each variable's causal contribution for each sample. The sign of these values indicates the increase or decrease of the prediction values after adding the variable, which

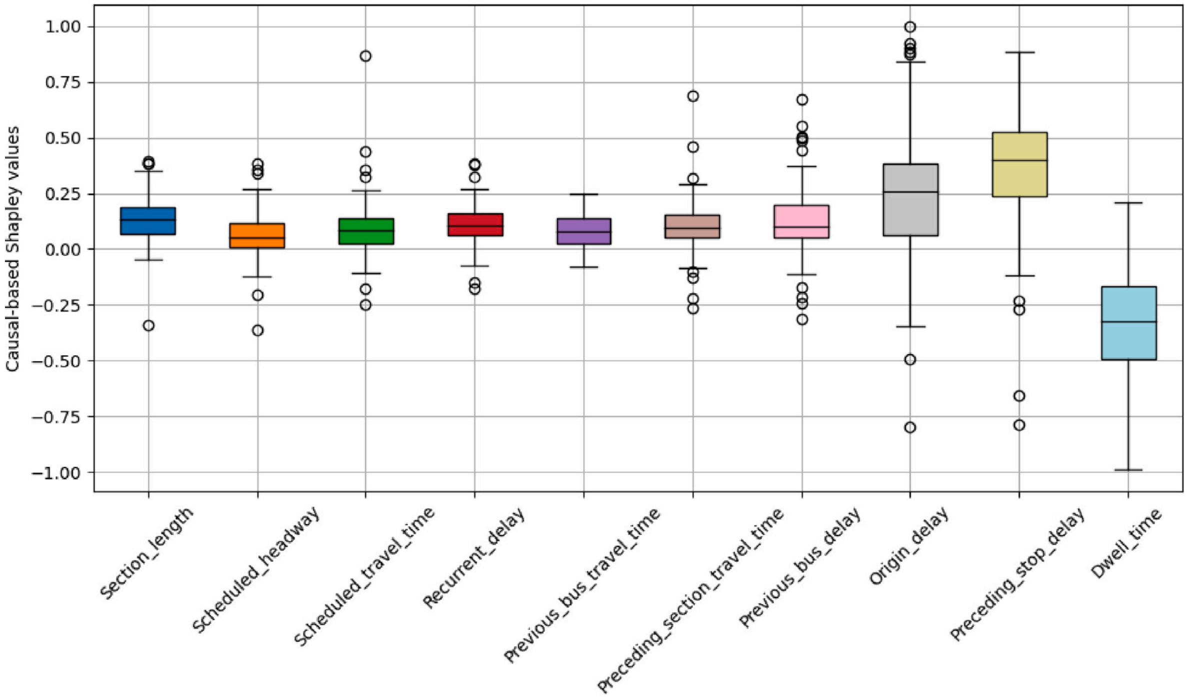

Fig. 6. Causality-based Shapley value.

is determined by the difference between the predefined initial bus delays (i.e., average value $\bar{y}$ shows in Alg. 1) and the actual bus delay y.

The results illustrate that 'Preceding Stop Delay' and 'Dwell Time' have high absolute median Shapley values of 0.4 and 0.32, respectively, proving their significant impact on bus arrival delays. The observation aligns with previous studies (Glick and Figliozzi, 2017; Park et al., 2020), which found that delays at the preceding stop and dwell times significantly contribute to subsequent delays due to their propagation effects. Interestingly, while lacking a direct causal link, origin delay has a median value of 0.26, indicating its significant contribution. This effect may be attributed to the cascading nature of delays, where the origin delay acts as the source of subsequent delays. Additionally, the average contributions of 'Previous Bus Delay' and 'Section Length' are 0.13 and 0.12, respectively, indicating relatively smaller impacts. In terms of numerical distribution, their contribution to bus delays is relatively concentrated but not very significant.

4.4. Cross-validation

This section conducts cross-validation to compare the differences in variable importance rankings and magnitudes between traditional methods (i.e., LR and SEM) and the causality-based method. LR is a statistical model that estimates the linear relationship between a dependent variable and one or more independent variables, without considering the interdependence among the independent variables. SEM is an extensive statistical methodology for hypothesis testing involving observed and latent variables. It combines multiple regression models, factor analysis, and path analysis, taking into account both direct and indirect effects, as well as the interrelationships between variables.

To compare these three approaches, we assess each variable's importance ranking to current bus arrival delay on a uniform scale. Standardized coefficients are utilized in both LR and SEM to measure the relative importance and impact of independent variables on the outcomes (Lleras, 2005). For SEM, the causal effect includes both indirect effects (e.g., $Origin\ delay \rightarrow Preceding\ stop\ delay \rightarrow Arrival\ delay$) and direct effects (e.g., $Preceding\ stop\ delay \rightarrow Arrival\ delay$). The overall importance of each variable is represented by the total effect, which is the sum of the direct and indirect effects. We implemented this analysis using the 'lavaan' R package (Rosseel, 2012) in R-Studio. Figs. 7 and 8 show the variable importance rankings (expressed in absolute values) for LR and SEM, respectively. In our analysis, all coefficients in LR and SEM are statistically significant, with p-values equal to 0.05. In Fig. 7, the coefficients of some variables (e.g., section length, previous bus delay, scheduled headway, and origin delay) are quite close to but not equal to 0 (less than 0.01), indicating a weak linear relationship. This suggests that while there is a statistically significant relationship, it has minimal or negligible impact.

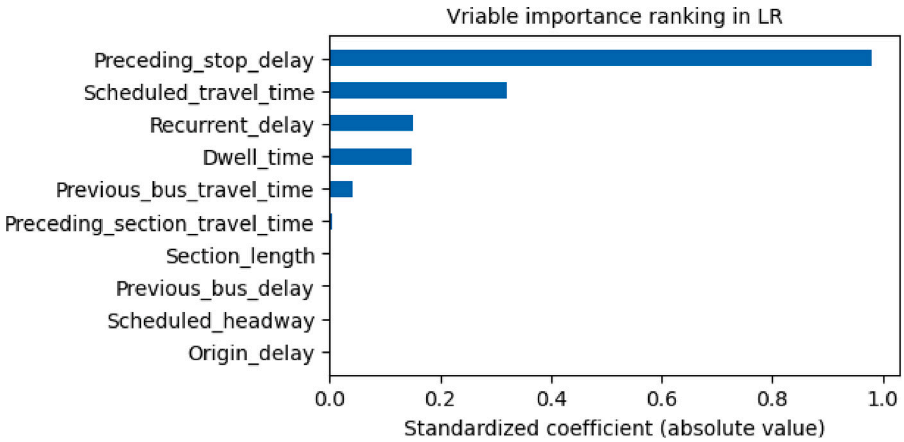

Fig. 7. Importance of variable in LR.

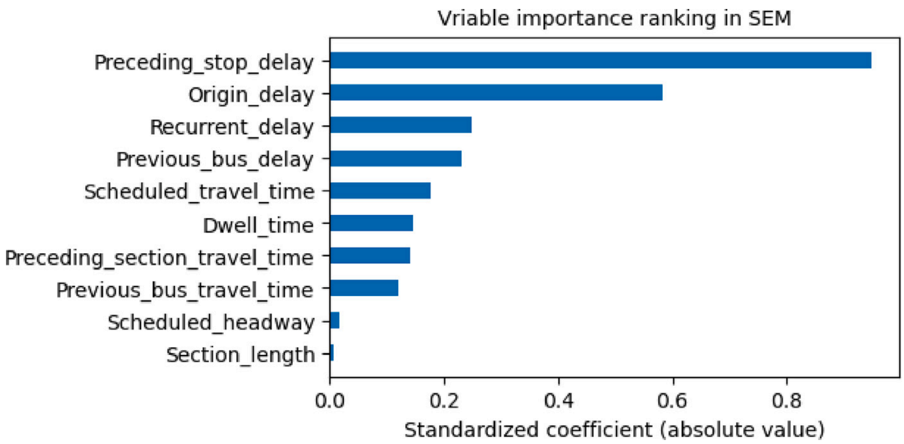

Fig. 8. Importance of variables in SEM model.

The causality-based Shapley value measures variable importance based on the total effect of variables. We employ the method described by Molnar (2020) to calculate the importance of the variables, where the importance of ith variable is defined as follows:

$$I_i = \frac{1}{|D_s|} \sum_{v_i \in D_s} |\phi_i| \tag{14}$$

where $D_s \in D$ is a subset of samples, $|D_s|$ is the number of samples selected. Fig. 9 shows the variable's importance in causality-based Shapley value.

The comparison presents significant differences in the variable importance rankings and impact magnitudes across these three models. In terms of importance ranking, all three methods consistently identify the variable 'Preceding stop delay' as the most significant influence on bus arrival delays. However, the importance ranking of origin delay differs across the three methods. It ranks second in both SEM and the causality-based Shapley value method but ranks last in LR. This discrepancy is because LR focuses on linear correlations between two variables, which cannot uncover pathways of influence. This also highlights that strong causation does not imply high correlation. Notably, starting from the third place, the importance ranking of variables in the three methods shows significant differences. For example, dwell time is ranked as the third most important factor in the causality-based Shapley analysis but is less prominent in SEM and LR. Additionally, the knock-on delay, attributed to the delay from the previous bus, is relatively important in causality-based Shapley value method and SEM but is almost negligible in LR. Moreover, section length is considered moderately important in our method but is ignored in LR and SEM. The difference may be because our method can capture not only marginal effects and interactions between variables but also the direct and indirect effects from pathways of influence, which may be overlooked by the linear assumptions and limited interaction modeling in LR and SEM.

From the perspective of the influence magnitude, the causality-based Shapley analysis is distinct from the other two methods. In LR and SEM, the importance magnitudes vary significantly, with clearly dominant variables (e.g., 'Previous stop delay' in LR, and 'Previous stop delay' and 'Origin delay' in SEM). In our method, no single variable exhibits absolute dominance (all values are less than 0.5). This difference arises because the causality-based Shapley value approach assigns importance by evaluating and ranking

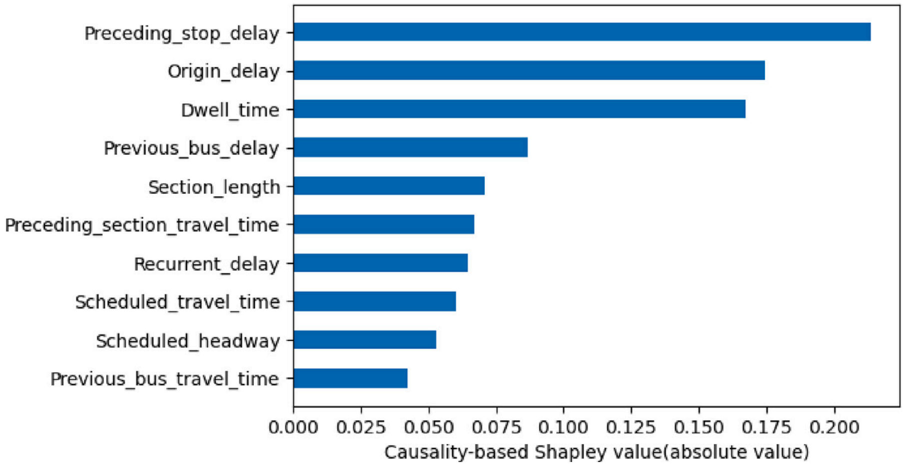

Fig. 9. Importance of variable in causality-based Shapley.

the contribution of each variable based on the causation, with a total sum of 1. In contrast, both LR and SEM derive importance based on correlations between variables, and although SEM considers the interrelationships between variables, it fundamentally measures correlation coefficients rather than causal effects.

5. Discussion

In real-world scenarios, determining why an event occurred often involves identifying causes and distinguishing between significant and negligible effects. Similarly, to understand why a specific outcome occurred, we must evaluate the importance and impact of each contributing factor. This understanding is crucial for managing the complexity of real-world systems. Moreover, we recognize that deciphering how complex systems function requires exploring the cause–effect relationships between their components.

To investigate the factors contributing to bus operation delays, this study developed a framework that utilizes the causality-based Shapley value to quantify the causal contribution of each variable, and the DML estimator to estimate these causal contributions. This method is distinctive as it captures the causal relationships among variables, obtaining the individual contributions of each—a facet not explored in previous research. The empirical analysis utilizes GTFS data collected from high-frequency bus routes in Stockholm, Sweden. Our results suggest that the various factors contributing to bus delays have complex causal effects, particularly the importance of previous stop delay and dwell time, which aligns with findings from previous studies (Zhang et al., 2024; Meng and Qu, 2013; Park et al., 2020). Additionally, the paper conducts cross-validation by comparing the variable importance derived from the causality-based Shapley value with those obtained from LR and SEM. The results show significant differences in terms of importance rankings and influence magnitudes. Our analysis highlights the important impact of origin delays starting from the route, which is often overlooked in previous studies. The in-depth causality-based analysis is not only of significant academic value but also crucial for uncovering the complex mechanisms underlying the operation of real-world transportation systems.

The causal graph generated in this study provides actionable insights into the complexity of bus delays, enhancing the interpretability of modeling results. It empirically highlights the direct causal relationships between operational factors such as previous stop delay, dwell time, and recurrent delay with bus arrival delays, advocating for targeted intervention measures. For example, significant positive relationships with bus delays suggest optimizing boarding and alighting processes through faster payment methods and efficient stop management. Conversely, scheduled travel time has a negative causal relationship with delays, indicating a mitigating effect. Additionally, the causal graph provides a more comprehensive view than traditional correlation-based methods by revealing pathways of influence that elucidate how various factors intricately affect bus delays. For example, the pathway '$Origin\ delay \rightarrow Preceding\ stop\ delay \rightarrow Arrival\ delay$' highlights the propagation of cascading delays in public transport systems, and strategies like dynamic interlining (Zahedi et al., 2023) could be implemented to reduce these cascading delays.

The causal contribution highlights that 'Preceding stop delay' and 'Dwell time' are significant factors influencing bus arrival delays. This is consistent with the findings of previous research, which indicated that delays at earlier stops have a significant impact on subsequent delays due to propagation effects (Park et al., 2020). Interestingly, 'Origin delay,' despite lacking a direct causal link, is identified as a substantial impact (contributing approximately 16% to the current arrival delay). Due to the propagation of delays along the bus route, delays at the origin station have a positive impact on arrival delays at downstream stations. Similar findings have been reported in previous research (Schmöcker et al., 2016). Conversely, 'Previous bus delay' demonstrates a smaller impact (contributing approximately 6% to the current arrival delay), which is different from a previous study. Rodriguez-Deniz and Villani (2022) mainly focused on using delays at upstream stops and previous bus delays to predict current delays. This finding can assist transit agencies in developing more targeted strategies, such as focusing on addressing origin delay issues rather than prioritizing the resolution of delays from preceding buses, which may not be easy to control in mixed traffic environments.

Moreover, the factors of ‘Section length’ and ‘Recurrent delay’ have a mild influence, with each factor contributing about 8% to the current delays. From the causal graph, the section length has a causal effect on scheduled travel time and then has an indirect causal effect on arrival delays. Few studies have focused on the impact of section length on bus delays. In the inner city, longer section length implies longer travel times, and due to factors such as traffic congestion, intersections, and traffic lights, they may face more unpredictable delays due to changes in traffic conditions. Unlike traffic conditions, recurrent delay reflects inherent factors that influence traffic flow and conditions at specific times of the day, such as frequent congestion during morning and afternoon peak hours on the same day of the week. The factor of ‘Recurrent delay’ has been introduced in previous research (Ma et al., 2015), which confirms a significant positive correlation between recurrent delay and current arrival delays. Other factors, such as ‘scheduled headway,’ ‘scheduled travel time,’ and ”previous bus travel time,’ have a minimal impact on bus delays, being almost negligible (with each factor contributing less than 5%). However, one interesting point is that scheduled travel time and current delay have a very strong causal effect (with a coefficient of −0.99). This is because the causal effect calculated in the causal graph is based on the SEM, which relies on correlations in the data and may not accurately reflect the true causal contributions.

Based on causality-based Shapley values, we recommend some practical traffic management strategies to reduce bus delays. Transit operators and managers should focus on addressing factors that significantly contribute to bus delays, such as preceding stop delays, dwell time, and origin delays, which collectively account for approximately 60% of total bus delays. To address delays at the preceding stop, some mitigation measures can be implemented, such as dynamic scheduling and dispatching (D’Ariano and Pranzo, 2009). For example, adjusting bus schedules in real-time based on current traffic conditions and delays can help buses stay on track. During peak hours or in congested areas, additional backup vehicles can be dispatched or vehicle routes can be adjusted. Additionally, traffic signal priority (Seredynski et al., 2019) can be applied, giving buses priority at key intersections, and reducing their waiting time at traffic lights. To address the factor of ‘Dwell time,’ several measures can be implemented to shorten dwell time and reduce its impact on delays. These measures include optimizing the ticketing system, streamlining the boarding process, implementing all-door boarding, and providing passengers with real-time traffic information so they can board more quickly. Additionally, allocating more time at busy stops can also mitigate the impact of ‘Dwell time’ on delays.

For the factor of ‘Origin delay,’ strategies can be implemented to reduce its impact, including effective scheduling, resource allocation, comprehensive pre-departure inspections, and regular maintenance to ensure that buses depart from the origin stop on time. For cascading delays, the literature suggests alleviating traffic constraints, adopting a modular operation approach, and dynamic interlining to prevent cascading delays (Zahedi et al., 2023). Furthermore, the knock-on delay may cause bus bunching, which may contribute to or exacerbate traffic congestion. This can be mitigated by adjusting bus frequencies dynamically, establishing bus-only routes, implementing dynamic holding, and providing driver guidance (He et al., 2019; Argote-Cabanero et al., 2015). In addition, studies have shown that locating bus stops downstream rather than upstream of adjacent signalized intersections can usually shorten bus delays (Gu et al., 2014). It should be noted that to maximize the punctuality and reliability of bus services, the implementation of the above strategies may need to target specific stations, periods, areas, or events.

It is important to note that the comparison with traditional common practice methods is not intended to demonstrate the superiority of causality-based analysis. Rather, this comparison aims to illustrate how each method performs in addressing our research problem and the considerations involved in choosing an appropriate method for specific research needs. LR is suited for binary or categorical outcomes and is commonly employed to predict event probabilities. SEM is ideal for analyzing complex relationships involving multiple interrelated variables and latent constructs, often used to test predefined hypotheses. Causality-based models, without prior assumptions, are suitable for uncovering causal structures and exploring causal interactions within complex systems. More importantly, their unique ability to simulate interventions and explore “what if” scenarios (as demonstrated in this study) is crucial for decision-making and policy-making. Therefore, given the nature of our research problem, causality-based analysis is more suitable (a more detailed explanation can be found in Section 3.1), and the results are more convincing.

Regarding validating our results, this is indeed a common challenge across various fields, such as meteorology and earth system science, where a definitive ground truth causal graph is often unavailable (Runge et al., 2019a). Thus, while our findings cannot be conclusively validated against a known truth, we aim to introduce a new analytical perspective and method, thereby providing a broader range of analytical tools and insights for researchers. Mathematically, as discussed in Section 3.1, it shows the necessity of controlling confounding factors in the delay analysis, which indicates the mathematically sound results of causality-based methods compared to the commonly used correlation-based ones in practice.

6. Conclusion

In this paper, we introduce a causality-based method to analyze the factors that cause bus delays and develop a causality-based Shapley value approach to quantify the causal contribution of each factor, considering the causal relationships among them. The DML estimator is applied to estimate these causal contributions, addressing the challenges of computational complexity and statistical bias. We conduct experiments on real-world bus delay data to generate the causal structure and calculate the causal contributions. The causal graph reveals a complex set of causal relationships that lead to bus delays (including both direct and indirect relationships) and interactions between factors, reflecting how various factors intricately affect bus delays. The results from the causality-based Shapley value analysis not only highlight the importance of generally significant factors like ‘Preceding Stop Delay’ and ‘Dwell Time,’ but also emphasize the importance of ‘Origin Delay,’ which is often underestimated in previous studies. This approach helps to address questions such as “*What are the important aspects to address?*” Cross-validation with conventional methods (e.g., LR, SEM) shows significant differences in terms of variable importance rankings and influence magnitudes, underscoring the importance of choosing an appropriate method for specific research questions.

This study represents promising progress in providing clear and intuitive explanations for the complexity of analyzing bus delays, aligning well with natural human understanding and expectations. It has the potential to improve current analytical methods by clearly describing the direct and indirect effects of operational factors on bus delays. Furthermore, these causality-based analytical methods, which align with human intuition, can significantly enhance confidence in advanced algorithms deployed to optimize and improve public transport systems.

The study explores the causal discovery and causal contribution quantification for public transport operation delays. However, the absence of the ground truth causal graph in public transport makes it difficult to validate our findings and real causality empirically. Also, the computational complexity of the Shapley value method poses challenges for a comprehensive bus delay analysis, particularly when scaling to larger datasets or more factors/causality edges. Future work could focus on verifying the accuracy and effectiveness of these preliminary findings through additional testing, such as laboratory experiments or A/B tests in real-world settings. Additionally, enhancing the computational efficiency of causal-based Shapley value is critical for comprehensive and targeted improvement strategies.

CRediT authorship contribution statement

Qi Zhang: Writing – original draft, Visualization, Software, Methodology, Conceptualization. **Zhenliang Ma:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Yuanyuan Wu:** Methodology, Data curation. **Yang Liu:** Methodology, Data curation. **Xiaobo Qu:** Writing – review & editing, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT to improve the readability and language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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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Data availability

Data will be made available on request.

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